Finanziato dall'Unione europea NextGenerationEU
Ministero dell'Università e della Ricerca
Italiadomani
UNIVERSITÀ DI SIENA 1240

Percorso dottorale sviluppato con il sostegno finanziario di NextGenerationEU: Missione 4, Componente 2, Investimento 3.3, CUP B63C22000950008 Borsa MUR ex DM 35/2022

Doctoral Programme of the Tuscan Universities

**Ph.D. in Economics**

XXXVIII° Cycle

Coordinator: Prof. Simone D'Alessandro

# Three Essays on Energy Transition: Challenges, Impacts and Policies Perspectives

Scientific Sector: ECON-01/A

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Firmato digitalmente da: EDOARDO ALBERTI

Academic Year of the fulfilment of the title PhD in Economics
2025/2026

University of Siena
PhD in Economics of the Tuscan Universities
XXXVIII° Cycle

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07.07.2026

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# Acknowledgments

To my mother and father, who are my pillars, even when everything around me seems to shake.

To my fellow PhD colleagues, with whom I shared joyful moments, challenges, and the struggles that come with doing research.

To my friends, for their support, joy, and deep affection.

To Agata, my wonderful partner, whom fate allowed me to meet precisely thanks to this PhD journey.

And to myself, because I never gave up, not even for a second. With humility and patience, I rolled up my sleeves and immersed myself in this world, driven by its greatest and strongest engine: curiosity.

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# Introduction to the Thesis

This thesis has been developed within the broader doctoral research topic of the economic impacts of the energy transition. The underlying premise is that the energy transition cannot be understood merely as a technological substitution between fossil fuels and renewable energy sources, nor only as an environmental policy aimed at reducing greenhouse-gas emissions. It is a structural economic transformation that affects how energy is produced, distributed and consumed; changes the behaviour of households, firms and institutions; reorganises mobility, work and daily routines; and reshapes industrial structures, employment, value chains and the geography of production.

The urgency of this transformation is widely acknowledged. Climate change, fossil-fuel market volatility, geopolitical tensions around energy security and the need to reduce dependence on finite and polluting resources have made decarbonisation a central policy objective. Yet the transition is neither linear nor neutral. It may reduce emissions while increasing costs for some households, generate savings in one sector while shifting consumption elsewhere, create new industrial opportunities while weakening existing supply chains, and improve aggregate efficiency while producing uneven effects across income groups, regions, firms and workers. For this reason, its economic consequences cannot be assessed only through aggregate indicators. They require an analysis of the mechanisms through which the transition operates at different levels of the economy.

This thesis contributes to this objective by examining three interconnected dimensions of the energy transition. The first concerns households, where electricity demand depends on appliance ownership, housing characteristics, socio-demographic heterogeneity and investments in efficiency. The second concerns the organisation of work, focusing on how

remote work reallocates energy use between homes, workplaces and commuting. The third concerns industrial restructuring, with particular attention to the shift from internal-combustion to electric vehicle production and its implications for the Italian automotive sector. Together, the three essays show that the economic effects of decarbonisation depend on heterogeneity, behavioural responses, institutional settings and productive capabilities.

Households are a crucial starting point because residential energy consumption represents a substantial share of final energy demand and is directly connected to essential services such as heating, cooling, lighting, cooking and appliance use. Policies promoting electrification and energy efficiency therefore require a detailed understanding of how households consume electricity. However, residential energy demand is highly heterogeneous. Families differ in income, age structure, dwelling size, geographical location, building quality, appliance ownership and daily routines. As a result, the same appliance or efficiency measure may produce different effects depending on who uses it, where it is installed and under which housing and climatic conditions. Ignoring this heterogeneity may lead to inefficient and inequitable policies, for instance by subsidising households already able to invest while leaving behind those facing financial constraints, inefficient dwellings or higher energy needs.

The organisation of work represents a second relevant channel. The COVID-19 pandemic suddenly relocated a large share of economic and daily activities from offices and workplaces to private dwellings. Although exceptional, this shock revealed a broader issue: work arrangements can alter the spatial distribution of energy demand. Remote work may reduce commuting and office energy use, but it may also increase residential electricity consumption. Its environmental impact is therefore not automatic. It depends on whether commuting is actually reduced, whether offices adapt their energy systems to lower occupancy, whether households absorb additional energy needs efficiently, and whether the costs of this reallocation are fairly distributed. In this sense, smart working is not only a labour-market arrangement or an organisational practice, but also a potential

instrument of energy-demand policy.

The third dimension concerns the industrial side of the transition. Transport decarbonisation, and especially the electrification of the automotive sector, is one of the most politically and economically sensitive components of the European climate strategy. The shift towards electric vehicles changes not only the type of cars sold to consumers, but also the production structure of the automotive industry, the demand for intermediate inputs, the role of suppliers, the importance of batteries and electronics, and the position of countries within European and global value chains. For Italy, whose automotive sector is strongly connected to traditional mechanical components and a dense network of suppliers, electrification may create opportunities but also significant risks. Without appropriate industrial and demand-side policies, it could weaken domestic production capacity, reduce employment and value added, and increase dependence on foreign suppliers for strategic components.

Against this background, the thesis addresses three main gaps in the literature. First, although residential energy demand has been widely studied, empirical evidence on appliance-level electricity consumption in Italy remains limited, especially when household and dwelling heterogeneity are taken into account. Detailed sub-metering data are costly and often unavailable, while many studies rely on aggregate consumption data or engineering assumptions. This limits the ability to identify which end-uses drive demand and how efficiency policies should be targeted. The first essay contributes to this gap by estimating residential electricity end-uses through a microeconometric framework based on Italian household data and by assessing the role of efficiency investments.

Second, the literature on telework and energy demand has often examined residential electricity, mobility or workplace energy use separately. This may provide an incomplete picture, since an increase in household electricity consumption may coexist with larger reductions in commuting-related energy use and office-building demand. Moreover, much pre-pandemic evidence is affected by self-selection, as workers and firms adopting telework voluntarily may differ systematically from those that do not. The second essay addresses

this gap by exploiting the first Italian COVID-19 lockdown as a quasi-experimental setting and by estimating the energy effects of home confinement across households, commuting and service-sector workplaces.

Third, while the economic implications of electric vehicles have received increasing attention, less is known about how a full electrification scenario would affect the Italian automotive sector through domestic and international input-output linkages. The transition is often discussed in terms of environmental gains or technological innovation, but its consequences for national value chains, employment and sectoral interdependencies require further investigation. The third essay contributes by constructing counterfactual scenarios for the electrification of automotive production and by assessing how changes in production technology and final demand propagate through the Italian economy.

The thesis comprises three essays.

The first chapter, '*The Role of the Heterogeneity of Household Characteristics, Building Features and Efficiency Choices in Residential End-uses Electricity Consumption in Italy*', focuses on residential electricity demand. The second chapter, '*When the Office Moves Home: Energy Demand Responses to the COVID-19 Lockdown in Italy*', examines the relationship between remote work, home confinement and energy demand. Finally, The third chapter, '*Towards a Fully Electric Vehicle Production by 2035: Economic Implications for Italy's Automotive Sector Through an Input-Output Approach*', turns to the industrial implications of the energy transition.

Overall, the thesis argues that the energy transition should be analysed as a multidimensional economic transformation whose effects extend beyond emissions and energy balances to household welfare, behavioural responses, labour organisation, mobility, industrial structures and national productive capabilities. The three essays show that policy design must account for the specific channels through which the transition operates: energy-efficiency incentives should reflect household and dwelling heterogeneity; remote work should be evaluated as a reallocation of energy demand across homes, transport systems and workplaces; and automotive electrification should be accompanied by industrial

strategies capable of preserving value added, employment and technological capacity.

The central policy implication is therefore clear: decarbonisation is necessary, but its economic outcomes are not predetermined. The energy transition can generate environmental gains and economic opportunities, but only if it is governed as a structural transformation rather than treated as a purely technological adjustment.

# CHAPTER 1

## The Role of the Heterogeneity of Household Characteristics, Building Features and Efficiency Choices in Residential End-uses Electricity Consumption in Italy


### Abstract

Understanding residential energy consumption is essential given its large contribution to global energy use and greenhouse-gas emissions. Accurate estimation of end-use consumption is hampered by privacy restrictions and the high cost of submetering, so empirical analyses often rely on engineering approximations. This paper investigates the determinants of electricity end-uses in Italian households using microdata from the Italian National Institute of Statistics. Applying a Conditional Demand Approach (CDA) with OLS and quantile regressions, we characterise heterogeneity in appliance ownership and use across household and dwelling attributes. We also implement a counterfactual framework within a Heckman selection model to estimate the impact of air-conditioning efficiency upgrades on total household electricity consumption. Results show that demand is concentrated in a few thermal end-uses and major appliances. Quantile estimates reveal pronounced heterogeneity: the marginal kWh associated with the same device is substantially larger among high-consumption households, suggesting that intensity of use and/or lower appliance efficiency drive upper-tail demand. Interaction terms indicate systematic variation by age, household size, building type and region. Heckman-corrected counterfactuals imply that investments in thermal systems efficiency are associated with an approximate 43% reduction in household electricity consumption, highlighting large potential gains from targeted technology upgrades and deeper retrofits. Policy implications include prioritising thermal end-uses, combining deep retrofit incentives with appliance replacement and targeted information campaigns, and scaling up appliance-level metering and access to smart-meter data to improve monitoring, targeting and ex-post evaluation. Region, building-type and income-differentiated policies would enhance both effectiveness and equity.



**Keywords**: Residential electricity consumption, Conditional Demand Analysis, Energy efficiency, Heterogeneity of households characteristics, Appliance-level end-uses, Quantile regression, Heckman Model.

## 1.1 Introduction

The residential sector's energy consumption constitutes a substantial share of total energy use in European economies, representing 28% of the overall consumption[1]. On a global scale, household energy consumption is estimated to be slightly higher, at 30% (Swan and Ugursal, 2009). This sector primarily employs secondary energy, which is adapted to be compatible with household systems to fulfill essential needs and end uses such as heating, cooling, hot water for sanitation, appliance operation, and lighting.

Energy resources, alongside food, water, and other natural resources, are considered critical for the environment and fundamental to the functioning and engagement of economic activities in both industrialized and developing countries (Suganthi and Samuel, 2012). Similarly, the production and consumption of secondary energy entail significant environmental costs. Specifically, energy consumption in the residential sector represents a substantial source of greenhouse gas emissions, accounting for 17.5% of global carbon dioxide (CO2) emissions in 2016 (Ritchie and Roser, 2023).

The management of energy demand has become critically important, as the future of our planet hinges on the decisions made today. Thus, optimizing the management of energy resources is a priority for planners and policymakers. Enhancing energy efficiency and reducing energy demand are widely recognized as the most effective, swift, economically viable, and reliable strategies for addressing climate change (Sorrell, 2015). Organizations such as the International Energy Agency (IEA) are increasingly prioritizing the reduction of energy demand[2][3]. The European Commission has also proposed long-term objectives for reducing energy demand[4]. Additionally, countries worldwide are implementing policies

[1] Odysee-mure, Sectoral profile - Overview.
https://www.odyssee-mure.eu/publications/efficiency-by-sector/overview/overall-eu.pdf.

[2] IEA. Global Commission for Urgent Action On Energy Efficiency – programmes.
https://www.iea.org/programmes/global-commission-for-urgent-action-on-energy-efficiency.

[3] IEA. Recommendations of the Global Commission for Urgent Action On Energy Efficiency – analysis.
https://www.iea.org/reports/recommendations-of-the-global-commission-for-urgent-\action-on-energyefficiency.

[4] Directive (EU) 2023/1791 of the European Parliament and of the council of 13 September 2023 on energy efficiency and amending Regulation (EU) 2023/955.
https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32023L1791.

to achieve this goal.

In the present-day context, the use of electrical household appliances accounts for a substantial share of residential energy consumption. This discussion refers specifically to appliances powered by electricity, excluding devices that rely on alternative energy sources such as natural gas. Understanding how these appliances are used is therefore essential. In particular, it is crucial to assess how the end-use of each individual appliance or electrical system contributes to total household electricity consumption in order to accurately predict energy consumption and conduct nuanced policy analyses. Increasingly, precise estimates of appliance consumption are used in forecasting end-use capacity requirements for electric power generation systems and within the realm of energy policy to define suitable thresholds for protective tariffs.

Managing energy consumption in the residential sector is particularly challenging because it is shaped by multiple and heterogeneous factors. These include differences in the size, geometry, and materials of dwellings; variations in the physical characteristics of buildings; meteorological conditions; and the wide heterogeneity in residents' attitudes and habits. In addition, privacy constraints often limit access to detailed household-level energy data, while the high cost of collecting precise sub-metering measurements[5] further complicates empirical analysis (Swan and Ugursal, 2009). Although residential electricity consumption can be readily observed through utility bill data, studies that directly measure the consumption and usage patterns of individual household appliances or electrical devices remain scarce. Even in engineering research, appliance-level electricity demand is usually inferred from technical specifications and standardized assumptions about usage rather than from observed behavioral data. Importantly, electricity consumption depends not only on whether households own appliances and energy systems such as heating, air conditioning, and washing machines, but also on how intensively and in what manner they are used. These usage patterns are influenced by households' socio-demographic, cultural, and economic characteristics, as well as by housing features such as dwelling size, exposure to environmental conditions, and wall insulation quality (Larsen and

[5]Surveys that encompass the electricity consumption of particular appliances are difficult to obtain.

Nesbakken, 2004; Zhou and Teng, 2013; Huang, 2015; Matsumoto, 2016; Frondel et al., 2019). Examining heterogeneity among electricity consumers therefore makes it possible to design more targeted energy-efficiency policies and to assess how household characteristics and preferences affect electricity consumption relative to a benchmark 'typical family', as well as how housing attributes compare with those of a 'standard dwelling'.

Since electricity consumption depends not only on household and dwelling characteristics but also on the efficiency of the devices in use, it is equally important to assess whether investments in energy efficiency translate into meaningful reductions in consumption. A comprehensive understanding of the impact of household investments in energy efficiency is therefore essential. Such analyses help determine whether investments in energy systems and/or more efficient appliances effectively reduce energy consumption. From a policy perspective, this also makes it necessary to assess whether efforts should prioritize improvements in energy infrastructure and the construction of more energy-efficient buildings, especially in urban areas. Reducing electricity consumption in metropolitan centers through eco-friendly practices and highly efficient dwellings is a key objective of contemporary public policy (Curtis et al. (2018); Zivin and Novan (2016); Liang et al. (2018); Giandomenico et al. (2022)).

Building on these considerations, this study investigates how appliance-level electricity consumption varies across Italian households and which factors drive such variation. In particular, we focus on the electricity end-use attributable to observable household appliances and electrical systems, and we examine how household characteristics, dwelling attributes, behavioral patterns, and efficiency-related investment choices shape consumption levels. To this end, we use the survey named 'Indagine sui Consumi Energetici delle Famiglie'[6] , a dataset collected by the Italian National Institute of Statistics (Istat), which provides information on household electricity expenditure as well as on the ownership and use of appliances and energy devices. By means of statistical matching, we further integrate income information from the EU-SILC dataset into the analysis for the first time. This enables us to assess the role of income in shaping electricity consumption, treating it as a

[6]More information can be found here: `https://www.istat.it/it/archivio/58343`.

determinant that may also influence time allocation and, consequently, the use of specific appliances, in line with the propositions of Matsumoto (2016); Antal et al. (2021); Becker (1965).

The study addresses three research questions. First, what is the amount of electricity consumption attributable to each household appliance or electrical system? Second, does heterogeneity in appliance ownership, socio-demographic characteristics, and dwelling features significantly affect electricity consumption, and if so, which are the main determinants? Third, do investments in energy efficiency, understood as improvements to individual appliances or electrical systems, generate significant savings in household electricity expenditure and offer a policy-relevant tool for reducing carbon emissions?

To answer these questions, we apply a Conditional Demand Approach (CDA) to residential electricity consumption. Building on the theoretical frameworks of Parti and Parti (1980) and Nielsen (1993), our specification accounts not only for appliance ownership but also for usage intensity, following Matsumoto (2016) and Frondel et al. (2019). We then use quantile regressions to examine how household and housing heterogeneity affect end-use electricity consumption across the distribution, thereby avoiding the limitations associated with subsampling. Finally, through counterfactual analysis, we assess whether energy-efficiency investments translate into meaningful reductions in the overall cost of electricity.

To the best of our knowledge, this is the first study that directly examines appliance-level residential electricity consumption in Italian households using this econometric framework. More broadly, the paper contributes to the scarce empirical literature on the disaggregation of household electricity use in Italy and offers evidence that may inform targeted energy-efficiency policies aimed at reducing residential emissions.

This manuscript is structured as follows. After reviewing the main residential energy end-use estimation methodologies in the literature (Section 1.2), Section 1.3 outlines the Italian dataset used for this analysis. Section 1.4 outlines the estimation strategy related to the conditional demand model and counterfactual analysis, while the main results

are reported in Section 1.5. Finally, Section 1.6 concludes with considerations on policy implications.

## 1.2 Literature Review

The household demand for energy arises directly from the fulfillment of needs and necessities through the utilization of energy devices and appliances. Factors impacting the demand for energy services encompass cost, climatic conditions, economic accessibility, that is, consumer income, and individual preferences for final energy services (Bhattacharyya and Timilsina, 2010).

Energy demand modeling is crucial for policymakers in undertaking energy planning and formulating strategies within energy policies. The legislative interest in the energy sector increased significantly during the 1970s, prompted by oil crises, and has greatly stimulated research in energy demand analysis (Bhattacharyya and Timilsina, 2010). The evolution of energy markets and growing political concerns, such as energy security, volatility in energy prices, and environmental issues, has had a significant impact on energy demand in recent times. Additionally, notable advancements in information and communication technologies, coupled with the development of analytical capabilities and continuous attention to energy issues, have led to a substantial proliferation of energy demand analysis in the past forty years.

The analysis of energy demand has endeavored to explore the aforementioned factors through different approaches. Conventional analysis focuses on optimizing individual behavior, employing the neoclassical economic theory approach and considering utility maximization in domestic demand scenarios. However, the limitations stemming from the assumptions about optimization and fully rational behavior in traditional analysis have led scholars to consider alternative perspectives, such as evolutionary approaches to technological change (Simon, 1978) as well as the inclusion of different belief structures in certain models (Wilson and Dowlatabadi, 2007), as discussed by Timothy Wilson, which depart from the notion of strictly rational behavior.

Delving into specifics, a wide array of models is employed for the analysis of energy demand. The most fundamental ones employ elementary indicators for forecasting trends, such as growth rates, price and income elasticity, specific or unit consumption, and energy intensity (Bhattacharyya and Timilsina, 2010). These indicators are applied across both traditional and commercial energy sources and adapted for various economic, metropolitan, and rural contexts. However, due to their simplicity, they fail to capture the underlying causes of energy demand and overlook specific technological details.

More advanced approaches can be broadly classified into two main categories, namely top-down and bottom-up models (Swan and Ugursal, 2009; Suganthi and Samuel, 2012). The distinction between the two lies in the level of aggregation. Top-down models operate at an aggregate level, using information on total residential energy consumption and related sector-wide variables to allocate energy demand across the housing stock. Bottom-up models, by contrast, start from disaggregated units such as specific end-uses, individual households, or homogeneous groups of households, and then extrapolate the estimated consumption patterns to a wider population, region, or country. In general, top-down models are grounded in econometric techniques and economic theory, whereas bottom-up models are more closely linked to engineering-economic accounting and to the detailed representation of energy systems.

Within the bottom-up family, different specifications can be distinguished according to the type of input data used and the level of disaggregation achieved (Swan and Ugursal, 2009). These models are commonly employed to estimate the energy consumption of representative dwellings or household groups in the residential sector, with regression techniques often used to quantify the contribution of specific end-uses and household characteristics.

Based on the analysis carried out in this study, we adopt a Conditional Demand Model, which was originally developed to address the lack of sub-metering data on the final electricity consumption of individual household appliances. In fact, obtaining such data requires detailed and costly measurement techniques that are difficult to implement in

practice. This model has been developed over the years (Parti and Parti, 1980; Aigner et al., 1984; Sebold and Parris, 1989; Lafrance and Perron, 1994; Bartels and Fiebig, 1995, 2000; Tiedemann, 2008; Aydinalp-Koksal and Ugursal, 2008; Rebman et al., 2008; Dalen and Larsen, 2015; Frondel et al., 2019; Papineau et al., 2021) and allows the allocation of the final energy use of each household appliance in relation to the overall electricity consumption. Essentially, the CDA model includes dummy variables that signify the presence of appliances. The core concept of this model is that the estimated coefficients for these dummy variables are interpreted as the average electricity consumption associated with those appliances. To derive estimates for the average electricity consumption across various types of appliances within an average household context, these estimates are multiplied by the proportions of households possessing the respective appliances (the saturation rate). Furthermore, the electricity consumption for each specific end-use is divided by the total electricity consumption to calculate the shares of end-use.

Starting from the theoretical framework developed by Larsen and Nesbakken (2004), the ideal regression model to be estimated would be:

$$x_{ij} = \gamma_j + \sum_{m=1}^{M} \rho_{jm} \left( C_{im} - \overline{C_{jm}} \right) + \epsilon_{ij} \tag{1.1}$$

where $x_{ij}$ is the annual electricity consumption for the end-use j of household i (with $i = 1,\ldots,N$); $C_{im}$ describes households and dwelling characteristics, electricity prices, heating degree days, etc. ($m = 1,\ldots, M$); $\overline{C_{jm}}$ is the average value of these variables for the households that own the appliance j; $\epsilon_{ij}$ is the stochastic error term which is not necessarily assumed to be i.i.d. and captures the unobserved heterogeneity among households. The parameter $\gamma_j$ represents the average electricity consumption for the end-use of appliance j given the household's characteristics, $C_{im}$, relevant to the end-use of appliance j. However, as the final energy consumption for each appliance varies due to differences in certain variables among families (e.g., variations in dwelling size, with electricity needs for heating assumed to increase with larger dwellings), the second element in the equation is used to account for the diverse final energy consumptions influenced

by demographic and economic factors. Put differently, the second term, $\rho$, represents economic and demographic variables in relation to the deviation from the average value for families owning appliance j. This adjustment is aimed at aligning the final consumption for appliance j with those families whose economic and demographic values deviate from the 'typical family' with a certain final consumption $\gamma_j$.

Since it is usually impossible to gather data on the final usage and consumption of each individual appliance, Equation (1.1) cannot be estimated. However, since the total electricity consumption for each family is known, Equation (1.1) can be used along with the other equations, $x_i = \sum_{j=1}^{J} x_{ij} D_{ij}$ and $\sum_{j=1}^{J} \epsilon_{ij} D_{ij} = \beta + \mu_i$, to derive the annual electricity consumption of family i as a function of the (conditional on) the owned appliances and economic and demographic variables. The final version of the conditional demand model becomes:

$$x_i = \sum_{j=1}^{J} \gamma_j D_{ij} + \sum_{j=1}^{J} \sum_{m=1}^{M} \rho_{jm} \left( C_{im} - \overline{C_{jm}} \right) D_{ij} + \beta + \mu_i \tag{1.2}$$

Where $D_{ij}$ is a binary variable that takes values of 0 or 1 depending on the possession of appliance or activity j ($j = 1, .., J$) by family i. The equation is estimated through the OLS model. The error term consists of two components: $\beta$, which is constant for all families, and $\mu_i$, which varies among families and is i.i.d. $\beta$ is estimated as the constant and represents the estimated electrical quantity associated with appliances that are not included in the model (miscellaneous electricity). After estimating the coefficients linked to the regressors and deviations (second term), they can be utilized for predictions, distributing the total electricity consumption to each type of appliance.

A notable advantage of the CDA econometric model is its ability to directly estimate parameters for end-use, eliminating the need to make assumptions about behavior or techniques (Swan and Ugursal, 2009). The coefficient estimated for each appliance is interpreted as the final consumption, measured in kilowatt-hours, providing consolidated information about the average technical condition of appliances and the typical behavior

of electricity demand—how frequently and for how long they are typically used in households. In addition to electricity consumption, only two types of information are necessary: whether the family owns specific electrical appliances or the number of appliances and socio-economic and dwelling characteristics. Obtaining these data is relatively straightforward through household surveys, and the econometric model's input, in this case, relies exclusively on micro-survey data, making them more manageable.

For what concerns the econometric specification of CDA models, there is a debated problem in the literature related to the estimation of price elasticity. Estimating price elasticity under block (tiered) tariffs is contested because consumers do not face a single marginal price (MP) and tariff design creates intramarginal effects and kinked budget constraints. Early work used average price (AP) as the observed signal (Barkatullah, 1996), while Taylor and Nordin argued AP or MP alone are insufficient and proposed the rate structure premium (RSP) to capture intramarginal consumer-surplus/income effects (Taylor, 1975; Nordin, 1976). Subsequent studies point to imperfect consumer price information (leading to perceived-price models) and produce mixed evidence on whether consumers react more to AP or MP (Shin, 1985; Nieswiadomy and Molina, 1989). Finally, block tariffs make marginal price endogenous (reverse causality), so researchers use IVs or more complex DCC/ML methods to correct bias, yet no consensus has emerged and many studies still rely on AP. (Barkatullah, 1996; Wilder and Willenborg, 1975; Borenstein, 2009; Filippini and Pachauri, 2004)

The international literature on residential energy efficiency has converged on two main strands: (i) empirical estimation of energy savings resulting from retrofit measures or appliance replacement; and (ii) analysis of the determinants of household investment decisions.

With respect to the economic and environmental impacts of investments in energy efficiency, energy improvements achieved through residential retrofit measures offer substantial potential to reduce final energy demand—particularly space heating—and the associated $CO_2$ emissions, while also strengthening energy security by diminishing de-

pendence on external fuel sources (Trotta (2018); Chuang et al. (2019); Gillingham et al. (2006)). Empirical analyses that exploit large administrative panels or billing datasets report measurable ex-post savings of modest to moderate magnitude; program-level evaluations and sectoral comparisons provide concrete examples of these effects (Liang et al. (2018); Zivin and Novan (2016)). A recent review and synthesis produces a weighted mean reduction of approximately 7–8% in total energy consumption, with randomized controlled trials clustering around 6.8% and simple before–after or single-difference designs tending to overstate effects relative to more robust methods (Giandomenico et al. (2022); Hondeborg et al. (2023).

Evidence from programmatic interventions indicates residential savings on the order of 8% in some urban initiatives, whereas commercial buildings may exhibit larger reductions (12%) under similar mixed-measure programmes. Research focused on low-income households finds that physical retrofit measures do generate savings but often fall short of engineering projections and vary substantially across income groups; behavioral responses and rebound effects appear to attenuate realized gains, especially among lower-income households (Ameli and Brandt (2015); Poortinga et al. (2018); Zivin and Novan (2016). Expenditure analyses further show that higher building energy performance ratings are associated with reductions in energy spending (positive elasticity), although the magnitude and functional form of this relationship are heterogeneous and not always linear (Besagni and Borgarello (2018); Curtis et al. (2018)). Finally, reviews and meta-analyses emphasize that comprehensive or deep retrofits (multiple simultaneous measures) deliver substantially larger energy savings than isolated interventions (Giandomenico et al. (2022); Hondeborg et al. (2023)). Higher levels of building efficiency have also been linked to improved occupant health and thermal comfort (Payne et al. (2015); Poortinga et al. (2018)), lower energy bills and maintenance costs (Agency, 2014), and increased property values (Hyland et al., 2013).

Across the body of research examined, the principal determinants of household investment in energy-efficiency measures are broadly consistent. Economic considerations-

expected energy savings, private installation costs, the availability of incentives—and access to capital are frequently identified as the primary drivers (Aravena et al. (2016); Alberini and Bigano (2015)). Information and prior experience are also crucial: households that perceive savings or have previously undertaken upgrades are more likely to invest again (Nair et al., 2010). Dwelling characteristics (building type, year of construction, heating system, floor area) strongly shape both technology choice and the likelihood of intervention (Laureti and Benedetti (2021); Laureti et al. (2012); Hamilton et al. (2014)). Socio-demographic variables produce mixed results: income and education often raise the probability of adopting efficient technologies, but effects are not uniformly monotonic (some middle-income groups invest more than the very highest income groups Nair et al. (2010); Laureti et al. (2012)). Individual preferences—risk aversion, time discounting, and environmental values—are important determinants of both the decision to retrofit and the depth of measures implemented; notably, higher risk aversion reduces propensity to undertake interventions perceived as uncertain (Fischbacher et al., 2021). Recurring barriers include lack of liquidity, perceived low added value, and uncertainty about realised savings (Osiolo and Kimuyu, 2017). Several studies indicate that information provision and simple behavioural interventions can increase uptake and completion rates (Zivin and Novan (2016); Alberini and Bigano (2015)), while the effectiveness of economic incentives depends critically on program design (Laureti et al. (2012); Aravena et al. (2016); Hondeborg et al. (2023)).

Comparing techniques, general findings, and policy implications reveals a rich and diverse methodological landscape. Among the approaches employed in the literature are correspondence analysis and clustering to identify consumption typologies (Lévy and Belaïd, 2018); OLS and LASSO regressions with predictor selection, as well as classification and regression tree methods for segmentation (Besagni and Borgarello, 2018); multinomial logit and probit models to analyse technology choice (Curtis et al. (2018); Laureti et al. (2012); Wang Zhen et al. (2019)); selection-correction models (Heckman and Bourguignon-type corrections) and maximum-likelihood estimators to address sample bias (Administration (2016); Laureti et al. (2012); Osiolo and Kimuyu (2017)); panel fixed-effects, event-study

designs and difference-in-differences approaches (including recent corrections for staggered treatment timing) for ex-post evaluations Liang et al. (2018); Hondeborg et al. (2023); quantile regression to investigate territorial heterogeneity (Kostakis, 2020); and randomized or quasi-experimental designs to isolate informational and behavioural effects (Zivin and Novan (2016); Giandomenico et al. (2022)).

The Heckman model, which is also employed in this paper, is appropriate when treatment assignment does not stem from an exogenous policy shock but is instead endogenous—i.e. it reflects individual choices driven by observable and unobservable characteristics of the treated units. Several studies in this field apply this methodology.

Laureti and Benedetti (2021) adopt a two-stage strategy to test and correct for potential endogeneity in fuel choice. In the first stage, they estimate—via a latent-choice model—the probability that a household uses renewable energy sources as a function of socio-economic characteristics, dwelling features, territorial factors and behavioural variables. In the second stage, these estimates are incorporated into a multinomial logit model explaining the intention to undertake energy-retrofit investments. To address potential selection bias, they implement the Heckman two-step procedure including the inverse Mills ratio; the lack of statistical significance of this term suggests limited selection bias in their sample, but the approach provides a formal test of endogeneity and yields more robust estimates.

Curtis et al. (2018), using the Household Budget Survey 2009–2010, address the presence of numerous zero expenditures for certain fuels (censoring) through a two-stage Heckman selection model. The first stage estimates the probability of purchasing a given fuel (selection equation), while the second stage estimates the Engel curve of expenditure (Leser–Working form) including the Mills ratio to correct for censoring. This separation between the purchase decision and the expenditure level allows them to isolate the effect of the building energy rating on spending and to reduce bias arising from non-random purchasing behaviour.

Fischbacher et al. (2021) analyse a context in which observed efficiency outcomes are available only for households that actually renovated. They first estimate, via probit, the

probability that a homeowner undertakes a renovation (selection stage) as a function of behavioural preferences, housing characteristics and financial conditions. In the second stage, they estimate the resulting energy performance including the Mills ratio to correct for correlation between outcome errors and selection. This approach distinguishes between (i) the decision to renovate and (ii) the intensity or quality of the intervention, showing that different preferences influence these two decision layers differently.

Finally, Administration (2016), in its analysis of ENERGY STAR appliance adoption using RECS 2009 data, addresses sample-selection bias due to non-response or lack of programme awareness. The authors apply both the traditional Heckman procedure and a joint maximum-likelihood estimation of awareness and adoption. Their methodological comparison shows that controlling for selection is crucial: Heckman-corrected estimates differ in magnitude and standard errors, confirming that selection correction improves the reliability of inference on the adoption of energy-efficient technologies.

Policy implications converge on several key points. First, incentivising comprehensive or deep retrofits is more effective than subsidising weak or isolated interventions (Hondeborg et al., 2023) (Hondeborg et al., 2023). Second, combining financial incentives with clear information and guarantees about expected savings reduces perceived uncertainty and investment risk (Fischbacher et al. (2021); Aravena et al. (2016); Hondeborg et al. (2023)). Third, targeting programmes by building typology, climatic context and income group increases both effectiveness and cost-effectiveness (Hamilton et al. (2014); Imani et al. (2023)). Fourth, systematic ex-post monitoring and calibration of engineering estimates with empirical evidence help prevent over-subsidisation (Zivin and Novan (2016); Liang et al. (2018)). Finally, low-cost behavioural and informational interventions can generate meaningful additional savings and should be integrated into policy design (Zivin and Novan (2016); Alberini and Bigano (2015)).

Although the present study does not directly evaluate specific policy instruments, our findings provide empirical evidence that can inform the design of residential energy-efficiency policies.

There are very few Italian studies that employ micro-level data and econometric methods to analyse residential energy consumption, fuel choice and investment in energy efficiency.

Laureti and Benedetti (2021), using data from Istat's Household Consumption Survey, examine the determinants of households' heating-fuel choice and their intentions to undertake energy-retrofit measures. Adopting a two-stage approach—first modelling the probability of adopting renewable sources and then estimating propensity to undertake measures via a multinomial logit—the authors show that adoption of renewable technologies and retrofit interventions depends on socio-economic characteristics, dwelling conditions, territorial factors and, crucially, prior investment experience and the household's level of energy information. The results indicate that household decisions are driven by a combination of economic, technical and behavioural constraints and point to territorially targeted policies that combine economic incentives with information and awareness-raising instruments.

Besagni and Borgarello (2018), drawing on Istat's Household Budget Survey, analyse determinants of residential energy expenditure in Italy by separating electricity, thermal and total spending. Using OLS regressions with LASSO variable selection and subsequent household segmentation with CART trees, they find that electricity expenditure is mainly explained by socio-demographic factors and appliance ownership, whereas thermal expenditure is more strongly related to building characteristics, the heating system and geographic location. Family structure emerges as a key determinant across expenditure types: per-capita consumption is higher for single-person and small households, while conditions of poverty and higher educational attainment are associated with lower consumption. Overall, the study highlights that domestic energy demand results from the joint influence of building, climatic and behavioural factors and suggests the need for differentiated policies by household type and dwelling characteristics.

Laureti et al. (2012) investigate the determinants of domestic heating-fuel choice in Italy and associated consumption levels by specifying a random utility model in which

the decision among alternatives (oil, piped gas, LPG, coal/wood, electricity/solar) is treated as an unordered discrete choice. To address potential endogeneity between fuel choice and quantity consumed, the authors jointly estimate a selection equation and a consumption equation, correcting for bias using the approach of Bourguignon et al. (2007). Their results indicate that income and education increase the probability of choosing natural gas, while isolated or older dwellings and residences in the South and on the islands are more likely to use alternative fuels. Dwelling characteristics affect both choice and consumption levels, with newer and better-insulated buildings associated with lower consumption. Policy simulations of fiscal incentives introduced since 2007 suggest that greater retrofit activity would moderately increase the probability of gas use and reduce reliance on more polluting fuels, underscoring the role of efficiency policies in shifting household technology choices.

Alberini and Bigano (2015) study Italian homeowners' willingness to invest in energy-efficiency measures—specifically the replacement of heating systems by combining revealed and stated preference data collected through an online questionnaire. Using a probit model to estimate the adoption curve at different subsidy levels, they show that the probability of investing rises with the subsidy amount and with expected energy savings, whereas informational prompts about environmental benefits have only modest effects. The average subsidy required is relatively small but highly heterogeneous across households, with lower-income households demanding larger subsidies. Simulation results indicate that fiscal incentives can increase adoption and reduce $CO_2$ emissions, but cost-effectiveness depends strongly on realized energy savings and on the subsidy level. The study therefore highlights the importance of economic incentives for promoting residential energy efficiency, the limits of standalone informational interventions, and the need to account for household heterogeneity in policy design.

The review indicates that, despite the existence of Italian studies on energy consumption, fuel choice and retrofit intentions, there is a lack of evidence that quantifies the effect of investments in energy efficiency on residential consumption using econometric methods

applied to micro-level consumption data. Our study therefore positions itself within this research strand and provides an original contribution by empirically investigating the potential impacts on households that have undertaken such investments relative to those that have not.

## 1.3 Data

To undertake this research, we employed the public-use dataset 'Household Energy Consumption Survey' (Indagine sui Consumi Energetici delle Famiglie), provided by the Italian Institute of Statistics (Istat). This survey collects statistical data on the energy behaviors of resident households in Italy. The most recent survey year made available is 2021. The household selection procedure is based on random sample, starting from the official computerized archive of households subscribed to the fixed-line telephone network. Respondents were subsequently selected from eligible individuals within the household (over 18 years of age) as indicated by the households themselves as the most suitable respondents to provide information on the phenomena under investigation. The sampling design adopted for the final survey is one-stage, with stratification of the approximately 8,000 Italian municipalities. Stratification was performed according to region of residence, population size crossed with altitude zone, for 7 municipal types. The survey was conducted using Computer Assisted Telephone Interviewing (CATI) and Computer-Assisted Web Interviewing (CAWI) technique. The dataset has 54,000 observations. Each record in the dataset corresponds to a single Italian household and each row includes information of each member of the household. Regarding the household-related variables, the dataset includes information on gender, age, relationship to the household reference person, employment status, geographic breakdown and region of residence, number of people living in the household, etc. The dataset also includes the list of major household appliances owned by the household. For many appliances, it reports information related to their frequency of use expressed in terms of hours, number of uses according to the type of appliance, and the year of purchase. In addition, there are variables related to the structural characteristics of the dwelling of residence such as type of dwelling, square meters of the house, the exposure of the dwelling, etc. Finally, other variables tell whether the household has made investments in the last 5 years to reduce the cost of the bill through improving the efficiency of some appliances or different energy systems, or if they plan to make them in the future together with the reasons for this choice. Table 1.3 below reports all the variables employed in the regression analysis.

The dataset used in this research does not provide information on residential annual energy consumption in kilowatts per hour. However, it does include annual electricity expenditure expressed in euros. Given that the variable of interest is annual household energy consumption in kilowatt-hours, there is a need to convert the expenditure into quantity consumed. To calculate the quantity of electricity consumed, we adopt a similar approach as Bardazzi and Pazienza (2020), which entails an implicit transformation from expenditure to quantity using prices, that is we divided the total annual expenditure by the average price faced by the household. In order to do so, we employed data from Eurostat, called 'Electricity Prices for Household Consumers - Annual Data (2007 onwards)'.

As we mentioned in the literature section, there is a broad discussion about the choice of the variable to use for energy price. The issue revolves around whether households respond to the marginal price or the average price when deciding their energy demand. The main approaches can be divided into two strands. In the first approach, Nordin (1976) suggests using the marginal price. The second approach involves using the average price (Shin, 1985), calculated by dividing the electricity bill by the quantity of electricity consumed. Considering the seminal paper employing the CDA, Michael Parti and Cynthia Parti (1980) posit that consumers react to the average price as opposed to the marginal price (Parti and Parti, 1980). Specifically, consumers are assumed to regard the average price derived from the most recent electric bill as the designated price for electricity. This assumption serves as a constraint in estimating price elasticity, given studies indicating that in the context of block pricing (whether increasing or decreasing), the consideration of the average price of electricity may yield biased and inconsistent estimations (Taylor, 1975). Numerous papers utilizing the CDA neglect this aspect by considering average prices (Zhou and Teng, 2013; Bardazzi and Pazienza, 2020; Larsen and Nesbakken, 2004; Branch, 1993; Wilder and Willenborg, 1975; Frondel et al., 2019). Moreover, it has been found that consumers exhibit a greater propensity to react to the average price rather than the marginal price for various reasons (Ito, 2014; Shin, 1985; Borenstein, 2009; Fell et al., 2014) . Firstly, there exists an informational cost attributable to the difficulty in comprehending monthly bills, thereby imposing limitations on understanding

the nonlinear structure of tariffing. Secondly, the complexity of monitoring cumulative electricity consumption without access to an in-home meter supplying information on actual usage poses a challenge. Conversely, it is more rational for consumers to look at the total payment and consumption data on their monthly bill, and consequently, at the average price, as an approximation of their genuine marginal price.

For all these reasons, for the conditional demand analysis part, we decided not to use prices as a covariate in the linear regression model. There are several studies that do not consider price when exploring the variability of residential household energy consumption (Fiebig et al., 1991; Lafrance and Perron, 1994; Bartels and Fiebig, 1995; Tiedemann, 2007; Rebman et al., 2008; Bartusch et al., 2012; Newsham and Donnelly, 2013; Huang, 2015; Matsumoto, 2016; Papineau et al., 2021). There are good reasons to believe that in the very short run, electrical consumption is mainly explained by the combination of electrical appliances and devices owned and the characteristics of households and buildings with respect to energy prices.

The household disposable income is absent from our dataset. This absence may engender challenges associated with endogeneity in the regression. Consequently, we chose to engage in a statistical matching procedure, wherein we impute the income levels from the European Statistics on Income and Living Conditions (Eu-Silc) dataset for the 2020 reference period to each household record in our dataset. A comprehensive delineation of the statistical matching procedure is meticulously expounded upon in the Appendix 1.A.4. Following that, in order to compute the equivalent household disposable income, we used the ascertained family income variable and implemented the OECD equivalence scale (see Appendix 1.A.1).

After removing missing values and applying the statistical matching procedure, the final Number of observations is 32,321 household units. Summary statistics of the main independent variables in the model are reported in Table 1.1 and 1.2. The detailed description of variables employed in the econometric analysis is reported in Table 1.3.

| Variables | Min | 1st Qu. | Median | Mean | 3rd Qu. | Max | SD |
|---|---|---|---|---|---|---|---|
| Age of the head of the household | 20.00 | 46.00 | 56.00 | 56.10 | 68.00 | 79.00 | 13.59 |
| Number of children | 0.00 | 0.00 | 1.00 | 0.79 | 1.00 | 8.00 | 0.91 |
| Square meters of the house | 14.00 | 75.00 | 95.00 | 99.21 | 115.00 | 400.00 | 42.36 |
| Weekly washing machine cycles | 1.00 | 2.00 | 3.00 | 4.12 | 5.00 | 40.00 | 2.88 |
| Number of computers | 0.00 | 1.00 | 1.00 | 1.51 | 2.00 | 9.00 | 1.33 |
| Number of energy-saving light bulbs | 0.00 | 7.00 | 11.00 | 12.16 | 17.00 | 28.00 | 6.60 |
| Number of standard light bulbs | 0.00 | 0.00 | 0.00 | 2.87 | 4.00 | 28.00 | 4.80 |
| Number of televisions | 1.00 | 1.00 | 2.00 | 2.02 | 3.00 | 8.00 | 0.91 |
| Household's equivalized disposable income (in euros) | 5.13 | 12716.12 | 18773.69 | 21081.53 | 27866.99 | 65398.93 | 11484.04 |
| Annual electricity consumption (kwh) | 238.8 | 816.3 | 2200.0 | 2320.3 | 3333.3 | 24516.7 | 1742.95 |
| Price | 0.18 | 0.21 | 0.24 | 0.33 | 0.49 | 0.49 | 0.13 |

Table 1.1: Descriptive statistics for continuous explanatory variables.

| Variables | Count | Percentage |
|---|---|---|
| Household size: 1 | 6754 | 20% |
| Household size: 2 | 10628 | 33% |
| Household size: 3 | 7735 | 25% |
| Household size: 4 | 6214 | 19% |
| Household size: 5 | 1242 | 3% |
| Household size: $\geq$6 | 0 | 0% |
| Number of Rooms: 1 | 7012 | 20.38% |
| Number of Rooms: 2 | 11058 | 32.14% |
| Number of Rooms: 3 | 8134 | 23.64% |
| Number of Rooms: 4 | 6556 | 19.06% |
| Number of Rooms: 5 | 1315 | 3.82% |
| Number of Rooms: $\geq$6 | 329 | 0.96% |
| Head of household's gender: Male | 22689 | 65.95% |
| Head of household's gender: Female | 11715 | 34.05% |
| Education: High school or vocational diploma | 14928 | 43.39% |
| Education: First-level degree | 1567 | 4.55% |
| Education: Second-level degree | 5079 | 14.76% |
| Education: Elementary school | 3184 | 9.25% |
| Education: Middle school | 9231 | 26.83% |
| Education: No diploma | 415 | 1.21% |
| Environmental attitude: No | 29498 | 85.74% |
| Environmental attitude: Yes | 4906 | 14.26% |
| Northern area: No | 18778 | 54.58% |
| Northern area: Yes | 15626 | 45.42% |
| Thermostat: No | 17149 | 49.85% |
| Thermostat: Yes | 17255 | 50.15% |
| Marital status: Not married | 11844 | 34.43% |
| Marital status: Married | 22560 | 65.57% |
| Single-family home: No | 28563 | 83.02% |
| Single-family home: Yes | 5841 | 16.98% |
| Built after 1990: No | 24705 | 71.81% |
| Built after 1990: Yes | 9699 | 28.19% |
| PVC or wooden windows: No | 10400 | 30.23% |
| PVC or wooden windows: Yes | 24004 | 69.77% |
| Wall exposure: No | 13922 | 40.47% |
| Wall exposure: Yes | 20482 | 59.53% |
| Geographical distribution: Center | 7223 | 20.99% |
| Geographical distribution: Islands | 3191 | 9.28% |
| Geographical distribution: North-East | 7008 | 20.37% |
| Geographical distribution: North-West | 8618 | 25.05% |
| Geographical distribution: South | 8364 | 24.31% |
| Employment status: Unemployed or seeking first job | 3331 | 9.68% |
| Employment status: Unable to work or other condition | 1307 | 3.80% |
| Employment status: Employed | 18992 | 55.20% |
| Employment status: Retired | 10421 | 30.29% |
| Employment status: Student | 353 | 1.03% |

Table 1.2: Descriptive statistics for categorical and dummy explanatory variables.

| Variables | Detailed Description |
|---|---|
| **Household's socio-demographic profile** | |
| *Household Size (categorical)* | Number of people actually living in the house. It is built on six levels. The last one depicts a household with six or more members. |
| *Single-member household (binary)* | It takes 1 whether the household is composed of only one member, and 0 otherwise. |
| *Head of household's age (continuous)* | It indicates the age of the head of the household. |
| *Head of household's gender (binary)* | It takes 1 whether the head of the household is male, and 0 otherwise. |
| *Head of household's high level of education (binary)* | It takes 1 whether the head of household owns a bachelor's degree or higher, and 0 otherwise. |
| *Older household members (continuous)* | It indicates the number of members over 60 years old in the household. |
| *Children (continuous)* | It indicates the number of children living in the household. |
| **Household's economic indicators** | |
| *Household's equivalent income in log (continuous)* | It indicates the household's level of equivalized income. |
| **Building-related features** | |
| *Rooms (continuous)* | It indicates the number of rooms in the house. |
| *Villa (binary)* | It takes 1 whether the house is a farmhouse, villa, or single-family home. |
| *Floor space in square meters (continuous)* | It indicates the dwelling's floor area in square meters. |
| *Property construction date after 1990 (binary)* | It takes 1 whether the house was built after 1990, and 0 otherwise. |
| *Windows with PVC or wood frames (binary)* | It takes 1 whether dwelling windows are made of PVC or wood, and 0 otherwise. |
| *Exposed walls of the home (binary)* | It takes 1 whether the house has at least two exterior sides, and 0 otherwise. |
| *Thermostat use for the heating system (binary)* | It takes 1 whether the heating system is regulated by a thermostat, and 0 otherwise. |
| **Location-based factors** | |
| *Geographical distribution – Northern area (binary)* | It takes 1 whether the house is situated in the north of Italy, and 0 otherwise (center or south). |
| **Household's electrical appliance equipment** | |
| *Electric heating system (binary)* | It takes 1 whether the appliance is owned by the household, and 0 otherwise. |
| *Electric water heating system (binary)* | It takes 1 whether the appliance is owned by the household, and 0 otherwise. |
| *Refrigerator (binary)* | It takes 1 whether the appliance is owned by the household, and 0 otherwise. |
| *Age of the refrigerator (binary)* | It takes 1 whether the appliance has been owned for more than 10 years, and 0 otherwise. |
| *Freezer (not included with the refrigerator) (binary)* | It takes 1 whether the appliance is owned by the household, and 0 otherwise. |
| *Loads of laundry per week (continuous)* | It indicates the number of washing machine loads run by the household per week. |
| *Age of the washing machine (binary)* | It takes 1 whether the appliance has been owned for more than 10 years, and 0 otherwise. |
| *Laundry dryer (not included with the washing machine) (binary)* | It takes 1 whether the appliance is owned by the household, and 0 otherwise. |
| *Dishwasher (binary)* | It takes 1 whether the appliance is owned by the household, and 0 otherwise. |
| *Electric stoves (binary)* | It takes 1 whether the appliance is owned by the household, and 0 otherwise. |
| *Electric oven (binary)* | It takes 1 whether the appliance is owned by the household, and 0 otherwise. |
| *Computer (continuous)* | It indicates the number of computers owned by the household. |
| *Traditional light bulbs (continuous)* | It indicates the number of traditional light bulbs in the dwelling. |
| *Energy-saving light bulbs (continuous)* | It indicates the number of energy-saving light bulbs in the dwelling. |
| *Color TV (continuous)* | It indicates the number of TVs owned by the household. |
| *Air conditioning (binary)* | It takes 1 whether the appliance is owned by the household, and 0 otherwise. |
| *Gardening electric tools (binary)* | It takes 1 whether the appliance is owned by the household, and 0 otherwise. |

Table 1.3: Description of variables used in the regression.

Regarding the saturation rate of electrical equipment, i.e., the ratio of households owning the $j^{th}$ appliance to the total sample, we observe that all households own a refrigerator. 82% of households own an electric oven, 60% of them own a dish washer, while air conditioning is present in 26% of the dwellings in the sample (Figure 1.1). Household appliances with lower saturation rates include gardening equipment (10%), electric stove (6%), water heater (11%), and electric heating system (6%).

Figure 1.2 illustrates the saturation rate of electric equipment across quartiles of annual electricity consumption. It shows that the saturation rate for each type of electrical equipment increases with higher quartiles of electrical consumption. Ownership of more energy-intensive appliances, such as air conditioners, electric stoves, freezers, and dryers, is strongly correlated with higher electrical consumption.

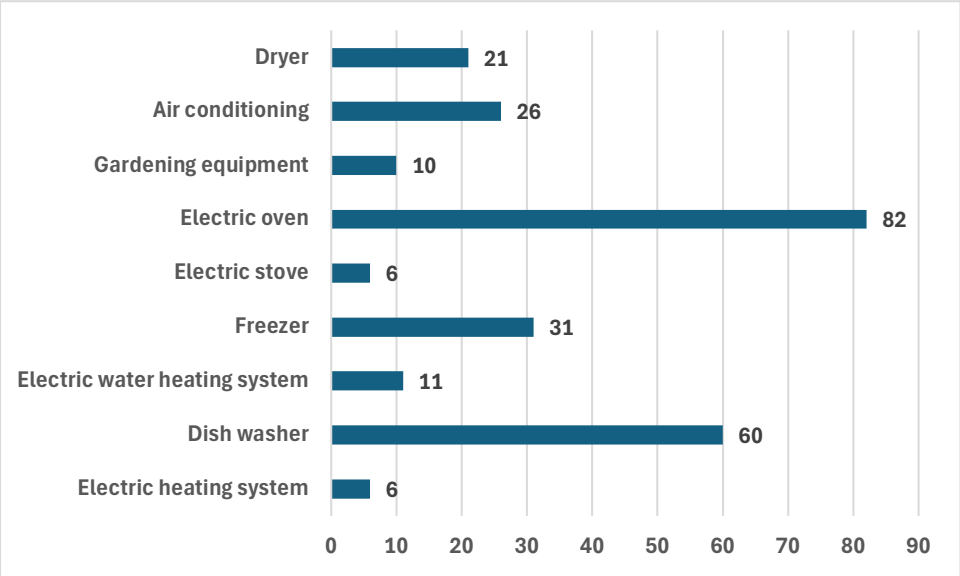



Figure 1.1: The percentages of saturation of each appliance. Each percentage describes the ratio of households owning the single appliance to the total number of households.

Figure 1.3 displays the saturation rates of electric equipment across geographic areas. In general, more technologically advanced and higher-cost appliances exhibit greater diffusion in the northern regions (North-East and North-West) than in the Centre and the South, a pattern consistent with the well-documented income disparities across Italian regions.

A different pattern emerges for electric heating devices and electric water heaters—intended

here as portable electric stoves and traditional electric boilers rather than modern heat pump systems. Although these technologies are relatively outdated and inefficient, their saturation rates are 10–20 percentage points higher in Southern and Insular regions compared to the rest of the country. This distribution likely reflects economic constraints and slower capital replacement dynamics, whereby households rely on low upfront-cost but energy-inefficient technologies. In this sense, the higher prevalence of these appliances in the South may signal delayed technological upgrading rather than greater purchasing power. Additionally, there are appliances such as freezers and air conditioners, whose ownership is more influenced by weather conditions, resulting in similar saturation rates in the central and southern regions as in other parts of the country.

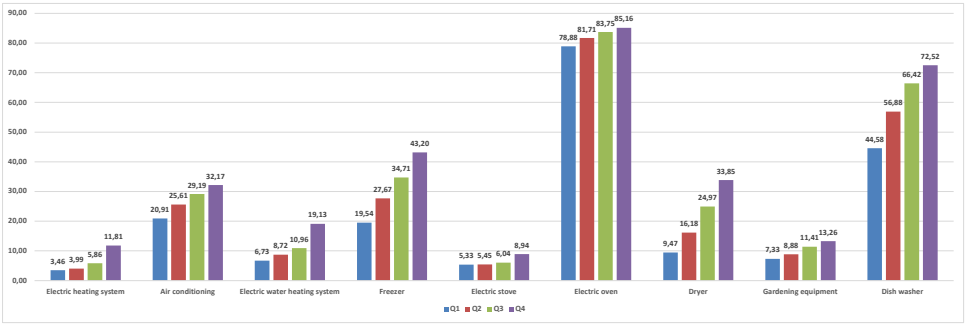



Figure 1.2: The percentages of saturation of each appliance by electricity consumption quartile.

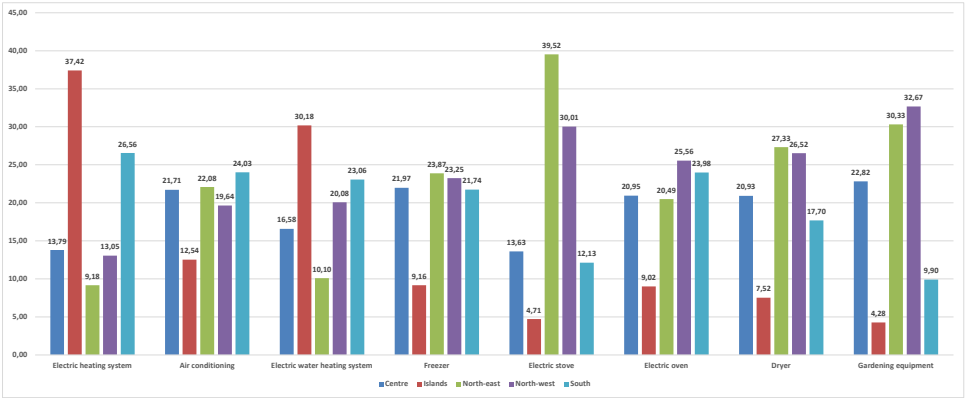



Figure 1.3: The percentages of saturation of each appliance by geographical distribution.

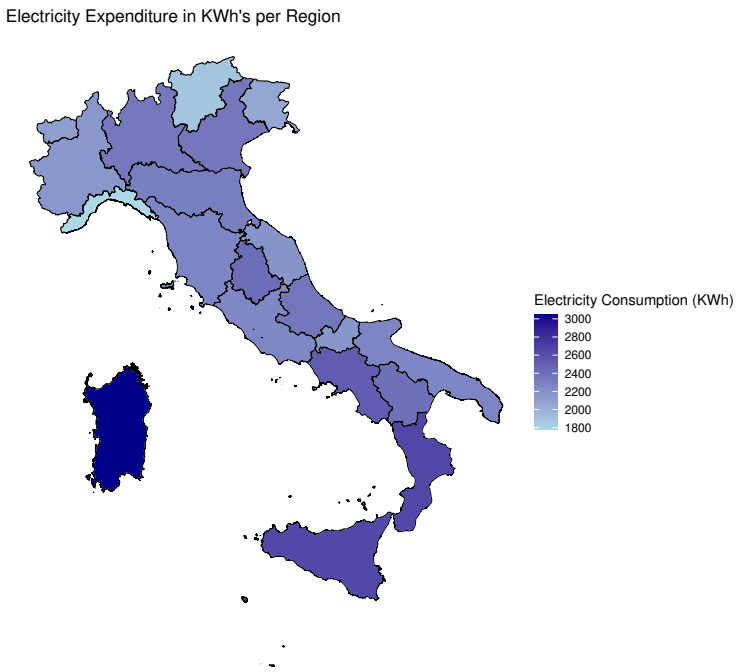



Figure 1.4: Regional distribution of household's annual electricity consumption by energy classes.

Figure 1.4 shows the average annual electricity consumption in Italian regions. The variability in the average consumption between regions is quite low, with consumption ranging from 1797 kWh to 3000 kWh per year. The regions with higher average consumption are mainly in southern Italy, such as Campania, Sicily, Calabria and Sardinia, but also in the north, such as Veneto and Lombardy. Conversely, regions with lower average consumption are Liguria, Trentino, and Friuli-Venezia Giulia.

For what concerns the average consumption per household size (Figure 1.5), it can be observed, as expected, that electricity consumption is positively correlated with the number of family members but it increases less than proportionally with household size, indicating the presence of significant economies of scale. Larger households might share energy services such as space heating, lighting, and appliances, leading to a declining per-capita consumption as household size increases.

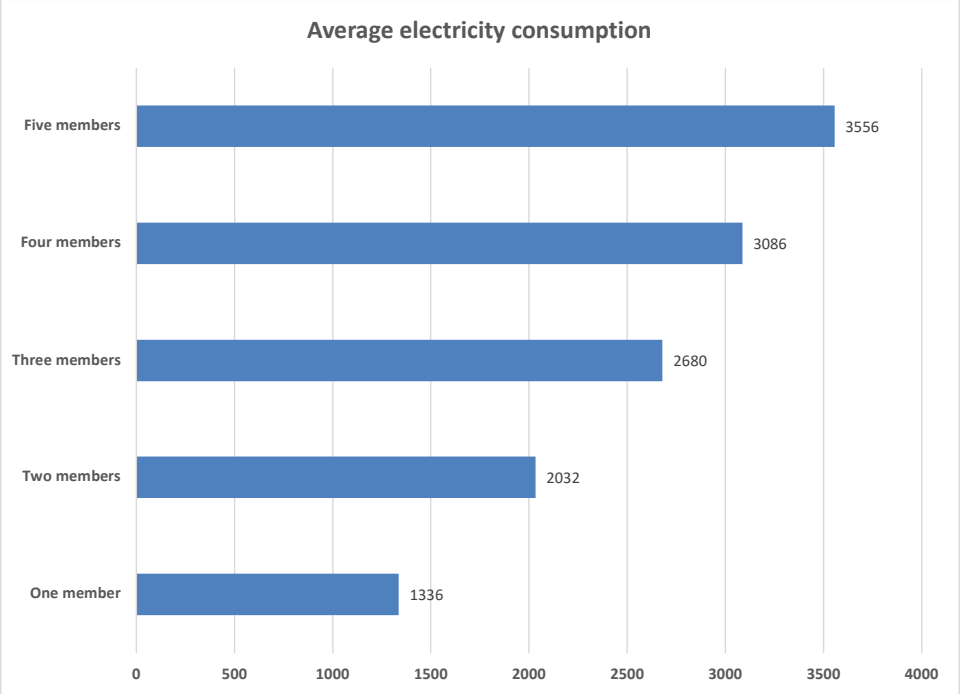



Figure 1.5: Household's annual electricity consumption by household size. On the y-axis the average household's annual consumption, expressed in kWh, is reported while on the x-axis the categorical variables describing the household's numerosity is reported.

## 1.4 Econometric Strategy

### 1.4.1 Conditional Demand Model

As explained above, CDA exploits appliances ownership in order to impute the overall energy consumption to each appliance type. We developed the following regression Equation (Parti and Parti, 1980; Larsen and Nesbakken, 2004; Frondel et al., 2019):

$$\begin{aligned} EC_i = \beta_1 + \sum_{j=1}^{J} \lambda_j HS_{ij} + \sum_{l=1}^{L} \theta_l D_{il} + \sum_{k=1}^{K} \gamma_k N_{ik} \\ + \sum_{l=1}^{L} \sum_{m=1}^{M} \rho_{lm} \left(C_{im} - \overline{C_{lm}}\right) D_{il} + \sum_{k=1}^{K} \sum_{m=1}^{M} \rho_{km} \left(C_{im} - \overline{C_{km}}\right) N_{ik} + \epsilon_i \end{aligned} \tag{1.3}$$

The response variable, $EC_i$, is the overall electricity consumption of household i (where $i = 1, .., N$). $\beta_1$ is the constant and captures all the electricity stemming from non-observable appliances. It is sometimes called *miscellaneous electricity*. $HS_{ij}$ reflects the household size associated to the number of household members[7]. $HS_{ij}$ takes the value 1 when family i has j members corresponding to the actual size of the family, and 0 otherwise. Household size accounts for those small appliances that are not observable whose number tends to increase with the number of household members. So, it is considered plausible to assume growing coefficients for the household size dummy variables.

$D_{il}$ takes value 1 whether the household i own the appliance l, $N_{ik}$ is a count variable for those (k's) appliances with high frequency such as TVs and for those for which usage intensity is available such as the number of washing-machine cycles. We must consider that the electricity consumption imputed to the single appliance is captured either by term $D_{il}$ or by $N_{ik}$, that is $l \neq k$.

From past studies, we know that residential electricity consumption is linked to various factors such as socio-demographic characteristics, physical characteristics of dwellings, residential location, environmental and climate factors, and the cost of energy use. These

[7]We considered the single-person household electricity base consumption level as the reference class of this categorical variable.

determinants are included in the interaction terms in the Equation (1.3). The first interaction term reflects the relationship between the deviation of the mean values of explanatory variables related to household characteristics and dwellings features such as household breadwinner's age, number of children in the house, square footage, number of rooms, etc., $\left(C_{im} - \overline{C_{lm}}\right)$, and the ownership of each single appliance l ($D_{il}$). The same holds for the second interaction term for the k appliances type ($\left(C_{im} - \overline{C_{km}}\right)$). Demeaning the covariates, typical of conditional demand models, does not alter the marginal coefficients in linear models with intercepts, but improves interpretation, reduces multicollinearity in specifications with non-linear and interaction terms, and facilitates the imposition of constraints typical of demand systems (adding-up and homogeneity). For explanatory variables expressed in the form of binary variables, interaction terms are delineated by the interdependence between the possession of an appliance or its frequency of utilization, and the associated dummy variable. As an illustration, such interactions might manifest in the context of owning an electric heating system in conjunction with considerations such as wall exposure or possessing an electric heating system in correlation with the attainment of a high school diploma.

$\beta_1$, $\beta_j$, $\theta_l$, $\gamma_k$, $\rho_{lm}$ and $\rho_{km}$ are the coefficients to be estimated. $\theta_l$ captures the mean electricity consumption of each single appliance l conditional on the availability of appliance l while $\gamma_k$ captures the average electricity consumption of an additional unit or intensity usage of the appliance k. Both parameters indicate the mean level of electricity consumption of appliances l and k when all the household and dwelling-related variables, $C_{im}$, with $m = 1, \ldots, M$, take values equal to their mean computed across all the observational units owning the appliance. So, these parameters, $\theta_l$ and $\gamma_k$, would indicate the average consumption for the *typical household*; while, parameters $\rho_{lm}$ and $\rho_{km}$ would capture the effect of heterogeneity in households and dwellings characteristics on the electricity consumption of each single appliance. $\overline{C_{lm}}$ and $\overline{C_{km}}$ are the means of m explanatory variables for those households owning appliances l and k, respectively. For instance, $\overline{C_{lm}} = \frac{1}{H_l} \sum_{i=1}^{N} C_{lm} D_{il}$, where $H_l$ is the fraction of household owining appliance l.

We consider 15 household electric devices and appliances and 146 interaction effects in regression Equation (1.3). Table 1.4 shows which regressors are interacted with individual appliances or electrical systems.

| Appliance | Age of head | Gender of head | Education of head | Number of elderly | Marital status | Number of children | Household size | Construction after 1990 | PVC/Wood windows |
|---|---|---|---|---|---|---|---|---|---|
| *Electric heating system* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Computers* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| *Electric water system* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| *Refrigerator* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| *Freezer* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| *Electric oven* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| *Washing machine cycles (per week)* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| *Dish-washer* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| *Electric stove* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| *Number of standard light bulbs* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| *Number of energy-saving light bulbs* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| *Televisions* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| *Air conditioning* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Electric gardening equipment* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| *Dryer* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |

| | Wall exposure | Thermostat use | Northern area | Villa | Disposable income | Employment status | Number of rooms | Age of refrigerator | Age of washing machine |
|---|---|---|---|---|---|---|---|---|---|
| *Electric heating system* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| *Computers* | | | | | ✓ | ✓ | | | |
| *Electric water system* | | | | ✓ | ✓ | ✓ | | | |
| *Refrigerator* | | | | | ✓ | ✓ | | ✓ | |
| *Freezer* | | | | | ✓ | ✓ | | | |
| *Electric oven* | | | | | ✓ | ✓ | | | |
| *Washing machine cycles (per week)* | | | | | ✓ | ✓ | | | ✓ |
| *Dish-washer* | | | | | ✓ | ✓ | | | |
| *Electric stove* | | | | | ✓ | ✓ | | | |
| *Number of standard light bulbs* | ✓ | | | | ✓ | ✓ | ✓ | | |
| *Number of energy-saving light bulbs* | ✓ | | | | ✓ | ✓ | | | |
| *Televisions* | | | | | ✓ | ✓ | ✓ | | |
| *Air conditioning* | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| *Electric gardening equipment* | | | | | ✓ | ✓ | | | |
| *Dryer* | | | | | ✓ | ✓ | | | |

Table 1.4: Interaction among electric appliances and household and building characteristics.

First, Equation 1.3 is estimated employing the Ordinary Least Squares (OLS) regression. Prior investigations (Larsen and Nesbakken, 2004; Dalen and Larsen, 2015; Rebman et al., 2008; Matsumoto, 2016) highlighted the existence of heteroscedasticity. By model specification, the error term systematically varies with the explanatory variables. For instance, larger dwelling size and a greater number of electrical appliances imply a higher potential for increased variation in electricity consumption among households (due to variability in the use of appliances). Consequently, the disparity between estimated and observed electricity consumption may escalate with the size of the appliance inventory. Hence, robust standard errors have been computed[8].

Assuming a very short time horizon, this study applies CDA under the assumptions that explanatory variables are exogenous to households and that the stock of electrical appliances does not change. One of CDA's strengths is the direct estimation of end-use parameters for each appliance—without requiring assumptions about individual behavior or appliance technical specifications—as in Larsen and Nesbakken (2004). Consequently, these parameters capture both the average technical conditions of appliances and the behavioral component of energy demand; additionally, by including controls for the frequency of appliance use, we obtain behavioral insights into household usage patterns.

Secondly, the quantile regression model is employed to estimate Equation 1.3 to capture the relationship between household electricity consumption and its determinants at different points along the conditional distribution of EC[9]. There are several advantages

[8]To further evaluate the adequacy of the classical OLS assumptions, a set of diagnostic tests and graphical analyses was performed on the residuals of the baseline specification. In particular, we assess the normality of the error term and the presence of heteroskedasticity, both of which are relevant for reliable statistical inference and for selecting an appropriate econometric framework. The Jarque–Bera test strongly rejects the null hypothesis of normally distributed residuals (Table 1.9 in the Appendix 1.A.2), with a test statistic of 201,820 and a p-value below conventional significance levels. This result indicates substantial departures from Gaussianity, reflecting skewness and heavy tails in the error distribution. Heteroskedasticity is further examined using the Breusch–Pagan test in both its studentized and non-studentized versions (Table 1.9 in the Appendix 1.A.2). In both cases, the null hypothesis of homoskedastic errors is decisively rejected (p-value $< 0.00$), indicating that the variance of the residuals systematically varies with household and dwelling characteristics. Graphical diagnostics corroborate these findings. The residuals-versus-fitted plot exhibits a clear fan-shaped pattern, with dispersion increasing at higher predicted levels of electricity consumption, providing visual evidence of heteroskedasticity (Figure 1.9 in the Appendix 1.A.2). The Normal Q–Q plot shows marked deviations from the reference line, particularly in the upper tail, confirming the presence of non-normal and heavy-tailed residuals (Figure 1.8 in the Appendix 1.A.2).

[9]While the use of robust standard errors ensures consistent inference for the conditional mean under

of using quantile regression: i) it can mitigate or avoid sampling bias by employing the entire sample to estimate the effects of explanatory variables on the distribution of energy use, instead of selecting a subsample or dividing the sample into different groups (Huang, 2015), ii) it is more efficient than OLS when the residual series is non-normally distributed and the vector of estimated coefficients is more robust to outliers and iii) it provides a more comprehensive view of the effects of potential factors on residential electricity consumption because the responses of household electricity consumption to a specific predictor can vary between the bottom and top quantiles[10] (Frondel et al., 2019). The general quantile regression model might be represented as follows:

$$Q\left(p|x,\beta\right)=x'\beta\left(p\right),p\in\left(0,1\right) \tag{1.4}$$

An estimate of $\beta\left(p\right)$ is obtained by minimizing:

$$L\left(\beta\left(p\right)|EC,X\right)=\sum_{i}\left(p-\omega_{i}\right)\left(EC_{i}-x_{i}'\beta\left(p\right)\right) \tag{1.5}$$

Where $\omega_{i}=I\left(EC_{i}\leq x_{i}'\beta\left(p\right)\right)$.

Selecting a variety of quantiles allows us to describe the entire distribution of data. The standard errors of $\hat{\beta}$ depend on the distribution around the quantile, which is unknown and not utilized by the estimator itself. Therefore, a commonly adopted solution is to employ the bootstrap. In fact, Bootstrap Standard Errors (BSE) are employed in our model[11].

heteroskedasticity, the combination of strong non-normality and systematic variance patterns suggests that the conditional distribution of household electricity consumption is highly heterogeneous and not adequately summarized by its mean alone. This motivates complementing the OLS analysis with a quantile regression framework.

[10]For instance, quartiles might be employed to determine how variations in predictors influence household consumption at the tails of the distribution, indicating which households consume less or more energy.

[11]To calculate standard errors in quantile estimates, we used the pair/xy bootstrap, the default method of the boot.rq function in the quantreg package in R.

### 1.4.2 Counterfactual Analysis

In this study, we do not evaluate the impact of a policy per se; rather, we assess the effect of households' decisions to invest in energy-efficiency measures. In particular, we estimate the effect of investments in energy efficiency for a specific end-use — namely air conditioning — on households' total annual electricity consumption.

Causal inference in this setting requires comparing the observed outcome with the unobserved outcome that would have prevailed in the absence of treatment. This issue is formalized by the potential outcomes framework (Roy, 1951; Rubin, 1974). Since only one potential outcome is observed for each unit, individual treatment effects are not identified, and the analysis must therefore focus on average causal parameters, such as the *Average Treatment Effect on the Treated* (ATET).

Energy-efficiency investments in the residential sector are an important lever for reducing greenhouse gas emissions and containing households' energy expenditures. In the case of air-conditioning systems, such investments may lower electricity use, improve indoor comfort, and contribute to broader environmental and distributional policy objectives.

Estimating a *causal effect* of these investments is, however, methodologically challenging. The decision to invest is not random, but depends on observable characteristics (such as income, household composition, and housing endowments) as well as unobservable factors (such as comfort preferences, innovativeness, or attention to energy efficiency) that may also affect subsequent electricity consumption. As a result, simple OLS estimates are likely to be biased by selection on observables and unobservables. Moreover, the empirical analysis is based on a cross-sectional survey observed in a single year, which does not allow the use of panel-data designs or stronger identification strategies. For this reason, an approach that explicitly models the non-random selection into treatment is more appropriate. The two-step Heckman method is particularly appropriate for cross-sectional data observed in a single year and characterized by strong non-random selection of households: compared with simple OLS regressions or propensity-score matching procedures (which assume conditional ignorability and therefore do not correct for selection on unobservables), the

switching model makes the participation mechanism explicit and allows inclusion of a control function (the inverse Mills ratio in the two-step procedure or the implicit correction in ML estimation) that removes bias arising from latent variables correlated with both the investment decision and consumption. Relative to an IV/2SLS approach, the adopted specification has the advantage of jointly estimating selection and outcome and — under the model's parametric assumptions (in particular joint normality of errors and correct functional form) — producing counterfactual predictions that permit computation of estimands such as ATET/ATT; conversely, IV is less dependent on parametric assumptions but typically identifies a local effect (LATE) linked to compliers induced by the instrument and does not directly recover the correlation between the selection and outcome processes.

To the best of our knowledge, this approach has not previously been applied to this specific research question, and it therefore represents an original contribution to the empirical literature on household energy-efficiency investments.

First, we define the treatment. In the survey used, respondents were asked whether, in the last five years, they had made investments aimed at reducing household energy consumption through energy-efficiency measures. These investments are recorded separately for different domains of the dwelling, including heating, air conditioning, hot water, and the electrical system. Since heating and air-conditioning systems may be functionally related, especially when devices such as reversible air conditioners or heat pumps provide both cooling and heating, we define a broader treatment variable capturing energy-efficiency investments in thermal systems. A household is classified as treated if it reported an investment in either heating or air conditioning.

The air-conditioning component of the treatment is based on whether the household reported investments aimed at reducing air-conditioning-related energy consumption. The heating component is based on the variable identifying whether the household reported heating-related energy-efficiency investments. Additional information in the survey allows us to distinguish whether heating investments involved a shift towards more efficient heating equipment or measures aimed at increasing the insulation of the dwelling. Table

1.5 reports the types of interventions considered.

| **Measures and interventions undertaken by households with the aim of reducing household energy consumption – Thermal systems** |
|---|
| **Air-conditioning system** |
| • Installation of a centralized autonomous system for the entire dwelling replacing single-room units. |
| • Replacement of a single unit with high energy-efficiency devices. |
| • Replacement of the central chiller with a more efficient model. |
| • Modification or refurbishment of the air distribution system, such as ductwork or splits, or replacement of system components. |
| • Use of solar-protection devices, such as awnings, blinds, solar-control glazing or sunshades. |
| • Other unspecified types of intervention. |
| **Heating system** |
| • Heating-related energy-efficiency investments. |
| • Shift towards, or replacement with, more energy-efficient heating equipment. |
| • Interventions aimed at increasing the insulation of the dwelling. |

Table 1.5: Types of interventions for thermal-system energy efficiency.

To avoid confounding this treatment with other simultaneous energy-efficiency measures, we restrict the estimation sample to two groups only. The treated group includes households that reported exactly one energy-efficiency investment, and this investment concerns either heating or air conditioning. The control group includes households that reported no energy-efficiency investment in any of the observed domains. We therefore exclude households that reported simultaneous investments, as well as households whose only investment concerned hot water or the electrical system. The estimated coefficient should therefore be interpreted as the effect associated with undertaking a single thermal-system efficiency investment, relative to undertaking no energy-efficiency investment.

As previously anticipated, the empirical strategy adopted is based on the Heckman's two-stage selection model (Heckman, 1976, 1979; Heckman and MaCurdy, 1986), a treatment/switching-regression specification implemented via the *treatReg* package for R. This specification combines a selection equation, where the dependent variable describes the probability of undertaking energy-efficiency investments, and an outcome equation, where the dependent variable is the logarithm of a household's total annual electricity

consumption, allowing the error terms to be correlated. The treatment decision is modelled as a latent probit process while the outcome is specified linearly conditional on participation, with the correlation between errors estimated by the parameter $\rho$ (Toomet, 2020).

Formally, the model can be defined as:

$$D_i^* = \alpha_0 + \alpha_1' x_i^{(s)} + u_i, \qquad D_i = \mathbf{1}\{D_i^* > 0\} \tag{1.6}$$

$$\log(\text{Electricity-Consumption}_i) = \beta_0 + \beta_1' x_i^{(o)} + \beta_2 D_i + v_i \tag{1.7}$$

where $D_i$ denote the treatment indicator, equal to one if household $i$ undertook an investment in energy-efficiency measures for the air-conditioning system and zero otherwise; $x_i^{(s)}$ includes household and dwelling characteristics entering the selection equation, and $x_i^{(o)}$ includes the regressors used in the outcome equation. In particular, $x_i^{(s)}$ comprises marital status, disposable income, household size, age, gender and education of the household head, the number of elderly and children, employment status, the number of children under 14, dwelling size and type, the year of construction, the presence of PVC or wooden frames, wall exposure, and regional area. The outcome equation includes the same set of core covariates, together with variables capturing the household's energy-related endowment and electricity-using equipment, such as thermostat ownership, electric heating system, freezer, electric stove, electric oven, computers, gardening equipment, traditional light bulbs, televisions, dryer, weekly laundry loads, and dishwasher.

The disturbance structure is assumed bivariate normal, $(u_i, v_i)' \sim \mathcal{N}(0, \Sigma)$, with variance–covariance matrix, $\begin{pmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{pmatrix}$, and this assumption allows conditional expectations to be written and the control function based on the inverse Mills ratio to be derived, $\lambda(z) = \frac{\varphi(z)}{\Phi(z)}$, where $\varphi$ and $\Phi$ denote the standard normal density and CDF, respectively.

Identification of the treatment effect parameter $\beta_2$ in the Heckman framework relies

on two possible sources of variation. The first is the presence of exclusion restrictions, i.e. variables included in the selection equation $x^{(s)}$ but excluded from the outcome equation $x^{(o)}$, which affect the probability of investment without directly influencing electricity consumption. In this framework, these variables are usually called instruments. Exclusion restrictions play a role analogous to instruments in that they shift selection without directly entering the outcome equation. However, unlike standard instrumental variables approaches, the Heckman framework uses these variables to construct the selection correction term rather than to instrument endogenous regressors directly. The second source of identification arises from the parametric structure of the model. Under the assumption of joint normality of the error terms, $(u_i, v_i) \sim \mathcal{N}(0, \Sigma)$, the selection correction term (the inverse Mills ratio) is fully determined by the covariates in the selection equation, allowing identification even in the absence of strong exclusion restrictions[12].

The instruments are defined at the regional level, hence there is variation across Italy's twenty regions. They are lagged, i.e. they refer to each of the three years preceding the year of the survey under analysis. The instruments are the following:

- The number of days of extreme heat and extreme cold in 2018–2020 (in logarithm);
- The number of days of heavy rainfall in 2018–2020 (in logarithm);
- The regional share of tax-bonus-financed renovation investments relative to the national total of investments carried out in 2018–2020;
- The regional incidence of owner-occupied dwellings in 2018–2020.

For the meteorological variables, we followed a consistent and reproducible workflow to convert raw daily data into annual, region-level instrumental measures. These data were obtained from the AGRI4CAST Resources Portal and produced and published by the Joint Research Centre (JRC) of the European Commission. The JRC is the European Union's in-house science service that provides technical-scientific support to EU policies,

[12]When identification relies solely on functional form, results become more sensitive to distributional misspecification and the validity of the normality assumption, as widely discussed in the literature (Angrist and Krueger, 2001; Hamilton and Nickerson, 2003).

notably the Common Agricultural Policy (CAP) and food security. A key component of the datasets is derived from meteorological station observations that are interpolated onto regular grids (typically to produce time series of variables such as temperature, precipitation, wind and radiation). After importing and cleaning the meteorological files, we geolocated the stations and assigned each latitude/longitude pair to the corresponding administrative region via a spatial join with the regional shapefile. Daily station values were then aggregated to the region–day level in order to reduce local noise and obtain a homogeneous regional measure. For each type of extreme event we defined operational thresholds as follows:

- **Extreme heat days** were defined as days with mean daily temperature greater than 30 °C;
- **Extreme cold days** as days with mean daily temperature below 0 °C;
- **Heavy-rainfall days** as days with total precipitation exceeding 50 mm.

The regional incidence of owner-occupied dwellings is computed as the number of households living in owner-occupied housing divided by the total number of resident households. It is derived from Istat based on household sample surveys, in particular the Household Budget Survey (HBS) and, consistently, the Survey on Income and Living Conditions (EU-SILC).

The regional share of investments financed through tax-bonuses therefore represents the percentage of actual investment expenditure allocated to a given region relative to the total expenditure allocated nationally, over the considered years. The data refer to the ecobonus, which is the tax relief instrument for the energy retrofit of buildings. It provides a personal or corporate income tax deduction on expenses incurred for interventions that reduce energy consumption (e.g. insulation, window replacement, heat pumps, condensing boilers, solar collectors, building automation, etc.). The aim is to incentivize investments that reduce the energy demand and emissions of the building stock (improving thermal performance, replacing obsolete systems, and promoting high-efficiency technologies),

thereby contributing to national and European energy-efficiency objectives[13].

Because of data availability constraints, we do not possess annual indicators prior to 2018; consequently, we cannot directly observe local conditions in 2017, when some households may have decided to invest. However, as documented by ENEA (Italian National Agency for New Technologies, Energy and Sustainable Economic Development), there is an operational lag of approximately one year between the investment decision and the execution/invoicing of the intervention, so many choices made around 2017 are reflected in the flows and activities observed in 2018. Therefore, the regional indicators available from 2018 onward can be regarded as plausible proxies for the conditions that influenced investment decisions in 2017–2018; moreover, this temporal discrepancy is more likely to introduce an attenuation-type measurement error (diminishing predictive power) rather than a systematic bias.

As discussed above, identification in the Heckman selection model requires the instruments to be valid exclusions. In particular, they must satisfy two conditions: (i) relevance, namely they must strongly affect the probability that a household undertook energy-efficiency investments in the relevant year; and (ii) exogeneity, meaning that, conditional on treatment and controls, they must not have a direct effect on 2021 consumption other than through the investment decision.

The economic mechanisms linking the instruments to selection support the relevance condition. Extreme climatic events and heavy precipitation in a given year may increase perceived damage or discomfort, thereby encouraging households to undertake energy-efficiency works. Similarly, a high regional incidence of tax-bonus use reflects the effectiveness of the local supply side and the local capacity to implement such interventions, while a larger share of owner-occupiers increases the financial incentive to invest. These channels provide a clear rationale for expecting the instruments to be strongly predictive of treatment. The timing of the variables, in turn, supports the exogeneity condition. The instruments are measured over the period 2018-2020, while the outcome is observed in

[13]ENEA, Tax Deductions for the Energy Retrofit of Buildings – Report. `https://www.pubblicazioni.enea.it/`.

2021. This temporal ordering reduces concerns about contemporaneous direct effects not mediated by treatment, although it does not fully rule out the presence of persistence or other dynamic channels.

We estimate the model by maximum likelihood (MLE). In practice, the package jointly estimates the selection equation, specified as a probit for the probability of investing, and the outcome equation, specified as the logarithm of consumption, by maximizing the log-likelihood function constructed from the conditional densities of participants and non-participants. The ML routine uses the two-step estimator as initial values and then optimizes the likelihood to obtain efficient estimates of $\beta$, $\sigma$, and $\rho$. The output also reports the log-likelihood, the estimated correlation between the error terms, and the distributional parameters in the model summary. The general consensus is that MLE is more efficient than the two-step Heckman estimator (Nelson, 1984). However, the absence of valid instruments remains problematic for any estimator. Although MLE is typically more efficient, it also relies on stronger distributional assumptions than the two-step Heckman method, making the availability of an instrument even more important (Winship and Mare, 1992).

## 1.5 Estimation Results and Discussion

### 1.5.1 CDA Results

First, we present the results of the conditional demand model without interactions and then with interactions. In the results we present, we only report coefficients for appliances and interaction variables that appear realistic and statistically significant at least at the 10% level. The complete results can be found in the Appendix 1.A.3. Figure 1.6 shows the CDA model estimated using OLS without interactions. It shows estimates for the coefficients $\theta_l$ and $\gamma_k$. We have sorted the coefficients associated with each device and electrical appliance in descending order of consumption and with the confidence interval. The coefficients $\theta_l$ and $\gamma_k$ can be interpreted as the electricity consumption related to single appliance ownership ($D_{il}$) or unit increase in the number of a type of appliance ($N_{ik}$) in terms of annual kWh for the 'typical household' and 'standard building'. The OLS coefficients display a clear structure: a small number of end-uses account for the largest share of average household electricity consumption, while a broader set of appliances contributes smaller amounts. The most prominent contributors are the electric water heater (986 kWh) and the electric heating system (910 kWh), which together constitute the dominant thermal loads in the sample. Large household appliances form the next tier of importance: the freezer (547 kWh), the clothes dryer (422 kWh) and the dishwasher (384 kWh). Appliances and loads of intermediate impact include the electric hob (271 kWh), the number of televisions (223 kWh), air conditioning (197 kWh) and electric gardening tools (121 kWh); televisions, despite their wide diffusion, exhibit a notable per-unit contribution. The coefficient on washing-machine cycles (117 kWh) represents the marginal effect per additional weekly cycle: each extra weekly cycle is associated with an increase of 117 kWh in average consumption, so the aggregate importance of the washing machine depends on the sample average of weekly cycles. Smaller contributions are observed for the number of computers (114 kWh), the electric oven (47 kWh), energy-saving bulbs (14 kWh) and standard bulbs (9 kWh), with lighting therefore appearing marginal relative to major appliances. Finally, the intercept (miscellaneous) equals 189

kWh and captures the portion of consumption not directly attributed to the observed appliances (small devices, standby loads, and unlisted equipment); while non-negligible, this residual term is smaller than many individual appliance contributions, indicating that most of the average consumption level is explained by the included regressors.

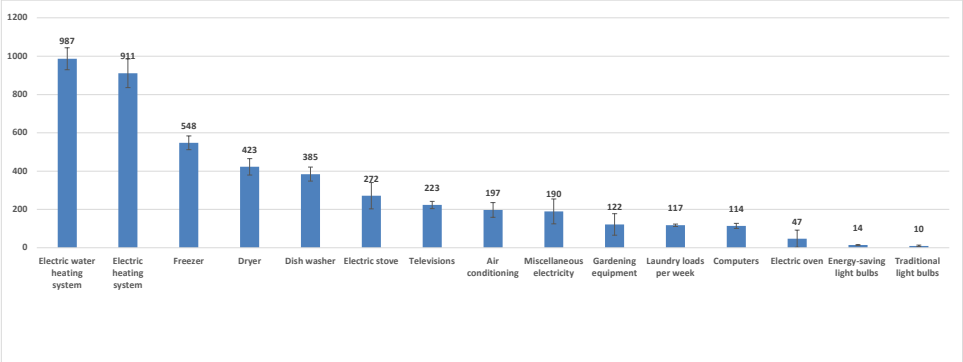



Figure 1.6: Estimated household consumption via ordinary least squares. The model includes only appliance ownership and endowment as covariates associated with significant coefficients at least at 10%. The response variable is the household's annual electricity consumption expressed as kilowatt per hours.

The allocation of electrical consumption among the different appliances is then disaggregated based on the distribution of electricity consumption across quartiles. Figure 1.7 shows coefficient estimates for the first, second, and third quartiles, respectively. As in the OLS specification, the dependent variable is measured in kilowatt-hours (kWh), and each coefficient represents the contribution to electricity consumption associated with the corresponding appliance or usage intensity within a given quartile.

A salient result concerns the miscellaneous electricity component, which captures consumption not directly attributable to the observed appliances. In the first quartile, this coefficient is small (22.6 kWh) and not statistically significant, indicating that residual consumption plays a negligible role among low-consumption households. By contrast, the same component becomes substantial and highly significant in the upper parts of the distribution, rising to 161.6 kWh in the second quartile and to 671.3 kWh in the third quartile. This pattern suggests that unobserved end-uses and standby loads become increasingly important as total electricity consumption rises.

Electric thermal technologies emerge as the dominant drivers of electricity use through-

out the distribution. The electric heating system is associated with an energy consumption of 602.5 kWh in the first quartile, 792.5 kWh in the second quartile, and 1,053.5 kWh in the third quartile. Similarly, the electric water heating system shows a pronounced and monotonic increase from 473.9 kWh in the first quartile to 1,057.9 kWh and 1,140.2 kWh in the second and third quartiles, respectively. These results indicate that, conditional on ownership, the electricity consumption associated with electric thermal appliances is substantially larger in higher-consumption households. In other words, the difference in kWh between owners and non-owners of these appliances increases across the consumption distribution, which may reflect higher intensity of use, lower average appliance efficiency, or compositional differences among owners in the upper quartiles.

Large household appliances form a second group with sizeable and increasing contributions across quartiles. The estimated contribution of the freezer rises from 267.6 kWh in the first quartile to 644.4 kWh in the second and 662.6 kWh in the third quartile. Dishwashing shows an even sharper increase, from 151.4 kWh in the first quartile to 462.4 kWh and 518.7 kWh in the second and third quartiles, respectively. The dryer is associated with high consumption levels across all quartiles, amounting to 517.2 kWh in the first quartile, 544.0 kWh in the second, and 429.8 kWh in the third. While the coefficient slightly declines in the upper quartile, it remains large in absolute terms, confirming the dryer as one of the most electricity-intensive appliances in the sample. Appliances with intermediate contributions also display clear heterogeneity across the distribution. The electric stove is associated with 73.8 kWh in the first quartile, increasing to 238.9 kWh in the second and 302.4 kWh in the third quartile. The electric oven shows no statistically significant effect in the first quartile (11.5 kWh), but becomes relevant in higher quartiles, with estimates of 37.5 kWh in the second quartile and 104.7 kWh in the third. This pattern suggests that the contribution of cooking appliances is concentrated among households with higher overall electricity consumption.

Entertainment, computing, and comfort-related appliances also exhibit increasing marginal contributions. The estimated effect of an additional television rises from 122.8

kWh in the first quartile to about 277.1 kWh in the second and 276.4 kWh in the third quartile. The contribution of computers increases from 63.8 kWh to 126.4 kWh and 140.8 kWh across the three quartiles. Similarly, air conditioning is associated with 88.4 kWh in the first quartile, 238.1 kWh in the second, and 258.7 kWh in the third, indicating a much stronger role among high-consumption households.

Usage intensity is particularly relevant for the washing machine. The coefficient on laundry loads per week represents the marginal effect of one additional weekly cycle and amounts to 100.3 kWh in the first quartile, 137.9 kWh in the second, and 136.3 kWh in the third quartile. These results imply that increases in washing frequency translate into substantial increases in electricity consumption, especially outside the lower tail of the distribution.

Finally, smaller end-uses such as electric gardening equipment and traditional light bulbs contribute relatively little in absolute terms but show increasing effects across quartiles. Electric gardening equipment accounts for 82.3 kWh in the first quartile, 198.2 kWh in the second, and 187.6 kWh in the third. Traditional light bulbs contribute only a few kilowatt-hours per unit—2.7 kWh in the first quartile, 6.9 kWh in the second, and 9.9 kWh in the third—indicating that lighting plays a marginal role compared with major appliances, even among high-consumption households.

Overall, the quantile estimates reveal substantial heterogeneity in appliance-specific electricity consumption. For most end-uses, the marginal contribution in kilowatt-hours increases markedly when moving from low- to high-consumption households, indicating that differences in intensity of use, efficiency, or both are systematically related to the position in the electricity consumption distribution.

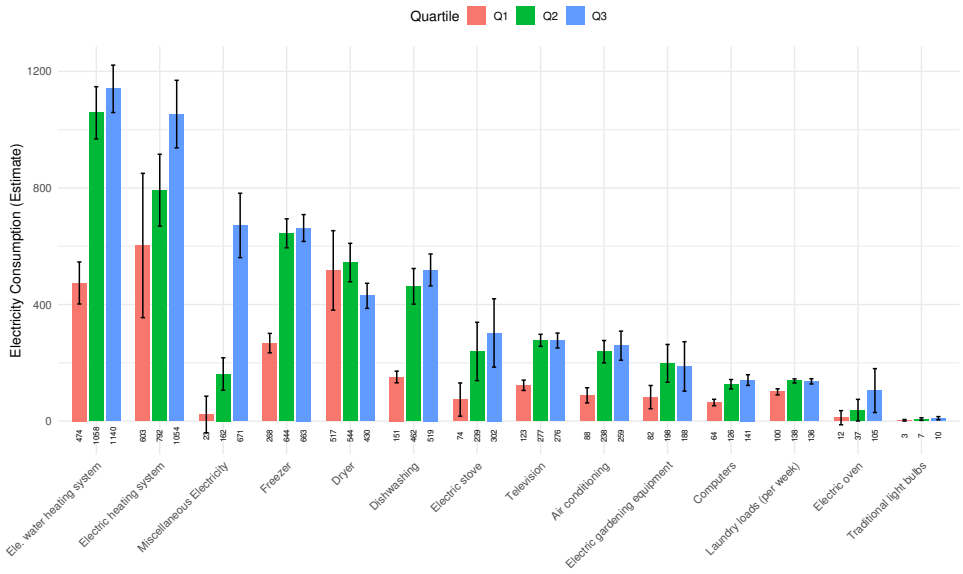



Figure 1.7: Estimated household consumption via quantile regression approaches. The model includes only appliances ownership and endowment as covariates associated with significant coefficients at least at 10%. The response variable is the household's annual electricity consumption expressed as kilowatt per hours.

Tables 1.6 reports the results of estimating the Equation (1.3) with interaction terms via OLS. The inclusion of interaction terms allows the conditional electricity consumption associated with each appliance to vary systematically with household socio-demographic characteristics, economic conditions, dwelling features, and location-based factors. In line with the model specification, interaction terms involving continuous covariates capture the effect of deviations from the mean value of the corresponding characteristic, while interactions with binary covariates measure discrete shifts relative to the reference group.

Introducing interaction terms does not substantially alter the overall hierarchy of appliance-related electricity consumption identified in the baseline OLS specification without interactions. Electric thermal technologies remain the dominant contributors to household electricity use. In particular, the electric water heater and the electric heating system continue to exhibit the largest coefficients, followed by other energy-intensive appliances such as the dryer, dishwasher, freezer, and air conditioning. Compared to the model without interactions, the absolute magnitude of some main appliance coefficients is reduced, which is expected given that part of the variation previously absorbed by average effects is now captured by interaction terms. Nevertheless, the relative ranking of

appliances remains broadly stable, indicating that the core structure of electricity demand is robust to the inclusion of household- and dwelling-specific heterogeneity. The intercept (miscellaneous electricity) increases relative to the specification without interactions, reflecting the fact that the model now conditions appliance-specific consumption on a richer set of characteristics, while the constant absorbs residual consumption not explained by either appliances or their interactions. The single-member household was taken as the reference category, so the interpretation of the coefficients reflects the incremental amount of consumption based on the number of members compared to the single-member household. It can be seen that a household with five members consumes four times as much as one with two members, holding other conditions constant. Household size coefficients remain large, positive, and increasing monotonically with the number of household members, confirming that residual electricity consumption associated with non-observed or low-consumption appliances, as well as general usage intensity, rises sharply with household size. Below we summarise the interaction effects given by the covariates.

- **Head of household's age**

  The interaction between the electric heating system and the age of the household head is positive and statistically significant. Since age enters the model as a deviation from its mean, this result indicates that households whose head is older than average exhibit higher electricity consumption associated with electric heating, conditional on ownership. A similar pattern emerges for the number of computers: an additional computer contributes more to electricity consumption in households where the head is older than the sample mean. In addition, the interaction between the head of household's age and the presence of a laundry dryer shows a further positive contribution of 5.27 kWh. By contrast, the interaction between age and the number of televisions is negative, implying that in households with older-than-average heads, the marginal electricity consumption associated with additional televisions is lower. An older head of household may want to spend more time at home, increasing the

intensity of use of certain appliances. Consequently, in line with the findings, the increase in the age of the head of household may lead to an increase in heating demand, as older people tend to prefer warmer indoor environments for greater comfort. At the same time, greater computer use may reflect the fact that households with older heads spend more time using computers for activities such as work or leisure. The reduction in television use could be due to a shift in entertainment preferences among older households, which may favor alternative forms of leisure.

- **Head of household's gender**

  Gender interactions reflect discrete differences relative to households headed by females (the reference category). The negative interaction between male headship and electric heating indicates that, conditional on ownership, households headed by males consume less electricity for electric heating than otherwise comparable households headed by females. In contrast, the positive interaction between male headship and refrigerator ownership implies higher refrigerator-related electricity consumption in male-headed households. A small positive interaction is also observed for electric ovens. This result is consistent with behavioural evidence reported in the energy economics literature, according to which women often report preferring warmer indoor environments and are more likely to adjust the heating to ensure their comfort, especially in colder seasons. Women's greater sensitivity to thermal comfort may translate into greater use of heating even when controlling for housing characteristics and appliance ownership. Conversely, men have been observed to tolerate lower indoor temperatures and adjust thermostats less frequently, which may lead to lower electricity consumption for heating in households headed by men with similar profiles in terms of housing and appliances. The positive interaction between the presence of a male head of household and electricity consumption related to refrigerators may reflect differences in food storage, purchasing behaviour and refrigerator use patterns. Some studies suggest that households headed by males may purchase larger quantities of food that require more refrigeration space or

maintain cold storage at lower temperatures. In addition, men may be less consistent in organising the contents of the refrigerator or optimising the frequency of door openings, resulting in increased electricity consumption due to greater heat influx. A small positive interaction for electric ovens in male-headed households could be interpreted similarly in the context of different cooking patterns and time use. While traditional gender roles have historically linked women to cooking activities, recent studies show that men in male-headed households often engage in cooking tasks that require the use of the oven, such as baking, grilling or preparing meals on weekends. If male heads of households or their families tend to use ovens for longer cooking cycles or at higher temperatures, this could increase the electricity consumption associated with electric ovens. Another plausible mechanism is that households with male heads may own kitchen appliances (e.g., larger ovens or additional cooking equipment) with higher power ratings, even if this is not directly observable in the dummy variable for ownership, and use them more intensively.

- **Education level of the head of household**

  Education interacts significantly with several appliances. The positive interaction with electric heating indicates higher conditional electricity consumption associated with heating in households where the head has a high level of education. Conversely, the interaction between education and refrigerator ownership is negative, implying lower refrigerator-related electricity consumption among more educated households. Education also positively interacts with electric ovens. The positive interaction between a high level of education and electric heating consumption is consistent with the literature linking higher education to greater expectations of indoor thermal comfort and a stronger preference for stable and comfortable living environments. Households with a higher level of education may also spend more time at home for remote work or intellectual activities, thereby increasing heating use. Conversely, the negative interaction between education and refrigerator ownership is consistent with evidence that higher education is associated with greater energy awareness,

better information processing, and more energy-efficient behavioural practices, such as setting appropriate temperature levels, minimising door opening frequency, and performing regular maintenance. In addition, educated households may be more likely to replace older refrigerators with newer, more energy-efficient models, reducing electricity consumption. The positive interaction between education and electric oven use likely reflects differences in cooking habits, time allocation, and lifestyle. Higher levels of education are often associated with more structured meal preparation practices and a greater propensity to cook at home, with activities that require intensive use of the oven, such as baking or roasting, which require longer operating times and higher temperatures. In addition, educated households may place a higher value on food quality and home-cooked meals, leading to more frequent or prolonged use of electric ovens.

- **Marital status**

  Marital status plays a relevant role in shaping appliance-related electricity consumption. Being married increases the electricity consumption associated with electric heating systems, conditional on ownership. In contrast, it reduces the marginal electricity consumption associated with washing machine cycles and with energy-saving light bulbs. These results indicate that marital status affects electricity use through differentiated appliance usage patterns rather than through a uniform shift in overall consumption.

- **Number of children**

  The number of children exhibits strong and systematic interaction effects. A higher-than-average number of children significantly increases electricity consumption associated with electric water heating and dishwashers. At the same time, the number of children reduces the marginal electricity consumption associated with computers and washing machine cycles. The positive interaction with air conditioning indicates that cooling-related electricity consumption rises as the number of children exceeds the sample mean. A larger number of children increases the demand for

hot water and cleaning activities: more showers, larger or more frequent laundry loads or more frequent dishwashing. This explains why the electricity consumption associated with these appliances increases in households with more children. The literature confirms that the presence of children increases the demand for hot water and the number of washing cycles, leading to a significant increase in electricity for these uses (Larsen et al., 2004; Frondel et al., 2019). Marginal consumption related to computers and washing machine cycles decreases when the number of children is higher. This does not mean that overall use decreases, but that for each additional unit (e.g. washing machine cycle or computer), average consumption increases less. Possible explanations: more shared use of resources (more people using the same computer or concentrating washing machine cycles) or greater efficiency in managing daily activities, typical in large households. Cooling consumption increases in households with more children. This may reflect the need to keep more rooms comfortable at the same time or to lower temperatures to ensure children's comfort during the hottest hours, thus increasing the electricity required by air conditioning systems.

- **Employment status**

  Employment status modifies electricity consumption for selected appliances. Being employed reduces electricity consumption associated with electric stoves, while increasing the marginal electricity consumption per washing machine cycle. Households with employed heads of household show a marginal increase in electricity consumption for each additional washing machine cycle. This may reflect more structured management of washing cycles: employed members often concentrate washing when they are at home, perhaps using the machine's capacity more fully, or running more intensive or longer washing cycles. Being employed reduces electricity consumption related to hobs. This may be because households with employed members spend less time at home cooking, eating out or simplifying their meal preparation habits.

- **Household equivalent income**

  Income-related interactions show mixed effects. A higher-than-average level of disposable income reduces electricity consumption associated with electric water heating. Conversely, income positively interacts with electric stoves. The negative coefficient for the electric water heating system suggests that households with above-average incomes tend to consume less electricity for water heating, probably due to the adoption of more efficient technologies, such as high-efficiency water heaters or hybrid/alternative systems, or greater attention to the rational use of hot water. On the other hand, the positive coefficient for electric hobs indicates that high-income households consume more electricity for cooking, consistent with the possibility of preparing more elaborate meals, more frequently or with additional appliances (e.g. built-in electric ovens, multiple hobs). In general, most income-related coefficients are not significant, suggesting that disposable income is not the main determinant of variation in electricity consumption per appliance. This highlights how energy consumption behaviour is more influenced by the habits, lifestyle and technological choices of households than by economic availability. High-income households may in fact adopt more sustainable or conscious behaviours, partially offsetting the potential effect of greater spending power.

- **Dwelling characteristics**

  Dwelling characteristics play a key role in shaping appliance-specific electricity consumption. Villas show higher consumption for electric heating compared to flats or terraced houses. It might reflect both the larger volumes to be heated and a potentially less efficient heat distribution compared to flats or terraced houses. Similarly, detached houses show an increase in electricity consumption for water heating and air conditioning, in line with the higher demand for hot water and cooling requirements in detached houses. Newer buildings, constructed after 1990, have higher electricity consumption associated with electric heating, possibly due to differences in heating technologies, insulation standards or usage patterns compared

to older constructions. More rooms mean higher consumption for electric heating, television use, and more lighting with traditional light bulbs. A larger than average home is positively correlated with the demand for energy-saving lighting and the number of televisions. Homes with at least two walls exposed to the outside show a reduction in air conditioning and increased lighting. Houses exposed on multiple sides may have more windows or views that allow for natural ventilation or passive cooling. More exposure does not guarantee uniform or sufficient natural light, so more light bulbs may be needed to compensate for the internal distribution or intended use of the rooms.

- **Regional location**

  Geographical location introduces strong and opposing effects across appliances. Electric heating systems exhibit substantially higher electricity consumption in northern Italy, ceteris paribus, consistent with higher heating needs. In contrast, air conditioning consumption is significantly lower in northern regions, reflecting climatic differences. These results confirm the importance of location-based heterogeneity in shaping electricity demand.

It can be seen that when the model includes covariates, the adjusted $R^2$ increases, explaining 32% of the variability in annual household consumption, indicating that the variability in household electricity consumption is more fully explained by the model specification.

| Ordinary Least Squares Regression | | |
|---|---|---|
| **Variables** | **Estimates** | **Standard Error** |
| *Intercept* | 316.41*** | 79.30 |
| *Electric heating system* | 550.49*** | 96.99 |
| *Dishwasher* | 325.36*** | 44.24 |
| *Water heater* | 867.63*** | 62.03 |
| *Freezer* | 350.70*** | 43.61 |
| *Electric stove* | 310.97*** | 91.94 |
| *Electric oven* | 114.05** | 51.10 |
| *Number of computers* | 316.86** | 155.89 |
| *Electric gardening equipment* | 124.98* | 73.68 |
| *Air conditioning* | 249.73*** | 57.40 |
| *Dryer* | 301.19*** | 69.23 |
| *Household size=2* | 385.87*** | 36.62 |
| *Household size=3* | 858.64*** | 53.14 |
| *Household size=4* | 1201.05*** | 72.33 |
| *Household size=5* | 1591.11*** | 93.91 |
| *Electric heating system * head of household age* | 9.37** | 4.08 |
| *Electric heating system * head of household gender* | -213.17** | 88.04 |
| *Electric heating system * education level* | 289.22*** | 97.12 |
| *Electric heating system * married* | 249.70*** | 92.46 |
| *Electric heating system * built since 1990* | 238.48*** | 75.91 |
| *Electric heating system * northern area* | 718.69*** | 86.62 |
| *Electric heating system * villa* | 441.04*** | 113.94 |
| *Electric heating system * number of rooms* | 84.13** | 42.87 |
| *Number of computers * head of household age* | 1.97** | 0.82 |
| *Number of computers * number of children* | -13.97* | 8.06 |
| *Water heater * number of children* | 239.78*** | 36.31 |
| *Water heater * villa* | 135.96* | 69.60 |
| *Water heater * disposable income* | -77.36* | 41.63 |
| *Refrigerator * head of household gender* | 172.61** | 76.63 |
| *Refrigerator * education level* | -322.12*** | 90.33 |
| *Refrigerator * number of elderly* | -149.85** | 68.28 |
| *Refrigerator * number of children* | -128.49** | 51.21 |
| *Electric oven * head of household gender* | 4.66* | 2.57 |
| *Electric oven * education level* | 131.16** | 62.25 |
| *Washing machine cycles * married* | -30.07*** | 9.28 |
| *Washing machine cycles * number of children* | -9.61** | 3.91 |
| *Washing machine cycles * employed* | 17.62** | 8.13 |
| *Washing machine cycles * washing machine age* | -13.31*** | 3.72 |
| *Dishwasher * number of children* | 115.11*** | 23.45 |
| *Electric stove * employed* | -225.38** | 100.09 |
| *Electric stove * log(disposable income)* | 86.18* | 48.63 |
| *Number of standard bulbs * house size* | 0.07* | 0.04 |
| *Number of standard bulbs * employed* | 9.32* | 5.33 |
| *Number of standard bulbs * number of rooms* | 4.55* | 2.46 |
| *Number of energy saving bulbs * married* | -6.88** | 3.36 |
| *Number of energy saving bulbs * house size* | 0.11*** | 0.02 |
| *Number of energy saving bulbs * wall exposure* | 13.45*** | 1.89 |
| *Number of televisions * head of household age* | -1.94* | 1.15 |
| *Number of televisions * number of rooms* | 54.98*** | 10.18 |
| *Number of televisions * house size* | 0.48*** | 0.18 |
| *Air conditioning * number of children* | 54.08** | 24.62 |
| *Air conditioning * wall exposure* | -130.03*** | 39.90 |
| *Air conditioning * northern area* | -109.70*** | 33.11 |
| *Air conditioning * villa* | 530.62*** | 46.58 |
| *Dryer * head of household age* | 5.27** | 2.59 |
| *Number of observation* | | 32,321 |
| *Adjusted* $R^2$ | | 0.32 |

Table 1.6: Estimated household consumption via an ordinary least squares approach. The model includes appliances ownership and endowment and interaction terms as covariates associated with significant coefficients at least at 10%. The response variable is the household's annual electricity consumption expressed as kilowatt per hours. *** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$; . $p \leq 0.1$.

We now turn to the quantile regression estimates, which allow us to explore how the contribution of electrical appliances varies across the conditional distribution of household electricity consumption. In particular, we focus on the first, second and third quartiles of the consumption distribution and compare them with the average effects obtained from OLS. Regarding the use of appliances and therefore electricity consumption across quartiles, a similar pattern and hierarchy of consumption are observed in the first, second and the third quartiles.

Since we cannot control for the size, type and intensity of use of all appliances, the OLS coefficient estimates pertain to an appliance with average size, efficiency, and usage. In the absence of these data, differences in these characteristics can be captured using a quantile regression model. We generally found that, in most cases, coefficients increase monotonically moving from the lower to the upper quartile, indicating that the same appliance contributes more to electricity consumption in high-consuming households than in low-consuming ones, as noted by Frondel et al. (2019). This might reflect the fact that families in the upper tail of the distribution, i.e., those with high electricity consumption, exhibit greater usage intensity or possess appliances with lower efficiency levels. Therefore, it is possible to compare the potential savings assuming the consumption differential is due to less efficient systems or appliances. The electric water heating system shows a substantial increase from about 412 kWh at the first quartile to more than 1,067 kWh at the third quartile, exceeding the OLS average effect (867 kWh). A similar pattern emerges for the electric heating system, whose contribution rises from 221 kWh in the lower quartile to over 762 kWh in the upper quartile, compared with 550 kWh in the OLS model. This indicates that thermal end-uses are a key driver of high electricity consumption and disproportionately affect high-consuming households. The freezer shows a similar pattern, with coefficients increasing from 202 kWh to about 465 kWh across quartiles, again higher than the OLS average (350 kWh).

Some devices do not show a significant increase in impact across quartiles. Computers, weekly laundry loads and lighting show relatively small differences between the first and

third quartiles, suggesting more homogeneous use among low- and high-consumption households and an intensity that does not grow proportionally to the overall level of demand; for these variables, OLS therefore provides a good approximation of the average effect. A notable exception is the dryer, whose coefficient is higher in the first quartile than in the third, indicating a relatively greater weight on the consumption of low-consumption households. This behaviour, which is not captured by OLS, highlights a different distributional incidence of the dryer across the consumption distribution. In the next section, using information on investments in air conditioning systems, we show how energy efficiency measures can lead to significant savings in annual energy consumption.

As regards interaction effects across quartiles, there are no marked differences to note. Concerning the age of the head of household, the signs of the coefficients are consistent with those of the OLS estimates for the dryer, the number of computers, and the number of televisions. A positive correlation is also observed between washing machine cycles and the age of the head of household, which increases across the quartiles, while a negative correlation appears with the electric water heater, showing a reduction along the quartiles. Regarding the interaction between electrical appliances and the gender of the head of household, a different pattern emerges for the electric oven, whose consumption decreases in the third quartile when the head of household is male compared to female-headed households. For the other appliances, a positive correlation is observed with the dryer (only in the first quartile), the number of standard and energy-saving light bulbs (across the second and third quartiles), and the electric stove (only in the second quartile), while a negative correlation appears with the number of televisions (in the second quartile).

Concerning the number of children, we observe an identical pattern for air conditioning and the electric water heating system: both correlations with the number of children are positive, although the coefficient for air conditioning is higher in the first quartile than in the second, and the coefficient for the water heater is higher in the first quartile than in the third. The relationship between number of children and washing machine cycles is negative in the second and third quartiles. Positive correlations also appear with the dryer

(only in the first quartile) and with the dishwasher (the effect is larger in the first quartile than in the third). Negative correlations are found with the electric oven (first quartile) and with the electric heating system (third quartile). The association with the freezer is ambiguous: positive in the first quartile and negative in the second. With respect to dwelling type (villa) and buildings constructed after 1990, the patterns are the same and involve the same appliances. The same holds for the house's geographic location and for wall exposure: these housing characteristics produce similar interaction patterns across the same set of devices.

| Variable | Quantile Regression Estimate (1th Quartile) | Estimate (2th Quartile) | Estimate (3th Quartile) |
|---|---|---|---|
| *Intercept* | 378.47***(21.97) | 194.59***(28.98) | 371.49***(44.39) |
| *Air conditioning* | 128.63***(40.20) | 222.49***(52.93) | 278.02***(69.35) |
| *Dryer* | 150.45*(76.99) | 419.36***(80.12) | 436.48***(81.78) |
| *Electric gardening equipment* | | | 221.74**(105.20) |
| *Freezer* | 202.67***(34.21) | 219.98***(44.79) | 465.88***(63.79) |
| *Electric oven* | | 91.31***(30.92) | 157.57***(48.58) |
| *Electric heating system* | 221.77**(113.11) | 729.64***(136.65) | 762.30***(179.56) |
| *Dishwasher* | 222.56***(28.94) | 269.88***(34.82) | 383.26***(63.66) |
| *Number of Televisions* | | 232.20*(136.79) | 357.00**(174.07) |
| *Electric stove* | | 145.49*(86.11) | 281.36**(127.49) |
| *Electric water heating system* | 412.17***(68.76) | 716.70***(85.05) | 1067.39***(78.06) |
| *Household size=2* | | 265.91***(26.17) | 683.02***(43.35) |
| *Household size=3* | 174.04***(37.38) | 920.12***(38.84) | 1253.12***(48.41) |
| *Household size=4* | 455.15***(68.97) | 1232.30***(56.10) | 1604.11***(69.87) |
| *Household size=5* | 579.88***(117.94) | 1563.91***(74.34) | 1997.29***(106.64) |
| *Air conditioning * northern area* | -64.98***(22.91) | -107.28***(31.46) | -111.53***(38.66) |
| *Air conditioning * wall exposure* | | -103.75***(30.68) | -164.58***(51.95) |
| *Air conditioning * windows with PVC or wood frames* | | | -86.72**(40.25) |
| *Air conditioning * house size* | 1.37**(0.64) | | |
| *Air conditioning * number of children* | 103.65***(27.19) | 64.60**(25.94) | |
| *Air conditioning * number of rooms* | -32.69**(14.91) | | |
| *Air conditioning * married* | 80.73**(33.72) | | |
| *Air conditioning * villa* | 419.26***(83.12) | 565.10***(56.62) | 601.05***(71.88) |
| *Dryer * head of household age* | | 6.31**(2.88) | |
| *Dryer * Number of elderly* | 188.83**(84.73) | | |
| *Dryer * number of children* | 105.35***(34.57) | | |
| *Dryer * employed* | | -128.27*(68.68) | |
| *Dryer * head of household gender* | 112.33**(45.10) | | |
| *Dryer * married* | 167.41***(50.15) | | |
| *Electric gardening equipment * employed* | 97.70*(53.93) | | |
| *Freezer * number of children* | 147.51***(24.63) | -58.01**(24.09) | |
| *Freezer * married* | | 224.39***(60.77) | |
| *Freezer * education level* | -66.20*(34.30) | | |
| *Electric oven * disposable income* | 32.74**(15.28) | | |
| *Electric oven * number of elderly* | 43.47*(24.61) | | |
| *Electric oven * number of children* | -76.54***(25.54) | | |
| *electic oven * head of household gender* | | | -79.34*(47.67) |
| *electric oven * married* | -105.93***(29.62) | -117.44***(40.76) | |
| *Electric heating system * northern area* | | 473.18**(198.13) | 1315.73***(240.75) |
| *Electric heating system * built since 1990* | 217.43**(108.40) | | |
| *Electric heating system * wall exposure* | 255.97**(108.97) | | |
| *Electric heating system * number of children* | | | -164.59**(71.72) |
| *Electric heating system * number of rooms* | 115.61**(58.35) | | |
| *Electric heating system * villa* | | 362.14**(161.48) | 627.89**(283.62) |
| *Washing machine cycles * head of household age* | 0.60**(0.26) | 0.72**(0.34) | 1.19**(0.48) |
| *Washing machine cycles * washing machine age* | -11.96***(3.23) | -7.60**(3.42) | -14.34***(4.15) |
| *Washing machine cycles * number of children* | | -10.47***(3.67) | -16.21***(4.72) |
| *Washing machine cycles * education level* | | | 22.24**(11.12) |
| *Dishwasher * Number of elderly* | | 92.89***(35.94) | |
| *Dishwasher * number of children* | 209.49***(27.60) | 125.51***(24.83) | 71.54**(34.48) |
| *Dishwasher * married* | 78.64***(21.91) | 182.78***(41.72) | 121.62**(60.54) |
| *Number of computers * log(disposable income)* | -10.52*(5.45) | | -22.96**(11.28) |
| *Number of computers * head of household age* | | | 2.18**(1.09) |
| *Number of computers * number of children* | -25.14***(8.49) | | -20.24*(11.45) |
| *Number of energy saving bulbs * wall exposure* | 4.74***(1.11) | 10.71***(1.80) | 16.39***(2.42) |
| *Number of energy saving bulbs * house size* | | 0.08***(0.03) | 0.08**(0.04) |
| *Number of energy saving bulbs * Number of elderly* | | | 7.29**(3.58) |
| *Number of energy saving bulbs *head of household gender* | | 5.23*(2.70) | 6.80*(3.81) |
| *Number of energy saving bulbs * married* | | | -10.63***(3.77) |
| *Number of energy saving bulbs * education level* | | | -9.72**(4.62) |
| *Number of standard bulbs * wall exposure* | | | 10.20**(4.03) |
| *Number of standard bulbs * number of children* | -6.88***(2.16) | | |
| *Number of standard bulbs * number of rooms* | -2.54**(1.29) | | 5.31*(2.91) |
| *Number of standard bulbs *head of household gender* | | 9.24***(3.46) | 13.35**(5.41) |
| *Number of standard bulbs * married* | | | -10.82*(5.81) |
| *Number of televisions * head of household age* | -1.84***(0.68) | -2.47***(0.77) | |
| *Number of televisions * house size* | 1.01***(0.28) | 1.14***(0.26) | 0.82***(0.28) |
| *Number of televisions * number of children* | 38.62***(10.69) | | |
| *Number of televisions * number of rooms* | 13.59**(6.77) | 37.09***(9.39) | 55.00***(11.42) |
| *Number of televisions * head of household gender* | | -32.23*(16.60) | |
| *Electric stove * head of household gender* | | 138.80**(62.65) | |
| *Electric stove * education level* | | 144.42*(83.34) | |
| *Electric water heating system * head of household age* | -4.65*(2.73) | -10.30**(4.25) | |
| *Electric water heating system * Number of elderly* | | 168.84**(73.14) | |
| *Electric water heating system * number of children* | 347.22***(67.63) | 93.54**(38.26) | 92.75*(51.44) |
| *Electric water heating system * married* | 337.93***(126.85) | 229.16**(102.09) | |
| *Electric water heating system * villa* | | 278.63***(93.79) | |
| *Number of observation* | | 32.321 | |
| *Pseudo R2* | 0.13 | 0.25 | 0.22 |

Table 1.7: Estimated household consumption via quantile regression approach. Estimates are referred to the three quartiles. The model includes appliances ownership and endowment and interaction terms as covariates associated with significant coefficients at least at 10%. The response variable is the household's annual electricity consumption expressed as kilowatt per hours. *** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$; . $p \leq 0.1$.

### 1.5.2 Counterfactual Estimation

An additional contribution of this study is to identify the effects of investments in the efficiency of thermal systems on annual residential electricity consumption. In our setting, because the decision to invest is endogenous, the application of the Heckman selection model allows us to correct for non-random selection into treatment by jointly estimating the participation probability and the treatment effect on the outcome. Table 1.8 reports the results.

The estimation is based on a total of 2,402 observations. Among these, 225 households are classified as participants (selection = 1), meaning they undertook a single investment in energy efficiency related to either heating or air-conditioning systems, while the remaining 2,177 households are non-participants (selection = 0), meaning they reported no energy-efficiency investments. Observations reporting multiple types of investment simultaneously are excluded from the estimation sample.

In the selection equation (Probit), climatic, socio-economic and housing characteristics emerge as determinants of participation. For instance, we observe opposite signs for variables measuring extreme-heat, extreme-cold and intense-rainfall days computed over different years. This pattern does not necessarily indicate a bias in the estimates: it is compatible with the nature of the devices under study, since air-conditioning systems commonly serve both cooling and heating functions, and with temporal and spatial heterogeneity in the relationship among climatic shocks, incentives and the investment decision. Moreover, home ownership and selected household and housing characteristics are important predictors of who participates in the treatment.

These findings confirm that participation is not random and justify the use of the Heckman model to correct selection bias, including the potential selection arising from unobserved factors that influenced the investment choice.

In the outcome equation, the treatment capturing investments in air-conditioning efficiency has a negative and marginally significant effect ($\beta \approx -0.57$). Converting the log-level coefficient to a percentage change, $(e^{\beta} - 1)$, this corresponds to an approximate

reduction of 43.3% in the outcome. This result indicates that the intervention is associated with a sizeable reduction in the variable of interest.

Finally, the error terms exhibit a positive and marginally significant correlation between the selection and outcome equations ($\rho \approx 0.416$). This provides suggestive evidence of non-random selection: participants may have unobserved characteristics that are correlated with the outcome. This further supports the use of the Heckman model, which accounts for selection bias and yields corrected estimates of the treatment effect.

| Variable | Estimate | Std. Error | t value | Pr(>t) |
|---|---|---|---|---|
| **Probit Selection Model** | | | | |
| Intercept | -8.30* | 4.30 | -1.93 | 0.05 |
| Log(days of extreme heat, 2018) | 2.14** | 0.92 | 2.33 | 0.02 |
| Log(days of extreme heat, 2019) | -1.99** | 0.88 | -2.27 | 0.02 |
| Log(days of extreme heat, 2020) | -0.06** | 0.03 | -2.39 | 0.02 |
| Log(days of extreme cold, 2018) | 0.04** | 0.02 | 2.47 | 0.01 |
| Log(days of extreme cold, 2019) | 0.01 | 0.01 | 1.43 | 0.15 |
| Log(days of extreme cold, 2020) | -0.03** | 0.01 | -2.10 | 0.04 |
| Regional share of investments financed through eco-bonuses, 2018 | 24.72 | 16.35 | 1.51 | 0.13 |
| Regional share of investments financed through eco-bonuses, 2019 | 28.84* | 16.56 | 1.74 | 0.08 |
| Regional share of investments financed through eco-bonuses, 2020 | -55.57* | 29.37 | -1.89 | 0.06 |
| Regional incidence of owner-occupied dwellings, 2018 | 0.23*** | 0.09 | 2.74 | 0.01 |
| Regional incidence of owner-occupied dwellings, 2019 | -0.26*** | 0.09 | -2.80 | 0.01 |
| Regional incidence of owner-occupied dwellings, 2020 | 0.10** | 0.05 | 1.98 | 0.05 |
| Log(days of intense rainfall, 2018) | 0.21 | 0.63 | 0.33 | 0.74 |
| Log(days of intense rainfall, 2019) | 2.22** | 1.09 | 2.04 | 0.04 |
| Log(days of intense rainfall, 2020) | -1.94*** | 0.69 | -2.83 | 0.00 |
| Married | -0.13 | 0.12 | -1.03 | 0.30 |
| Log(disposable income) | -0.01 | 0.05 | -0.21 | 0.84 |
| log(number of occupants) | 0.24 | 0.16 | 1.48 | 0.14 |
| Head of household age | 0.00 | 0.00 | 0.72 | 0.47 |
| Head of household gender | 0.06 | 0.09 | 0.65 | 0.51 |
| Head of household education level: primary school | -0.15 | 0.15 | -0.96 | 0.34 |
| Head of household education level: tertiary-education | 0.14 | 0.16 | 0.86 | 0.39 |
| Head of household education level: advanced tertiary-education | 0.26** | 0.10 | 2.45 | 0.01 |
| Head of household education level: middle school | -0.00 | 0.10 | -0.02 | 0.98 |
| Head of household education level: none | -0.21 | 0.36 | -0.58 | 0.56 |
| Log(number of elderly) | 0.00 | 0.00 | 1.15 | 0.25 |
| Log(number of children) | -0.00 | 0.00 | -1.13 | 0.26 |
| Employed | 0.15 | 0.11 | 1.41 | 0.16 |
| log(number of children under 14) | 0.00 | 0.00 | 1.32 | 0.19 |
| Villa | -0.04 | 0.12 | -0.35 | 0.73 |
| House size | -0.43 | 0.26 | -1.61 | 0.11 |
| Built since 1990 | -0.33*** | 0.09 | -3.76 | 0.00 |
| Windows with PVC or wood frames | 0.03 | 0.09 | 0.33 | 0.74 |
| Wall exposure | -0.05 | 0.08 | -0.56 | 0.58 |
| Northern area | -0.78 | 0.50 | -1.57 | 0.12 |
| **Outcome Equation** | | | | |
| Intercept | 6.38*** | 0.23 | 27.81 | 0.00 |
| Treatment effect of energy-efficient investments | -0.57* | 0.31 | -1.84 | 0.07 |
| Married | -0.04 | 0.05 | -0.76 | 0.45 |
| Log(disposable income) | -0.01 | 0.02 | -0.29 | 0.77 |
| Log(number of occupants) | 0.56*** | 0.07 | 8.49 | 0.00 |
| Head of household age | 0.00 | 0.00 | 1.37 | 0.17 |
| Head of household gender | 0.01 | 0.03 | 0.42 | 0.67 |
| Head of household education level: primary school | -0.08 | 0.06 | -1.42 | 0.15 |
| Head of household education level: tertiary education | 0.08 | 0.06 | 1.31 | 0.19 |
| Head of household education level: advanced tertiary education | 0.02 | 0.04 | 0.54 | 0.59 |
| Head of household education level: middle school | 0.01 | 0.04 | 0.16 | 0.87 |
| Head of household education level: none | 0.13 | 0.12 | 1.08 | 0.28 |
| Log(number of elderly) | -0.00 | 0.00 | -0.56 | 0.58 |
| Log(number of children) | -0.00 | 0.00 | -0.47 | 0.64 |
| Employed | -0.03 | 0.04 | -0.82 | 0.41 |
| log(number of children under 14) | -0.00 | 0.00 | -1.43 | 0.15 |
| Villa | 0.15*** | 0.04 | 3.33 | 0.00 |
| Household size | 0.23*** | 0.08 | 2.79 | 0.01 |
| Built since 1990 | 0.03 | 0.03 | 0.77 | 0.44 |
| Windows with PVC or wood frames | 0.00 | 0.03 | 0.04 | 0.97 |
| Wall exposure | 0.05 | 0.03 | 1.57 | 0.12 |
| Thermostat | -0.05 | 0.03 | -1.59 | 0.11 |
| Northern area | -0.03 | 0.03 | -0.92 | 0.36 |
| Electric heating system | 0.53*** | 0.03 | 15.25 | 0.00 |
| Freezer | 0.14*** | 0.03 | 4.41 | 0.00 |
| Electric stove | 0.22*** | 0.05 | 4.60 | 0.00 |
| Electric oven | -0.01 | 0.03 | -0.30 | 0.76 |
| Number of traditional light bulbs | 0.00 | 0.00 | 0.59 | 0.55 |
| Log(number of computers) | 0.00 | 0.00 | 0.85 | 0.39 |
| Gardening equipment | 0.03 | 0.05 | 0.65 | 0.51 |
| log(number of traditional light bulbs) | -0.00 | 0.00 | -0.80 | 0.42 |
| Log(number of televisions) | 0.10*** | 0.03 | 3.07 | 0.00 |
| Dryer | 0.11*** | 0.04 | 3.21 | 0.00 |
| log(Laundry loads per week) | 0.12*** | 0.02 | 5.18 | 0.00 |
| Dish washer | 0.22*** | 0.03 | 6.86 | 0.00 |
| sigma | 0.67*** | 0.02 | 29.53 | 0.00 |
| rho | 0.42* | 0.22 | 1.85 | 0.06 |

Table 1.8: Heckman Model Estimates. Impact of investments in air-conditioning system efficiency on log annual household energy consumption. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

## 1.6 Conclusion and Policy Implications

The residential sector makes up a significant share of total energy consumption in European and global economies, requiring secondary energy to meet household needs. Household appliances account for a substantial portion of household energy consumption.

Variations in building size and specifications, weather fluctuations, and differences in residents' habits complicate the management and analysis of residential energy end-uses. Privacy concerns and the costs associated with measuring residential energy end-uses are additional obstacles. As a result, little information is available on household appliance use and, consequently, the actual consumption attributable to each appliance. In addition, the actual engineering assessment of the energy impact of household appliances based only on their technical specifications is somewhat reductive, as it would not consider several factors related to the intensity of use, and the heterogeneity in household and dwelling characteristics.

Encompassing these dynamics is essential to optimize the management of energy resources and is a priority in addressing climate change. From a demand-side policy perspective, improving energy efficiency and reducing demand are key strategies in the international policy agenda. Studying the heterogeneity in residential end-use energy consumption and ranking end-use consumption for the 'typical household' and 'standard dwelling' , are crucial for predicting energy consumption and conducting policy analysis and deriving policy implications.

In this research, we use Istat microdata from the 2020 'Indagine sui Consumi Energetici delle Famiglie' and employ a conditional demand modeling via OLS and quantile regression on a sample of approximately 32,000 households, to examine how the heterogeneity of the socio-demographic and economic characteristics of households and the structural elements of dwellings affects the consumption of household appliances and, consequently, residential electricity consumption by Italian households. Furthermore, we estimate the impact of energy-efficient investment in the air-condition system on household energy consumption, exploiting Heckman's two-stage selection model. We also performed statistical matching

between the Istat dataset and Eu-SILC to incorporate household income, absent in our dataset.

The empirical results paint a clear and consistent picture: electricity demand at the household level is heavily concentrated in a limited set of thermal and large appliances, and the contribution of those appliances is highly heterogeneous across the consumption distribution and across household and dwelling characteristics. Electric water heating and space heating are the two largest contributors to annual household electricity consumption. In the OLS baseline these two end-uses were dominant, and quantile estimates show that their impacts increase markedly in the upper tail of the distribution. This indicates that thermal end-uses are the principal drivers of high-electricity-consumption households, either because those households use thermal appliances more intensively, own less efficient systems, or both. Freezers, dryers, and dishwashers constitute a second tier of high-impact appliances. Their per-unit contributions are substantial and also tend to rise with the household's position in the consumption distribution. The clothes dryer is particularly noteworthy: it is among the highest single-appliance contributors and—uniquely—exhibits non-monotonic distributional behavior (being relatively more important in lower consumption quartiles in some specifications). Quantile regressions reveal systematic heterogeneity: for most devices the marginal kWh associated with ownership or an additional unit increases from low- to high-consumption households. In practical terms, the same appliance explains far more electricity for a household in the third quartile than for one in the first quartile. A few exceptions (e.g., lighting, some computing uses, and weekly laundry loads) display more homogeneous effects across quartiles, suggesting more uniform usage patterns for those end-uses. The intercept term, the miscellaneous electricity, is small and insignificant for low-consumption households but becomes large and significant in higher quantiles. This suggests that unobserved end-uses, standby loads, or non-listed devices account for a growing share of electricity in higher-consumption households. If the variation in electricity consumption associated with individual appliances across quartiles is interpreted, at least partly, as reflecting differences in appliance efficiency, then these results suggest substantial potential for reducing electricity demand through policies aimed

at promoting more efficient technologies and practices.

When interaction terms are added to the OLS baseline, the picture of heterogeneous electricity demand becomes markedly richer: the unconditional, average appliance coefficients are partially decomposed into a baseline effect and systematic shifts that depend on socio-demographic, economic, dwelling and locational characteristics. Introducing interactions reduces the absolute magnitude of several main appliance coefficients, as some of the variation previously attributed to average ownership effects is now absorbed by covariate-specific differentials, while the intercept increases because the model now conditions on more explanatory structure and the constant must capture residual usages not explained by appliances or their interactions. Part of the consumption and ownership habits of devices is also captured by household size, which, in addition to indicating an increase in consumption as the number of family members increases, reflects different usage and a portfolio of unobserved household appliances. Overall, the OLS interactions increase the model's explanatory power (adjusted $R^2$ rising to roughly 32%).

Concerning the interaction effects, age of the household head systematically amplifies electric heating and computer-related consumption, suggesting older-than-average heads both demand more space heating and use computers more intensively, whereas the marginal electricity associated with additional televisions declines with age, consistent with shifting leisure patterns. Gender interactions reveal that male-headed households use less electricity for electric heating but more for refrigeration and, to a lesser extent, ovens; these patterns align with behavioural interpretations about thermal comfort and food/cooking practices. Education produces contrasting interactions: higher education associates with increased conditional consumption for heating and ovens (potentially reflecting higher comfort expectations and more home cooking), but with lower refrigerator-related consumption, consistent with greater adoption of efficient practices or newer, more efficient appliances. The presence of children raises conditional consumption for water heating and dishwashing while reducing the marginal contributions of additional computers and individual washing cycles—an effect plausibly explained by sharing of devices, consolidated laundry practices,

and increased hot-water demands. Employment status and income show heterogeneous, appliance-specific roles: being employed reduces hob-related electricity (less home cooking) but increases the electricity associated with each washing-machine cycle (perhaps due to more concentrated or intensive cycles), while higher disposable income is associated with lower electricity for water heating—likely reflecting the adoption of efficient water-heating technologies—but with higher consumption for electric stoves. Nevertheless, the analysis indicates that household income does not significantly affect individual consumption of household appliances, suggesting that lifestyle and habits are more influential. Dwelling attributes also matter: villas and detached houses display larger heating and water-heating coefficients (bigger volumes and different systems), newer buildings (post-1990) and homes with more rooms show distinct increases in heating and television use, and houses with more external exposure exhibit lower conditional air-conditioning use but higher lighting needs. Finally, regional location produces strong, opposing interactions: northern regions show significantly higher conditional electricity for heating and lower conditional air-conditioning use, underlining how climate and geography modulate appliance impacts.

Turning to the quantile regression results, the heterogeneous interaction patterns largely confirm the OLS findings but add an essential distributional dimension: many interaction effects persist across quartiles, yet their magnitudes and, in some cases, signs vary with the household's position in the consumption distribution, indicating that socio-demographic and dwelling modifiers operate differently for low- and high-consumption households.

Then, we modelled households' decisions to invest in energy-efficient improvements to their air conditioning systems and the consumption outcome within a unified counterfactual framework. Since the decision to invest is endogenous, we implemented a Heckman two-stage selection model and estimated it by maximum likelihood. The selection equation was formulated as a latent probit for the probability of undertaking an energy-efficiency intervention, while the outcome equation modelled the log of annual household electricity consumption conditional on participation. Identification relied on a combination of exclusion restrictions — lagged, region-level 'instruments' capturing meteorological extremes,

regional shares of eco-bonus-financed renovation investments, and regional incidence of owner-occupation measured for 2018–2020 — and the parametric structure of the bivariate normal error specification.

The estimates demonstrate a large and robust reduction in electricity consumption associated with investments in air-conditioning system efficiency. The treatment coefficient in the outcome equation is approximately -0.88 in log terms, which translates to an approximate 58.6% reduction in annual electricity consumption. This effect is stable across model specifications: when we retained only instrument combinations that were jointly significant in the first stage, the implied percentage reductions ranged narrowly between -58.67% and -57.61% (mean = -58.31%, SD = 0.26).

Because 26% of households own air-conditioning systems, promoting the efficiency of these appliances could yield substantial aggregate benefits. Given that only 6.44% of air-conditioning owners reported having invested in such upgrades over the past five years, and that a large share of the installed base is plausibly composed of relatively old units, policymakers should consider strengthening incentives for these investments. Expanding support for high-efficiency replacements and retrofits would likely maximize reductions in residential electricity demand and $CO_2$ emissions, and could also serve as a hedge against increased reliance on gas for space heating in light of international and geopolitical dynamics that affect gas prices. Furthermore, our study revealed that as total household consumption and income quartiles increased, a larger percentage of households invested in energy efficiency upgrades for air-conditioning system. Given that these investments were more common among higher-income households, it is crucial for policies to ensure equitable access to incentives for lower-income households.

Summing up the empirical evidence, from a policy perspective, investments in energy efficiency can meaningfully reduce households' annual electricity expenditures and substantially curb emissions, particularly when the electricity mix relies heavily on fossil fuels. Targeted instruments such as subsidies, rebates and other preferential schemes for high-efficiency appliances can accelerate the retirement of inefficient units and lower

consumption from end-uses that account for a large share of total demand—most notably electric space heating in winter and air conditioning in summer—whose usage is difficult to curtail without compromising thermal comfort but can nonetheless be optimised through technology and behavioural measures. Incentive design should follow an equity principle, ensuring that lower-income households can access and benefit from efficiency upgrades even in contexts with limited fiscal space that preclude widespread tax-deduction schemes, so that reductions in consumption translate into real monetary savings across income groups.

Although many countries have adopted a broad set of policies to restrain residential electricity demand, policy design has paid comparatively little attention to how appliances are actually used: households allocate time heterogeneously and, as a consequence, operate devices in different ways. Our analysis could not incorporate detailed time-use information, but it is essential that researchers and policymakers understand how household time allocation affects appliance use because the ultimate effectiveness of energy-saving policies depends on these behavioural patterns. Information campaigns remain a low-cost, high-leverage complement to technology policy: promoting efficient practices—such as avoiding leaving televisions on standby or running dishwashers with partial loads—can reduce electricity demand, and their reach should be expanded. For example, requiring electricity suppliers to include appliance-specific savings information on customer bills could materially increase awareness and uptake of energy-saving behaviours. Such informational efforts are particularly important given the existence of rebound effects, which can offset gains from more efficient appliances when new devices are larger or feature-rich and therefore used more intensively. Finally, demographic trends—declining household size combined with an ageing population—underscore the need to pay greater attention to how family structure shapes electricity demand.

It is important to acknowledge several limitations that constrain the interpretation of these results. First, the absence of direct measures of appliance size and efficiency means that ownership dummies and counts do not capture rated power, appliance age, or

efficiency class; consequently, the OLS and quantile estimates represent the average effect of a 'typical' appliance and some of the observed heterogeneity is likely driven by unobserved appliance characteristics. Second, the cross-sectional and observational nature of the data limits causal inference: ownership and usage choices may be endogenous to unobserved preferences or constraints, so while interaction terms help to explicate heterogeneity, credible causal identification would require instruments, panel variation, or randomized interventions. Third, self-reported measures of ownership, counts or usage intensity are susceptible to measurement error, which can bias coefficient estimates toward zero or otherwise distort estimated magnitudes. Fourth, the growing miscellaneous component in the upper quantiles points to unobserved residual loads: missing device categories or behavioural patterns not captured by the survey likely account for part of the unexplained consumption, and future work should aim to measure these directly.

With respect to the evaluation of households' investment choices, this component of the analysis presents several limitations. First, the identification of the causal effect relies substantially on assumptions about the model's functional form and on the joint-normality assumption for the errors in the selection procedure. If these assumptions do not hold, estimates of the parameter of interest may be biased or highly sensitive to the chosen specification, as documented in the selection-model literature. A second concern relates to the instruments, which may exhibit limited variation because they are measured at the level of the twenty regions; this reduces informational granularity and increases vulnerability to unobserved regional heterogeneity. A further limitation concerns the definition of the treatment. The investment in the efficiency of the air-conditioning system encompasses interventions that are highly heterogeneous in cost, technology and energy intensity, yet it is treated empirically as a single binary variable. Such aggregation can obscure meaningful differences among interventions and complicate the interpretation of the estimated effect as the average impact of any specific technology. Unfortunately, due to the limited sample size it was not possible to disaggregate this analysis in greater detail. The observational nature of the data also implies a risk of residual confounding: unobserved variables such as comfort preferences, propensity to adopt innovations, environmental concern, or attention

to energy savings may affect both the investment decision and subsequent consumption levels. Although the selection model attempts to correct for unobserved heterogeneity, bias from latent, unmeasured factors cannot be entirely ruled out. Finally, the very large magnitude of the estimated effect on total household consumption may partly reflect the influence of contemporaneous, unobserved changes or the omission of relevant covariates, given that air conditioning accounts for only a portion of total electricity use.

Looking ahead, several paths would substantially strengthen and extend this analysis. High-resolution metering—smart meter data combined with sub-metering—would permit direct attribution of kWh to end-uses and would allow disentangling usage intensity from appliance efficiency. Collecting appliance-level characteristics such as age, rated power and efficiency labels would enable more precise counterfactual simulations and realistic estimates of potential savings from replacements. Causal evaluation strategies that exploit quasi-experimental variation (for instance, phased subsidy roll-outs or staggered retrofit programs) would clarify the causal responses to technological upgrades and behavioural interventions. Finally, integrating the estimated per-appliance kWh impacts with replacement costs and appliance lifetimes would facilitate a rigorous cost–benefit assessment to identify the most cost-effective policy mixes.

# Appendix

## 1.A.1 Computation for the Equivalized Income

The equivalized disposable income denotes the entire income of a household, post-taxation and other deductions, available for expenditure or savings. It is computed by dividing total income by the number of household members adjusted to equalized adults, with household members equalized through a process of weighting based on their age. This weighting is accomplished using the modified OECD equivalence scale (Chanfreau and Burchardt, 2008).

The calculation of equivalized disposable income involves three steps:

- Aggregating all monetary incomes received by each household member from any source, encompassing earnings from employment, returns on investments, social benefits, and other household income. This total is then adjusted by deducting taxes and social contributions paid. This is also known as disposable income.
- To account for variations in household size and composition, the total (net) household income is divided by the number of 'equivalent adults'. The modified OECD scale is employed for this purpose, assigning weights to each household member based on their age. Specifically, the weights are: 1.0 for the first adult, 0.5 for the second and subsequent individuals aged 14 and over, 0.3 for each child aged under 14.
- The resulting value is designated as the equivalized disposable income and is evenly attributed to each member of the household

Hence, the computation is based on the following expression:

$$\text{Equivalised Income} = \frac{\text{Household Income}}{\sqrt{1 + 0.5\,(\text{N. of adults and children at least 14}) + 0.3\,(\text{N. of children under 14})}}$$

## 1.A.2 Diagnostic tests for OLS residuals

| Test | Statistic | df | p-value |
|---|---|---|---|
| Jarque–Bera test | 201820 | 2 | 0.00 |
| Breusch–Pagan (studentized) | 842.33 | 163 | 0.00 |
| Breusch–Pagan (non-studentized) | 5767.60 | 163 | 0.00 |

Table 1.9: Diagnostic tests for OLS residuals

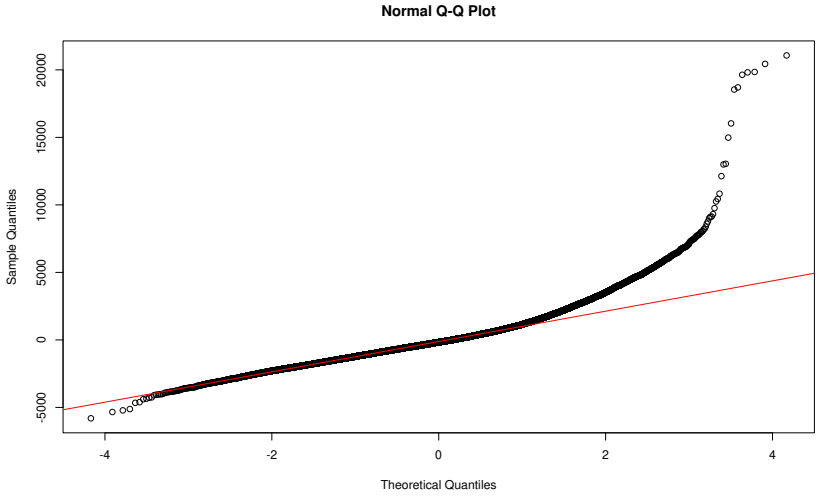



Figure 1.8: Normal Q-Q Plot of OLS Residuals from Conditional Demand Model (model specification with interactions).

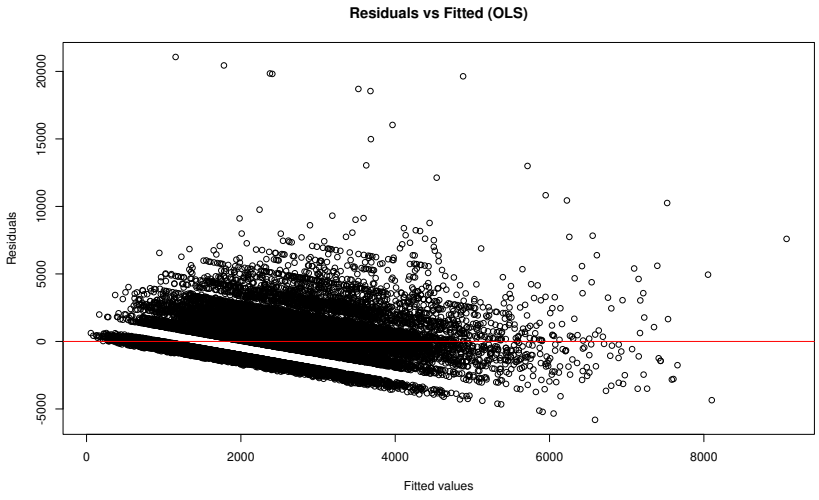



Figure 1.9: Residuals vs Fitted Values from the OLS Conditional Demand Model (model specification with interactions).

## 1.A.3 Extended Results

| Variables | Estimates | Standard Error | Statistic | P value |
|---|---|---|---|---|
| *Intercept* | 189,87 | 33,32 | 5,70 | 0 |
| *Electric heating system* | 910,71 | 38,21 | 23,84 | 0 |
| *Dish washer* | 384,54 | 18,65 | 20,62 | 0 |
| *Electric water heating system* | 986,92 | 29,13 | 33,88 | 0 |
| *Freezer* | 547,65 | 18,41 | 29,75 | 0 |
| *Electric stove* | 271,78 | 34,88 | 7,79 | 0 |
| *Electric oven* | 47,45 | 22,91 | 2,07 | 0,04 |
| *Traditional light bulbs* | 9,88 | 1,98 | 5,00 | 0 |
| *Energy-saving light bulbs* | 14,18 | 1,35 | 10,51 | 0 |
| *Computers* | 114,16 | 6,83 | 16,72 | 0 |
| *Gardening equipment* | 121,76 | 28,38 | 4,29 | 0 |
| *Televisions* | 223,42 | 9,87 | 22,64 | 0 |
| *Air conditioning* | 197,34 | 19,54 | 10,10 | 0 |
| *Dryer* | 422,66 | 22,12 | 19,11 | 0 |
| *Laundry loads per week* | 117,47 | 3,08 | 38,14 | 0 |
| *Adjusted R squared* | | 0.24 | | |

Table 1.10: Estimated household consumption via ordinary least squares approach. The model includes appliances ownership and endowment associated with significant coefficients at least at 10%. The response variable is the household's annual electricity consumption expressed as kilowatt per hours.

| Variables | Estimates | Standard Error | Statistic | P value |
|---|---|---|---|---|
| *Intercept* | 316,41 | 79,30 | 3,99 | 0,00 |
| *Electric heating system* | 550,49 | 96,99 | 5,68 | 0,00 |
| *Dish washer* | 325,36 | 44,24 | 7,35 | 0,00 |
| *Electric water heating system* | 867,63 | 62,63 | 13,99 | 0,00 |
| *Freezer* | 350,70 | 43,61 | 8,04 | 0,00 |
| *Electric stove* | 310,97 | 91,94 | 3,38 | 0,00 |
| *Electric oven* | 114,05 | 51,10 | 2,23 | 0,03 |
| *Traditional light bulbs* | 87,82 | 173,11 | 0,51 | 0,61 |
| *Computers* | 316,86 | 155,89 | 2,03 | 0,04 |
| *Gardening equipment* | 124,98 | 73,68 | 1,70 | 0,09 |
| *Televisions* | 247,78 | 156,46 | 1,58 | 0,11 |
| *Air conditioning* | 249,73 | 57,40 | 4,35 | 0,00 |
| *Dryer* | 301,19 | 69,23 | 4,35 | 0,00 |
| *Laundry loads per week* | 16,61 | 142,75 | 0,13 | 0,90 |
| *household size==2* | 385,87 | 36,62 | 10,54 | 0,00 |
| *household size==3* | 858,64 | 53,14 | 16,16 | 0,00 |
| *household size==4* | 1201,05 | 72,33 | 16,60 | 0,00 |
| *household size==5* | 1591,11 | 93,91 | 16,94 | 0,00 |
| *electric heating system * Head of household age* | 9,37 | 4,08 | 2,30 | 0,02 |
| *electric heating system * Head of household gender* | -213,17 | 88,04 | -2,42 | 0,02 |
| *electric heating system * Education level* | 289,22 | 97,12 | 2,98 | 0,00 |
| *electric heating system * Number of elderly* | -119,74 | 75,86 | -1,58 | 0,11 |
| *electric heating system * married* | 249,70 | 92,46 | 2,70 | 0,01 |
| *Electric heating system * Number of children* | -22,81 | 47,23 | -0,48 | 0,63 |
| *Electric heating system * House size* | -0,23 | 1,12 | -0,20 | 0,84 |
| *electric heating system * Built since 1990* | 238,48 | 75,91 | 3,14 | 0,00 |
| *Electric heating system * Windows with PVC or wood frames* | 56,70 | 66,67 | 0,85 | 0,40 |
| *electric heating system * wall exposure* | 63,04 | 74,92 | 0,84 | 0,40 |
| *Electric heating system * Thermostat* | 25,85 | 93,95 | 0,28 | 0,78 |
| *electric heating system * northern area* | 718,69 | 86,62 | 8,30 | 0,00 |
| *Electric heating system * Villa* | 441,04 | 113,94 | 3,87 | 0,00 |
| *Electric heating system * Income* | -17,19 | 57,28 | -0,30 | 0,76 |
| *Electric heating system * Employed* | -34,45 | 93,63 | -0,37 | 0,71 |
| *electric heating system * number of rooms* | 84,13 | 42,87 | 1,96 | 0,05 |
| *Computers * Head of household age* | 1,97 | 0,82 | 2,39 | 0,02 |
| *Computers * Head of household gender* | -19,27 | 16,15 | -1,19 | 0,23 |
| *Computers * Education level* | 10,78 | 16,62 | 0,65 | 0,52 |
| *Computers * Number of elderly* | -8,56 | 14,00 | -0,61 | 0,54 |
| *Computers * Married* | -2,31 | 17,69 | -0,13 | 0,90 |
| *Computers * Number of children* | -13,97 | 8,06 | -1,73 | 0,08 |
| *Computers * Income* | -5,15 | 9,42 | -0,55 | 0,59 |
| *Computers * Employed* | -26,94 | 19,16 | -1,41 | 0,16 |
| *Electric water heating system * Head of household age* | -3,91 | 3,21 | -1,22 | 0,22 |
| *Electric water heating system * Head of household gender* | 53,56 | 67,17 | 0,80 | 0,43 |
| *Electric water heating system * Education level* | 36,76 | 76,41 | 0,48 | 0,63 |
| *Electric water heating system * Number of elderly* | 35,11 | 57,25 | 0,61 | 0,54 |
| *Electric water heating system * Married* | 77,22 | 70,32 | 1,10 | 0,27 |
| *Electric water heating system * Number of children* | 239,76 | 36,31 | 6,60 | 0,00 |
| *Electric water heating system * Villa* | 135,96 | 69,60 | 1,95 | 0,05 |
| *Electric water heating system * Income* | -77,36 | 41,63 | -1,86 | 0,06 |
| *Electric water heating system * Employed* | 37,21 | 72,63 | 0,51 | 0,61 |
| *Refrigerator * Head of household age* | 0,52 | 3,71 | 0,14 | 0,89 |
| *Refrigerator * Head of household gender* | 172,61 | 76,63 | 2,25 | 0,02 |
| *Refrigerator * Education level* | -322,12 | 90,33 | -3,57 | 0,00 |
| *Refrigerator * Number of elderly* | -140,85 | 68,28 | -2,19 | 0,03 |
| *Refrigerator * Married* | 80,49 | 88,89 | 0,91 | 0,37 |
| *Refrigerator * Number of children* | -128,49 | 51,21 | -2,51 | 0,01 |
| *Refrigerator * cfiddfrigerator* | -16,60 | 17,27 | -0,96 | 0,34 |
| *Refrigerator * Income* | -14,08 | 42,70 | -0,33 | 0,74 |
| *Refrigerator * Employed* | -109,76 | 88,30 | -1,24 | 0,21 |
| *freezer * Head of household age* | 0,71 | 2,18 | 0,33 | 0,74 |
| *freezer * Head of household gender* | -1,47 | 44,72 | -0,03 | 0,97 |
| *freezer * Education level* | 4,76 | 52,58 | 0,09 | 0,93 |
| *freezer * Number of elderly* | 7,29 | 36,26 | 0,20 | 0,84 |
| *freezer * Married* | 27,10 | 48,04 | 0,56 | 0,57 |
| *freezer * Number of children* | 0,28 | 22,91 | 0,01 | 0,99 |
| *freezer * Income* | 6,29 | 25,08 | 0,25 | 0,80 |
| *freezer * Employed* | 24,60 | 51,01 | 0,48 | 0,63 |
| *Electric oven * Head of household age* | 4,66 | 2,57 | 1,81 | 0,07 |
| *Electric oven * Head of household gender* | -83,72 | 51,83 | -1,62 | 0,11 |
| *Electric oven * Education level* | 131,16 | 62,25 | 2,11 | 0,04 |
| *Electric oven * Number of elderly* | 6,85 | 45,16 | 0,15 | 0,88 |
| *Electric oven * Married* | -73,87 | 55,33 | -1,34 | 0,18 |
| *Electric oven * Number of children* | 2,02 | 29,70 | 0,07 | 0,95 |
| *Electric oven * Income* | 33,06 | 30,26 | 1,09 | 0,27 |
| *Electric oven * Employed* | -10,71 | 59,75 | -0,18 | 0,86 |
| *Laundry loads per week * Head of household age* | 0,27 | 0,36 | 0,75 | 0,45 |
| *Laundry loads per week * Head of household gender* | 2,35 | 8,09 | 0,29 | 0,77 |
| *Laundry loads per week * Education level* | 12,34 | 8,47 | 1,46 | 0,15 |
| *Laundry loads per week * Number of elderly* | 5,47 | 6,52 | 0,84 | 0,40 |
| *Laundry loads per week * Married* | -30,07 | 9,28 | -3,24 | 0,00 |
| *Laundry loads per week * Number of children* | -9,61 | 3,91 | -2,46 | 0,01 |
| *Laundry loads per week * Income* | -2,95 | 4,44 | -0,66 | 0,51 |
| *Laundry loads per week * Employed* | 17,62 | 8,13 | 2,17 | 0,03 |
| *Laundry loads per week * Washing machine age* | -13,31 | 3,72 | -3,57 | 0,00 |
| *Dish Washer * Head of household age* | 1,36 | 2,12 | 0,64 | 0,52 |
| *Dish Washer * Head of household gender* | 3,76 | 43,80 | 0,09 | 0,93 |
| *Dish Washer * Education level* | 39,86 | 51,34 | 0,78 | 0,44 |
| *Dish Washer * Number of elderly* | 39,26 | 36,74 | 1,07 | 0,29 |
| *Dish Washer * Married* | 53,99 | 45,93 | 1,18 | 0,24 |
| *Dish Washer * Number of children* | 115,11 | 23,45 | 4,91 | 0,00 |
| *Dish Washer * Employed* | -16,13 | 49,38 | -0,33 | 0,74 |
| *Dish Washer * Income* | -3,28 | 25,34 | -0,13 | 0,90 |
| *Electric stove * Head of household age* | -4,79 | 3,82 | -1,26 | 0,21 |
| *Electric stove * Head of household gender* | 76,28 | 76,50 | 1,00 | 0,32 |
| *Electric stove * Education level* | 24,91 | 81,25 | 0,31 | 0,76 |
| *Electric stove * Number of elderly* | -9,02 | 76,01 | -0,12 | 0,91 |
| *Electric stove * Married* | 81,02 | 81,72 | 0,99 | 0,32 |
| *Electric stove * Number of children* | 34,82 | 41,81 | 0,83 | 0,41 |
| *Electric stove * Employed* | -225,38 | 100,09 | -2,25 | 0,02 |
| *Electric stove * Income* | 86,18 | 48,63 | 1,77 | 0,08 |
| *Traditional light bulbs * Head of household age* | -0,24 | 0,23 | -1,03 | 0,30 |
| *Traditional light bulbs * Head of household gender* | 2,84 | 4,64 | 0,61 | 0,54 |
| *Traditional light bulbs * Education level* | 5,34 | 4,88 | 1,09 | 0,27 |
| *Traditional light bulbs * Number of elderly* | 5,29 | 3,90 | 1,36 | 0,18 |
| *Traditional light bulbs * Married* | -4,89 | 4,90 | -1,00 | 0,32 |
| *Traditional light bulbs * Number of children* | 1,02 | 2,51 | 0,41 | 0,68 |
| *Traditional light bulbs * House size* | 0,07 | 0,04 | 1,86 | 0,06 |
| *Traditional light bulbs * Wall exposure* | 4,59 | 3,16 | 1,45 | 0,15 |
| *Traditional light bulbs * Income* | -0,76 | 2,71 | -0,28 | 0,78 |
| *Traditional light bulbs * Employed* | 9,32 | 5,33 | 1,75 | 0,08 |
| *Traditional light bulbs * Number of rooms* | 4,55 | 2,46 | 1,85 | 0,06 |
| *Energy-saving light bulbs * Head of household age* | -0,04 | 0,15 | -0,24 | 0,81 |
| *Energy-saving light bulbs * Head of household gender* | 2,28 | 3,08 | 0,74 | 0,46 |
| *Energy-saving light bulbs * Education level* | -4,86 | 3,38 | -1,44 | 0,15 |
| *Energy-saving light bulbs * Number of elderly* | 3,72 | 2,67 | 1,39 | 0,16 |
| *Energy-saving light bulbs * Married* | -6,88 | 3,36 | -2,05 | 0,04 |
| *Energy-saving light bulbs * Number of children* | -0,14 | 1,66 | -0,09 | 0,93 |
| *Energy-saving light bulbs * House size* | 0,11 | 0,02 | 4,73 | 0,00 |
| *Energy-saving light bulbs * Wall exposure* | 13,45 | 1,89 | 7,11 | 0,00 |
| *Energy-saving light bulbs * Income* | 0,08 | 0,75 | 0,10 | 0,92 |
| *Energy-saving light bulbs * Employed* | 2,18 | 3,65 | 0,60 | 0,55 |
| *Televisions * Head of household age* | -1,94 | 1,15 | -1,70 | 0,09 |
| *Televisions * Head of household gender* | -19,38 | 23,83 | -0,81 | 0,42 |
| *Televisions * Education level* | 22,84 | 25,55 | 0,89 | 0,37 |
| *Televisions * Number of elderly* | 20,66 | 19,39 | 1,07 | 0,29 |
| *Televisions * Married* | 13,05 | 25,66 | 0,51 | 0,61 |
| *Televisions * Number of children* | 12,23 | 11,88 | 1,03 | 0,30 |
| *Televisions * Number of rooms* | 54,98 | 10,18 | 5,40 | 0,00 |
| *Televisions * House size* | 0,48 | 0,18 | 2,67 | 0,01 |
| *Televisions * Income* | -13,20 | 13,88 | -0,95 | 0,34 |
| *Televisions * Employed* | 15,26 | 26,81 | 0,57 | 0,57 |
| *Air conditioning * Head of household age* | 0,80 | 2,29 | 0,35 | 0,73 |
| *Air conditioning * Head of household gender* | 51,12 | 46,11 | 1,11 | 0,27 |
| *Air conditioning * Education level* | 46,33 | 49,55 | 0,98 | 0,33 |
| *Air conditioning * Number of elderly* | -42,37 | 39,46 | -1,07 | 0,28 |
| *Air conditioning * Married* | 53,85 | 49,05 | 1,10 | 0,27 |
| *Air conditioning * Number of children* | 54,08 | 24,62 | 2,20 | 0,03 |
| *Air conditioning * Number of rooms* | -18,44 | 26,61 | -0,69 | 0,49 |
| *Air conditioning * House size* | 0,35 | 0,49 | 1,14 | 0,25 |
| *Air conditioning * Built since 1990* | 15,87 | 34,50 | 0,46 | 0,65 |
| *Air conditioning * Windows with PVC or wood frames* | -50,50 | 34,31 | -1,47 | 0,14 |
| *Air conditioning * Wall exposure* | -130,03 | 39,90 | -3,26 | 0,00 |
| *Air conditioning * Northern Area* | -109,70 | 33,11 | -3,31 | 0,00 |
| *Air conditioning * Villa* | 530,62 | 46,58 | 11,39 | 0,00 |
| *Air conditioning * Income* | -15,62 | 26,64 | -0,59 | 0,56 |
| *Air conditioning * Employed* | -36,27 | 54,08 | -0,67 | 0,50 |
| *Gardening equipment * Head of household age* | -1,40 | 3,45 | -0,41 | 0,68 |
| *Gardening equipment * Head of household gender* | -53,75 | 66,69 | -0,81 | 0,42 |
| *Gardening equipment * Education level* | -14,98 | 73,17 | -0,20 | 0,84 |
| *Gardening equipment * Number of elderly* | 24,56 | 57,67 | 0,42 | 0,67 |
| *Gardening equipment * Married* | -38,54 | 72,49 | -0,53 | 0,60 |
| *Gardening equipment * Number of children* | -11,09 | 35,22 | -0,31 | 0,75 |
| *Gardening equipment * Employed* | -6,99 | 83,84 | -0,08 | 0,93 |
| *Gardening equipment * Income* | 22,49 | 39,74 | 0,57 | 0,57 |
| *Dryer * Head of household age* | 5,27 | 2,59 | 2,04 | 0,04 |
| *Dryer * Head of household gender* | -37,86 | 52,28 | -0,72 | 0,47 |
| *Dryer * Education level* | -47,74 | 55,24 | -0,86 | 0,39 |
| *Dryer * Number of elderly* | 1,35 | 47,41 | 0,03 | 0,98 |
| *Dryer * Married* | 88,93 | 57,62 | 1,54 | 0,12 |
| *Dryer * Number of children* | -25,15 | 25,83 | -0,90 | 0,37 |
| *Dryer * Income* | 23,20 | 29,45 | 0,79 | 0,43 |
| *Dryer * Employed* | -21,89 | 61,84 | -0,35 | 0,72 |
| *Number of observation* | 32221,00 | | | |
| *Adjusted R squared* | | | 0,32 | |

Table 1.11: Estimated household consumption via ordinary least squares approach. The model includes appliances ownership and endowment and interaction terms as covariates associated with significant coefficients at least at 10%. The response variable is the household's annual electricity consumption expressed as kilowatt per hours. *** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$; . $p \leq 0.1$.

| Variables | Estimates | Standard Error | Statistic |
|---|---|---|---|
| *Intercept* | 328.4686*** | (21.9668) | 0 |
| *Electric heating system* | 221.771** | (113.1129) | 0.0499 |
| *Dish washer* | 222.5578*** | (28.9399) | 0 |
| *Electric water heating system* | 412.1745*** | (68.7574) | 0 |
| *Freezer* | 202.6703*** | (34.2102) | 0 |
| *Electric stove* | 79.8801 | (73.0193) | 0.274 |
| *Electric oven* | -8.4894 | (26.1959) | 0.7459 |
| *Traditional light bulbs* | -97.4051 | (83.6941) | 0.2445 |
| *Computers* | -93.7635 | (84.2177) | 0.2655 |
| *Gardening equipment* | 14.0003 | (53.0674) | 0.7919 |
| *Televisions* | 106.8205 | (86.4481) | 0.2166 |
| *Air conditioning* | 126.6257*** | (40.1957) | 0.0014 |
| *Dryer* | 150.4536* | (76.9684) | 0.0507 |
| *Laundry loads per week* | -9.6158 | (132.9753) | 0.9424 |
| *household size===2* | 12.2863 | (16.121) | 0.4459 |
| *household size===3* | 174.0413*** | (37.3816) | 0 |
| *household size===4* | 455.1468*** | (69.9674) | 0 |
| *household size===5* | 529.8773*** | (117.9377) | 0 |
| *electric heating system * Head of household age* | 2.5874 | (4.9039) | 0.6044 |
| *electric heating system * Head of household gender* | -74.1816 | (106.4682) | 0.486 |
| *electric heating system * Education level* | -15.972 | (108.3802) | 0.8828 |
| *electric heating system * Number of elderly* | -20.2263 | (104.7941) | 0.847 |
| *electric heating system * married* | 239.3629 | (157.3764) | 0.1282 |
| *Electric heating system * Number of children* | 75.0172 | (83.9681) | 0.3716 |
| *Electric heating system * House size* | 1.1401 | (2.0861) | 0.5847 |
| *electric heating system * Built since 1990* | 247.4282** | (108.4839) | 0.0449 |
| *Electric heating system * Windows with PVC or wood frames* | -48.6705 | (96.2451) | 0.613 |
| *electric heating system * wall exposure* | 255.9685** | (108.972) | 0.0188 |
| *Electric heating system * Thermostat* | 2.9659 | (158.2432) | 0.9856 |
| *electric heating system * northern area* | 75.0238 | (115.6946) | 0.5167 |
| *Electric heating system * Villa* | 355.7786 | (238.9203) | 0.1365 |
| *Electric heating system * Income* | 19.5741 | (58.6385) | 0.7385 |
| *Electric heating system * Employed* | 80.8286 | (103.9141) | 0.4367 |
| *electric heating system * number of rooms* | 115.612** | (58.3538) | 0.0476 |
| *Computers * Head of household age* | 0.4344 | (0.5179) | 0.4017 |
| *Computers * Head of household gender* | -2.6507 | (11.7749) | 0.8219 |
| *Computers * Education level* | -6.3308 | (11.4042) | 0.5788 |
| *Computers * Number of elderly* | 12.3039 | (11.8773) | 0.3002 |
| *Computers * Married* | -7.7366 | (11.5994) | 0.5047 |
| *Computers * Number of children* | -25.1357*** | (8.489) | 0.0031 |
| *Computers * Income* | -10.5161* | (5.4519) | 0.0538 |
| *Computers * Employed* | 6.4412 | (14.1322) | 0.6486 |
| *Electric water heating system * Head of household age* | -4.6496* | (2.7339) | 0.089 |
| *Electric water heating system * Head of household gender* | 19.6839 | (56.9699) | 0.7365 |
| *Electric water heating system * Education level* | -63.6815 | (59.0624) | 0.2809 |
| *Electric water heating system * Number of elderly* | 53.3055 | (72.9147) | 0.4649 |
| *Electric water heating system * Married* | 337.9298*** | (126.8461) | 0.0077 |
| *Electric water heating system * Number of children* | 347.2153*** | (67.6322) | 0 |
| *Electric water heating system * Villa* | 121.6856 | (117.8504) | 0.3018 |
| *Electric water heating system * Income* | 4.9068 | (31.718) | 0.8771 |
| *Electric water heating system * Employed* | 76.6436 | (52.831) | 0.1469 |
| *freezer * Head of household age* | -0.4423 | (1.5885) | 0.7807 |
| *freezer * Head of household gender* | 34.1081 | (28.8166) | 0.2366 |
| *freezer * Education level* | -66.1999* | (34.3032) | 0.0536 |
| *freezer * Number of elderly* | 14.1351 | (30.1033) | 0.6387 |
| *freezer * Married* | 40.7312 | (37.0697) | 0.2719 |
| *freezer * Number of children* | 147.5142*** | (24.6299) | 0 |
| *freezer * Income* | -9.7889 | (13.9164) | 0.4818 |
| *freezer * Employed* | 37.8225 | (38.908) | 0.331 |
| *Electric oven * Head of household age* | 0.0536 | (1.9483) | 0.9592 |
| *Electric oven * Head of household gender* | -4.3778 | (23.7087) | 0.8535 |
| *Electric oven * Education level* | -14.8171 | (24.995) | 0.5533 |
| *Electric oven * Number of elderly* | 43.4661* | (24.6134) | 0.0774 |
| *Electric oven * Married* | -105.926*** | (29.6221) | 0.0003 |
| *Electric oven * Number of children* | -76.5374*** | (25.5391) | 0.0027 |
| *Electric oven * Income* | 32.7379** | (15.2791) | 0.0321 |
| *Electric oven * Employed* | 10.4681 | (29.3894) | 0.7217 |
| *Laundry loads per week * Head of household age* | 0.6037** | (0.2551) | 0.0179 |
| *Laundry loads per week * Head of household gender* | 5.4368 | (6.4889) | 0.4021 |
| *Laundry loads per week * Education level* | -2.618 | (9.3667) | 0.7799 |
| *Laundry loads per week * Number of elderly* | -9.6222 | (7.4533) | 0.1967 |
| *Laundry loads per week * Married* | -0.0212 | (8.1431) | 0.9979 |
| *Laundry loads per week * Number of children* | 3.4946 | (4.644) | 0.4518 |
| *Laundry loads per week * Income* | -4.9956 | (4.2483) | 0.2396 |
| *Laundry loads per week * Employed* | 3.614 | (8.2086) | 0.6621 |
| *Laundry loads per week * Washing machine age* | -11.9958*** | (3.2317) | 0.0002 |
| *Dish Washer * Head of household age* | 0.1988 | (1.1476) | 0.8625 |
| *Dish Washer * Head of household gender* | 13.7057 | (21.3043) | 0.52 |
| *Dish Washer * Education level* | -25.7649 | (24.7459) | 0.2978 |
| *Dish Washer * Number of elderly* | 0.9311 | (25.0286) | 0.9703 |
| *Dish Washer * Married* | 78.6407*** | (21.9072) | 0.0003 |
| *Dish Washer * Number of children* | 209.4870*** | (27.5964) | 0 |
| *Dish Washer * Employed* | 9.9469 | (30.5494) | 0.7447 |
| *Dish Washer * Income* | -4.7673 | (12.3437) | 0.6993 |
| *Electric stove * Head of household age* | 2.8139 | (2.2944) | 0.22 |
| *Electric stove * Head of household gender* | 68.5458 | (46.6046) | 0.1585 |
| *Electric stove * Education level* | 40.4681 | (54.0559) | 0.4541 |
| *Electric stove * Number of elderly* | -83.8153 | (67.179) | 0.2122 |
| *Electric stove * Married* | 26.9621 | (53.0596) | 0.6113 |
| *Electric stove * Number of children* | 50.2194 | (64.1515) | 0.4337 |
| *Electric stove * Employed* | -57.5356 | (86.8102) | 0.5171 |
| *Electric stove * Income* | -65.7862 | (45.8076) | 0.151 |
| *Traditional light bulbs * Head of household age* | -0.037 | (0.1183) | 0.7543 |
| *Traditional light bulbs * Head of household gender* | 0.8152 | (1.9997) | 0.6835 |
| *Traditional light bulbs * Education level* | 2.2376 | (2.6105) | 0.3914 |
| *Traditional light bulbs * Number of elderly* | -1.4314 | (2.1856) | 0.5125 |
| *Traditional light bulbs * Married* | 2.6698 | (2.1459) | 0.2101 |
| *Traditional light bulbs * Number of children* | -6.8751*** | (2.1612) | 0.0015 |
| *Traditional light bulbs * House size* | 0.0413 | (0.0431) | 0.3378 |
| *Traditional light bulbs * Wall exposure* | 0.0465 | (1.5677) | 0.9763 |
| *Traditional light bulbs * Income* | 0.2033 | (1.3739) | 0.8823 |
| *Traditional light bulbs * Employed* | -3.5824 | (2.6586) | 0.1779 |
| *Traditional light bulbs * Number of rooms* | -2.5362** | (1.2906) | 0.0492 |
| *Energy-saving light bulbs * Head of household age* | -0.0004 | (0.0886) | 0.9961 |
| *Energy-saving light bulbs * Head of household gender* | 2.2799 | (1.4073) | 0.1202 |
| *Energy-saving light bulbs * Education level* | -0.3732 | (1.8029) | 0.836 |
| *Energy-saving light bulbs * Number of elderly* | -0.8352 | (1.7016) | 0.6235 |
| *Energy-saving light bulbs * Married* | 0.1295 | (1.6399) | 0.937 |
| *Energy-saving light bulbs * Number of children* | -2.3399 | (1.7896) | 0.1911 |
| *Energy-saving light bulbs * House size* | 0.007 | (0.0284) | 0.8064 |
| *Energy-saving light bulbs * Wall exposure* | 4.7351*** | (1.1053) | 0 |
| *Energy-saving light bulbs * Income* | 0.3165 | (0.4516) | 0.4834 |
| *Energy-saving light bulbs * Employed* | -1.981 | (2.13621) | 0.3538 |
| *Televisions * Head of household age* | -1.8434*** | (0.6816) | 0.0068 |
| *Televisions * Head of household gender* | -14.9479 | (12.7812) | 0.2422 |
| *Televisions * Education level* | -3.0543 | (15.0578) | 0.8393 |
| *Televisions * Number of elderly* | 5.9296 | (14.562) | 0.6843 |
| *Televisions * Married* | 13.9665 | (13.777) | 0.3142 |
| *Televisions * Number of children* | 38.6388*** | (10.6855) | 0.0003 |
| *Televisions * Number of rooms* | 13.5899** | (6.7609) | 0.0446 |
| *Televisions * House size* | 1.0122*** | (0.28) | 0.0003 |
| *Televisions * Income* | -10.1978 | (7.9698) | 0.2007 |
| *Televisions * Employed* | 3.9456 | (17.0032) | 0.8165 |
| *Air conditioning * Head of household age* | -0.5674 | (1.4927) | 0.704 |
| *Air conditioning * Head of household gender* | 18.5155 | (24.0766) | 0.4419 |
| *Air conditioning * Education level* | -39.818 | (32.9105) | 0.7424 |
| *Air conditioning * Number of elderly* | 18.4229 | (31.5509) | 0.5593 |
| *Air conditioning * Married* | 80.7342** | (33.7223) | 0.0167 |
| *Air conditioning * Number of children* | 103.6454*** | (27.1949) | 0.0001 |
| *Air conditioning * Number of rooms* | -32.6655** | (14.9092) | 0.0284 |
| *Air conditioning * House size* | 1.3672** | (0.6424) | 0.0333 |
| *Air conditioning * Built since 1990* | 7.2242 | (27.1343) | 0.7901 |
| *Air conditioning * Windows with PVC or wood frames* | -40.5183 | (29.4153) | 0.1684 |
| *Air conditioning * Wall exposure* | -26.685 | (21.9688) | 0.2224 |
| *Air conditioning * Northern Area* | -64.9843** | (22.9099) | 0.0046 |
| *Air conditioning * Villa* | 419.2639*** | (83.1176) | 0 |
| *Air conditioning * Income* | 18.8474 | (14.6206) | 0.1974 |
| *Air conditioning * Employed* | 43.0327 | (41.0552) | 0.2946 |
| *Gardening equipment * Head of household age* | 0.9458 | (2.5762) | 0.7137 |
| *Gardening equipment * Head of household gender* | -26.353 | (35.8454) | 0.4622 |
| *Gardening equipment * Education level* | -38.8209 | (59.0007) | 0.5106 |
| *Gardening equipment * Number of elderly* | 6.2647 | (50.8272) | 0.9019 |
| *Gardening equipment * Married* | 8.7525 | (52.7534) | 0.8682 |
| *Gardening equipment * Number of children* | 39.9491 | (35.7016) | 0.2559 |
| *Gardening equipment * Employed* | 97.7038* | (53.9291) | 0.07 |
| *Gardening equipment * Income* | -10.9333 | (21.2599) | 0.6071 |
| *Dryer * Head of household age* | 3.6215 | (2.6925) | 0.1786 |
| *Dryer * Head of household gender* | 112.3281** | (45.1041) | 0.0128 |
| *Dryer * Education level* | -2.9041 | (52.2897) | 0.9557 |
| *Dryer * Number of elderly* | 188.8276** | (84.7318) | 0.0259 |
| *Dryer * Married* | 167.4987** | (50.1462) | 0.0008 |
| *Dryer * Number of children* | 105.3535*** | (34.5708) | 0.0023 |
| *Dryer * Income* | 12.5345 | (30.2274) | 0.6794 |
| *Dryer * Employed* | 5.7723 | (74.8011) | 0.9385 |
| *Pseudo R squared* | | 0.13 | |

Table 1.12: Estimated household consumption via quantile regression approach. Estimates are referred to the 25th percentile. The model includes appliances ownership and endowment and interaction terms as covariates associated with significant coefficients at least at 10%. The response variable is the household's annual electricity consumption expressed as kilowatt per hours. *** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$; . $p \leq 0.1$.

| Variables | Estimates | Standard Error | Statistic |
|---|---|---|---|
| *Intercept* | 194.5949*** | (26.9752) | 0 |
| *Electric heating system* | 729.6357*** | (136.451) | 0 |
| *Dish washer* | 269.8772*** | (34.8211) | 0 |
| *Electric water heating system* | 716.6064*** | (85.0456) | 0 |
| *Freezer* | 219.9796*** | (44.7869) | 0 |
| *Electric stove* | 145.4898* | (86.1055) | 0.0911 |
| *Electric oven* | 91.3145*** | (30.9247) | 0.0032 |
| *Traditional light bulbs* | -24.8885 | (139.6596) | 0.8586 |
| *Computers* | 12.6413 | (130.6404) | 0.9231 |
| *Gardening equipment* | 32.7405 | (76.3135) | 0.6759 |
| *Televisions* | 232.197* | (136.7656) | 0.0896 |
| *Air conditioning* | 222.488*** | (52.9256) | 0 |
| *Dryer* | 419.362*** | (80.1208) | 0 |
| *Laundry loads per week* | 100.164 | (152.7123) | 0.5119 |
| *household size==2* | 265.9008*** | (26.1747) | 0 |
| *household size==3* | 920.1218*** | (38.8416) | 0 |
| *household size==4* | 1232.3649*** | (56.1004) | 0 |
| *household size==5* | 1563.9131*** | (74.3371) | 0 |
| *electric heating system * Head of household age* | 7.0703 | (5.7799) | 0.2212 |
| *electric heating system * Head of household gender* | -73.2222 | (114.3302) | 0.5219 |
| *electric heating system * Education level* | 167.3354 | (160.4086) | 0.2969 |
| *electric heating system * number of elderly* | -107.9974 | (106.2114) | 0.3092 |
| *electric heating system * married* | 13.7719 | (138.941) | 0.921 |
| *Electric heating system * Number of children* | -67.2969 | (63.109) | 0.2863 |
| *Electric heating system * House size* | 0.5152 | (2.2538) | 0.8192 |
| *electric heating system * Built since 1990* | 116.8927 | (112.4367) | 0.2985 |
| *Electric heating system * Windows with PVC or wood frames* | 47.6994 | (85.7628) | 0.5781 |
| *electric heating system * wall exposure* | -25.2128 | (96.4651) | 0.7979 |
| *Electric heating system * Thermostat* | -79.5349 | (173.7885) | 0.6472 |
| *electric heating system * northern area* | 473.1787** | (198.1292) | 0.0169 |
| *Electric heating system * Villa* | 362.136** | (161.4814) | 0.0249 |
| *Electric heating system * Income* | 5.7168 | (94.1693) | 0.9516 |
| *Electric heating system * Employed* | -107.9075 | (127.6605) | 0.3977 |
| *electric heating system * number of rooms* | 112.9181 | (72.7231) | 0.1208 |
| *Computers * Head of household age* | 0.6613 | (0.7433) | 0.3735 |
| *Computers * Head of household gender* | -5.8434 | (15.7799) | 0.7112 |
| *Computers * Education level* | -4.771 | (17.1652) | 0.7803 |
| *Computers * Number of elderly* | 10.6877 | (17.5045) | 0.5415 |
| *Computers * Married* | -18.0063 | (18.4002) | 0.3278 |
| *Computers * Number of children* | -12.8509 | (8.5312) | 0.1329 |
| *Computers * Income* | -14.0725 | (8.6407) | 0.1034 |
| *Computers * Employed* | -14.34 | (18.9659) | 0.4496 |
| *Electric water heating system * Head of household age* | -10.301** | (4.2528) | 0.0154 |
| *Electric water heating system * Head of household gender* | 40.2121 | (96.0491) | 0.6755 |
| *Electric water heating system * Education level* | -127.4273 | (103.854) | 0.2198 |
| *Electric water heating system * Number of elderly* | 168.8436** | (73.1426) | 0.021 |
| *Electric water heating system * Married* | 229.1585** | (102.0896) | 0.0248 |
| *Electric water heating system * Number of children* | 93.5417** | (36.2569) | 0.0145 |
| *Electric water heating system * Villa* | 278.6255*** | (93.7873) | 0.003 |
| *Electric water heating system * Income* | 14.7039 | (44.3877) | 0.7405 |
| *Electric water heating system * Employed* | 148.3274 | (110.057) | 0.1778 |
| *freezer * Head of household age* | -1.6543 | (1.9308) | 0.3916 |
| *freezer * Head of household gender* | 48.5377 | (56.2101) | 0.3879 |
| *freezer * Education level* | -26.1707 | (58.9894) | 0.6572 |
| *freezer * Number of elderly* | 54.3641 | (36.007) | 0.1311 |
| *freezer * Married* | 224.3874*** | (60.7698) | 0.0002 |
| *freezer * Number of children* | -58.0148** | (24.0941) | 0.0161 |
| *freezer * Income* | 15.974 | (20.429) | 0.4343 |
| *freezer * Employed* | 7.9055 | (47.7794) | 0.8686 |
| *Electric oven * Head of household age* | 1.6933 | (1.394) | 0.2245 |
| *Electric oven * Head of household gender* | 6.588 | (30.0045) | 0.8262 |
| *Electric oven * Education level* | -13.4759 | (36.2249) | 0.7244 |
| *Electric oven * Number of elderly* | 6.9268 | (32.7325) | 0.8324 |
| *Electric oven * Married* | -117.4384*** | (40.7606) | 0.004 |
| *Electric oven * Number of children* | 15.0692 | (23.8806) | 0.5297 |
| *Electric oven * Income* | 12.9924 | (18.7112) | 0.4875 |
| *Electric oven * Employed* | -19.3383 | (36.1525) | 0.6123 |
| *Laundry loads per week * Head of household age* | 0.7157** | (0.3361) | 0.0332 |
| *Laundry loads per week * Head of household gender* | 1.5034 | (7.7371) | 0.8459 |
| *Laundry loads per week * Education level* | 0.0276 | (8.6642) | 0.9975 |
| *Laundry loads per week * Number of elderly* | -8.9962 | (7.0799) | 0.2039 |
| *Laundry loads per week * Married* | -9.553 | (10.6166) | 0.3682 |
| *Laundry loads per week * Number of children* | -10.4798*** | (3.6676) | 0.0043 |
| *Laundry loads per week * Income* | -1.496 | (4.9223) | 0.7612 |
| *Laundry loads per week * Employed* | 6.5124 | (7.7424) | 0.4003 |
| *Laundry loads per week * Washing machine age* | -7.5956** | (3.424) | 0.0265 |
| *Dish Washer * Head of household age* | -1.4089 | (1.6102) | 0.3843 |
| *Dish Washer * Head of household gender* | 18.5689 | (32.0024) | 0.5538 |
| *Dish Washer * Education level* | -45.951 | (39.5029) | 0.2447 |
| *Dish Washer * Number of elderly* | 92.8912** | (35.9423) | 0.0098 |
| *Dish Washer * Married* | 182.7794*** | (41.7157) | 0 |
| *Dish Washer * Number of children* | 125.5143*** | (24.831) | 0 |
| *Dish Washer * Employed* | -15.6922 | (36.7661) | 0.6695 |
| *Dish Washer * Income* | 25.6274 | (18.9182) | 0.2115 |
| *Electric stove * Head of household age* | -2.1602 | (3.2389) | 0.5048 |
| *Electric stove * Head of household gender* | 138.7986** | (62.6545) | 0.0267 |
| *Electric stove * Education level* | 144.4198* | (83.3422) | 0.0851 |
| *Electric stove * Number of elderly* | -45.7848 | (83.712) | 0.5844 |
| *Electric stove * Married* | 112.2524 | (88.6654) | 0.2055 |
| *Electric stove * Number of children* | 5.7426 | (52.7303) | 0.9133 |
| *Electric stove * Employed* | -157.1251 | (97.3215) | 0.1064 |
| *Electric stove * Income* | -56.3123 | (48.766) | 0.2482 |
| *Traditional light bulbs * Head of household age* | 0.274 | (0.1838) | 0.1357 |
| *Traditional light bulbs * Head of household gender* | 9.244*** | (3.4575) | 0.0075 |
| *Traditional light bulbs * Education level* | 3.5106 | (3.5391) | 0.3212 |
| *Traditional light bulbs * Number of elderly* | -4.4511 | (3.4767) | 0.2005 |
| *Traditional light bulbs * Married* | -3.5218 | (3.859) | 0.3614 |
| *Traditional light bulbs * Number of children* | -0.2622 | (2.3871) | 0.9126 |
| *Traditional light bulbs * House size* | 0.0892 | (0.06) | 0.137 |
| *Traditional light bulbs * Wall exposure* | 3.3455 | (2.5775) | 0.1943 |
| *Traditional light bulbs * Income* | -0.6104 | (1.9008) | 0.7481 |
| *Traditional light bulbs * Employed* | 6.6047 | (4.2025) | 0.1531 |
| *Traditional light bulbs * Number of rooms* | -3.3029 | (2.167) | 0.1275 |
| *Energy-saving light bulbs * Head of household age* | -0.1114 | (0.139) | 0.4225 |
| *Energy-saving light bulbs * Head of household gender* | 5.23* | (2.697) | 0.0525 |
| *Energy-saving light bulbs * Education level* | -3.7945 | (3.1845) | 0.2334 |
| *Energy-saving light bulbs * Number of elderly* | 1.1636 | (2.7239) | 0.6693 |
| *Energy-saving light bulbs * Married* | -4.7024 | (3.5162) | 0.1814 |
| *Energy-saving light bulbs * Number of children* | 0.0376 | (1.8132) | 0.9835 |
| *Energy-saving light bulbs * House size* | 0.0628*** | (0.0294) | 0.0049 |
| *Energy-saving light bulbs * Wall exposure* | 10.7003*** | (1.8004) | 0 |
| *Energy-saving light bulbs * Income* | 0.65 | (0.6885) | 0.3451 |
| *Energy-saving light bulbs * Employed* | -1.4462 | (3.4479) | 0.6749 |
| *Televisions * Head of household age* | -2.4735*** | (0.7688) | 0.0013 |
| *Televisions * Head of household gender* | -32.2256* | (16.5983) | 0.0522 |
| *Televisions * Education level* | 5.0927 | (21.2315) | 0.8104 |
| *Televisions * Number of elderly* | 1.8519 | (17.7361) | 0.9169 |
| *Televisions * Married* | 30.4774 | (21.1146) | 0.1463 |
| *Televisions * Number of children* | -7.9377 | (11.7175) | 0.4981 |
| *Televisions * Number of rooms* | 37.0698*** | (9.3906) | 0.0001 |
| *Televisions * House size* | 1.1369*** | (0.2628) | 0 |
| *Televisions * Income* | -8.1532 | (12.411) | 0.5112 |
| *Televisions * Employed* | 3.1704 | (22.5479) | 0.8882 |
| *Air conditioning * Head of household age* | 0.6156 | (1.8822) | 0.7436 |
| *Air conditioning * Head of household gender* | -3.4664 | (39.0859) | 0.9293 |
| *Air conditioning * Education level* | 26.5503 | (45.9678) | 0.5635 |
| *Air conditioning * Number of elderly* | 32.6287 | (40.0526) | 0.4153 |
| *Air conditioning * Married* | 67.4703 | (46.1471) | 0.1611 |
| *Air conditioning * Number of children* | 64.5974** | (25.9379) | 0.0128 |
| *Air conditioning * Number of rooms* | 3.713 | (23.7014) | 0.8755 |
| *Air conditioning * House size* | 0.3618 | (0.6496) | 0.5722 |
| *Air conditioning * Built since 1990* | 4.2427 | (30.2311) | 0.8884 |
| *Air conditioning * Windows with PVC or wood frames* | -48.613 | (30.5999) | 0.1121 |
| *Air conditioning * Wall exposure* | -103.7492*** | (30.6845) | 0.0007 |
| *Air conditioning * Northern Area* | -107.276*** | (31.4627) | 0.0007 |
| *Air conditioning * Villa* | 565.1041*** | (56.6182) | 0 |
| *Air conditioning * Income* | 3.6631 | (22.2746) | 0.8694 |
| *Air conditioning * Employed* | 51.0135 | (40.1275) | 0.2036 |
| *Gardening equipment * Head of household age* | -0.9441 | (3.2095) | 0.7686 |
| *Gardening equipment * Head of household gender* | -116.8398 | (72.7153) | 0.1081 |
| *Gardening equipment * Education level* | 42.7803 | (71.6247) | 0.5503 |
| *Gardening equipment * Number of elderly* | 19.2717 | (63.1928) | 0.7604 |
| *Gardening equipment * Married* | 95.2208 | (83.8556) | 0.2562 |
| *Gardening equipment * Number of children* | -28.4312 | (41.1442) | 0.4896 |
| *Gardening equipment * Employed* | 65.1051 | (89.5963) | 0.4674 |
| *Gardening equipment * Income* | -10.6329 | (32.8709) | 0.7463 |
| *Dryer * Head of household age* | 6.3137** | (2.8783) | 0.0283 |
| *Dryer * Head of household gender* | -14.3775 | (61.7756) | 0.816 |
| *Dryer * Education level* | 13.9279 | (72.0463) | 0.8467 |
| *Dryer * Number of elderly* | -6.54 | (55.3629) | 0.906 |
| *Dryer * Married* | 33.476 | (62.4761) | 0.6848 |
| *Dryer * Number of children* | -34.59 | (33.8464) | 0.3068 |
| *Dryer * Income* | 36.6242 | (30.252) | 0.2259 |
| *Dryer * Employed* | -126.2714* | (66.682) | 0.0618 |
| *Pseudo R squared* | | 0.25 | |

Table 1.13: Estimated household consumption via quantile regression approach. Estimates are referred to the 50th percentile median. The model includes appliances ownership and endowment and interaction terms as covariates associated with significant coefficients at least at 10%. The response variable is the household's annual electricity consumption expressed as kilowatt per hours. *** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$; . $p \leq 0.1$.

| Variables | Estimates | Standard Error | Statistic |
|---|---|---|---|
| *Intercept* | 371.4916*** | (44.3012) | 0 |
| *Electric heating system* | 762.2978*** | (179.5631) | 0 |
| *Dish washer* | 383.2553*** | (63.6649) | 0 |
| *Electric water heating system* | 1087.3602*** | (78.065) | 0 |
| *Freezer* | 465.8834*** | (63.7879) | 0 |
| *Electric stove* | 281.3595** | (127.4918) | 0.0273 |
| *Electric oven* | 157.57*** | (48.5622) | 0.0012 |
| *Traditional light bulbs* | -35.3686 | (175.4565) | 0.8399 |
| *Computers* | 173.5832 | (199.8617) | 0.385 |
| *Gardening equipment* | 221.7396** | (105.1967) | 0.0351 |
| *Televisions* | 356.9966** | (174.6664) | 0.0403 |
| *Air conditioning* | 278.6214*** | (69.3527) | 0.0001 |
| *Dryer* | 436.4838*** | (61.783) | 0 |
| *Laundry loads per week* | 245.8528 | (228.04) | 0.281 |
| *Household size==2* | 683.0195*** | (43.3532) | 0 |
| *Household size==3* | 1253.1204*** | (48.4126) | 0 |
| *Household size==4* | 1604.1107*** | (60.8682) | 0 |
| *Household size==5* | 1997.2933*** | (106.6355) | 0 |
| *electric heating system * Head of household age* | 3.4547 | (6.972) | 0.6202 |
| *electric heating system * Head of household gender* | -122.9643 | (174.9537) | 0.4822 |
| *electric heating system * Education level* | 231.6287 | (159.4883) | 0.1464 |
| *electric heating system * number of elderly* | -95.6038 | (140.8747) | 0.4974 |
| *electric heating system * married* | 140.3957 | (152.7758) | 0.3581 |
| *Electric heating system * Number of children* | -164.5982** | (71.7193) | 0.0217 |
| *Electric heating system * House size* | -2.3361 | (2.479) | 0.346 |
| *electric heating system * Built since 1990* | 205.6624 | (159.035) | 0.196 |
| *Electric heating system * Windows with PVC or wood frames* | 187.0889 | (146.0407) | 0.2002 |
| *electric heating system * wall exposure* | -124.8033 | (140.9169) | 0.3758 |
| *Electric heating system * Thermostat* | -162.4265 | (228.7816) | 0.4777 |
| *electric heating system * northern area* | 1315.7284*** | (240.7509) | 0 |
| *Electric heating system * Villa* | 627.8899** | (283.6197) | 0.0268 |
| *Electric heating system * Income* | 54.4329 | (75.0431) | 0.4682 |
| *Electric heating system * Employed* | -89.3571 | (136.7269) | 0.5134 |
| *electric heating system * number of rooms* | 125.9001 | (76.7766) | 0.1011 |
| *Computers * Head of household age* | 2.1766** | (1.0894) | 0.0457 |
| *Computers * Head of household gender* | -33.1597 | (22.9761) | 0.149 |
| *Computers * Education level* | -0.9123 | (25.0508) | 0.971 |
| *Computers * Number of elderly* | -13.7969 | (20.9068) | 0.5493 |
| *Computers * Married* | 20.0772 | (21.0212) | 0.3395 |
| *Computers * Number of children* | -20.2296* | (11.449) | 0.0771 |
| *Computers * Income* | -22.9552** | (11.2795) | 0.0418 |
| *Computers * Employed* | -33.1979 | (27.4862) | 0.2258 |
| *Electric water heating system * Head of household age* | 3.2262 | (4.8252) | 0.5037 |
| *Electric water heating system * Head of household gender* | 9.3057 | (91.3347) | 0.9188 |
| *Electric water heating system * Education level* | -121.4867 | (102.4494) | 0.2357 |
| *Electric water heating system * Number of elderly* | -79.8687 | (93.2371) | 0.3917 |
| *Electric water heating system * Married* | 39.6706 | (89.2903) | 0.6568 |
| *Electric water heating system * Number of children* | 92.7467 | (51.4434) | 0.0714 |
| *Electric water heating system * Villa* | 131.7749 | (105.1659) | 0.2102 |
| *Electric water heating system * Income* | -30.1865 | (57.8918) | 0.602 |
| *Electric water heating system * Employed* | 111.3734 | (106.188) | 0.2943 |
| *freezer * Head of household age* | -1.6159 | (2.9637) | 0.5856 |
| *freezer * Head of household gender* | 13.0179 | (60.612) | 0.8299 |
| *freezer * Education level* | 36.0558 | (72.3338) | 0.6182 |
| *freezer * Number of elderly* | 49.9215 | (50.2261) | 0.3203 |
| *freezer * Married* | -25.454 | (68.9877) | 0.7122 |
| *freezer * Number of children* | -52.2348 | (35.372) | 0.1168 |
| *freezer * Income* | 44.247 | (27.4628) | 0.1072 |
| *freezer * Employed* | 18.9608 | (64.62) | 0.7692 |
| *Electric oven * Head of household age* | 1.9223 | (2.3463) | 0.4126 |
| *Electric oven * Head of household gender* | -79.3367* | (47.6662) | 0.096 |
| *Electric oven * Education level* | -34.8398 | (58.6458) | 0.5525 |
| *Electric oven * Number of elderly* | 42.5051 | (55.7508) | 0.4458 |
| *Electric oven * Married* | -32.5963 | (53.0162) | 0.5342 |
| *Electric oven * Number of children* | 21.1938 | (35.2702) | 0.5241 |
| *Electric oven * Income* | 32.2988 | (25.8763) | 0.212 |
| *Electric oven * Employed* | 6.7083 | (60.0098) | 0.911 |
| *Laundry loads per week * Head of household age* | 1.1918** | (0.4821) | 0.0134 |
| *Laundry loads per week * Head of household gender* | 7.9211 | (8.5272) | 0.3529 |
| *Laundry loads per week * Education level* | 22.2372** | (11.1213) | 0.0456 |
| *Laundry loads per week * Number of elderly* | -10.8722 | (8.751) | 0.2141 |
| *Laundry loads per week * Married* | -16.3398 | (12.0322) | 0.1745 |
| *Laundry loads per week * Number of children* | -16.2114*** | (4.7217) | 0.0006 |
| *Laundry loads per week * Income* | 1.1728 | (7.5883) | 0.8772 |
| *Laundry loads per week * Employed* | 15.9462 | (10.9027) | 0.1436 |
| *Laundry loads per week * Washing machine age* | -14.3413*** | (4.146) | 0.0005 |
| *Dish Washer * Head of household age* | 1.6425 | (3.0837) | 0.5943 |
| *Dish Washer * Head of household gender* | -16.7395 | (49.5547) | 0.7355 |
| *Dish Washer * Education level* | -80.5455 | (61.4213) | 0.1908 |
| *Dish Washer * Number of elderly* | 20.4638 | (61.1007) | 0.7377 |
| *Dish Washer * Married* | 121.6233** | (60.5412) | 0.0446 |
| *Dish Washer * Number of children* | 71.5381** | (34.4834) | 0.038 |
| *Dish Washer * Employed* | -51.7267 | (65.6841) | 0.431 |
| *Dish Washer * Income* | 22.3287 | (28.2656) | 0.4296 |
| *Electric stove * Head of household age* | 0.8267 | (5.113) | 0.8716 |
| *Electric stove * Head of household gender* | 107.6021 | (107.9806) | 0.3166 |
| *Electric stove * Education level* | 210.1709 | (128.0955) | 0.1089 |
| *Electric stove * Number of elderly* | -111.1799 | (117.2633) | 0.3431 |
| *Electric stove * Married* | 76.4028 | (124.2794) | 0.5387 |
| *Electric stove * Number of children* | -19.0922 | (60.4033) | 0.7519 |
| *Electric stove * Employed* | -194.5681 | (143.0852) | 0.1737 |
| *Electric stove * Income* | -81.5631 | (88.1125) | 0.3546 |
| *Traditional light bulbs * Head of household age* | -0.0498 | (0.274) | 0.8557 |
| *Traditional light bulbs * Head of household gender* | 13.3498** | (5.4129) | 0.0137 |
| *Traditional light bulbs * Education level* | 0.8113 | (6.1985) | 0.8957 |
| *Traditional light bulbs * Number of elderly* | -3.7416 | (5.0082) | 0.455 |
| *Traditional light bulbs * Married* | -10.822** | (5.8128) | 0.0626 |
| *Traditional light bulbs * Number of children* | -4.1543 | (3.1449) | 0.1865 |
| *Traditional light bulbs * House size* | 0.0331 | (0.0524) | 0.5271 |
| *Traditional light bulbs * Wall exposure* | 10.1959** | (4.0289) | 0.0113 |
| *Traditional light bulbs * Income* | -3.0037 | (2.9273) | 0.2906 |
| *Traditional light bulbs * Employed* | -0.1626 | (6.572) | 0.9803 |
| *Traditional light bulbs * Number of rooms* | 5.3121* | (2.9141) | 0.0683 |
| *Energy-saving light bulbs * Head of household age* | -0.2824 | (0.1795) | 0.1137 |
| *Energy-saving light bulbs * Head of household gender* | 6.7987* | (3.8143) | 0.0747 |
| *Energy-saving light bulbs * Education level* | -9.7191** | (4.6167) | 0.0353 |
| *Energy-saving light bulbs * Number of elderly* | 7.3866** | (3.5803) | 0.0418 |
| *Energy-saving light bulbs * Married* | -10.6276*** | (3.7711) | 0.0048 |
| *Energy-saving light bulbs * Number of children* | 0.6671 | (2.3424) | 0.7758 |
| *Energy-saving light bulbs * House size* | 0.0827** | (0.0357) | 0.0216 |
| *Energy-saving light bulbs * Wall exposure* | 16.3888*** | (2.4213) | 0 |
| *Energy-saving light bulbs * Income* | 1.1308 | (0.8576) | 0.1873 |
| *Energy-saving light bulbs * Employed* | 0.1595 | (4.2385) | 0.97 |
| *Televisions * Head of household age* | -0.9647 | (1.2789) | 0.4507 |
| *Televisions * Head of household gender* | -7.6192 | (26.5466) | 0.7741 |
| *Televisions * Education level* | 21.026 | (30.868) | 0.4958 |
| *Televisions * Number of elderly* | 3.1376 | (26.0559) | 0.9042 |
| *Televisions * Married* | 21.9496 | (27.805) | 0.4299 |
| *Televisions * Number of children* | -5.4826 | (16.3378) | 0.7372 |
| *Televisions * Number of rooms* | 55.8023*** | (11.422) | 0 |
| *Televisions * House size* | 0.8217*** | (0.2771) | 0.003 |
| *Televisions * Income* | -10.0046 | (16.4188) | 0.5423 |
| *Televisions * Employed* | 7.1572 | (35.7517) | 0.8321 |
| *Air conditioning * Head of household age* | -0.651 | (2.424) | 0.7983 |
| *Air conditioning * Head of household gender* | 34.821 | (52.9213) | 0.5106 |
| *Air conditioning * Education level* | 19.3524 | (55.4183) | 0.7269 |
| *Air conditioning * Number of elderly* | -19.2419 | (64.9402) | 0.767 |
| *Air conditioning * Married* | 57.9334 | (59.2158) | 0.3279 |
| *Air conditioning * Number of children* | 8.7725 | (34.2838) | 0.798 |
| *Air conditioning * Number of rooms* | -2.4236 | (20.1662) | 0.9338 |
| *Air conditioning * House size* | 0.9281 | (0.8292) | 0.2631 |
| *Air conditioning * Built since 1990* | 65.9324 | (41.1214) | 0.1089 |
| *Air conditioning * Windows with PVC or wood frames* | -86.719** | (40.2515) | 0.0312 |
| *Air conditioning * Wall exposure* | -164.5794*** | (51.9508) | 0.0015 |
| *Air conditioning * Northern Area* | -111.526*** | (36.6612) | 0.0059 |
| *Air conditioning * Villa* | 601.0537*** | (71.8796) | 0 |
| *Air conditioning * Income* | 35.8643 | (29.0545) | 0.2171 |
| *Air conditioning * Employed* | -17.9163 | (69.9177) | 0.7977 |
| *Gardening equipment * Head of household age* | 1.2797 | (5.3534) | 0.8111 |
| *Gardening equipment * Head of household gender* | -76.0449 | (84.2448) | 0.3667 |
| *Gardening equipment * Education level* | 72.939 | (113.6162) | 0.5269 |
| *Gardening equipment * Number of elderly* | -26.7831 | (86.4273) | 0.762 |
| *Gardening equipment * Married* | -111.6884 | (108.3822) | 0.3055 |
| *Gardening equipment * Number of children* | -38.2373 | (51.3394) | 0.4564 |
| *Gardening equipment * Employed* | 19.6112 | (116.2262) | 0.866 |
| *Gardening equipment * Income* | -99.0968 | (65.474) | 0.1302 |
| *Dryer * Head of household age* | 3.3714 | (3.3392) | 0.3127 |
| *Dryer * Head of household gender* | -85.3107 | (71.2676) | 0.2314 |
| *Dryer * Education level* | 3.6922 | (75.7997) | 0.9612 |
| *Dryer * Number of elderly* | 22.2585 | (71.4184) | 0.7553 |
| *Dryer * Married* | 45.2418 | (73.9924) | 0.5404 |
| *Dryer * Number of children* | -17.6088 | (34.7139) | 0.6104 |
| *Dryer * Income* | 35.9003 | (42.7367) | 0.4009 |
| *Dryer * Employed* | -64.8155 | (82.4791) | 0.432 |
| *Pseudo R squared* | | 0.22 | |

Table 1.14: Estimated household consumption via quantile regression approach. Estimates are referred to the 75th percentile. The model includes appliances ownership and endowment and interaction terms as covariates associated with significant coefficients at least at 10The response variable is the household's annual electricity consumption expressed as kilowatt per hours. *** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$; . $p \leq 0.1$.

### 1.A.4 Statistical Matching Strategy to Impute Household's Income

In this section, we formally introduce and summarize the main elements of the statistical matching techniques theory and we show how we imputed the missing variable 'household's income' from Eu-Silc dataset in our dataframe.

The literature on strategies and approaches to statistical matching emerges and develops to address the problem of missing information crucial to the analysis of interest. Instead of resorting to procedures involving the collection of new data through surveys and questionnaires, which can be costly, it is possible to meet informational needs by using already available data from other sources.

The example illustrated in Figure 1.10 depicts the primary objective of statistical matching, namely, the integration of one or more pieces of information available in different datasets. In the figure, A and B represent two independent sample surveys of sizes $n_a$ and $n_b$; the samples from both surveys contain distinct units. Both datasets have common information, sharing the same variables (referred to as $X$). Suppose that, for our analysis, we are interested in associating the variable of interest $Y$ in the first dataset with the variable $Z$ in the second dataset.




Figure 1.10: The two rows describe dataset A and B, respectively. Variables of interest are $Y$ and $Z$ which are included in dataset A and B, respectively. $X$ is the set of variables commonly shared by the sources of data. Missing data are the blank squares, so in the dataset A, variable $Z$ is missing, while, in the dataset B, variable $Y$ is not available.

The resolution of this problem has led to two distinct approaches. The first approach addresses the issue of missing data through imputation procedures, as described by Singh et al. (1990) while the second does not aim to create a synthetic dataset but rather intends to directly estimate some parameters of interest using calibration estimators, as presented in Romano (2008) and Kroese and Renssen (2000). In our context, we are interested in

imputation techniques where the goal is to create a synthetic dataset by filling in missing or completely absent values using plausible ones, imputing them record by record. In this approach, what we aim to create is a *micro synthetic dataset*, where the observational units represent microscopic entities, in particular, households.

Generally, statistical matching techniques can be classified into three groups: (a) non-parametric techniques, (b) parametric methods, and (c) mixed methods (Data; D'Orazio et al., 2006).

Among the non-parametric techniques, the hot deck method includes three different versions. The first is the random hot deck, which associates with each record in the first dataset a value of $Z$ observed on a unit randomly selected from the second dataset. Typically, this method is performed within imputation classes defined using the values of common variables, $X$, often utilizing common categorical variables.

The second is the Nearest Neighbor hot deck, which involves selecting a distance measure (Mahalanobis, Euclidean, etc.) and calculating the distance between each record in the first dataset and all records in the second dataset. Subsequently, each record in the first dataset is associated with a corresponding value of $Z$ in the second dataset with the minimum distance. The distance is calculated using the values of variables common to both datasets.

The third is the rank hot deck, which entails ordering the observational units in datasets A and B based on the values of common variables. The first dataset A is then completed by associating each record with the corresponding value of $Z$ in the second dataset that has the same percentile points as the empirical distribution function calculated for $X$.

A second methodology involves parametric techniques of statistical matching, which rely on a parametric model whose coefficients are estimated using the two datasets. Once the model is estimated, it is employed to impute missing values ($Z$) from the second dataset, either by randomly selecting values from the estimated probability distribution function or by imputing the conditional mean value from the estimated model. An example of this is the application of a linear regression model (OLS), where the data from the

second dataset are used to regress $Z$ on the set of common variables $X$. Subsequently, missing values of $Z$ in the first dataset are predicted by applying the estimated regression model using the values of $X$ present in the first dataset. At times, a random residual is added to each predicted value.

A parametric approach to statistical matching requires the explicit adoption of a model for $(X; Y; Z)$; naturally, the reliability of the results depends on the accurate specification of the model. In contrast, the non-parametric approach is more flexible in handling complex situations, especially when dealing with mixed-type variables.

The various types of statistical matching (parametric, non-parametric, etc.) described earlier implicitly assume conditional independence (CIA) between $Y$ and $Z$ given $X$. This assumption is particularly strong and can be challenging to justify in practice.

The process of statistical matching involves a series of preliminary steps to be undertaken on the two datasets before applying various matching techniques. These practical considerations are detailed in the work of Scanu (2008). Furthermore, a detailed exploration of statistical matching and data imputation in surveys is provided in the work by D'Orazio (2017). The first fundamental aspect is that the two data sources pertain to the same population of interest. Subsequently, target variables $Y$ and $Z$ are chosen, easily identifiable as both are necessary for conducting the analysis. Next, the identification and selection of variables present in both datasets are carried out. Often, if the two sources do not originate from the same institution adopting identical data collection standards, procedures are required to harmonize common variables due to potential differences in definitions or classifications. If two similar variables cannot be harmonized, they are discarded. Common variables should not have missing values, and observed values should be accurate, with low or absent measurement error.

It is crucial that common variables in the two datasets share the same marginal or joint distribution, especially if A and B are representative samples of the same population. In theory, all variables $X$ can be used as matching variables, but in practice, not all are employed in the statistical matching process.

In our study, we need to impute the household income for each record in the household energy consumption dataset, as this information is missing. To address this gap, we used another data source, namely the EU-SILC dataset. EU-SILC serves as a comprehensive statistical data repository providing detailed information on income and living conditions in Europe. Jointly managed by the European Commission and EU member states, it collects data from surveys conducted in all member states to offer a comprehensive overview of the economic and social conditions of families and individuals. The collected information includes data on income, poverty, social exclusion, employment, housing conditions, and other aspects related to economic well-being. We used the Italian EU-SILC dataset with the same reference year as the household energy consumption dataset, which is 2020. To use terms commonly employed in statistical matching literature, the household energy consumption dataset was employed as the *recipient survey*, while the EU-SILC dataset was designated as the *donor survey*.

The two datasets share a common reference population which represents a fundamental condition in order to obtain a proper statistical matching. The dataset on energy consumption gathers data pertaining to actual Italian households obtained from the official computerized registry of households subscribed to the fixed telephone network[14]. Similarly, the Eu-Silc dataset, specifically for the Italian data collection, identifies the reference population as follows: '*The primary unit of analysis is the de facto household, defined as the group of individuals who habitually reside, are currently present, or temporarily absent from the same household, connected by familial, marital, adoptive, guardianship, affectionate, or friendship ties*'. This definition aligns with the standards employed in Istat surveys on households and is used as an exception to the family definition stipulated by European regulations, as it is deemed a suitable proxy for the latter[15].

For what concerns the sampling design, in the Eu-silc dataset, the adopted design is a two-stage composite random sampling with stratification of first-stage units. The stratification of municipalities by demographic size (within each region) defines strata

[14]Reference: *Indagine sui consumi energetici delle famiglie Anno 2013. Aspetti metodologici dell'indagine. Istat, 2013.*

[15]Reference: *L'indagine Eu-Silc. Innovazioni nella metodologia di rilevazione e di stima. Istat, 2021.*

composed of either a single self-representative municipality (AR) or strata formed by multiple municipalities (NAR). For AR strata, the sampling is at a single stage with random selection of sample households using a systematic method. For NAR strata, 4 sample municipalities are randomly selected (or only 2 in strata consisting of 2 or 3 municipalities), with the probability of inclusion proportional to the demographic size of the municipalities themselves. The families are then selected within the sample municipalities, similar to the AR case. In the dataset on energy consumption, the sampling design adopted for the final survey is single-stage, with stratification of approximately 8,000 Italian municipalities by Region and demographic size. The household selection procedure is simple random sampling, starting from the continually updated official computerized archive of families subscribed to the landline telephone network.

We can consider the two-sampling design very similar since they share important common aspects that are geographic stratification, random selection, and the use of official archives that share the same target population.

The initial step involved the manipulation of the EU-SILC dataset. To obtain this dataset, it was necessary to merge four separate sub-datasets provided by Eurostat, namely i) Household Register (D), ii) Household Data (H), iii) Personal Register (R), and iv) Personal Data (P). The 'Household Register' contains information related to the family registry, including demographic details about family composition such as the number of members, family relationships, residence, and other family registry data. The 'Household Data' pertains to information about households, including family income, living conditions, poverty, and other socioeconomic aspects across European Union families. These family data are aggregated and may include indicators of poverty, housing, and other economic features. The 'Personal Register' encompasses information from the personal registry, including demographic data about individual family members, such as age, gender, marital status, and other demographic characteristics. The 'Personal Data' involves personal information about individual family members, including individual income, occupation, education, and other specific aspects of individual living conditions. The initial step

involved the manipulation of the EU-SILC dataset. To obtain this dataset, it was necessary to merge four separate sub-datasets provided by Eurostat, namely i) Household Register (D), ii) Household Data (H), iii) Personal Register (R), and iv) Personal Data (P). The 'Household Register' contains information related to the family registry, including demographic details about family composition such as the number of members, family relationships, residence, and other family registry data. The 'Household Data' pertains to information about households, including family income, living conditions, poverty, and other socioeconomic aspects across European Union families. These family data are aggregated and may include indicators of poverty, housing, and other economic features. The 'Personal Register' encompasses information from the personal registry, including demographic data about individual family members, such as age, gender, marital status, and other demographic characteristics. The 'Personal Data' involves personal information about individual family members, including individual income, occupation, education, and other specific aspects of individual living conditions.

To obtain the complete dataset of interest, we initially combined datasets P and R using the 'personal ID' variable, followed by the combination of datasets H and D using the 'household ID' variable. Utilizing the household ID variable again, we constructed the comprehensive dataset.

From this dataset, we selected all variables that are common with the household energy consumption dataset, including the gender of the family reference person, marital status of the reference person, age of the reference person (derived from the year of birth), education level of the reference person, occupational status of the reference person, number of rooms in the residence, presence of certain appliances (color TV, washing machine, and computer), and the geographical area of residence. The family reference person was defined as the oldest member of the family (at least 18 years old) and, in case of age parity, with the highest level of education. Subsequently, we harmonized the variables of the EU-SILC dataset to align them with those of the household energy consumption dataset. Table 1.15 summarizes the process of harmonizing the variables.

| Common Variables | Harmonization process |
|---|---|
| *Gender* | In both datasets, the variable 'gender' has been recoded; it takes the value 1 if the head of the household is male, and 0 otherwise. |
| *Geographical Distribution* | In the EU-SILC dataset, codes have been converted to the names of the geographical area they refer to: "ITC" is North-west, "ITF" is South, "ITG" is Island, "ITH" is North-East, "ITI" is center. |
| *Household's Breadwinner Level of Education* | In the EU-SILC dataset, levels of the variable representing the highest level of education attained have been recoded as follows: 0 is "No diploma", 100 is "Elementary school diploma", 200 is "Primary school diploma", 300 is "High school diploma or vocational qualification diploma", 400 is "High school diploma or vocational qualification diploma" and 500 is "Tertiary education". |
| *Appliance Ownership* | In both datasets, household appliance endowments have been recoded as follows: the variables are binary and take the value 1 if the family owns such appliances (washing machine, color TV, and computer), and 0 otherwise. |
| *Household's Breadwinner Employment Status* | In the EU-SILC dataset, levels of the variable 'occupational status' have been recoded as follows: i) 'Employee working full-time' as 'Employed'; ii) 'Employee working part-time' and 'Self-employed working full-time (including family worker)' as 'Employed'; iii) 'Self-employed working part-time (including family worker)' as 'Employed'; iv) 'Unemployed' as 'Homemaker/Unemployed or seeking first employment'; v) 'Pupil, student, further training, unpaid work experience' as 'Student'; vi) 'In retirement or in early retirement or has given up business' as 'Retired from work (pensioner)'; vii) 'Permanently disabled or/and unfit to work' as 'Unable to work or in another condition'; viii) 'In compulsory military community or service' as 'Employed'; ix) 'Fulfilling domestic tasks and care responsibilities' as 'Homemaker/Unemployed or seeking first employment'; x) 'Other inactive person' as 'Unable to work or in another condition.' In the Household Energy Consumption Survey dataset, one category of the 'occupational status' variable was recoded as follows: 'Homemaker' as 'Unemployed or seeking first employment.' |
| *Number of Household's members* | In the EU-SILC dataset, the number of family members was extrapolated using the variables household ID and personal ID; subsequently, this variable was transformed into a categorical variable with 6 levels associated with each number, where the 6th level includes '6 or more family members. Similarly, the variable 'number of family members' in the Household Energy Consumption Survey dataset was recoded accordingly. |

Table 1.15: Preliminary harmonization process for those variables which are in common to both datasets.

As mentioned earlier, common variables between the two data sources should share the same marginal distribution if A and B represent representative samples of the same population. This alignment was verified by examining the frequency distribution of matching variables (Figure 1.11). It can be seen that most of the common variables have a sufficiently similar marginal frequency distribution, despite the substantial number of recodifications required for harmonization[16].

The necessary condition for a statistical match between two datasets to be made is that the two datasets have some variables in common. The most relevant ones will be used for the matching procedure. We define these variables as $X_M$. They are often named matching variables and are selected through various statistical methods. If auxiliary information is available through the availability of other datasets to observe $(X, Y, Z)$ one can select the matching variables in a multivariate manner (Cohen, 1991). However, since we do not have other auxiliary sources, we usually proceed in considering the relationship between the common variables and the respective variables of interest, Y and Z (D'Orazio, 2017). Then, once these two analyses are conducted, the results are combined in a certain way. Usually two criteria are applied: $X_M = X_Y \cup X_Z$ or $X_M = X_Y \cap X_Z$, where $X_Y$ is the subset of common variables that best explain Y in the first dataset, while $X_Z$ is the

[16]Marginal distribution of continuous variables can be provided under request.

subset of common variables that best explain variable Z in the second dataset.

The simplest approach to assess the relationship between the response variable Y and all available predictors X is to measure the correlation/association between Y and each predictor X. When both the response variable and predictors are categorical, association measures based on the Chi-square test (such as Cramer's association coefficient, V) or measures of proportional variance reduction can be considered. In the case of a continuous response variable, correlation with predictors can be examined. To identify any non-linear relationships, it may be advisable to consider ranks, such as the Spearman rank correlation coefficient. An insightful suggestion by Groenwold et al. (2012) involves analyzing the adjusted $R^2$ concerning the regression model between the ranks of Y and the ranks of X (the unadjusted $R^2$ corresponds to the square of the Spearman rank correlation coefficient). When X is a nominal categorical variable, the corrected $R^2$ of the regression model between the ranks of Y and the dummy variables of X can be considered. The *spearman2 function* in the Hmisc package automatically calculates the corrected $R^2$ for each response-predictor variable pair.

Table 1.17 displays the Spearman's rank correlation coefficient for the common variable *Age* in the Household Energy Consumption Survey. Table 1.18 displays the Spearman's rank correlation coefficient for the common variable *Age* in the EU-Silc dataset. Table 1.19 and Table 1.20 show a measure of association when the response variable is continuous and predictors are all categorical as in our context where total electricity consumption and household's disposable income are continuous and the remaining common variables are categorical. $\eta^2$ is a measure of effect size that can be used to assess the strength of the relationship between a categorical variable and a continuous variable. It is particularly useful in an ANOVA context. Looking at Table 1.19, the total electricity consumption shows a particular strong association with the number of household's members. It is also correlated with marital status, number of rooms and computer. Similarly, to the Household Energy Consumption Survey, it seems that the number of household members has a good predictive power for the total disposable income of the family in the Eu-Silc

dataset. We also consider marital status, level of education, computer, employment status, gender and level of education. Since there are not many variables with predictive power, we decide that the selection criterion will be $X_M = X_Y \cup X_Z$, where $X_M$ consists of number of rooms, computer ownership, number of household's members, employment and marital status. We will not employ variables *Gender* and *level of Education* as common variables. They are employed as donor classes as explained later on.

Since there is no optimal matching method that can be defined ex-ante with this type of data, we decided to apply different approaches, parametric and nonparametric. Then we evaluated the different outcomes according to an ex-post evaluation that allows to identify the approach that conferred more consistent results.

| Common Variables | Household Energy Consumption Survey | Eu-Silc |
|---|---|---|
| *Gender* | Male: **66%** , Female: **34%** | Male: **62%** , Female: **37%** |
| *Marital Status* | Married: **65%** , Not Married: **34%** | Married: **51%** , Not Married: **48%** |
| *Household's Breadwinner Level of Education* | Tertiary Education:**19%**<br>High school diploma or voc. qualification diploma: **43%**<br>Primary School diploma: **27%**<br>Elementary school diploma: **9,2 %**<br>No formal education: **1,2 %** | Tertiary Education:**17%**<br>High school diploma or voc. qualification diploma: **38 %**<br>Primary School diploma: **27%**<br>Elementary school diploma: **14 %**<br>No formal education: **2,39 %** |
| *Household's Number of Rooms* | 1: **0%**<br>2: **32%**<br>3: **4%**<br>4: **10%**<br>5: **20%**<br>>6: **66%** | 1: **4%**<br>2: **24%**<br>3: **40%**<br>4: **21%**<br>5: **7%**<br>>6: **4%** |
| *Household's Breadwinner Employment Status* | Unemployed or seeking first employment: **10%**<br>Unable to work or in another condition: **4%**<br>Employed: **55%**<br>Retired from work (pensioner): **30%**<br>Student: **1%** | Unemployed or seeking first employment: **4%**<br>Unable to work or in another condition: **4%**<br>Employed: **44%**<br>Retired from work (pensioner): **47%**<br>Student: **1%** |
| *Geographical Distribution* | Center: **21%**<br>Islands: **9%**<br>North-east: **20%**<br>North-west: **25%**<br>South: **24%** | Center: **26%**<br>Islands: **8%**<br>North-east: **25%**<br>North-west: **22%**<br>South: **18%** |
| *Age of Household's Breadwinner* | 24< Age <30: **3%**<br>34< Age <40: **14%**<br>44< Age <50: **25%**<br>54< Age <60: **26%**<br>64< Age <70: **21%**<br>Age>74: **10%** | 24< Age <30: **2%**<br>34< Age <40: **11%**<br>44< Age <50: **20%**<br>54< Age <60: **18%**<br>64< Age <70: **17%**<br>Age>74: **32%** |
| *Number of Household's members* | One Member: **20%**<br>Two Members: **32 %**<br>Three Members: **23%**<br>Four Members: **19 %**<br>Five Members: **4 %**<br>Six Members: **0.7%**<br>Seven Members: **0.1%**<br>Eight Members: **0.03%**<br>>Eight Members: **0.02%** | One Member: **37%**<br>Two Members: **33 %**<br>Three Members: **16%**<br>Four Members: **10 %**<br>Five Members: **2 %**<br>Six Members: **0.3%**<br>Seven Members: **0.09%**<br>Eight Members: **0.001%**<br>>Eight Members: **0.009%** |

Table 1.16: Marginal frequency distributions of variables shared between the Household Energy Consumption Survey dataset and EU-SILC.

| **Common Variables** | **Spearman $\rho^2$** | **F** | **df1** | **df2** | **P** | **Adjusted $\rho^2$** | **n** |
|---|---|---|---|---|---|---|---|
| *Breadwinner's Age* | 0.005 | 181.19 | 1 | 34,631 | 0 | 0.005 | 34,633 |

Table 1.17: Spearman's rank correlation coefficient for the common variable *Age* in Household Energy Consumption Survey.

| **Common Variables** | **Spearman $\rho^2$** | **F** | **df1** | **df2** | **P** | **Adjusted $\rho^2$** | **n** |
|---|---|---|---|---|---|---|---|
| *Breadwinner's Age* | 0.000 | 2.83 | 1 | 10,294 | 0.0924 | 0.000 | 10,296 |

Table 1.18: Spearman's rank correlation coefficient for the common variable *Age* in Eu-Silc Dataset.

| **Common Variables** | $\eta^2$ |
|---|---|
| *Breadwinner's Gender* | 0.014 |
| *Marital Status* | 0.10 |
| *Level of Education* | 0.002 |
| *Employment Status* | 0.005 |
| *Number of Rooms* | 0.10 |
| *Computer* | 0.017 |
| *Geographical Distribution* | 0.008 |
| *Number of Household's Members* | 0.13 |

Table 1.19: Association among the response variable *Total Electricity Consumption* and the common categorical variables.

| **Common Variables** | $\eta^2$ |
|---|---|
| *Breadwinner's Gender* | 0.12 |
| *Marital Status* | 0.11 |
| *Level of Education* | 0.10 |
| *Employment Status* | 0.02 |
| *Number of Rooms* | 0.10 |
| *Computer* | 0.10 |
| *Geographical Distribution* | 0.01 |
| *Number of Household's Members* | 0.20 |

Table 1.20: Association among the response variable *Disposable Income* and the common categorical variables.

The first technique applied is distance hot deck. This function searches in the donor dataset for the Nearest Neighbor of each unit in the vessel dataset based on a distance calculated on the corresponding $X_M$ variables. To reduce the effort in calculating distances, it is preferable to define some donor classes: for a record in a given donor class, a donor in the same class will be selected. In this case, distances are calculated only between units belonging to the same class. Usually, donation classes are defined based on one or more common categorical variables. Since we employed matching variables both continuous and categorical, we employed distance calculate dissimilarity by Gower (1971). This is an average of distances computed on individual variables according to different rules, depending on the type of variable. All distances are scaled to range from 0 to 1, so the overall distance can take a value in the range $[0; 1]$ (D'Orazio, 2017). We tested four versions. In the first only matching variables are used to calculate distance, while in the other three distance is calculated within specific donor classes which are gender and

region, gender and level of education, and region, respectively.

The second method is the random distance hot deck, which is a variation of the distance-based hot deck method. For each recipient record, a subset of the closest donors is maintained and then a donor is randomly selected from this subset. This algorithm performs random selection of each donor from a suitable subset of all available donors. This subset can be formed in different ways, such as considering all donors who share the same recipient characteristics (defined by matching variables). The traditional random hot deck (Singh et al., 1990) is performed within the imputation classes by simply specifying the donor classes (classes are formed by crossing the categories of the categorical variables being considered). For each record in the recipient dataset in a given donation class, a donor is chosen completely at random within the same donation class. For this second method, we produced several combinations. The first employs only donor classes region and education without matching variables, the second employs donor classes gender and education without matching variables, the third employs both matching variables and donor classes gender and education, and the last employs matching variables and donor classes gender and region.

The third method employed is the rank distance hot deck which was introduced by Singh et al. (1990). It searches for the donor at a minimum distance from the given recipient's record, but in this case the distance is calculated on the percentage points of the empirical cumulative distribution function of the single (continuous) common variable under consideration. The empirical cumulative distribution function is estimated as $\hat{F}(x) = \frac{1}{n}\sum_{i=1}^{n} I(x_i \leq x)$, where $I() = 1$ if $x_i \leq x$, and 0 otherwise. This transformation provides uniformly distributed values in the range $[0; 1]$; moreover, it can be useful when $X_M$ values cannot be directly compared because of measurement errors that in any case do not affect the 'position' of a unit in the entire distribution (D'Orazio et al., 2006). The only continuous matching variable available to us is breadwinner's age. We have, again, opted for several versions. The first using only the common variable, the second and third applying both the common variables and the donor classes gender and education and

gender and region, respectively.

Next, we employed OLS, which falls among the parametric models, to match the two variables of interest. Specifically, employing the $X_M$ matching variables we built a model to see how they affect the income variable: $Z_i = \beta_0 + \sum_{m=1}^{M} \beta_{im} x_m^{Eu-Silc} + \epsilon_i$, where $x_m^{Eu-Silc}$ are the values of the matching variables of each record in the Eu-Silc dataset. Next, once the coefficients of the regression were estimated, we imputed to each record in the first dataset the value of household income calculated as: $\widehat{Z}_i = \widehat{\beta}_0 + \sum_{m=1}^{M} \widehat{\beta_{im}} x_m^{hhcs}$, where $x_m^{hhcs}$ are the values of the matching variables of each record in the household energy consumption dataset.

In general, four broad categories of accuracy assessment procedures can be defined (D'Orazio et al., 2006), from the most difficult objective to the simplest: (i) Synthetic records should match true (but unobserved) values. (ii) The joint distribution of all variables is reflected in the statistically matched file, (iii) The correlation structure of the variables is preserved and (iv) The marginal and joint distributions of the variables in the source files are preserved in the matched file.

The first point is the most ambitious and difficult requirement to meet. It can be achieved when logical or mathematical rules are available that determine a single value for each individual unit. However, when statistical rules are used, it is not as important to reproduce the exact value as the joint distribution f$(x, y, z)$, which contains all the relevant statistical information. The third and fourth points do not guarantee that the final synthetic data set is suitable for any kind of inference for $(X, Y, Z)$, contradicting one of the main characteristics that a synthetic data set should possess. For example, the fourth point ensures only reasonable inferences for the distributions of $(X, Y)$ and $(X, Z)$. When the second goal is achieved, the synthetic dataset can be considered as a sample generated from the joint distribution of $(X, Y, Z)$. Thus, the synthetic data set is representative of f $(x, y, z)$ and can be used as a general-purpose sample to infer its characteristics.

Let's proceed with the evaluation of our statistical matching process for the data. After

a thorough analysis, we present, in a condensed form (the rest can be provided under request), the technique that should yield more consistent and representative results for the variable 'household disposable income' in the new synthetic dataset. In particular, we have chosen to adopt **Rank Distance Hot Deck** approach[17]. Below, we provide ex-post evaluation we did on the selected statistical matching approach by following D'Orazio et al. (2006).

| Summary Statistics | | | | | | |
|---|---|---|---|---|---|---|
| **Dataset** | **Min.** | **1st Qu.** | **Median** | **Mean** | **3rd Qu.** | **Max.** |
| *Eu-Silc* | 10 | 18.234 | 27.450 | 33.187 | 42.196 | 413.174 |
| *Sinthetic dataset Rank hot distance with gender and level of education as donor classes* | 10 | 19.419 | 28.882 | 34.429 | 43.898 | 271.026 |

Table 1.21: Descriptive Statistics for *Disposable Income* in dataset Eu-Silc and in synthetic dataset.

Table 1.21 illustrates the key characteristics of the distribution of the *household disposable income* variable. The first row shows the distribution of the household disposable income variable in the EU-Silc dataset, while the following row depicts that for the synthetic datasets. It can be noticed that the distributions of disposable income in the synthetic closely approximate the distribution of income in the EU-Silc dataset.

Figure 1.11 depicts the comparison between the probability density functions (PDFs) of the household disposable income variable in the EU-Silc dataset and the synthetic dataset created. It is evident that the two PDFs are highly similar. When the PDFs of a continuous variable are nearly identical in two different datasets, it suggests that the probability distributions of the two datasets are very similar or even indistinguishable. The coincidence of the probability density functions implies that the variables being measured in the two datasets are distributed in a very similar manner. The consistency between distributions may indicate that independently collected data follows the same probabilistic model. This can be valuable in data analysis as it allows for generalizing results from one dataset to another. If a probabilistic model is employed to describe the data, the alignment of probability density functions suggests that the model can be validly

[17]We selected the version when we employ breadwinner's age as continuous common variables with gender and level of education as donor classes.

applied to both datasets. If the datasets are representative and sufficiently large, the similarity between distributions might suggest that conclusions drawn from one dataset are generalizable to the other.

Afterwards, we examined the joint distribution of the income variable and several variables in the original dataset to assess if these relationships are preserved in the synthetic dataset. In particular, following the approach outlined in Romano (2008), it is essential to consider variables that were not used in the statistical matching procedure, referred to as control variables. We thus took into account: breadwinner's gender, geographical distribution and level of education. Table 1.22 reports these results. As it can be noticed, all this relationshis are succesfully preserved.

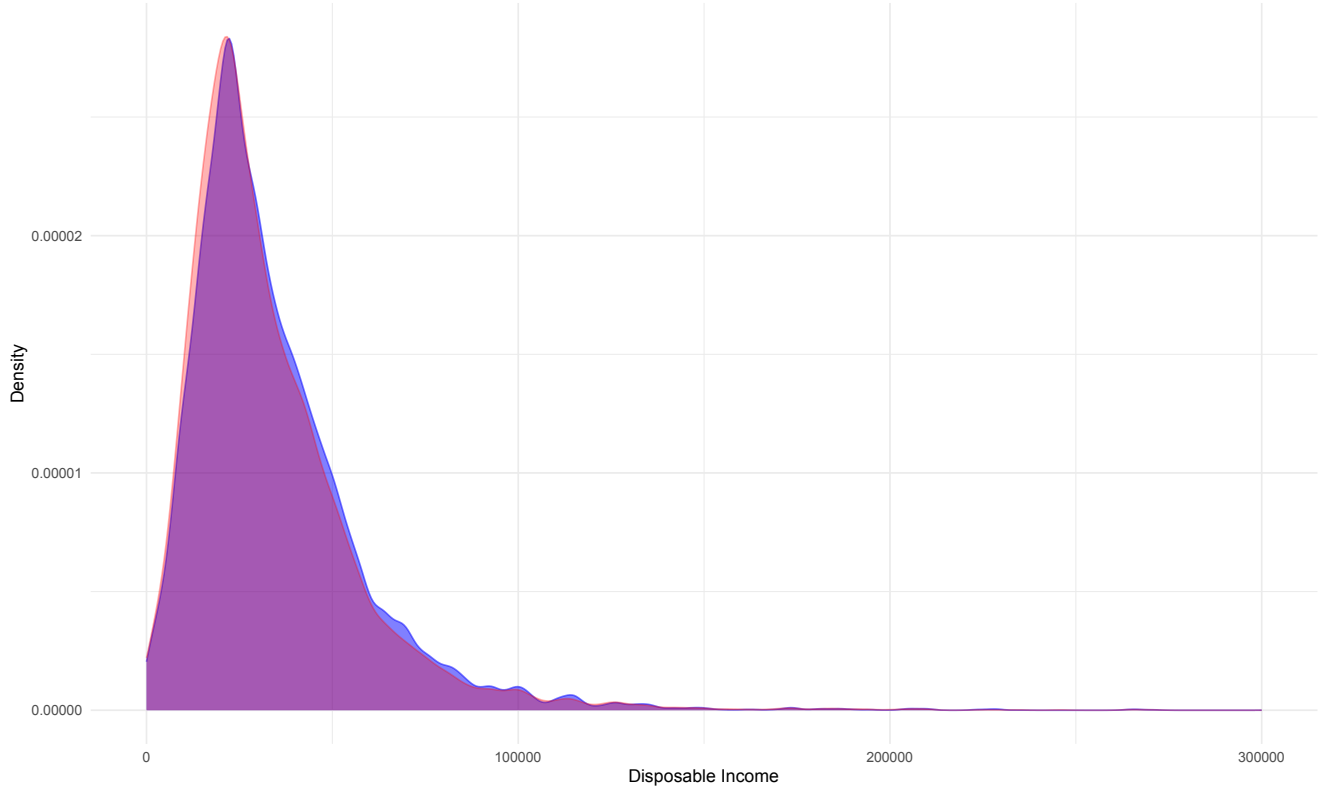



Figure 1.11: Comparison between the probability density functions of the variable *Disposable Income* in the EU-SILC dataset in blue and in the synthetic dataset in red.

| Control Variables | Summary Statistics | | | | | |
|---|---|---|---|---|---|---|
| | Min. disposable income | 1th quartile disposable income | Median disposable income | Mean disposable income | 3th quartile disposable income | Max. disposable income |
| **Gender** | | | | | | |
| **Eu-Silc dataset** | | | | | | |
| *Male* | 10 | 21.118 | 30.680 | 36.706 | 45.749 | 270.174 |
| *Female* | 10 | 14.454 | 22.464 | 27.432 | 34.700 | 234.717 |
| **Synthetic dataset** | | | | | | |
| *Male* | 10 | 21.635 | 31.919 | 37.356 | 46.663 | 271.026 |
| *Female* | 10 | 15.100 | 23.454 | 28.753 | 36.568 | 234.717 |
| **Geographical Distribution** | | | | | | |
| **Eu-Silc dataset** | | | | | | |
| *Center* | 10 | 18.000 | 27.752 | 33.360 | 42.322 | 228.238 |
| *Island* | 20 | 16.221 | 24.223 | 29.487 | 38.114 | 208.130 |
| *North-east* | 10 | 20.061 | 30.188 | 36.080 | 46.514 | 263.989 |
| *North-west* | 10 | 19.629 | 28.855 | 34.644 | 43.254 | 413.174 |
| *South* | 10 | 15.960 | 24.291 | 28.757 | 36.285 | 173.179 |
| **Synthetic dataset** | | | | | | |
| *Center* | 10 | 19.742 | 29.418 | 35.165 | 45.303 | 271.026 |
| *Island* | 10 | 19.531 | 28.926 | 34.207 | 43.561 | 228.238 |
| *North-east* | 10 | 19.370 | 28.658 | 34.271 | 43.319 | 271.026 |
| *North-west* | 10 | 19.160 | 28.461 | 33.783 | 43.451 | 266.314 |
| *South* | 10 | 19.407 | 29.073 | 34.673 | 43.952 | 271.026 |
| **Level of Education** | | | | | | |
| **Eu-Silc dataset** | | | | | | |
| *No formal education* | 10 | 20.560 | 30.140 | 35.068 | 44.617 | 266.314 |
| *Elementary school* | 50 | 25.542 | 40.185 | 46.823 | 57.897 | 270.543 |
| *Primary school* | 20 | 14.432 | 20.975 | 24.189 | 29.207 | 234.717 |
| *High school diploma or voc. qualification diploma* | 10 | 16.279 | 23.987 | 27.902 | 35.994 | 173.179 |
| *Tertiary Education* | 110 | 12.343 | 17.564 | 21.172 | 25.817 | 92.533 |
| **Synthetic dataset** | | | | | | |
| *No formal education* | 10 | 21.244 | 30.807 | 35.742 | 45.782 | 266.314 |
| *Elementary school* | 50 | 24.593 | 39.367 | 45.442 | 57.270 | 271.026 |
| *Primary school* | 20 | 14.729 | 21.571 | 24.575 | 29.818 | 234.717 |
| *High school diploma or voc. qualification diploma* | 10 | 16.434 | 24.563 | 28.378 | 36.970 | 140.630 |
| *Tertiary Education* | 110 | 12.836 | 17.719 | 21.056 | 23.270 | 92.533 |

Table 1.22: Joint distributions between the variable *disposable income* and *control variables* for the Eu-SILC dataset and for the rank distance hot deck with gender and level of education as donor classes.

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# CHAPTER 2

## When the Office Moves Home: Energy Demand Responses to the COVID-19 Lockdown in Italy


### Abstract

This paper estimates the energy-demand effects of the large-scale shift from on-site to home-based work induced by the first COVID-19 lockdown in Italy. We exploit the institutional classification of economic activities under the ATECO system, which determined whether workers could continue operating on site or were required to suspend on-site activity and remain at home where remote work was feasible, and use this regulatory discontinuity in a difference-in-differences framework. The analysis combines household-level data from the Italian Household Budget Survey, matched time-use information on commuting, and monthly sector-region electricity consumption data for service-sector activities from Terna. We examine three channels through which remote work can affect energy demand: residential electricity consumption, commuting-related energy use, and electricity consumption in service-sector workplaces. The results show that households exposed to lockdown-induced home confinement increased residential electricity consumption by about 12 percent relative to comparable households whose members continued working on site. This increase, however, was more than offset by reductions in other components of energy demand. Commuting-related energy use declined by approximately 48 percent, while electricity consumption in treated service-sector workplaces fell by about 45 percent relative to control sectors. Combining the three channels yields an estimated net reduction in energy consumption of about 47 percent relative to the pre-treatment scenario. These findings show that the energy impact of remote work cannot be inferred from residential electricity demand alone. Remote work reallocates energy use across homes, transport systems, and workplaces, and its net effect depends on the balance between additional household consumption, avoided commuting, and the ability of service-sector buildings to adjust to lower occupancy. The results provide new microeconometric evidence for Italy and highlight the importance of evaluating telework as an integrated energy-demand phenomenon rather than as a purely labour-market arrangement.



**Keywords**: Remote work; Italian COVID-19 lockdown; Energy demand; Residential electricity consumption; Commuting energy use; Service-sector buildings; Difference-in-differences; Italy; Energy policy.

## 2.1 Introduction

### 2.1.1 COVID-19 Pandemic

The coronavirus disease 2019 (COVID-19) pandemic represented an exceptional global health shock. According to the World Health Organization (WHO), as of 2 January 2022 nearly 289 million confirmed cases and just over 5.4 million reported deaths had been recorded worldwide (World Health Organization, 2022b). Subsequent estimates suggest that the overall mortality burden was substantially higher, reaching 14.91 million excess deaths globally in 2020-2021 (World Health Organization, 2022a). The crisis also placed extraordinary pressure on health systems and health workforce, with WHO estimating that between 80,000 and 180,000 health and care workers may have died from COVID-19 between January 2020 and May 2021 (World Health Organization, 2021).

Europe was among the regions most severely affected. By April 2021, the WHO European Region had surpassed 1 million confirmed COVID-19 deaths, and by late 2021 WHO/Europe was warning of severe hospital and intensive-care stress across much of the Region (World Health Organization Regional Office for Europe, 2021a,b). Italy experienced one of the most acute impacts during the first two years of the pandemic: by 21 December 2021, the country had recorded more than 5.4 million confirmed cases and 135,187 deaths (Istituto Superiore di Sanità, 2021). All-cause mortality rose sharply in 2020 and remained well above pre-pandemic levels in 2021, while the hospital system faced a major disruption in ordinary activity and a rapid reorganization of capacity (Istituto Nazionale di Statistica, 2023, 2024; Istituto Nazionale di Statistica and Agenzia Nazionale per i Servizi Sanitari Regionali, 2022; Ministero della Salute, 2020).

The public-health emergency quickly became an economic and social shock because the measures adopted to contain transmission altered mobility, production, consumption, and daily routines. Governments introduced a broad set of non-pharmaceutical interventions, including quarantine, physical distancing, school closures, and lockdowns (World Health Organization, 2020). These measures generated an abrupt contraction in energy demand:

in 2020, global primary energy demand declined by around 4% and energy-related $CO_2$ emissions by 5.8%, while countries under full lockdown experienced much sharper short-term reductions (International Energy Agency, 2020a, 2021b). However, the rebound observed in 2021, when global energy demand exceeded its 2019 level and energy-related $CO_2$ emissions rose to 36.3 Gt, indicates that the pandemic should be interpreted less as a permanent reduction in energy consumption than as a temporary shock revealing the vulnerability and flexibility needs of energy systems (International Energy Agency, 2021b, 2022; D'Orazio, 2024).

The electricity sector followed the same pattern. Global electricity demand fell by around 1% in 2020, although reductions were much larger during the strictest lockdown periods, especially because of lower activity in industry and services (International Energy Agency, 2021b,a). In the European Union, electricity consumption declined by 4%, while renewables overtook fossil fuels in the generation mix for the first time, reflecting both the demand shock and pre-existing trends in renewable deployment (European Commission, 2021; Ember and Agora Energiewende, 2021; International Energy Agency, 2021a). Italy also experienced a marked but temporary decline, concentrated in March-May 2020, followed by a recovery of electricity consumption in 2021 toward pre-pandemic levels (Terna, 2021, 2022). Overall, the pandemic acted more as a stress test for security of supply, network flexibility, efficiency, and renewable integration than as a structural break in electricity demand (International Energy Agency, 2021c; D'Orazio, 2024).

A key feature of the pandemic shock is that it did not simply reduce energy use, but redistributed it across sectors, places, and times of day. Remote work sharply reduced commuting and business travel, generating substantial travel-time savings, but its net energy effect was more ambiguous because lower transport demand could be partly offset by higher residential consumption (International Energy Agency, 2020b; Aksoy et al., 2023). In Europe, telework expanded rapidly and remained above pre-pandemic levels after the emergency phase, suggesting a more persistent change in work-related mobility (Eurofound, 2022). Italy followed a similar trajectory, with remote work remaining

significantly above pre-2020 levels in 2023, although its environmental and energy benefits depend on rebound effects, travel behaviour, and the relative energy performance of homes and offices (Istat, 2026; ENEA, 2025).

At the same time, lower office occupancy did not translate into proportional energy savings, because commercial buildings retain substantial fixed loads, including ventilation, servers, lighting in common areas, and other systems that often remain active even when occupancy falls (U.S. Energy Information Administration, 2024). European and Italian evidence therefore suggests that hybrid work can reduce office energy use only if buildings are actively adapted to lower and more variable occupancy; otherwise, the main effect is a reallocation of electricity demand from workplaces to dwellings rather than a simple disappearance of consumption (Cortiços and Duarte, 2022a; Branchetti et al., 2021). The pandemic thus left its most relevant legacy not in a lasting fall in total energy demand, but in the reorganization of demand across transport, homes, and offices, highlighting the importance of flexibility and resilience in energy systems.

## 2.2 Covid Pandemic - The Italian Context

Starting on 8 January 2020, Italy began introducing the first measures aimed at preventing the entry and spread of SARS-CoV-2, including thermal screening for passengers arriving from China and the activation of surveillance procedures for suspected cases. Following the international public health emergency declared by the WHO, the Italian Council of Ministers declared a six-month state of emergency on 31 January. In early February, the Technical-Scientific Committee was established to support the government in defining containment strategies, while the Ministry of Health, the Istituto Superiore di Sanità (ISS), and regional and professional authorities disseminated operational guidance and public information campaigns on case reporting, hygiene practices, and the prevention of misinformation.

The situation changed rapidly after 21 February, when the first major clusters were detected in the provinces of Lodi and Padua. Quarantine requirements were introduced for individuals who had been in contact with confirmed cases or had travelled through high-risk areas, and the first local *red zones* were established in Lombardy and Veneto. Schools, public events, non-essential businesses, museums, and local transport services were suspended in the most affected municipalities. During the following days, restrictions were progressively extended to several northern regions, while the Department of Civil Protection facilitated the procurement of personal protective equipment and strengthened emergency coordination.

At the beginning of March, containment measures were first harmonized across the national territory and then rapidly tightened. On 4 March, in-person teaching was suspended nationwide and general distancing and hygiene requirements were introduced. During the night of 7-8 March, stricter closures were imposed on Lombardy and fourteen provinces in central and northern Italy, affecting approximately sixteen million people. On 9 March, the decree known as *IoRestoACasa* (Stay at Home) extended restrictions to the entire country, closing non-essential educational, commercial, and recreational activities and prohibiting unnecessary travel and gatherings. Further measures adopted on 21-22

March suspended all non-essential economic activities and banned movement between municipalities except for proven work-related, health-related, or essential reasons.

These restrictions remained broadly in force until 3 May. As epidemiological conditions improved, the government announced the so-called Phase 2, which began on 4 May and gradually relaxed the lockdown while maintaining mask-wearing, social distancing, and other preventive measures. Parks reopened, restaurants were allowed to provide takeaway services, and selected wholesale and productive activities resumed. Between 8 and 11 May, the Autonomous Province of Bolzano and then the country as a whole reopened bars, restaurants, hairdressers, and museums, while interregional travel resumed on 3 June. This sequence marked the end of the first emergency phase and provides the institutional background for interpreting the electricity-demand patterns observed during spring 2020.

Figure 2.1 shows the timeline of the evolution of the COVID-19 pandemic and the measures taken throughout 2020.

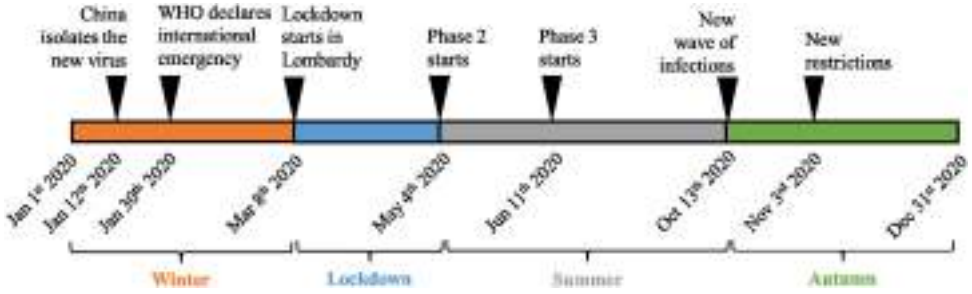



Figure 2.1: Timeline of the COVID-19 development and measures during the year 2020, with a focus on Italy and the Lombardy region. Source: Ferrando et al. (2023).

To get an initial impression of the dynamics of energy demand during the lockdown, we show exclusive data kindly provided by ARERA (Autorità di Regolazione per Energia Reti e Ambiente), reported in Figures 2.2-2.4. The data measure monthly year-on-year changes in electricity withdrawals during March, April, and May 2020. In this context, withdrawal denotes the quantity of electricity, measured in kilowatt-hours (kWh), drawn from the national distribution system by each user category. ARERA distinguishes between households and businesses; within the business sector, users are classified by voltage level: high voltage (AT), medium voltage (MT), and low voltage (BT). For April

and May 2020, the household category is further divided between primary residences and secondary homes. The figures therefore compare the physical volumes withdrawn from the grid in each month of 2020 with the corresponding month of 2019.

The data show that the lockdown produced a sharp reallocation of electricity demand across customer groups. In March 2020, the initial phase of restrictions was already associated with a rise in residential withdrawals, which increased by 12% relative to March 2019, while non-residential demand declined as commercial and industrial activity slowed (Figure 2.2). The effect became more pronounced in April, the month most closely associated with the strict national lockdown. Total withdrawals fell by 20.2% compared with April 2019, whereas residential demand increased by 8.2%. Within the household sector, the increase was driven by primary residences, whose withdrawals rose by 9.5%, while secondary homes recorded a decline of 2.3% (Figure 2.3). By May, as restrictions began to ease, total withdrawals were still 12% below their May 2019 level, but the contraction was smaller than in April. Household consumption returned closer to normal, increasing by only 1.4% year-on-year, with primary residences still slightly above the previous year and secondary homes still below it (Figure 2.4).

Overall, the ARERA data confirm that the first lockdown reduced aggregate electricity consumption, mainly through the contraction of industrial and commercial activity. At the same time, the increase in household withdrawals shows that the shock did not simply reduce electricity use, but shifted part of it from workplaces and public spaces to dwellings. This pattern is consistent with the restrictions imposed by decree, which curtailed production and mobility while forcing households to spend more time at home. However, the data do not allow the residential increase to be attributed specifically to remote work, since the household category includes both individuals working from home and individuals who continued to commute or were inactive during the lockdown.

ARERA

## Variazioni nei volumi fisici marzo-20 *vs* marzo-19

(numero punti di prelievo, energia e potenza)

**VOLUMI FISICI (primi 3 distributori aggregati)**

| | Marzo-20 | | | Marzo-19 | | | Variaz. YoY [%] | | | mix prelievi % TWh | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Tipologia di utenza** | **pp (mil)** | **GW*** | **TWh** | **pp (mil)** | **GW*** | **TWh** | **pp (mil)** | **GW*** | **TWh** | **2020** | **2019** |
| Domestici | 27,4 | 88,7 | 5,0 | 27,4 | 87,5 | 4,4 | 0,2% | 1,4% | 12,2% | *28%* | *21%* |
| Non domestici BT | 6,3 | 45,9 | 4,0 | 6,3 | 47,2 | 5,0 | -0,6% | -2,7% | -20,4% | *23%* | *24%* |
| Non domestici MT | 0,1 | 22,4 | 6,0 | 0,1 | 23,7 | 7,3 | -0,9% | -5,5% | -17,6% | *34%* | *35%* |
| Non domestici AT | 0,001 | 8,3 | 2,1 | 0,001 | 9,7 | 3,3 | 0,9% | -14,9% | -34,3% | *12%* | *16%* |
| IP e DSO sottesi | 0,3 | 0,9 | 0,6 | 0,3 | 0,9 | 0,7 | 0,6% | -4,1% | -6,1% | *4%* | *3%* |
| **TOTALE** | **34,1** | **166,1** | **17,7** | **34,1** | **169,0** | **20,6** | **0,1%** | **-1,7%** | **-14,2%** | ***100%*** | ***100%*** |

** GW fatturati, non GW di potenza effettiva*

Figure 2.2: Changes in physical volumes March 2020 vs March 2019 (Source: ARERA).

ARERA

## Variazioni nei volumi fisici aprile-20 *vs* aprile-19

(numero punti di prelievo, energia e potenza)

| | Aprile-20 | | | Aprile-19 | | | Variaz. YoY [%] | | | mix prelievi % TWh | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Tipologia di utenza** | **pp (mil)** | **GW*** | **TWh** | **pp (mil)** | **GW*** | **TWh** | **pp (mil)** | **GW*** | **TWh** | **2020** | **2019** |
| Dom. residenti | 27,3 | 68,7 | 3,9 | 27,3 | 68,2 | 3,5 | 0,4% | 0,7% | 9,5% | *26%* | *19%* |
| Dom.non residenti | 5,2 | 17,3 | 0,4 | 5,2 | 17,1 | 0,4 | 0,9% | 1,2% | 2,3% | *3%* | *2%* |
| **Domestici (tutti)** | **26,6** | **86,0** | **4,3** | **26,5** | **85,3** | **4,0** | **0,5%** | **0,8%** | **8,2%** | ***29%*** | ***21%*** |
| Non domestici BT | 6,0 | 43,9 | 3,0 | 6,1 | 45,6 | 4,5 | -0,9% | -10,2% | -33,1% | *20%* | *24%* |
| Non domestici MT | 0,1 | 23,6 | 5,0 | 0,1 | 25,5 | 6,6 | -0,7% | -16,3% | -23,5% | *34%* | *36%* |
| Non domestici AT | 0,001 | 7,5 | 1,9 | 0,001 | 9,5 | 2,9 | -0,3% | -21,2% | -33,1% | *13%* | *16%* |
| **Non domest. (tutti)** | **6,1** | **68,1** | **10,0** | **6,2** | **78,6** | **14,0** | **-0,9%** | **-13,4%** | **-28,8%** | ***67%*** | ***76%*** |
| IP e DSO sottesi | 0,3 | 0,8 | 0,5 | 0,3 | 0,8 | 0,6 | -0,7% | -7,9% | -7,6% | *4%* | *3%* |
| **TOTALE** | **33,0** | **154,9** | **14,8** | **32,9** | **164,8** | **18,5** | **0,2%** | **-6,0%** | **-20,2%** | ***100%*** | ***100%*** |

** GW fatturati, non GW di potenza effettiva*

Figure 2.3: Changes in physical volumes April 2020 vs April 2019 (Source: ARERA).

ARERA

## Variazioni nei volumi fisici maggio-20 *vs* maggio-19

(numero punti di prelievo, energia e potenza)

**MAGGIO VOLUMI FISICI (primi 3 distributori aggregati)**

| | Maggio-20 | | | Maggio-19 | | | Variaz. YoY [%] | | | mix prelievi % TWh | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Tipologia di utenza** | **pp (mil)** | **GW*** | **TWh** | **pp (mil)** | **GW*** | **TWh** | **pp (mil)** | **GW*** | **TWh** | **2020** | **2019** |
| Dom. residenti | 27,1 | 67,6 | 3,6 | 27,2 | 67,4 | 3,5 | -0,1% | 0,3% | 2,9% | *21%* | *18%* |
| Dom.non residenti | 5,2 | 17,2 | 0,4 | 5,2 | 16,9 | 0,5 | 1,2% | 1,5% | -10,8% | *2%* | *2%* |
| **Domestici (tutti)** | **26,3** | **84,8** | **4,0** | **26,3** | **84,3** | **3,9** | **0,1%** | **0,5%** | **1,3%** | ***23%*** | ***20%*** |
| Non domestici BT | 6,0 | 44,0 | 3,7 | 6,0 | 46,1 | 4,7 | -1,4% | -4,5% | -21,5% | *21%* | *24%* |
| Non domestici MT | 0,1 | 24,2 | 6,4 | 0,1 | 26,0 | 7,3 | -0,5% | -7,0% | -13,1% | *37%* | *37%* |
| Non domestici AT | 0,001 | 9,0 | 2,7 | 0,001 | 9,6 | 3,1 | -0,3% | -6,0% | -13,6% | *16%* | *16%* |
| **Non domest. (tutti)** | **6,0** | **77,2** | **12,7** | **6,1** | **81,6** | **15,1** | **-1,4%** | **-5,5%** | **-15,8%** | ***74%*** | ***77%*** |
| IP e DSO sottesi | 0,3 | 0,8 | 0,5 | 0,3 | 0,8 | 0,6 | 1,2% | 5,9% | -5,2% | *3%* | *3%* |
| **TOTALE** | **32,6** | **162,8** | **17,2** | **32,7** | **166,7** | **19,6** | **-0,1%** | **-2,4%** | **-12,1%** | ***100%*** | ***100%*** |

** GW fatturati, non GW di potenza effettiva*

Figure 2.4: Changes in physical volumes May 2020 vs May 2019 (Source: ARERA).

## 2.3 Literature Review

The COVID-19 pandemic, and especially the lockdown measures adopted to contain it, can be interpreted as a natural experiment for analysing the energy implications of large-scale telework. During this period, a substantial share of the population was required to remain at home, while many workers shifted to remote work and only a limited share continued commuting to on-site workplaces. Unlike pre-pandemic telework adoption, this transition was largely exogenous, as it was driven by public-health restrictions rather than by individual preferences or firm-level self-selection. The lockdown therefore provides a useful empirical setting for examining how a sudden and widespread reorganization of work affected energy consumption across residential buildings, office spaces, and transport systems.

The chapter is organized accordingly. The first part reviews the broader literature on telework and energy demand, focusing on the residential, office, and transport dimensions. The second part examines studies on the COVID-19 lockdown period, assessing how this exceptional episode reshaped energy consumption across the same domains.

### 2.3.1 Conceptual Framework of Telework Effects

Telework refers to the partial or full performance of work from remote locations enabled by information and communication technologies (ICTs) (O'Brien and Aliabadi, 2020). Its origins are commonly traced to the development of early ICTs in the 1960s and to the pioneering work of Nilles in the 1970s, which emphasized its potential to reduce commuting, congestion, and organizational inefficiencies (Mokhtarian and Salomon, 1997; Nilles and Gray, 1975; Nilles, 1988). Initially framed as a way to improve work-life balance and reduce travel demand, telework has since been associated with broader changes in travel behaviour, spatial organization, and workplace design (Sorrell, 2015; Koenig et al., 1996). These changes include the diffusion of activity-based workplaces, hot-desking, coworking spaces, digital hubs, and other flexible working models, all aimed at increasing flexibility, collaboration, and resource efficiency (Göçer et al., 2018). Their spread reflects wider

transformations in organizational structures, ICT infrastructures, smart-city development, and sharing-based resource use (Yu et al., 2019; Bentley et al., 2016).

From an energy perspective, telework affects consumption through three main channels: commuting, office buildings, and residential energy use (Figure 2.5). The most direct effect concerns mobility, since remote work can substitute daily commuting and reduce vehicle distance travelled, trips, congestion, and related emissions (Mokhtarian and Salomon, 1997; Sorrell, 2015). Flexible schedules may further shift travel away from peak hours, although the size of these gains depends on the transport modes replaced and is generally smaller where public transport, walking, or cycling already account for a large share of commuting (O'Brien and Aliabadi, 2020). Moreover, because telework is often adopted only part-time, its aggregate impact on mobility remains limited (O'Brien and Aliabadi, 2020).

A second channel concerns office energy use. By reducing workplace occupancy, telework can lower demand for office space and therefore for heating, cooling, and lighting (Sorrell, 2015). Flexible workspace arrangements such as hot-desking may allow firms to reduce office capacity, potentially by up to 30%, although actual savings depend on organizational choices, contractual rigidities, and the ability to adapt buildings to variable occupancy (O'Brien and Aliabadi, 2020). Smart building technologies, including occupancy-based lighting and climate control, can reinforce these savings, but their effect may be smaller in temperate regions and partly offset by equipment duplication between home and office (O'Brien and Aliabadi, 2020; Kitou and Horvath, 2003).

Finally, telework shifts part of energy consumption from offices to homes. Its direct residential effect is often considered close to neutral, since work-related energy use is partly relocated rather than eliminated (O'Brien and Aliabadi, 2020). Some efficiency gains may arise if households respond to energy prices or shift activities to off-peak hours, but the overall environmental impact depends on the interaction between reduced travel, lower office demand, higher residential consumption, and rebound effects (O'Brien and Aliabadi, 2020). Thus, telework should not be interpreted as automatically energy-saving:

its net effect depends on how work practices, buildings, transport systems, and household behaviour adjust together.




Figure 2.5: Conceptualization of the balance between the lack of impact from telework, indicating the absence of net energy benefits—and the maximum theoretical potential. However, it is important to acknowledge the possibility that the net impact could actually be negative (O'Brien and Aliabadi, 2020).

These potential benefits are moderated by several rebound effects that may partially or entirely offset the environmental gains associated with telework. First, reductions in commuting on teleworking days may be compensated by longer commutes on non-teleworking days, especially if greater flexibility encourages workers to live farther from the workplace (Sorrell, 2015; Balepur et al., 1998; Chakrabarti, 2018; Lachapelle et al., 2018). The net effect therefore depends not only on whether telework is adopted, but also on its frequency and on the spatial distribution of workers.

Second, time saved from commuting may be reallocated to other forms of mobility, including personal, household, or leisure trips (Mokhtarian, 2002, 2009). Empirical evidence suggests that these additional trips can absorb a non-negligible share of the distance initially saved, especially when telework reduces trip-chaining efficiency or alters intra-household travel patterns (Zhu, 2012; Kim et al., 2015; De Abreu e Silva and Melo, 2018). In this sense, telework may substitute commuting with other forms of discretionary travel rather than simply reducing total mobility (Lachapelle et al., 2018; Rietveld, 2011).

Third, office energy savings are not automatic. When employees retain dedicated workspaces and buildings are not adapted to lower occupancy, partial telework may generate only limited reductions in energy use (O'Brien and Aliabadi, 2020). This is because offices often have substantial base loads, while lighting, HVAC systems, and equipment may remain active even when employees are absent (O'Brien and Aliabadi, 2020).

Finally, telework can increase residential energy consumption through greater use of heating, cooling, lighting, and appliances during working hours. The magnitude of this effect varies with climate, building characteristics, energy systems, and household behaviour (O'Brien and Aliabadi, 2020). Overall, these mechanisms imply that the environmental impact of telework is highly context-dependent: potential savings in commuting and office energy use may be reduced, or in some cases offset, by additional travel, persistent office loads, and higher household consumption.

### 2.3.2 COVID-19 Pandemic-Related Studies

The COVID-19 pandemic and the related lockdown measures offer a useful empirical setting for studying how sudden changes in work organization affected energy demand. The literature generally identifies three main channels: residential energy consumption, work-related mobility, and the use of office and commercial buildings. Across these domains, the pandemic did not simply reduce energy use; rather, it redistributed demand across places, sectors, and times of day.

A first strand of studies focuses on residential electricity demand. International evidence shows that lockdowns increased the amount of time spent at home and shifted household load profiles toward daytime and lunchtime hours, blurring the traditional separation between home and workplace energy use (Ku et al., 2022; Kawka and Cetin, 2021; Li et al., 2021; Aldubyan and Krarti, 2022; Rouleau and Gosselin, 2021). This effect appears in different forms across countries: flatter daily profiles, more midday-oriented peaks, and greater working-hour consumption (Abdeen et al., 2021; Bielecki et al., 2021; Ferrando et al., 2023; Mayr and Agnolucci, 2024). However, the magnitude and persistence of the increase in residential demand vary substantially across contexts. Some studies report sizeable increases, such as in Ottawa and Los Angeles, while others find more moderate or temporary effects, suggesting that climate, building characteristics, restriction intensity, and behavioural adaptation strongly mediate the relationship between home occupancy and energy use (Abdeen et al., 2021; Klopfer et al., 2021; Rouleau and Gosselin, 2021; Li et al., 2021; Zapata-Webborn et al., 2023).

The residential effect was also heterogeneous in composition and distribution. Part of the increase was linked to non-temperature-sensitive uses, such as lighting, cooking, appliances, and digital activities, while heating and cooling needs amplified the effect depending on season and climate (Kawka and Cetin, 2021; Abdeen et al., 2021; Aldubyan and Krarti, 2022; Todeschi et al., 2022). Moreover, the impact differed across income groups, dwelling types, household composition, gender roles, and housing efficiency, showing that lockdown transformed homes into more intensively used but socially differentiated energy spaces (Ku et al., 2022; Kawka and Cetin, 2021; Zapata-Webborn et al., 2023; Matsumoto et al., 2024). These changes also have implications for forecasting, tariffs, grids, and distributed generation, since more daytime residential demand can both create operational challenges and improve the match between household load and photovoltaic production (Bielecki et al., 2021; Bosisio et al., 2022; Klopfer et al., 2021; Branchetti et al., 2022).

The Italian evidence is consistent with these international findings. Smart-meter data from Milan show that lockdown increased household electricity use and shifted weekday demand toward midday, with changes not explained by weather alone (Ferrando et al., 2023). Survey evidence further links this increase to everyday practices such as cooking, appliance use, streaming, and longer time spent at home, with relevant differences by gender, age, income, and housing insulation (Balest et al., 2021; Balest and Stawinoga, 2022). Simulation evidence confirms that changed occupancy patterns also affected comfort and thermal demand, reducing winter discomfort but increasing summer cooling needs (Palladino et al., 2021). Overall, the Italian literature confirms that the residential impact of lockdown was not only quantitative, but also temporal, behavioural, and social.

A second strand of literature examines mobility and commuting. International studies consistently show that lockdowns and remote work sharply reduced work-related travel, especially among white-collar and office-based workers, transforming commuting from a daily routine into a more selective activity (Salon et al., 2022; Reiffer et al., 2023; Kalter et al., 2021; Liang et al., 2023; Beck and Hensher, 2022). The most robust effect was time saving: workers who shifted to home-based work reduced commuting and reallocated

time toward sleep, household activities, childcare, food preparation, and time at home (Restrepo and Zeballos, 2022). Reduced commuting also implied lower congestion and potential reductions in transport energy use and emissions, although the literature warns that these benefits should not be interpreted as automatic net energy savings because of rebound effects, additional discretionary trips, longer occasional commutes, and higher household energy use (Mohammadi et al., 2023; Salon et al., 2022; Reiffer et al., 2023). The long-term outcome is therefore better described as a partial restructuring of commuting than as its disappearance.

Italian studies reach similar conclusions, while emphasizing territorial and labour-market heterogeneity. Italy is particularly relevant because it was among the first European countries to impose severe mobility restrictions. Evidence shows that lockdown sharply reduced mobility, but that the recovery varied across local labour markets depending on the share of occupations compatible with remote work, contagion risk, and contractual fragility (Caselli et al., 2022). Studies on Sicily and national mobility networks confirm that telework reduced weekly trips and peak-hour traffic, with possible benefits for congestion, pollution, and noise, but also with potential rebound effects through longer occasional travel and uneven impacts across territories (Campisi et al., 2022; Smolyak et al., 2021). Thus, in Italy as internationally, the benefits of reduced commuting were real but unevenly distributed across workers, sectors, and places.

A third strand concerns office and commercial buildings. International evidence shows that lockdown reduced energy use in many commercial buildings, but not proportionally to the fall in occupancy. This is because offices, retail buildings, universities, and mixed-use buildings retain substantial base loads related to HVAC systems, lighting, equipment, servers, maintenance, and operating routines (Cai and Gou, 2024; Su et al., 2022; Tavakoli et al., 2023). The size of the reduction therefore depended strongly on building type and use: retail and mixed-use buildings were often more affected than offices, while laboratories and specialized spaces maintained more rigid demand profiles (Cai and Gou, 2024; Tavakoli et al., 2023). More broadly, the pandemic revealed that energy savings from

lower occupancy require active building adaptation, space reconfiguration, and flexible control systems; otherwise, per-capita energy use may even rise under partial occupancy (Mantesi et al., 2022; Tavakoli et al., 2023).

At the same time, post-lockdown health measures complicated the energy picture. Enhanced ventilation, longer HVAC operation, reduced air recirculation, and filtration requirements could increase energy demand and emissions even when occupancy remained lower than before the pandemic (Cortiços and Duarte, 2022b). The key lesson from the international literature is therefore that commercial-building energy use is not mechanically determined by the number of occupants. It depends on whether building systems are able to adjust to intermittent, hybrid, and health-constrained occupancy patterns.

The Italian literature on this channel is more limited, but it highlights two important mechanisms. First, evidence on smart working shows that lockdown shifted electricity consumption from offices to homes, altering daily load curves and photovoltaic self-consumption patterns: in the case examined, office self-consumption fell while household self-consumption increased (Branchetti et al., 2021). Second, evidence from a public office building in Bolzano shows that energy-saving measures such as lower heating setpoints, reduced ventilation schedules, and window closure can substantially reduce demand, but may also worsen thermal comfort, indoor air quality, infection-risk mitigation, and occupants' performance (Albertin et al., 2023). The Italian evidence therefore confirms the broader conclusion that post-pandemic office energy management cannot be reduced to energy efficiency alone, because it is closely linked to ventilation, comfort, health, and the spatial redistribution of work.

Taken together, pandemic-related studies suggest that the main effect of lockdown and remote work was not a simple reduction in energy demand, but a reorganization of demand across homes, transport systems, and workplaces. Residential loads became more daytime-oriented, commuting became less regular and more selective, and office energy use became more dependent on the ability of buildings to adapt to variable occupancy. The net energy and environmental effects of telework therefore remain context-dependent,

shaped by behavioural responses, building characteristics, transport systems, climate conditions, and social inequalities.

## 2.4 Research Questions and Objectives

Despite the growing literature on telework, lockdowns, and energy demand, at least five important gaps remain. First, most existing studies examine only one dimension of the phenomenon at a time—typically residential electricity use, commuting and mobility, or office and commercial building consumption—without providing an integrated assessment of how these channels interact and of what the overall net energy effect may be. As a result, the literature offers substantial evidence on partial effects, but much less on the combined balance generated by the shift from on-site to home-based work. Second, much of the available evidence is based on simulations, engineering models, case studies, descriptive comparisons, or highly aggregated data. While these approaches are useful for documenting changes in consumption patterns, they are generally less suited to identifying causal effects. Third, although several contributions acknowledge that the effects of remote work are highly heterogeneous across households, workers, and productive activities, only a limited number of studies adopt a sufficiently disaggregated empirical perspective to capture these differences in a rigorous way. Fourth, studies that jointly analyse households, commuting, and firms within a coherent empirical framework are extremely rare, so the reallocation of energy demand across homes, transport, and workplaces remains insufficiently understood. Fifth, for Italy, the evidence is particularly limited: although some studies document the aggregate evolution of energy demand before, during, and after the lockdown, to the best of our knowledge no study has identified the causal effect of lockdown-induced home confinement as a proxy for exposure to smart working by explicitly comparing treated and control groups of households and service-sector activities.

This study contributes to filling these gaps by adopting an integrated and microeconometric perspective on the energy implications of smart working. In this essay, we draw on multiple data sources—including the Istat Household Budget Survey, the Istat Time Use Survey, and Terna's energy data for service-sector activities—to quantify the net impact of the SARS-CoV-2 lockdown, used as a proxy for the widespread adoption of smart working, on (i) the residential energy consumption of Italian households; (ii) energy consumption

associated with commuting; and (iii) the energy consumption of commercial buildings used by firms in the service sector. To this end, we adopt a counterfactual framework based on a quasi-experimental econometric approach. More specifically, the Decree of the President of the Council of Ministers of 8 March 2020 (DPCM) makes it possible, for many sectors, to distinguish between workers who were forced to remain at home during the lockdown—thus approximating exposure to remote-working arrangements—and those who continued to work on-site by travelling to their workplace.

The average difference in consumption between the home-confined group, whether engaged in smart working or simply 'confined by the lockdown', and those who continued commuting to the workplace provides a credible benchmark for estimating the aggregate effect of the widespread use of smart working on residential electricity demand and commuting-related energy consumption, as well as the variation in energy use in the commercial buildings where workers in the sectors considered normally perform their activities. In this sense, the paper not only estimates the separate effects of remote work across different domains, but also reconstructs their overall net balance, which is precisely one of the central dimensions still missing in the literature. At the same time, by combining detailed household-level information, time-use data, and sectoral electricity data, the analysis moves beyond purely aggregate and descriptive approaches and provides a more disaggregated account of how the effects of lockdown-induced remote work differ across units of observation and across sectors.

In a forward-looking scenario in which smart working becomes more widespread or even partly normalized, the gap observed during the restrictive measures may serve as an initial indicator of the extent to which residential electricity demand could increase and of how energy consumption may be reallocated across households, mobility, and workplaces.

To the best of our knowledge, this is the first study in the Italian literature to quantify these effects in such a disaggregated way, using a microeconometric approach, and to estimate the net effect as the sum of the different affected dimensions. Its relevance also extends beyond the Italian context, since very few studies have constructed two

comparable groups—a treated group, consisting of households staying at home and working remotely, and a control group, consisting of households whose members continued to work on site—thereby allowing a clearer identification of the differential impact of lockdown-induced smart working on energy demand.

## 2.5 Data

To address our research questions, we relied on multiple data sources. The primary dataset underpinning this study is the Household Budget Survey (HBS) conducted by Istat[1]. This survey captures the spending behavior of households residing in Italy, detailing both the amount and composition of expenditures in relation to key socio-economic and geographic characteristics. The unit of observation is the 'de facto household', defined as a group of cohabiting individuals bound by affection, marriage, kinship, affinity, adoption, or guardianship; institutional living arrangements and households with permanent members residing abroad are excluded. Further information about the survey can be found in the Appendix 2.A.1. The observation period analyzed spans from 1 January 2019 to 31 May 2020, thus encompassing the final phase of the first lockdown and the initial phase of easing. This timeframe was constructed by merging the 2019 and 2020 cross-sectional surveys, resulting in a 17-month window.

The second data source is the Agri4Cast Resources Portal[2], developed by the Monitoring Agricultural Resources (MARS) unit of the European Commission's Joint Research Centre. This open-access portal provides an extensive collection of agrometeorological time series dating back to 1975, as well as weather-forecast products essential to the MARS crop-yield estimation system. In particular, we extracted the 'Monthly Heating and Cooling Degree Days' in the European Union dataset, which is already disaggregated by month, year, and Italian region. We also retrieved the 'Gridded Agro-Meteorological Data in Europe'. For this dataset, geographical coordinates (latitude and longitude) were mapped to their corresponding administrative regions, and then monthly and annual regional averages were calculated to ensure a representative measure of local meteorological conditions.

The third data source consists of electricity retail prices for households in Italy, obtained from Eurostat's 'Electricity prices for household consumers – bi-annual data'. This database reports average prices in euros per kWh, disaggregated by consumption

[1]More information about the dataset can be found here: `https://www.istat.it/microdati/indagine-sulle-spese-delle-famiglie-file-ricerca/`.

[2]More information about the dataset can be found here: `https://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx`.

band and inclusive/exclusive of taxes, on a bi-annual basis from the second half of 2007 to the most recent available period. In addition, on the energy side, to complete our picture of energy costs, we incorporated zonal wholesale electricity prices from the Day-Ahead Market[3] (Mercato del Giorno Prima, MGP), operated by the Gestore dei Mercati Energetici (GME). These prices are differentiated for each national market zone.

Another data source is the Time Use Survey (TUS), conducted by ISTAT with 2013 as the reference period. This survey was essential for obtaining data on commuting time. This survey includes 24-hour time-use diaries for approximately 50,000 individuals living in about 20,000 Italian households. These diaries—reporting the precise timing of distinct activities—serve as cognitive anchors that reduce both the overestimation of highly salient activities and the underestimation of less salient ones, since respondents are not required to directly estimate durations. This dataset was used to perform statistical matching in order to calculate the commuting time for each individual or head of household in the HBS. Matching was performed separately for HBS 2019 and HBS 2020, after harmonizing the common variables and checking the ex ante overlap between the two surveys. We experimented with multiple matching techniques, both parametric and non-parametric, to verify the robustness of the results. The preferred specification is propensity score matching, as it produced the most satisfactory covariate balance and preserved the distributional features of commuting time more effectively. The methodology, the approach actually employed, and the robustness analyses of this procedure are set out in detail in the Appendix 2.A.7.

To analyze the effect of the lockdown on commercial building consumption, we used the Monthly Index of Electricity Consumption in the Services Sector (IMSER) dataframe, published by Terna, the operator of Italy's national transmission grid, to monitor electricity demand in the Italian services sector[4]. More specifically, IMSER provides a monthly index that tracks the evolution of electricity consumption across service activities, including

[3]More information about these prices could be found here: `https://www.mercatoelettrico.org/it-it/Home/Esiti/Elettricita/MGP/Esiti/PrezziZonali`.

[4]For detailed information about this dataset, see `https://www.terna.it/it/sistema-elettrico/statistiche/imser`.

hotels, restaurants and bars, retail trade, education, public administration, transport, and other service-related categories. The index is constructed using actual monthly electricity consumption data, measured in GWh, supplied by some of the main distribution companies, such as E-Distribuzione, Unareti, A-Reti, Edyna, and Deval. It covers roughly 80 percent of total electricity consumption in the Italian services sector. The data are available by sectoral classification, according to the ATECO 2007 scheme, with monthly electricity consumption levels and year-on-year changes, as well as by geographic area, namely Italian regions and provinces. In the IMSER data, electricity consumption refers to the electricity withdrawn from the grid by service-sector users, that is, all electricity actually used by the relevant business units. In practical terms, this includes the energy required to power indoor and outdoor lighting; electronic and IT equipment; machinery and professional equipment; ventilation and air-conditioning systems; electric heating systems; refrigeration equipment, such as refrigerated display units in food retail; elevators, escalators, and similar facilities. In other words, the measure captures the entire electricity demand of the production unit, as recorded through grid withdrawals and metered by the distribution companies. This dataset therefore constitutes a panel in which each observation corresponds to the monthly electricity consumption of a given services sector in a specific Italian region. The observations are repeated over the same time window—January 2019 to May 2020, inclusive—allowing us to track sectoral electricity demand across regions over time.

## 2.6 Empirical Strategy

This study investigates three interrelated dimensions associated with the adoption of remote work. The context of the lockdown during the COVID-19 pandemic is used as a quasi-experiment, with the resulting effects serving as a simulation of what might happen if such a measure were adopted for work purposes, subject to the necessary limitations. Specifically, treating the lockdown as a proxy for remote work, it examines how the implementation of smart working modifies individual behavior and energy use across two work-related aspects of daily life. First, remote work affects the energy directly required to perform job-related tasks, leading to changes in electricity consumption within the individual's residence. Furthermore, it alters energy use at the employer's premises, as reduced physical presence may decrease office-related electricity demand. Second, it influences the energy consumed for commuting, encompassing all forms of energy used for travel to and from the workplace, converted into electricity-equivalent terms for comparability.

The analysis focuses exclusively on electricity consumption. Accordingly, we assess how substituting remote work for on-site work generates variations in (i) residential electricity consumption (section 2.6.1 and 2.7.1), (ii) electricity-equivalent energy consumption associated with commuting (section 2.6.2 and 2.7.2), and (iii) electricity consumption required to operate and maintain office spaces where employees would otherwise work in person (section 2.6.3 and 2.7.3). The primary objective is to identify and isolate the causal effect attributable specifically to the Italian lockdown event as a proxy for the adoption of this innovative work arrangement.

Prior to the pandemic, the decision to engage in remote work was largely endogenous, shaped by a range of individual characteristics and preferences, thereby complicating the identification of causal effects. In contrast, the outbreak of COVID-19 constituted an exogenous shock. The policy response implemented by the Italian government was driven exclusively by public health considerations rather than economic objectives. Among European countries, Italy adopted some of the most stringent containment measures,

including a nationwide lockdown.

In particular, the March 2020 ATECO decree, which classified economic sectors as essential or non-essential, generated a quasi-experimental setting. Assignment to treatment—defined as remaining at home due to the suspension of non-essential activities—was determined solely by sectoral classification according to ATECO codes, and was therefore orthogonal to household socio-economic characteristics and pre-existing consumption patterns. Compliance with the restrictions was nearly universal, with no observable instances of systematic non-compliance.

This exogenous variation provides a credible basis for identifying the causal effect of lockdown-induced home confinement on the three dimensions of energy consumption. Moreover, it enables us to interpret the estimated impact as a plausible benchmark—or proxy—for electricity demand under large-scale adoption of remote work arrangements.

In the following three subsections, we present the econometric specification adopted for each of the three dimensions under analysis.

All models share a common underlying identification strategy, namely the exploitation of the exogenous shock generated by the COVID-19 pandemic and the subsequent nationwide lockdown to assess differential consumption effects across groups. Specifically, we compare individuals who, during the lockdown months, were required to remain at home and had the chance to perform their work remotely with those who were allowed to continue working on-site.

The triggering event is the COVID-19 pandemic itself, which constitutes an exogenous shock and underpins the definition of the lockdown period indicator. This variable equals 1 for observations corresponding to March, April, and May 2020—the period of the national lockdown—and 0 otherwise. The assignment mechanism, by contrast, is determined by the decree issued by the President of the Council of Ministers, which classified economic sectors into essential and non-essential activities, thereby determining eligibility to continue in-person work and, consequently, treatment status. The Italian government imposed the first national lockdown with the Prime Minister's decree 'Io resto a casa' of march 9,

2020[5] (effective March 10, 2020). This decree mandated the closure of all retail companies except food stores, pharmacies, and other essential suppliers; suspended the operation of bars, restaurants, gyms, theaters, and recreational centers (allowing only home delivery); ordered the closure of schools and universities; shifted most work activities to remote (smart-working) arrangements; and restricted all travel to strictly necessary work, health, or other essential reasons, subject to self-certification, while prohibiting public gatherings. The decree specified, down to ATECO code, which categories of workers were permitted to continue on-site and which were prohibited from doing so.

### 2.6.1 Impact on Residential Energy Consumption

This first model is employed to estimate the causal effect of the COVID-19 lockdown on household energy consumption for a subset of Italian families, distinguishing between those whose members remained at home throughout the lockdown period and those whose members continued to work on-site. Since we do not directly observe the share of workers in suspended sectors who actually adopted remote work arrangements, we use forced home confinement as a proxy for the adoption of smart working. Workers employed in non-essential sectors were legally required to stay at home during the lockdown, regardless of the specific organizational arrangements implemented by their employers. It is plausible that the time spent at home by this group exceeded the amount of time typically associated with standard remote work conditions. For this reason, the estimated effect on their household energy consumption can be interpreted as an upper bound of the potential impact of smart working adoption on residential energy use. In this sense, our empirical strategy approximates the effect of remote work through an observable measure—mandated home permanence during the lockdown—providing a benchmark for comparison with households whose members continued to work on-site.

We expect that households forced to conduct their entire workday at home will, all else equal, exhibit higher electricity consumption than those who continued to go to work

[5]The decree can be read here: `https://www.lavoro.gov.it/documenti-e-norme/normative/Documents/2020/DPCM-8-marzo-2020.pdf`.

on site. Theoretically, prolonged residence in the home extends the hours during which lighting, heating or cooling systems, and everyday appliances are used, thereby increasing the intensity and duration of their operation.

To estimate the causal effect of the lockdown on household electricity consumption, we employed a pooled OLS Difference-in-Differences model.Hereafter, we refer to it as the *Pooled-DiD* model. In a pooled OLS framework, cross-sectional and time-series observations are treated as independent, and it is assumed that the relationship between energy consumption and the regressors is homogeneous across all households and all monthly periods (Wooldridge, 2016; Baltagi and Baltagi, 2008; Gujarati, 2002; Hsiao, 2022). Although this approach is straightforward and efficient under homogeneity, it can yield biased estimates if there exist unobserved household-specific effects or if temporal dynamics differ across groups. Consequently, it is essential to include a comprehensive set of seasonal, regional, socio-demographic, housing, price, and climatic controls to mitigate bias and support a credible causal interpretation of the lockdown's impact.

We were able to identify who stayed home during the pandemic and who continued to work on-site by examining the economic sector of each survey respondent, as indicated by the ATECO code system. Because the HBS dataset reports ATECO codes only at the 1-digit level, we included only those sections that were entirely consistent with either in-person work or mandatory home confinement, excluding mixed sections containing both permitted and prohibited activities. To do this, we made a considerable effort to start with the most detailed breakdown of ATECO codes provided for in the decree and then work backwards to select only the coherent 1-digit sectors. The treated group comprises ATECO sections 12, 13, 16, 18, 20, and 21—each of which was explicitly authorized to remain closed and work from home—while the control group includes sections 4, 5, 8, 10, 11, 15, and 17, whose activities were allowed to continue in person. Table 2.22 in the Appendix 2.A.3 lists each industrial sector and its corresponding treatment/control status. According to our goal, since we want to estimate the lockdown's effect on household energy consumption, we excluded household types whose consumption patterns could

not be unambiguously attributed to the working behaviours and mechanisms stemming from the lockdown itself. Indeed, the final sample comprises single-person households and dual-headed couples in which both partners were employed. In order to avoid ambiguous effects on household energy consumption, we restrict the sample of couples to those in which both partners are employed in sectors classified as either treated or control. This ensures that there are no mixed-status households (e.g., one partner working from home while the other continues in-person work). Households with children, couples with only one employed partner, and unemployed households were excluded. The sample was also restricted to individuals aged 18–70. In total, the analysis covers 2,264 units.

In the context of pooled repeated cross-sections, that is, with different households observed in each monthly survey wave, the Pooled-DiD specification can be formalized as follows. The index $i$ denotes a household observation, rather than a household followed over time, while $m$, $y$, and $r$ denote, respectively, the month, year, and region associated with each observation:

$$\log\big(Consumption_{imyr}\big) = \alpha + \theta\, Treat_{imyr} + \eta\, Post_{my} + \beta\,(Treat_{imyr} \times Post_{my}) + \gamma_m + \rho_y + \mu_r + X'_{imyr}\boldsymbol{\delta} + e_{imyr} \quad (2.1)$$

where: $\log(Consumption_{imyr})$ is the logarithm of the per-capita electricity consumption in month $m$ and year $y$ for the household i living in region r, in kWh. $\alpha$ is the intercept. $Treat_{imyr}$ takes the value 1 if household observation $i$ belongs to the treated group, namely households whose employed member or members were forced to remain at home during the lockdown, and 0 otherwise. $Post_{my}$ takes the value 1 if the household is observed during the lockdown months, March-May 2020, and 0 otherwise. The interaction term $Treat_{imyr} \times Post_{my}$ identifies treated households observed during the lockdown period. The terms $\gamma_m$, $\rho_y$, and $\mu_r$ denote month, year, and region fixed effects, respectively. Month fixed effects capture seasonal patterns in electricity consumption; year fixed effects absorb

aggregate shocks common to all households in a given year; and region fixed effects account for time-invariant regional differences in consumption patterns, climate, infrastructure, and socioeconomic conditions. The vector $\mathbf{X}'_{imyr}$ contains the control covariates, all expressed in levels except for the price variable, which is specified in logarithmic form. Socio-demographic and economic characteristics refer to the household head in dual-headed families. Finally, $e_{imyr}$ denotes the idiosyncratic error term. Standard errors are clustered at the survey-wave level, defined by the month-year of observation, allowing for arbitrary correlation and heteroskedasticity of the disturbances among households interviewed in the same monthly wave.

The HBS records only the monetary expenditure on electricity supply, without reporting the quantities consumed in kWh. To express the dependent variable in terms of monthly consumption, we converted the reported expenditures in euros using the semiannual retail prices observed for each household. Specifically, we employed the aforementioned Eurostat data, which provide semiannual prices per kWh for different annual consumption bands. Because our dataset is monthly, the conversion was performed in several steps. First, we calculated the annual average price for each consumption band. Next, we computed the annual expenditure in euros for each band. We then allocated that amount equally across the twelve months of the year, assuming uniform monthly spending. In this way, for each semester of each year, we reconstructed the euro-denominated consumption bands and reported their corresponding semiannual average prices (see Tables 2.23 and 2.24 in the Appendix 2.A.4). Finally, monthly consumption in kWh was obtained by dividing the actual monetary expenditure reported by each household (from the HBS) by the semiannual average price applicable to that household's consumption band.

To verify the robustness of the estimates of household electricity consumption for the HBS derived from Eurostat prices, we compared the final household electricity consumption figures from the national accounts with those we derived. Table 2.1 compares the annual household electricity consumption estimated from the HBS survey, reconstructed from monthly spending using semi-annual prices, calculating the data on an annual basis and

aggregating it using the sample weights, with the official Eurostat data for Italy. The results show that the survey overestimates consumption in 2018 (+5.4%) and underestimates it in the following years (-7% to -14.6%), with the largest discrepancies between 2019 and 2021. Despite these differences, the estimates are within approximately ±10% measurement error, and correctly captures the overall magnitude and temporal trend, indicating that the robustness check is satisfactory and that the micro–bottom-up reconstruction of kWh provides a reliable validation of the estimated values for the dependent variable.

| Year | Energy consumption (KWh) in millions (A) | Estimated energy consumption (KWh) in the HBS in millions (B) | (B)-(A) | % |
|---|---|---|---|---|
| 2018 | 65137,80 | 68684,45 | 3546,65 | 5,44 |
| 2019 | 65588,00 | 56021,38 | -9566,62 | -14,59 |
| 2020 | 66211,65 | 59171,18 | -7040,47 | -10,63 |
| 2021 | 67119,69 | 59430,10 | -7689,59 | -11,46 |
| 2022 | 64640,03 | 60110,68 | -4529,36 | -7,01 |

Table 2.1: Annual household electricity consumption: HBS estimates versus Eurostat official data. The table compares, for the years 2018-2022, the annual national household electricity consumption estimated from the HBS survey with the official Eurostat consumption data for Italy (dataset *nrg_cb_e*, final consumption of households, in kWh). The HBS-based estimates are obtained by reconstructing kWh from monthly spending using semi-annual prices, annualizing the figures, and aggregating them with sample weights. The columns report the year, official consumption, consumption estimated from the survey, the absolute difference in kWh, and the percentage difference, allowing an assessment of the consistency between the micro-based bottom-up estimate and the official macro data.

To ensure the robustness of our estimates and to mitigate the influence of extreme values, we identified and removed outliers in monthly kWh consumption. Specifically, for each calendar month, we excluded all observations lying more than 1.5 times the interquartile range below the first quartile or above the third quartile, thereby eliminating anomalous spikes in consumption.

Sociodemographic and occupational attributes of the household are similarly crucial. Family composition in terms of age, gender, education, occupation, occupational rank, and income source shapes consumption patterns, daytime presence at home, and resilience to economic shocks. The household's income decile further provides a concise indicator of socioeconomic status. Energy price is another key control: using the observed price allows us to adjust for cost variations that directly affect consumption through saving or substitution behaviors. Finally, local weather conditions—monthly temperature extremes, wind speed, precipitation, solar radiation, and the heating degree day (HDD) and cooling degree day (CDD) indices—represent direct physical determinants of heating and cooling

demand. By including all of these controls, we aim to ensure that any remaining variation in electricity use is attributable to the lockdown itself rather than to concurrent structural or contextual factors. Table 2.2 shows the detailed description of the variables that were employed in the model.

| Variables | Type | Description | Source of data |
|---|---|---|---|
| **Housing Variables** | | | |
| Housing type | Categorical | Villa; apartment in a building with fewer than 10 apartments; apartment in a building with more than 10 apartments. | Household Budget Survey (HBS), Istat |
| Number of rooms | Continuous | Number of dwelling rooms. | Household Budget Survey (HBS), Istat |
| Square meters of living space | Continuous | Dwelling square meters. | Household Budget Survey (HBS), Istat |
| House ownership | Binary | individual (or multiple individuals as co-owners); private enterprise or company. | Household Budget Survey (HBS), Istat |
| House construction period | Categorical | post-2009; 2000–2009; 1990s; 1950s–1980s. | Household Budget Survey (HBS), Istat |
| Internet availability = no | Binary | Yes or no | Household Budget Survey (HBS), Istat |
| **Socio-demographic and economic characteristics** | | | |
| Source of Income | Binary | Income from employment; Income from self-employment. | Household Budget Survey (HBS), Istat |
| Income decile | Categorical | Belonging to the income decile. | Household Budget Survey (HBS), Istat |
| Age of the head of the household | Continuous | Age of the head of the household. | Household Budget Survey (HBS), Istat |
| Gender of the head of the household = female | Binary | Gender of the head of the household. | Household Budget Survey (HBS), Istat |
| Level of education of the head of the household | Categorical | No formal education; primary school diploma; middle school diploma; two- or three-year vocational diploma; five-year secondary-school diploma; university degree or equivalent; other. | Household Budget Survey (HBS), Istat |
| **Job-market features** | | | |
| Occupation of household member | Categorical | Legislators, entrepreneurs, and senior management; Intellectual, scientific, and highly specialized professions; Technical professions; Executive professions in office work; Skilled professions in commercial activities and services; Craftsmen, skilled workers, and farmers; Plant operators, stationary and mobile machinery operators, and vehicle drivers; Unskilled occupations; Armed forces. | Household Budget Survey (HBS), Istat |
| Job position of the head of the household | Categorical | Manager; executive; office worker; factory worker; entrepreneur or freelancer. | Household Budget Survey (HBS), Istat |
| **Energy market** | | | |
| Electricity price | Continuous | Average half-yearly electricity price (Euros). | Electricity prices for household consumers – bi-annual data, Eurostat |
| **Geographical features** | | | |
| Type of municipality | Categorical | Metropolitan area center; Metropolitan area suburbs and municipalities with 50,000 inhabitants or more; Other municipalities with up to 50,000 inhabitants. | Household Budget Survey (HBS), Istat |
| Region | Categorical | Italian Regions | Household Budget Survey (HBS), Istat |
| **Meteorological variables** | | | |
| Average maximum temperature | Continuous | Average monthly maximum temperature recorded at regional level (°C). | Agri4Cast Resources Portal |
| Average minimum temperature | Continuous | Average monthly minimum temperature recorded at regional level (°C). | Agri4Cast Resources Portal |
| Average wind speed | Continuous | Average monthly wind speed recorded at regional level. | Agri4Cast Resources Portal |
| Average rainfall | Continuous | Average monthly rainfall recorded at regional level (mm). | Agri4Cast Resources Portal |
| Average solar radiation | Continuous | Average monthly solar radiation recorded at regional level (KJ/m$^2$). | Agri4Cast Resources Portal |
| Cooling Degree Day (CDD) | Continuous | A climatological index describing the amount of energy required for indoor cooling, computed on a monthly and regional basis. | Agri4Cast Resources Portal |
| Heating Degree Day (HDD) | Continuous | A weather-based technical index designed to estimate the heating energy requirement of buildings on a monthly and regional basis. | Agri4Cast Resources Portal |

Table 2.2: Model variables description. This table presents the variables included in Models 1 and 2.

The estimated coefficients $\gamma_m$, $\rho_a$, and $\mu_r$ correspond to month, year, and region dummy variables, respectively, capturing fixed effects for each month, each year, and each region. The vector $\boldsymbol{\delta}$ contains the coefficients on the control covariates. The parameter of primary interest, $\beta$, is the DiD estimator: it quantifies the average additional change in logged electricity consumption for treated households following the lockdown, after netting out all time-specific and region-specific trends as well as other controls. A positive $\beta$ indicates that, from March 2020 onward, households forced to stay home consumed more electricity—relative to what they would have consumed absent the lockdown—than did households in the control group. Since the specification is in log-levels, the lockdown effect on treated households is interpreted as a $(e^{\beta} - 1) \times 100\%$ increase in consumption.

Because the HBS uses a two-stage monthly stratified sampling design, each household has a different inclusion probability. To correct for this, we apply the sampling weights provided in the dataset; doing so ensures that the estimated mean consumption and all regression coefficients are representative of the entire Italian population, free from bias arising from over- or under-representation of particular geographic units or household types.

In our econometric model, the electricity price cannot be treated as a fully exogenous variable. This concern is well known in the literature on residential electricity demand, especially in studies estimating price elasticities. The first issue concerns the definition of the relevant price faced by consumers. From a theoretical perspective, consumers should respond to the marginal price, that is, the cost of the last kWh consumed, especially under increasing-block tariff structures (Taylor, 1975; Reiss and White, 2005). However, other studies argue that consumers may respond more strongly to the average price, since this is more visible and easier to infer from the electricity bill (Shin, 1985; Borenstein, 2008; Ito, 2014).

The use of average prices, however, raises an important endogeneity problem. When tariffs are structured in consumption blocks, the average price paid by a household depends mechanically on the quantity of electricity consumed. As a result, price and demand are jointly determined: higher consumption may move a household into a different tariff block and therefore change the average price, while the price itself may affect consumption decisions. This simultaneity problem has been widely discussed in the literature on residential electricity demand (Bardazzi and Pazienza, 2020; Alberini and Filippini, 2011; Fell et al., 2014; Miller and Alberini, 2016).

A second issue is measurement error. The observed or reconstructed average price may not accurately represent the actual tariff faced by each household. This problem is particularly relevant under block pricing, because different portions of consumption may be charged at different rates. With the available data, however, we cannot observe how much of each household's monthly expenditure was incurred within each tariff block. Moreover, an ex post average price may differ from the price perceived or expected by consumers when making their consumption decisions (Borenstein, 2008; Ito, 2014).

These general concerns are particularly relevant in our empirical setting. The HBS does not report electricity consumption in kWh, but only household expenditure on electricity. Therefore, monthly electricity consumption is reconstructed by dividing observed expenditure by an estimated average price. This means that, among expenditure,

price, and quantity, only expenditure is directly observed, while both the applicable price and the corresponding quantity consumed are inferred.

This reconstruction introduces an additional source of endogeneity and measurement error. Since we assign to each observation a precomputed average price based on annual consumption bands and semiannual Eurostat prices, we do not observe the actual marginal price faced by the household, nor the exact distribution of monthly expenditure across tariff blocks. Consequently, the estimated price does not fully reproduce the tariff mechanism through which higher consumption may lead to a higher applicable price. At the same time, because consumption in kWh is obtained as the ratio between expenditure and the estimated price, the dependent variable is mechanically linked to the price used in its construction.

For this reason, the relationship between electricity consumption and price in our model should not be interpreted as a standard behavioural price-response relationship. Rather, the price variable mainly serves to convert monetary expenditure into physical consumption and to control, as far as possible, for differences in electricity costs across consumption bands and periods. The estimated coefficient on price should therefore be interpreted with caution, as it may reflect both genuine behavioural responses and the mechanical features of the consumption reconstruction procedure.

A more detailed discussion of the issue is provided in the Appendix 2.A.2.

To obtain a consistent estimate for the price regressor, we employ an instrumental variables approach. Specifically, the model described above is estimated via two-stage least squares. We use three instruments well established in the literature: the lagged semiannual price (Alberini and Filippini, 2011; Mamkhezri, 2025; Fell et al., 2014), the municipality-level 'leave-one-out' average price (Filippini and Kumar, 2021; Miller and Alberini, 2016), and the zonal wholesale market price. For the first instrument, since the repeated cross-section design does not provide consumption observations for the same household six months apart, we use the official regulated semiannual average price from the previous semester, which serves as a pre-determined value independent of any current

consumption decisions.

The second instrument relies on the local average price and is constructed in three steps: for each municipality and each year-month combination, we calculate the total expenditure on electricity by all resident households and count the corresponding number of consumer units; for each household $i$, we then subtract its own expenditure from the municipal total to obtain the aggregate amount paid by all other households during that period; finally, this residual sum is divided by the number of remaining households to yield the average price actually paid by other residents.

The third instrument is defined as the average monthly wholesale market price traded on the Day-Ahead Market managed by the Gestore dei Mercati Energetici (GME). To construct this, the national territory is divided into five large zones: the North zone (Piemonte, Liguria, Lombardia, Valle d'Aosta, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, Emilia-Romagna); the Center-North zone (Toscana, Marche); the Center-South zone (Lazio, Abruzzo, Campania, Umbria); the South zone (Molise, Puglia, Basilicata); and three autonomous areas consisting of Sardegna, Sicilia, and Calabria individually. This zonal division allows the instrument to capture wholesale market price fluctuations that vary by geographic area.

Each instrument satisfies, at least apriori, the two conditions for validity: relevance—each is strongly correlated with the actual price paid (the lagged price mirrors the household's tariff cycle; the leave-one-out measure reflects local price variation excluding the household's own consumption; and the zonal price reflects the wholesale market); and exogeneity—none of these measures is influenced by the household's idiosyncratic error or current consumption decisions (the lagged price is predetermined; the leave-one-out excludes the household from its own municipal average; and the zonal price is determined at the market level). Under these conditions, we can reasonably assume that the instruments are uncorrelated with the demand error term, ensuring consistent estimation.

Finally, we would like to emphasize the fact that in the pooled-DiD model, however, the consistency of the interaction effect, $treat \times post$, does not depend on the absolute

accuracy of the price–consumption elasticity estimate, but rather on the fact that the average price is assigned to observations consistently, symmetrically, and invariantly across groups and over time. In other words, if all units—treated and control—during both the 'pre' and 'post' periods receive the same algorithm for assigning the price, then systematic inaccuracies cancel out in the differential comparison. The mechanical fluctuations in $Q$ (due to the calculation $Q = E/P$) affect both groups equally and therefore do not influence the coefficient on the interaction *treat* $\times$ *post*, which is our main coefficient of interest.

### 2.6.2 Impact on Commuting and Related Energy Consumption

The second model is designed to estimate the causal effect of the COVID-19 lockdown on the commuting time of the household head. It compares individuals who were required to remain at home during the lockdown, and therefore did not commute, with individuals who continued to work on site. The expected direction of this effect is straightforward: commuting time should decrease for treated individuals during the lockdown. However, only a model incorporating time-use information can provide an estimate of the time saved, which is subsequently needed to calculate the energy savings associated with commuting.

In the context of pooled repeated cross-sections, the model can be formalized as follows. The index $i$ denotes an individual observation, corresponding to the household head observed in a given survey wave, while $m$, $y$, and $r$ denote, respectively, the month, year, and region associated with that observation:

$$CT_{imyr} = \alpha + \theta\, Treat_{imyr} + \eta\, Post_{my} + \beta\,(Treat_{imyr} \times Post_{my}) + \gamma_m + \rho_y + \mu_r + X'_{imyr}\boldsymbol{\delta} + e_{imyr} \quad (2.2)$$

The model specification is analogous to that described for Equation 2.2, with one exception: the dependent variable, $CT_{imyr}$, denotes the commuting time of the household head. Specifically, it measures the total number of minutes spent commuting over a 24-hour day by individual observation $i$, observed in month $m$, year $y$, and region $r$.

This variable is not available in the HBS and was therefore imputed using statistical matching techniques. Appendix 2.A.7 provides a detailed, step-by-step description of the procedure used to obtain realistic and internally consistent commuting-time values. It is important to note that these imputed commuting times reflect the situation of Italian workers at the time of the time-use survey, when no COVID-19-related work restrictions were in place. Consequently, for observations corresponding to the lockdown months, commuting time was set to zero for treated individuals, under the assumption

that individuals required to remain at home did not commute by definition.

An additional methodological issue concerns the presence of a considerable number of zero values in the commuting time variable. During the construction of the synthetic dataset, missing values for commuting time in the donor dataset were recoded as zero prior to the matching procedure with the HBS. As a consequence, a zero value in the dependent variable may reflect two distinct situations: on the one hand, individuals who genuinely incur no home-to-work travel time (for instance, because they work from home or did not work on the reference day); on the other hand, observations for which commuting time was not originally observed in the donor dataset. The coexistence of these types of zero values may influence the interpretation of the econometric estimates, as it introduces a form of imperfect measurement of the dependent variable. In particular, the transformation of missing values into zeros tends to artificially increase the frequency of observations with zero commuting time, compressing the distribution of the variable and reducing its mean. From an econometric perspective, this phenomenon may lead to a potential attenuation of the estimated effect or, conversely, amplify it if the probability of observing a zero is correlated with certain individual characteristics. Therefore, the estimation results must be interpreted taking into account this possible source of bias, which stems from the method of constructing the commuting variable in the synthetic dataset.

Since we are taking into account only the head of the household for each family, the number of observation is equal to 1,935 single units.

### 2.6.3 Impact on Energy Consumption in Service Sectors

The third model was built to estimate the impact of the lockdown on energy consumption in the service sector, in its different sub-sectors. We restricted the analysis to this sector because our aim is to estimate the electricity consumption associated with the performance of work activities, that is, the electricity linked to human activity within the workplace or commercial building where the service is produced. For this reason, we did not include manufacturing or other sectors in which energy is primarily used as an input in the production process of a final good that is then sold on product markets.

The dataset, provided by TERNA, is a balanced panel. Each observation corresponds to the monthly electricity consumption, measured in kWh, of a specific service sub-sector at the regional level. Each sector–region unit is observed consistently over time, so that changes in electricity consumption are not driven by variations in sample composition. The time window covered by the data runs from January 2019 to May 2020. This period includes a full pre-treatment year and the first months affected by the Covid-19 lockdown, allowing for a comparison between pre- and post-lockdown dynamics within the same sector–region units. The units of observation are 2,720.

The basic idea is the same as in the previous sections: to compare the sectors that, due to the decree, shifted their operations to remote work during the lockdown with those sectors where work continued on-site despite the restrictions. Table 2.3 reports this classification. As can be seen from the table, not all service subsectors are included; those sectors for which a complete shutdown was mandated—with no option to work from home—have been excluded, such as the restaurant industry, etc.

In this sense, the lockdown does not represent a 'pure' treatment; rather, it acts as a strong exogenous shock that forced the reorganization of work and therefore provides a plausible proxy for the adoption of remote work. This logic is coherent because the lockdown imposed uniform constraints from above, thereby reducing the endogeneity problem that typically affects studies on remote work, where firms themselves decide whether to adopt it. Here, instead, the regulatory discontinuity creates a natural experiment: sectors

required to have their employees work remotely are likely to consume energy differently than sectors where business continuity requires physical presence.

The distinction between treated and control groups is motivated ex ante, always considering those service sub-sectors that were effectively subjected to one regime or the other as a consequence of the decree. Using monthly regional electricity consumption data by sector means that our dependent variable captures an aggregated outcome reflecting not only labor intensity, but also the physical presence of workers in production sites, the use of offices and auxiliary services, operating hours, continuity of activities, reductions in internal mobility, and more generally the energy intensity of the organizational structure. Therefore, our exercise does not simply estimate 'how much electricity is saved through remote work'; rather, it captures the differential change in the electricity component of sectoral activity induced by the lockdown.

Econometrically, we identify a differential effect through a DiD framework, where the parameter of interest measures how much more, or how much less, the telework-compatible sectors reduced their electricity consumption relative to the non-telework-compatible sectors after the introduction of the restrictions. Model 3 is specified as follows:

$$\log\big(EC_{srmy}\big) = \alpha + \theta\, Treat_s + \eta\, Post_{my} + \beta\,(Treat_s \times Post_{my}) + \gamma_m + \rho_y + \mu_r + \lambda_s + X'_{srmy}\boldsymbol{\delta} + e_{srmy} \quad (2.3)$$

In this specification, the dependent variable, $EC_{srmy}$, denotes electricity consumption in service sub-sector $s$, region $r$, month $m$, and year $y$. Unlike the previous models based on pooled repeated cross-sections, this specification has a panel structure, since each service sub-sector is observed repeatedly over time across monthly waves.

$Treat_s$ takes the value 1 if service sub-sector $s$ belongs to the treated group, namely activities that were subject to closure or substantial operating restrictions during the lockdown, and 0 otherwise. $Post_{my}$ takes the value 1 for lockdown months, March–May

| **ATECO Codes (1-digit)** | **IMSER Survey** | **Description** | **Treatment Indicator** |
|---|---|---|---|
| 8 Trasporto e magazzinaggio | Trasporto e magazzinaggio | Transportation and storage | Controlled |
| 10 Servizi di informazione e comunicazione | Informazione e comunicazione | Information and communication services | Controlled |
| 11 Attività finanziarie e assicurative | Finanza e assicurazione | Financial and insurance activities | Controlled |
| 12 Attività immobiliari | Immobiliare | Real estate activities | Treated |
| 13 Attività professionali, scientifiche e tecniche | Attività professionali, scientifiche e tecniche | Professional, scientific and technical activities | Treated |
| 15 Amministrazione pubblica e difesa | Amministrazione pubblica e difesa | Public administration and defense; compulsory social security | Controlled |
| 16 Istruzione | Istruzione | Education | Treated |
| 17 Sanità e assistenza sociale | Sanità e assistenza sociale | Human health and social work activities | Controlled |

Table 2.3: Composition of treatment and control groups across service sectors. This table reports the service sectors included in the treatment and control groups.

2020, and 0 otherwise. The interaction term $Treat_s \times Post_{my}$ identifies treated service sub-sectors during the lockdown period.

The terms $\gamma_m$, $\rho_y$, $\mu_r$, and $\lambda_s$ denote month, year, region, and sub-sector fixed effects, respectively. Month fixed effects control for seasonality in electricity consumption; year fixed effects absorb aggregate annual shocks; region fixed effects account for time-invariant territorial differences; and sub-sector fixed effects control for time-invariant heterogeneity across service activities. The vector $\mathbf{X}'_{srmy}$ contains the control covariates, while $e_{srmy}$ denotes the idiosyncratic error term.

The set of covariates differs from the earlier specifications. It only includes meteorological variables, the national wholesale electricity price (PUN), and three indicators related to the evolution of the pandemic: the number of confirmed new Covid-19 cases per month and region, the number of patients in intensive care per month and region, and the number of hospitalized patients with symptoms per month and region. All three epidemiological variables are expressed per 100,000 inhabitants and are included with a one-month lag. These data on the COVID-19 pandemic are provided by the Italian Civil Protection Department that compiled and systematized official data for the Covid-19 period 2020–2022, which were subsequently released through its dedicated online platform[6].

Again, $\beta$ is the coefficient that reflects the causal effect. The correct interpretation of the coefficient is the average difference in the change in consumption between treated and control sectors in the post-lockdown period, net of fixed differences across sectors, regions, and time. In this setting, the coefficient can be interpreted as the differential reduction in workplace electricity consumption generated by the lockdown-induced shift from on-site work to remote work in the treated sectors, relative to sectors that remained predominantly on-site. It is important to emphasize that the coefficient is not intended to capture an abstract lockdown effect detached from the mechanism of interest. On the contrary, the mechanism we are interested in is precisely the fact that workers in the

[6]Data are available here: `https://github.com/pcm-dpc/COVID-19`.

treated sectors were sent home, while workers in the control sectors continued to work in person. The expected implication is that commercial buildings and workplaces in the treated sectors should exhibit a reduction in electricity use, because fewer workers are physically present and therefore the demand for lighting, heating, ventilation, elevators, equipment, and other workplace-related services declines. The estimate should therefore be read as the electricity-saving component associated with the transition to remote work. At the same time, the estimate should still be interpreted with some caution, because our data are sectoral and regional at a monthly frequency, not micro-level observations on individual workplaces or individual workers. As a consequence, the coefficient may also reflect other effects that move together with the lockdown, such as changes in operating schedules, partial closures, altered business intensity, or demand-side contractions. This does not weaken the interpretation we are interested in; rather, it means that the estimate should be understood as the observed differential reduction in electricity consumption associated with the remote-work regime, as revealed by the lockdown, rather than as a mechanically isolated measure of remote work alone[7].

Figure 2.6 shows a diagram of the conceptual and empirical framework that we are about to analyse.

[7]An important point to make explicit in the methodological discussion is that our exercise does not identify a universal causal effect valid in all contexts, but a local effect specific to the Covid period. The lockdown was an exceptional shock, both in intensity and in speed of implementation, and it allowed us to observe how electricity consumption responds when a portion of productive activity is suddenly moved from the workplace to home. This makes the analysis highly informative for estimating the potential energy savings associated with remote work, but specifically in a context of emergency and forced change.

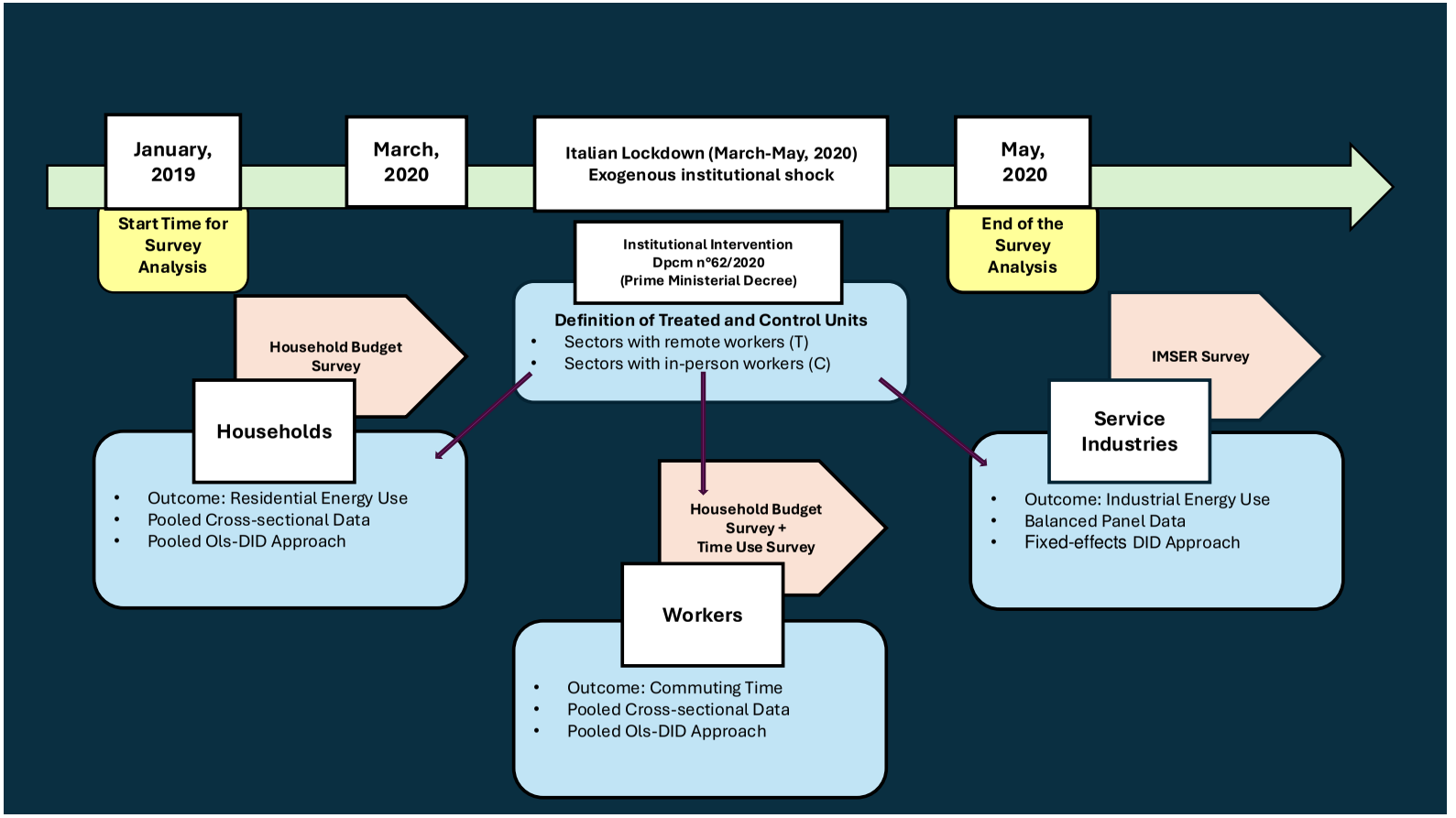



Figure 2.6: Conceptual and Empirical Framework.

## 2.7 Estimation Results

This section presents the empirical results of the analysis. For each model, we discuss the identification strategy, report the main estimates, and provide robustness checks aimed at assessing the consistency and reliability of the results.

### 2.7.1 Model 1

#### 2.7.1.1 Identification

For the estimates from the pooled-DiD model based on repeated cross-sectional data to be consistent, three key identification conditions must hold: parallel trends between treated and control groups in the pre-intervention period, absence of treatment anticipation, and the SUTVA (Stable Unit Treatment Value Assumption).

We show evidence in favour of the validity of the parallel trends assumption through two distinct approaches. First, a graphical analysis (Figure 2.4) plots average residential consumption over the twelve months preceding the quarantine, smoothed with a three-month moving average to attenuate seasonal fluctuations. This visualization reveals a substantively parallel trajectory for the treated and control groups.

Second, we re-estimated Equation (2.1) with an event-study approach, which estimates the outcome dynamically relative to the treatment date, and the monthly coefficient plot with 90% confidence intervals allows us to assess the parallel trends assumption by checking whether pre-treatment estimates are close to zero and statistically indistinguishable from one another (Figure 2.5).

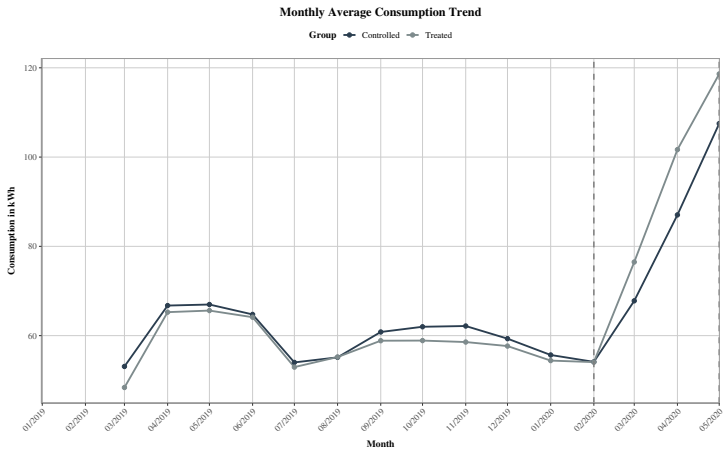



Table 2.4: Parallel trends in electricity consumption: treatment vs. control groups. This figure shows the monthly trend in average electricity consumption (kWh) for the treatment and control groups. The dotted vertical line marks the onset of the lockdown associated with the SARS-CoV-2 pandemic.

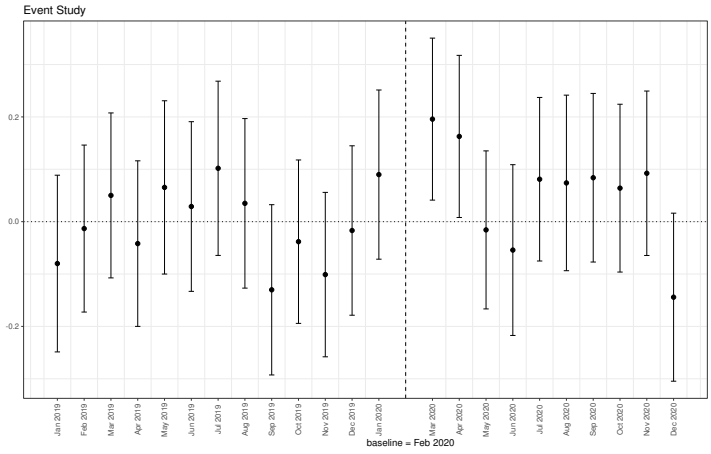



Table 2.5: Event-study estimates of treatment effects on log energy consumption. This figure presents the estimated differences in the logarithm of monthly household energy consumption between the treatment and control groups relative to the treatment date. Monthly coefficients are reported with 90% confidence intervals.

Finally, we report the mean values of the main observed confounding variables—namely, those included as controls in the model—for the treated and control groups, both before and after treatment (Table 2.6). Although this comparison is not required for identification in a DiD framework, it provides a useful descriptive check on the comparability of the two groups. The evidence shows substantial similarity in observed characteristics prior to the intervention, and a broadly similar pattern afterward, suggesting that the estimated treatment effect is unlikely to be driven by major differences in observables. In this sense, the balance in covariate means complements, rather than replaces, the identification strategy based on the parallel trends assumption. Taken together, the graphical evidence and the descriptive covariate balance support the credibility of the DiD design.

For what concerns the absence of anticipation, it is guaranteed by the extremely short notice given for the lockdown decrees: on 7 March 2020, the government announced measures that took effect on 8 or 9 March, leaving households insufficient time to adjust their consumption habits in advance. There was neither a secondary market for forward-contracted energy nor any credible signal of an impending shutdown that could have induced anticipatory changes in usage.

Regarding the SUTVA, it is satisfied because each household independently determines its own energy requirements. There are no localized market mechanisms or peer-to-peer arrangements that could alter electricity prices or availability at the condominium or neighborhood level. Any local shocks—such as an overloaded transformer—are exceptional events and non-differential between treated and control groups. Moreover, the lockdown was applied uniformly throughout the national territory, with no variation in severity at the individual level, ensuring that each household experienced the same treatment without interference from neighboring units.

| Variables | Control, pre-march 2020 | Control, post-march 2020 | Treated, pre-march 2020 | Treated, post-march 2020 |
|---|---|---|---|---|
| Log (price) | -0.78 (0.28) | -0.97 (0.42) | -0.74 (0.25) | -0.95 (0.42) |
| Average maximum temperature | 16.90 (7.54) | 18.08 (4.67) | 17.64 (7.64) | 18.59 (4.22) |
| Average minimum temperature | 7.95 (6.76) | 8.09 (4.25) | 8.81 (6.92) | 8.52 (3.93) |
| Average wind speed | 2.61 (0.82) | 2.69 (0.67) | 2.64 (0.82) | 2.71 (0.67) |
| Average rainfall | 2.48 (2.75) | 2.29 (1.06) | 2.46 (2.71) | 2.17 (1.05) |
| Average solar radiation | 13348.28 (6732.55) | 18306.53 (3920.04) | 13655.27 (6950.02) | 18446.67 (3722.60) |
| CDD | 15.92 (35.88) | 0.70 (2.62) | 19.35 (40.41) | 0.74 (2.61) |
| HDD | 202.66 (160.80) | 155.24 (124.89) | 186.43 (158.75) | 140.41 (114.13) |
| Number of rooms | 2.98 (1.12) | 2.99 (1.01) | 2.86 (1.15) | 2.95 (0.94) |
| Square meters of living space | 86.65 (36.25) | 86.28 (34.77) | 82.85 (37.72) | 86.54 (30.79) |
| Age of the head of the household | 53.31 (11.93) | 54.47 (11.69) | 52.44 (11.84) | 54.19 (11.76) |
| Gender of the head of the household = female | 1.45 (0.50) | 1.47 (0.50) | 1.60 (0.49) | 1.58 (0.49) |
| Region= Abruzzo | 0.01 (0.11) | 0.04 (0.18) | 0.02 (0.15) | 0.01 (0.07) |
| Region= Basilicata | 0.02 (0.13) | 0.02 (0.15) | 0.02 (0.12) | 0.01 (0.07) |
| Region= Calabria | 0.02 (0.13) | 0.02 (0.14) | 0.03 (0.17) | 0.01 (0.10) |
| Region= Campania | 0.04 (0.20) | 0.02 (0.15) | 0.06 (0.24) | 0.07 (0.25) |
| Region= Emilia-Romagna | 0.09 (0.28) | 0.07 (0.26) | 0.06 (0.24) | 0.12 (0.32) |
| Region= Friuli-Venezia Giulia | 0.04 (0.18) | 0.04 (0.20) | 0.03 (0.17) | 0.04 (0.20) |
| Region= Lazio | 0.09 (0.29) | 0.11 (0.31) | 0.12 (0.33) | 0.14 (0.34) |
| Region= Liguria | 0.08 (0.28) | 0.05 (0.21) | 0.07 (0.26) | 0.06 (0.23) |
| Region= Lombardia | 0.12 (0.32) | 0.12 (0.32) | 0.11 (0.31) | 0.10 (0.30) |
| Region= Marche | 0.03 (0.16) | 0.03 (0.16) | 0.03 (0.18) | 0.02 (0.12) |
| Region= Molise | 0.02 (0.15) | 0.03 (0.16) | 0.03 (0.17) | 0.02 (0.12) |
| Region= Piemonte | 0.08 (0.27) | 0.07 (0.26) | 0.05 (0.23) | 0.09 (0.28) |
| Region= Puglia | 0.04 (0.20) | 0.04 (0.19) | 0.03 (0.18) | 0.04 (0.18) |
| Region= Sardegna | 0.03 (0.18) | 0.01 (0.11) | 0.03 (0.18) | 0.03 (0.17) |
| Region= Sicilia | 0.03 (0.16) | 0.04 (0.19) | 0.04 (0.19) | 0.06 (0.23) |
| Region= Toscana | 0.05 (0.21) | 0.11 (0.32) | 0.05 (0.22) | 0.11 (0.31) |
| Region= Trentino-Alto Adige | 0.09 (0.29) | 0.05 (0.21) | 0.08 (0.27) | 0.04 (0.18) |
| Region= Umbria | 0.04 (0.20) | 0.01 (0.09) | 0.03 (0.16) | 0.01 (0.07) |
| Region= Valle d'Aosta | 0.05 (0.21) | 0.06 (0.23) | 0.03 (0.16) | 0.03 (0.16) |
| Region= Veneto | 0.04 (0.21) | 0.07 (0.26) | 0.06 (0.24) | 0.06 (0.24) |
| Type of dwelling= villa | 0.30 (0.46) | 0.31 (0.46) | 0.24 (0.43) | 0.30 (0.46) |
| Type of dwelling= apartment in a building with fewer than 10 apartments | 0.25 (0.43) | 0.34 (0.47) | 0.29 (0.45) | 0.29 (0.46) |
| Type of dwelling= apartment in a building with more than 10 apartments | 0.45 (0.50) | 0.35 (0.48) | 0.46 (0.50) | 0.41 (0.49) |
| Type of municipality: Metropolitan area center | 0.23 (0.42) | 0.24 (0.43) | 0.25 (0.43) | 0.35 (0.48) |
| Type of municipality: Metropolitan area suburbs and municipalities with 50,000 inhabitants or more | 0.33 (0.47) | 0.25 (0.43) | 0.34 (0.48) | 0.33 (0.47) |
| Type of municipality: Other municipalities with up to 50,000 inhabitants | 0.43 (0.50) | 0.51 (0.50) | 0.40 (0.49) | 0.32 (0.47) |
| Working area= Legislators, entrepreneurs, and senior management | 0.03 (0.16) | 0.03 (0.17) | 0.02 (0.13) | 0.01 (0.07) |
| Working area= Intellectual, scientific, and highly specialized professions | 0.16 (0.36) | 0.20 (0.40) | 0.48 (0.50) | 0.56 (0.50) |
| Working area= Technical professions | 0.30 (0.46) | 0.25 (0.44) | 0.16 (0.36) | 0.19 (0.39) |
| Working area= Executive professions in office work | 0.22 (0.41) | 0.28 (0.45) | 0.07 (0.26) | 0.07 (0.25) |
| Working area= Skilled professions in commercial activities and services | 0.11 (0.32) | 0.09 (0.29) | 0.10 (0.30) | 0.07 (0.25) |
| Working area= Craftsmen, skilled workers, and farmers | 0.02 (0.13) | 0.03 (0.16) | 0.01 (0.08) | 0.02 (0.12) |
| Working area= Plant operators, stationary and mobile machinery operators, and vehicle drivers | 0.07 (0.26) | 0.06 (0.23) | 0.00 (0.05) | 0.00 (0.00) |
| Working area= Unskilled occupations | 0.07 (0.25) | 0.04 (0.18) | 0.16 (0.36) | 0.10 (0.30) |
| Working area= Armed forces | 0.03 (0.16) | 0.03 (0.16) | 0.00 (0.05) | 0.00 (0.00) |
| Source of income= Income from employment | 0.63 (0.48) | 0.61 (0.49) | 0.52 (0.50) | 0.44 (0.50) |
| Source of income= Income from self-employment | 0.06 (0.24) | 0.06 (0.23) | 0.22 (0.41) | 0.25 (0.43) |
| First income decile | 0.06 (0.23) | 0.04 (0.18) | 0.16 (0.37) | 0.11 (0.31) |
| Second income decile | 0.05 (0.22) | 0.05 (0.23) | 0.10 (0.29) | 0.10 (0.30) |
| Third income decile | 0.09 (0.29) | 0.09 (0.29) | 0.10 (0.30) | 0.06 (0.24) |
| Fourth income decile | 0.15 (0.36) | 0.17 (0.37) | 0.12 (0.33) | 0.17 (0.37) |
| Fifth income decile | 0.16 (0.36) | 0.15 (0.36) | 0.13 (0.34) | 0.15 (0.35) |
| Sixth income decile | 0.14 (0.34) | 0.14 (0.35) | 0.11 (0.31) | 0.15 (0.36) |
| Seventh income decile | 0.08 (0.28) | 0.10 (0.30) | 0.07 (0.26) | 0.10 (0.29) |
| Eighth income decile | 0.08 (0.27) | 0.07 (0.25) | 0.07 (0.26) | 0.04 (0.18) |
| Ninth income decile | 0.10 (0.30) | 0.10 (0.30) | 0.07 (0.26) | 0.07 (0.25) |
| Tenth income decile | 0.10 (0.29) | 0.09 (0.29) | 0.07 (0.25) | 0.07 (0.26) |
| Level of education= no formal education | 0.00 (0.04) | 0.00 (0.06) | 0.01 (0.08) | 0.01 (0.10) |
| Level of education= primary school diploma | 0.02 (0.15) | 0.03 (0.16) | 0.03 (0.16) | 0.01 (0.10) |
| Level of education= middle school diploma | 0.19 (0.39) | 0.18 (0.39) | 0.15 (0.35) | 0.10 (0.30) |
| Level of education= two- or three-year vocational diploma | 0.08 (0.27) | 0.08 (0.27) | 0.06 (0.23) | 0.05 (0.21) |
| Level of education= five-year secondary-school diploma | 0.47 (0.50) | 0.46 (0.50) | 0.33 (0.47) | 0.37 (0.48) |
| Level of education= university degree or equivalent | 0.21 (0.41) | 0.25 (0.43) | 0.42 (0.49) | 0.46 (0.50) |
| Level of education= other | 0.03 (0.16) | 0.00 (0.00) | 0.01 (0.11) | 0.00 (0.00) |
| Job position= manager | 0.04 (0.20) | 0.05 (0.21) | 0.02 (0.15) | 0.03 (0.16) |
| Job position= executive | 0.11 (0.31) | 0.14 (0.34) | 0.10 (0.30) | 0.10 (0.29) |
| Job position= office worker | 0.57 (0.50) | 0.60 (0.49) | 0.41 (0.49) | 0.45 (0.50) |
| Job position= factory worker | 0.20 (0.40) | 0.15 (0.36) | 0.21 (0.41) | 0.15 (0.35) |
| Job position= entrepreneur or freelancer | 0.08 (0.28) | 0.07 (0.25) | 0.25 (0.44) | 0.29 (0.45) |
| Ownership= individual (or multiple individuals as co-owners) | 0.16 (0.37) | 0.12 (0.33) | 0.22 (0.41) | 0.20 (0.40) |
| Ownership= private enterprise or company | 0.04 (0.19) | 0.04 (0.18) | 0.04 (0.19) | 0.01 (0.10) |
| Construction period= post-2009 | 0.04 (0.19) | 0.02 (0.12) | 0.04 (0.20) | 0.01 (0.10) |
| Construction period= 2000–2009 | 0.11 (0.32) | 0.11 (0.32) | 0.09 (0.29) | 0.07 (0.26) |
| Construction period= 1990s | 0.09 (0.29) | 0.10 (0.30) | 0.07 (0.26) | 0.08 (0.26) |
| Construction period=1950s–1980s | 0.76 (0.43) | 0.77 (0.42) | 0.80 (0.40) | 0.84 (0.36) |
| Internet availability= no | 0.79 (0.40) | 0.78 (0.42) | 0.79 (0.41) | 0.88 (0.32) |
| Internet availability= yes | 0.21 (0.40) | 0.22 (0.42) | 0.21 (0.41) | 0.12 (0.32) |

Table 2.6: Household characteristics before and after treatment: treatment vs. control groups. This table reports the characteristics of households in the treatment and control groups, before and after the treatment period.

#### 2.7.1.2 Pooled-DiD Estimation

In the main analysis, we report the results obtained from the pooled-DiD estimator rather than from the two-stage least squares specification. This choice is motivated by the diagnostic tests reported below, which do not provide evidence that the average price variable is endogenous in our setting. In this case, the pooled-DiD estimator is preferred because it is more efficient than the two-stage least squares alternative. The 2SLS estimates are therefore used as a robustness check to assess whether the main results are sensitive to potential price endogeneity.

In the preceding section, we introduced a two-stage least squares specification to address

the potential endogeneity of the average price. We considered all possible instrument combinations: each instrument individually, each possible pair of instruments, and the full set of three instruments. The validity of each candidate specification was assessed in two steps. First, we evaluated instrument relevance using the first-stage F-statistic. Second, whenever the model was over-identified, we used the Sargan-J test to assess the joint exogeneity of the instruments. In exactly identified specifications, instead, instrument exogeneity cannot be tested statistically and must rely on the economic plausibility of the exclusion restriction.

Among the instrument combinations considered, only two specifications satisfied the relevance condition and, where testable, did not reject the overidentifying restrictions: (1) the lagged semiannual price used as the sole instrument, and (2) the combination of the local 'leave-one-out' price and the lagged semiannual price. For the first specification, based on a single instrument, the first-stage F-statistic supports instrument relevance, but exogeneity cannot be tested through the Sargan-J test because the model is exactly identified. For the second specification, which is over-identified, the first-stage F-statistic supports instrument relevance and the Sargan-J test does not reject the null hypothesis that the instruments are jointly exogenous.

Table 2.7 reports the first-stage F-statistics, the Sargan-J statistics where applicable, and the Hausman test for endogeneity. The Hausman test fails to reject the null hypothesis of exogeneity of the price variable. Consistent with this result, and given the greater efficiency of the pooled-DiD estimator when the suspected endogenous regressor can be treated as exogenous, we present the pooled-DiD estimates as our baseline results. The 2SLS estimates, obtained using the admissible instrument sets, are virtually identical to the baseline estimates and are therefore interpreted as supporting evidence for the robustness of the main findings.

The pooled-DiD model is reported in table 2.8. The coefficient on the interaction between the treatment indicator and the lockdown period is statistically significant and indicates that households forced to remain at home increased their electricity consumption

by approximately 12 percent relative to those who continued working on-site. For what concerns the coefficient associated to the price variable indicating the price elasticity of the demand, the very high estimated price-consumption elasticity of $-1.33$ arises almost entirely from the fact that, in our dataset, the consumption variable was constructed by dividing monthly expenditure by an ex post average price. Although the Hausman test indicates that the *ex-post* price is sufficiently exogenous and that a simple aggregate DiD model can therefore be used, the problem regarding the estimation of consumption in kWh remains unchanged. This phenomenon produces a coefficient on the log of price that appears in absolute value greater than one—i.e., larger than what one would expect from a true elasticity of electricity demand (which in the literature typically lies between $-0.3$ and $-0.6$). Added to this is the fact that the assigned average price never actually corresponds to a marginal price observed by the consumer, but is a smoothed measure of a semiannual price spread evenly over twelve months: this leveling flattens real differences and further amplifies the mechanical price effect. In short, the value of $-1.33$ does not signal hyper-elastic demand, but is the inevitable consequence of how we constructed $Q$ as expenditure divided by an average price.

Overall, the model explains approximately 56% of the variability in residential household electricity consumption, confirming its high explanatory power.

| **Lagged semestral price** | | | | |
|---|---|---|---|---|
| Test | df1 | df2 | Statistic | p-value |
| Weak instruments | 1,00 | 12402,00 | 0.00 | 0.00 |
| Wu-Hausman | 1,00 | 2170,00 | 0.012 | 0.91 |
| **Local price** | | | | |
| Test | df1 | df2 | Statistic | p-value |
| Weak instruments | 1 | 2171 | 0.10 | 0.74 |
| Wu-Hausman | 1 | 2170 | 1.51 | 0.22 |
| **Lagged semestral price + local price** | | | | |
| Test | df1 | df2 | Statistic | p-value |
| Weak instruments | 2 | 2170 | 6200,00 | 0.00 |
| Wu-Hausman | 1 | 2170 | 0.017 | 0.89 |
| Sargan | 1 | | 1.57 | 0.20 |

Table 2.7: Instrumental variables specification tests. This table reports diagnostic tests for instrument relevance, instrument exogeneity where testable, and price endogeneity. Instrument relevance is assessed through the first-stage F-statistic, while the Sargan-J test is reported only for over-identified specifications to assess the overidentifying restrictions. In exactly identified models, instrument exogeneity cannot be tested statistically. The Hausman test is used to assess the potential endogeneity of the average price variable. For each test, the relevant degrees of freedom, test statistic, and corresponding p-value are presented.

| Regression Table | | | |
|---|---|---|---|
| Intercept | 2.94 (0.51)*** | Working area= Armed forces | -0.03 (0.07) |
| Treated | -0.06 (0.02)*** | Source of income= Income from self-employment | 0.1 (0.05)** |
| Post | -0.03 (0.05) | Second income decile | 0.01 (0.04) |
| **Treated * Post** | **0.11 (0.06)*** | Third income decile | 0.03 (0.05) |
| February | 0.03 (0.07) | Fourth income decile | -0.01 (0.05) |
| March | 0.08 (0.16) | Fifth income decile | -0.05 (0.05) |
| April | 0.11 (0.26) | Sixth income decile | -0.05 (0.04) |
| May | 0.01 (0.35) | Seventh income decile | -0.1 (0.04)** |
| June | -0.17 (0.45) | Eighth income decile | -0.35 (0.06)*** |
| July | -0.22 (0.46) | Ninth income decile | -0.48 (0.04)*** |
| August | -0.2 (0.43) | Tenth income decile | -0.52 (0.08)*** |
| September | -0.01 (0.33) | Log (price) | -1.33 (0.08)*** |
| October | 0.11 (0.26) | Average maximum temperature | -0.02 (0.03) |
| November | 0.06 (0.19) | Average minimum temperature | 0.03 (0.03) |
| December | 0.05 (0.1) | Average wind speed | -0.01 (0.04) |
| Year: 2020 | 0.06 (0.05) | Average rainfall | -0.01 (0.01) |
| Region= Basilicata | -0.11 (0.06)* | Average solar radiation | 0 (0) |
| Region= Calabria | -0.06 (0.1) | CDD | 0 (0) |
| Region= Campania | -0.03 (0.08) | HDD | 0 (0) |
| Region= Emilia-Romagna | -0.13 (0.06)** | Gender of the head of the household = male | 0.08 (0.02)*** |
| Region= Friuli-Venezia Giulia | 0.04 (0.08) | Level of education= primary school diploma | 0.05 (0.21) |
| Region= Lazio | -0.05 (0.04) | Level of education= middle school diploma | 0.04 (0.17) |
| Region= Liguria | -0.16 (0.08)** | Level of education= two- or three-year vocational diploma | -0.02 (0.18) |
| Region= Lombardia | 0 (0.07) | Level of education= five-year secondary-school diploma | -0.04 (0.18) |
| Region= Marche | 0.02 (0.05) | Level of education= university degree or equivalent | 0.02 (0.19) |
| Region= Molise | -0.05 (0.05) | Level of education= other | 0.02 (0.21) |
| Region= Piemonte | -0.09 (0.08) | Age of the head of the household | 0 (0)** |
| Region= Puglia | -0.07 (0.07) | Job position= executive | -0.24 (0.06)*** |
| Region= Sardegna | -0.04 (0.09) | Job position= office worker | -0.22 (0.06)*** |
| Region= Sicilia | -0.13 (0.1) | Job position= factory worker | -0.27 (0.07)*** |
| Region= Toscana | -0.01 (0.06) | Job position= entrepreneur or freelancer | -0.27 (0.08)*** |
| Region= Trentino-Alto Adige | -0.06 (0.13) | Ownership= private enterprise or company | 0.03 (0.05) |
| Region= Umbria | 0.05 (0.09) | Internet availability= yes | 0.01 (0.02) |
| Region= Valle d'Aosta | -0.09 (0.16) | Construction period= post-2009 | -0.05 (0.08) |
| Region= Veneto | -0.03 (0.08) | Construction period= 2000–2009 | -0.06 (0.05) |
| Type of dwelling= apartment in a building with fewer than 10 apartments | 0.05 (0.03)* | Construction period= 1990s | -0.03 (0.06) |
| Type of dwelling= apartment in a building with more than 10 apartments | -0.02 (0.02) | Number of rooms | -0.01 (0.01) |
| Type of dwelling= other | -0.25 (0.12)** | Square meters of living space | 0 (0)** |
| Type of municipality: Metropolitan area suburbs and municipalities with 50,000 inhabitants or more | -0.01 (0.03) | | |
| Type of municipality: Other municipalities with up to 50,000 inhabitants | -0.05 (0.03) | | |
| Working area= Intellectual, scientific, and highly specialized professions | -0.01 (0.07) | | |
| Working area= Technical professions | 0.02 (0.06) | | |
| Working area= Executive professions in office work | -0.01 (0.08) | | |
| Working area= Skilled professions in commercial activities and services | -0.09 (0.09) | | |
| Working area= Craftsmen, skilled workers, and farmers | 0.08 (0.12) | | |
| Working area= Plant operators, stationary and mobile machinery operators, and vehicle drivers | 0 (0.09) | | |
| Working area= Unskilled occupations | -0.12 (0.1) | | |
| Adjusted R-squared: 0.56<br>Observations: 2,264 | | | |

Table 2.8: Pooled-DiD regression results for household electricity consumption. This table reports the estimates from regression equation (2.1), where the dependent variable is the logarithm of household electricity consumption (kWh). Standard errors are clustered at the month level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Bold values indicate the difference-in-differences coefficient of interest.

Moving to the event-study results, the coefficients associated with the event period are positive and statistically significant in the first two lockdown months (Table 2.5), suggesting that treated households experienced higher domestic electricity consumption than the control group and pointing to a clear structural break. In March, the first month of the lockdown, electricity consumption among treated households increased by approximately 20.9 percent relative to households whose members continued to work on site. In April, the estimated effect remains sizeable and statistically significant, at around 17.3 percent. Although slightly lower than the March estimate, this effect is still economically meaningful. By May, however, the coefficient is no longer statistically significant. This result is consistent with the timing of the easing of restrictions: on May 4, 2020, the Italian government launched 'Phase 2', which marked the gradual relaxation of containment measures following the decline in infection rates. In the immediate post-lockdown period, the estimated effect remains positive but gradually loses statistical significance and attenuates toward zero. This pattern suggests that the observed impact is primarily concentrated in the initial phase of the shock. One possible interpretation is that the increase in household energy consumption was most pronounced immediately after the

sudden shift to remote work, when families abruptly relocated a substantial share of daily activities to the home environment. Over time, the relative effect appears to diminish, likely because other lockdown-related factors—such as the increased time spent at home by the broader population—reduced differences between treated and control households. Overall, the results indicate that the transition to remote work during the lockdown is associated with an immediate increase in residential energy consumption among treated households relative to those that continued working on-site. However, this differential does not appear to persist in the medium term. The empirical evidence therefore points to a short-run effect rather than a structural and lasting change in relative household energy consumption between the two groups.

| **Term** | **Estimate** | **Std.error** | **P-value** |
|---|---|---|---|
| $\beta_{-14}$ | -0.08 | 0.102542 | 0.435326 |
| $\beta_{-13}$ | -0.01319 | 0.096895 | 0.891752 |
| $\beta_{-12}$ | 0.050102 | 0.095722 | 0.600719 |
| $\beta_{-11}$ | -0.0419 | 0.096071 | 0.662759 |
| $\beta_{-10}$ | 0.065403 | 0.100546 | 0.515426 |
| $\beta_{-9}$ | 0.028908 | 0.098451 | 0.76906 |
| $\beta_{-8}$ | 0.101891 | 0.101108 | 0.313647 |
| $\beta_{-7}$ | 0.034957 | 0.098384 | 0.722373 |
| $\beta_{-6}$ | -0.13015 | 0.0988 | 0.18782 |
| $\beta_{-5}$ | -0.03822 | 0.094828 | 0.686922 |
| $\beta_{-4}$ | -0.10108 | 0.095408 | 0.289454 |
| $\beta_{-3}$ | -0.0169 | 0.098311 | 0.863506 |
| $\beta_{-2}$ | 0.08987 | 0.098175 | 0.360044 |
| $\beta_0$ | 0.195793 | 0.094003 | 0.037337 |
| $\beta_1$ | 0.162752 | 0.094075 | 0.083715 |
| $\beta_2$ | -0.01574 | 0.091702 | 0.863758 |
| $\beta_3$ | -0.05425 | 0.099094 | 0.584066 |
| $\beta_4$ | 0.081029 | 0.094904 | 0.393273 |
| $\beta_5$ | 0.073954 | 0.101874 | 0.467924 |
| $\beta_6$ | 0.083881 | 0.097839 | 0.391315 |
| $\beta_7$ | 0.063988 | 0.097376 | 0.511144 |
| $\beta_8$ | 0.092419 | 0.095425 | 0.332859 |
| $\beta_9$ | -0.14421 | 0.097501 | 0.139219 |

Table 2.9: Event-study dynamics of treatment effects on log household energy consumption. This table reports the estimated differences in the logarithm of monthly household energy consumption between treated and control households relative to the treatment date. Each coefficient corresponds to a specific month before (t−k) or after (t+k) treatment, along with the associated standard errors and p-values.

#### 2.7.1.3 Heterogeneous Effects

From the estimation of Equation (2.1), several covariates-such as region, type of dwelling, source of income, income decile, gender, job position, and housing characteristics-display statistically significant coefficients. In this section, we investigate whether these characteristics are associated with heterogeneous effects of the lockdown on residential electricity consumption. To do so, we estimate a series of three-way interaction models, obtained by interacting the baseline specification in Equation (2.1) with the variables of interest. In Table 2.10, we report the estimated interaction terms. For ease of interpretation, the subgroup-specific treatment effect is obtained by summing the baseline *treated* $\times$ *post* coefficient and the corresponding interaction term. Since the dependent variable is expressed in logs, we then convert the resulting coefficients into percentage changes as $100 \times (\exp(\beta) - 1)$.

In all specifications, the coefficient *treated* $\times$ *post* is not statistically different from zero, except in the gender specification, where the baseline effect for male household heads is 0.09 (s.e. 0.04, $p < 0.10$), corresponding to an increase of about 9.4% in level. The female interaction term is small and not statistically significant, indicating no meaningful gender heterogeneity in the post-lockdown effect.

In the first column, the interaction effect with region is reported. Tuscany is the omitted category, and the estimated post-lockdown effect for the reference region is essentially zero. Relative to Tuscany, treated households in Campania exhibit an implied increase of 0.33 log-points, corresponding to about 39.1% in level. Emilia-Romagna and Lazio both show an increase of about 33.6% in levels, while Trentino-Alto Adige shows an increase of about 41.9%. By contrast, some regions display lower consumption: Friuli-Venezia Giulia shows a decline of about 47.3%, Molise of about 42.9%, and Umbria an exceptionally large decline of about 80.4%. All remaining regions, namely Abruzzo, Basilicata, Calabria, Liguria, Lombardia, Marche, Piemonte, Puglia, Sardegna, Sicilia, Valle d'Aosta, and Veneto, do not differ significantly from Tuscany.

In the second column, the interaction effect with job position is reported, with factory

workers as the reference category. The baseline post-lockdown effect for the reference group is not statistically significant. The implied effect for office workers corresponds to an increase of about 19.7% in levels. For entrepreneurs or self-employed individuals, the implied effect is about 10.5%. Managers and executives do not differ significantly from the factory-worker baseline.

In the third column, the interaction effect with type of dwelling is presented. The reference category is a dwelling in a building with more than 10 apartments. The implied effect for households living in a villa corresponds to a decline of about 8.6%. By contrast, households living in an apartment in a building with fewer than 10 units show an implied increase of about 36.3% in levels.

In the fourth column, the interaction effect with gender is shown. The post-lockdown effect for male household heads corresponds to an increase of about 9.4% in levels. For female household heads, the implied effect is approximately 13.9%. However, the gender differential is not statistically significant, indicating no robust heterogeneity by gender.

In the fifth column, the interaction effect with income decile is reported. The reference category is the 10th income decile. The implied effects for the other deciles are heterogeneous: +85.9% for the first decile, +27.1% for the second, -7.7% for the third, +8.3% for the fourth, +9.4% for the fifth, +3.0% for the sixth, +25.9% for the seventh, -21.3% for the eighth, and +16.2% for the ninth. The statistically significant differential terms indicate that the post-lockdown effect varies across income groups, with the strongest negative deviations observed in the third and eighth deciles.

In the sixth column, the interaction effects concerning the building construction period are reported. The reference category is dwellings built after 2009. The implied effects for dwellings built in the 2000–2009 period, in the 1990s, and in the 1950s–1980s correspond to +40.5%, +13.9%, and +9.4%, respectively. These estimates do not indicate pronounced heterogeneity across construction periods.

In the seventh column, the interaction effects with the number of rooms are reported. The omitted category is one-room dwellings. The implied effects correspond approximately

to +6.2% for two-room dwellings, +17.4% for three-room dwellings, -3.9% for four-room dwellings, and +24.6% for dwellings with more than four rooms. The only statistically significant differential term is observed for four-room dwellings, although the implied total effect is close to zero.

Finally, in the eighth column, the interaction effects with square meters are reported. The reference category is dwellings smaller than 55 $m^2$. The implied effects correspond approximately to +15.0% for dwellings of 56–70 $m^2$, -8.6% for 71–80 $m^2$, +1.0% for 81–90 $m^2$, +23.4% for 91–110 $m^2$, and +22.1% for dwellings of at least 111 $m^2$. The main statistically significant differential term is found for dwellings of 71–80 $m^2$, although the implied total effect remains modest in size.

In the first column, the interaction effect with region is reported. Tuscany is the omitted category, and the estimated post-lockdown effect for the reference region is essentially zero. Relative to Tuscany, treated households in Campania exhibit an implied increase of 0.33 (s.e. 0.10), corresponding to about 39.1% in level; Emilia-Romagna and Lazio both show an increase of 0.29 (s.e. 0.17), or about 33.6%; and Trentino-Alto Adige shows an increase of 0.35 (s.e. 0.17), or about 41.9%. By contrast, some regions display lower consumption: Friuli-Venezia Giulia has an implied effect of -0.64 (s.e. 0.20), equal to about -47.3%; Molise shows -0.56 (s.e. 0.18), or about -42.9%; and Umbria shows -1.63 (s.e. 0.20), corresponding to an exceptionally large decline of about -80.4%. All remaining regions (Abruzzo, Basilicata, Calabria, Liguria, Lombardia, Marche, Piemonte, Puglia, Sardegna, Sicilia, Valle d'Aosta, and Veneto) do not differ significantly from Tuscany.

In the second column, the interaction effect with job position is reported, with factory workers as the reference category. The baseline post-lockdown effect for the reference group is -0.06 (s.e. 0.07), which is not statistically significant. The implied effect for office workers is 0.18, obtained as -0.06 + 0.24, corresponding to an increase of about 19.7% in level. For entrepreneurs or self-employed individuals, the implied effect is 0.10 (-0.06 + 0.16), equal to about 10.5%. Managers and executives do not differ significantly from the factory-worker baseline.

In the third column, the interaction effect with type of dwelling is presented. The reference category is a dwelling in a building with more than 10 apartments. The baseline post-lockdown effect is 0.10 (s.e. 0.10), and the implied effect for households living in a villa is -0.09 (0.10 - 0.19), corresponding to a decline of about -8.6%. By contrast, households living in an apartment in a building with fewer than 10 units show an implied effect of 0.31 (0.10 + 0.21), equal to about 36.3% in level.

In the fourth column, the interaction effect with gender is shown. The baseline post-lockdown effect for male household heads is 0.09 (s.e. 0.04), while the additional effect for female household heads is 0.04 (s.e. 0.05). The implied effect for female heads is therefore 0.13, but the gender differential is not statistically significant, indicating no robust heterogeneity by gender.

In the fifth column, the interaction effect with income decile is reported. The reference category is the 10th income decile, for which the baseline post-lockdown effect is 0.34 (s.e. 0.21). The implied effects for the other deciles are obtained by adding the corresponding interaction term to this baseline. The resulting effects are 0.62 for the first decile, 0.24 for the second, -0.08 for the third, 0.08 for the fourth, 0.09 for the fifth, 0.03 for the sixth, 0.23 for the seventh, -0.24 for the eighth, and 0.15 for the ninth. In percentage terms, these correspond respectively to +85.9%, +27.1%, -7.7%, +8.3%, +9.4%, +3.0%, +25.9%, -21.3%, and +16.2%. The statistically significant differential terms indicate that the post-lockdown effect is heterogeneous across income groups, with the strongest negative deviations observed in the third and eighth deciles.

In the sixth column, the interaction effects concerning the building construction period are reported. The reference category is dwellings built after 2009, for which the baseline post-lockdown effect is 0.15 (s.e. 0.18). The implied effects for dwellings built in the 2000-2009 period, in the 1990s, and in the 1950s-1980s are 0.34, 0.13, and 0.09, respectively, corresponding to +40.5%, +13.9%, and +9.4%. These estimates do not indicate pronounced heterogeneity across construction periods.

In the seventh column, the interaction effects with the number of rooms are reported.

The omitted category is one-room dwellings, with a baseline post-lockdown effect of 0.24 (s.e. 0.16). The implied effects are 0.06 for two-room dwellings, 0.16 for three-room dwellings, -0.04 for four-room dwellings, and 0.22 for dwellings with more than four rooms. In percentage terms, these correspond approximately to +6.2%, +17.4%, -3.9%, and +24.6%, respectively. The only statistically significant differential term is observed for four-room dwellings, but once the baseline is added, the implied effect is close to zero.

Finally, in the eighth column, the interaction effects with square meters are reported. The reference category is dwellings smaller than 55 $m^2$, with a baseline post-lockdown effect of 0.06 (s.e. 0.06). The implied effects are 0.14 for dwellings of 56-70 $m^2$, -0.09 for 71-80 $m^2$, 0.01 for 81-90 $m^2$, 0.21 for 91-110 $m^2$, and 0.20 for dwellings of at least 111 $m^2$. These correspond approximately to +15.0%, -8.6%, +1.0%, +23.4%, and +22.1%, respectively. The main statistically significant differential term is found for dwellings of 71-80 $m^2$, although the implied total effect remains modest in size.

| Variables | Region | Job position | Type of dwelling | Gender of the head of the household | Income decile | Building construction period | Number of rooms | Square meters |
|---|---|---|---|---|---|---|---|---|
| Treat * post | −0.00 (0.11) | −0.06 (0.07) | 0.10 (0.10) | 0.09 (0.04)* | 0.34 (0.21) | 0.15 (0.18) | 0.24 (0.16) | 0.06 (0.06) |
| Abruzzo | 0.21 (0.14) | | | | | | | |
| Basilicata | 0.00 (0.20) | | | | | | | |
| Calabria | 0.31 (0.22) | | | | | | | |
| Campania | 0.33 (0.10)*** | | | | | | | |
| EmiliaRomagna | 0.29 (0.17)* | | | | | | | |
| FriuliVenezia Giulia | −0.64 (0.20)*** | | | | | | | |
| Lazio | 0.29 (0.17)* | | | | | | | |
| Liguria | −0.02 (0.32) | | | | | | | |
| Lombardia | −0.08 (0.19) | | | | | | | |
| Marche | 0.08 (0.26) | | | | | | | |
| Molise | −0.56 (0.18)*** | | | | | | | |
| Piemonte | 0.21 (0.22) | | | | | | | |
| Puglia | 0.24 (0.21) | | | | | | | |
| Sardegna | 0.05 (0.16) | | | | | | | |
| Sicilia | 0.19 (0.16) | | | | | | | |
| TrentinoAlto Adige | 0.35 (0.17)** | | | | | | | |
| Umbria | −1.63 (0.20)*** | | | | | | | |
| Valle d'Aosta | −0.20 (0.18) | | | | | | | |
| Veneto | −0.15 (0.17) | | | | | | | |
| | | | | | | | | |
| Manager | | 0.28 (0.39) | | | | | | |
| Executive | | −0.12 (0.12) | | | | | | |
| Office worker | | 0.24 (0.06)*** | | | | | | |
| Entrepreneur or freelancer | | 0.16 (0.08)* | | | | | | |
| | | | | | | | | |
| Villa | | | −0.19 (0.19) | | | | | |
| Apartment in a building with fewer than 10 apartments | | | 0.21 (0.06)*** | | | | | |
| | | | | | | | | |
| Female | | | | 0.04 (0.05) | | | | |
| | | | | | | | | |
| First income decile | | | | | 0.28 (0.36) | | | |
| Second income decile | | | | | −0.10 (0.20) | | | |
| Third income decile | | | | | −0.42 (0.16)*** | | | |
| Fourth income decile | | | | | −0.26 (0.22) | | | |
| Fifth income decile | | | | | −0.25 (0.12)** | | | |
| Sixth income decile | | | | | −0.31 (0.18)* | | | |
| Seventh income decile | | | | | −0.11 (0.17) | | | |
| Eighth income decile | | | | | −0.58 (0.27)** | | | |
| Ninth income decile | | | | | −0.19 (0.10)* | | | |
| | | | | | | | | |
| 2000–2009 | | | | | | 0.19 (0.22) | | |
| 1990s | | | | | | −0.02 (0.09) | | |
| 1950s–1980s | | | | | | −0.06 (0.22) | | |
| | | | | | | | | |
| 2 | | | | | | | −0.18 (0.25) | |
| 3 | | | | | | | −0.08 (0.21) | |
| 4 | | | | | | | −0.28 (0.15)* | |
| >4 | | | | | | | −0.02 (0.30) | |
| | | | | | | | | |
| 56–70 m² | | | | | | | | 0.08 (0.13) |
| 71–80 m² | | | | | | | | −0.15 (0.09)* |
| 81–90 m² | | | | | | | | −0.05 (0.18) |
| 91–110 m² | | | | | | | | 0.15 (0.11) |
| 111 m² | | | | | | | | 0.14 (0.13) |
| Observations | 2,264 | 2,264 | 2,264 | 2,264 | 2,264 | 2264 | 2,264 | 2,264 |
| Adjusted $R^2$ | 0.56 | 0.56 | 0.55 | 0.55 | 0.56 | 0.55 | 0.55 | 0.55 |

Table 2.10: Heterogeneous effects of the treatment on household electricity consumption. The dependent variable is the logarithm of household electricity consumption (kWh). Standard errors are clustered at the month level. The baseline specification includes region, month, and year fixed effects. Each column reports estimates for a different subgroup definition: Column 1 uses Tuscany as the omitted category; Column 2 uses factory workers; Column 3 considers buildings with more than 10 apartments; Column 4 refers to male household heads; Column 5 to households in the 10th income decile; Column 6 to dwellings built after 2009; Column 7 to households with one room; and Column 8 to dwellings smaller than 55 square meters. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

#### 2.7.1.4 Quantile Regression

An in-depth analysis was conducted to determine whether the effect of the treatment on the treatment group differs from that on the control group across the various quantiles of monthly electricity consumption. Equation (2.1) is therefore estimated using quantile regression; specifically, the three quantiles are estimated. The results are shown in Table 2.11 (full results are reported in Tables 2.25-2.27 in Appendix 2.A.5). The *treated * post* coefficient measures the effect of the lockdown on energy consumption among individuals who worked from home, relative to those who continued to work on-site. In the results, this coefficient is positive but not always statistically significant: at the median quantile (0.5), it equals 0.09 and is significant (p = 0.028), whereas it is not significant at the lower (0.25) and upper (0.75) quantiles. This suggests that the lockdown led to an increase in consumption mainly for households with average consumption levels, while households with very low or very high consumption did not significantly alter their energy behavior. The positive effect indicates that, on average, smart working shifted part of energy consumption from the workplace to the home, but the impact was not uniform across the full consumption distribution.

| | $\tau = 0.25$ | | | $\tau = 0.50$ | | | $\tau = 0.75$ | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Estimate** | **SE** | **P-value** | **Estimate** | **SE** | **P-value** | **Estimate** | **SE** | **P-value** |
| Treated | -0.07399** | 0.03452 | 0.03216 | -0.02475 | 0.01992 | 0.21433 | -0.01261 | 0.01835 | 0.49223 |
| Post | 0.00454 | 0.06595 | 0.94511 | 0.05821 | 0.06153 | 0.34418 | 0.07277 | 0.09634 | 0.45009 |
| **Treated * Post** | **0.06822** | 0.06776 | 0.31406 | **0.09242**** | 0.04200 | 0.02782 | **0.05913** | 0.08029 | 0.46153 |

Table 2.11: Quantile regression results for selected coefficients at the 25th, 50th, and 75th percentiles. The dependent variable is the logarithm of household electricity consumption in kWh. The table reports the coefficients of the treatment indicator, the post-lockdown indicator, and their interaction. The full set of controls, month, year, and region fixed effects are included in all specifications. Standard errors are clustered at the month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

#### 2.7.1.5 Robustness Check

As a robustness check, we assess whether the estimated effect of the lockdown is driven by the identification strategy rather than by pre-existing differences between treated and control households. To this end, we conduct placebo and falsification tests. These exercises are intended to verify that the model does not detect significant treatment effects in periods in which no treatment occurred, while still identifying the expected effect during the actual lockdown period. The placebo test consists of shifting the reference period to a fictitious pre-lockdown date, using January 2019 as the placebo baseline. If the identification strategy is valid, the estimated coefficients before the actual lockdown should be close to zero and statistically insignificant, indicating the absence of differential pre-trends between treated and control households. Conversely, significant effects should emerge only around the true lockdown period, when treated households were actually required to remain at home.

The falsification test further examines whether the model detects an effect of the lockdown on household expenditure categories that should not plausibly respond to the treatment. The rationale is that, if the identification strategy is credible, the estimated treatment effect should emerge for residential electricity consumption, but not for unrelated or weakly related household costs. Finding no significant effects on these placebo outcomes would therefore reduce the concern that the main results are driven by unobserved shocks, differential trends, or broader changes in household expenditure unrelated to electricity use.

Taken together, the placebo and falsification tests provide evidence on the credibility of the Difference-in-Differences design and on the reliability of the estimated impact of the lockdown on residential electricity consumption.

The placebo regression results (Figure 2.12), with the baseline shifted to January 2019, confirm the validity of the methodology employed. In the periods preceding the presumed treatment, the coefficients are generally close to zero and not statistically significant, indicating that there were no systematic differences between the treated and control

groups prior to the reference period. This suggests that the groups were comparable before the onset of the 'placebo treatment'.

In the months corresponding to the actual lockdown, by contrast, statistically significant coefficients emerge, consistent with the expected effect: individuals working from home exhibit energy consumption patterns different from those who continued to work on-site. For example, at time t0 a significant coefficient is observed (0.196, $p = 0.037$), while in subsequent periods the differences between the two groups remain consistent. This pattern suggests that the model correctly detects genuine effects when they are present, without generating false positives in the periods preceding treatment.

Overall, the placebo test confirms that shifting the baseline to a fictitious period does not produce artefacts, and that the estimated impact of the lockdown on the energy consumption of workers in smart working, relative to those who continued to work on-site, can be regarded as reliable.

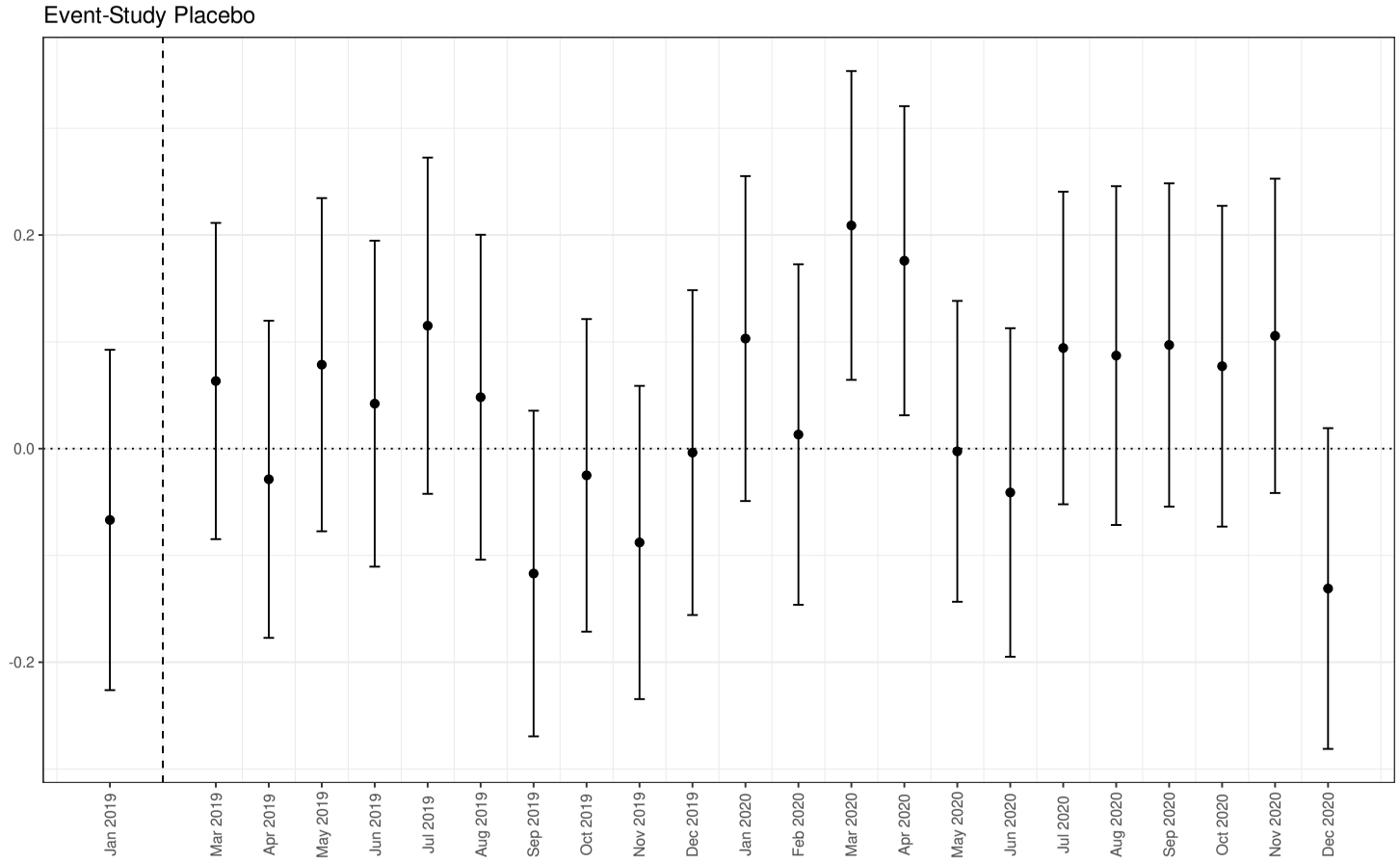



Table 2.12: Placebo event-study estimates of treatment effects on log household energy consumption. This figure reports the differences in the logarithm of monthly household energy consumption between the treatment and control groups using a placebo specification with the baseline shifted to January 2019. Monthly coefficients are shown with 90% confidence intervals.

For what concerns the falsification tests, they are implemented by estimating the same Pooled-DiD model used in the main analysis, but replacing the dependent variable with a set of placebo outcomes, namely variables that should not be affected by the treatment. Specifically, we consider indicators related to different components of household expenditure: expenses for installment payments on durable goods, condominium fees, and the rent for owner-occupied housing. These variables are, by their nature, determined by contractual arrangements or relatively rigid consumption habits in the short run and should therefore not react to the intervention under study.

The results are consistent with this expectation. Across all specifications (Table 2.13), the coefficient on the interaction term between treatment and the post period is statistically insignificant and very close to zero. This provides no evidence of an effect of the treatment on these placebo variables. The absence of spurious effects is an important piece of evidence supporting the validity of the empirical approach adopted here, as it suggests that the differences estimated in the main analysis are not driven by pre-existing dynamics or confounding factors, but rather plausibly reflect a genuine impact of the treatment on the outcomes of interest. Full results are reported in Tables 2.28-2.30 in Appendix 2.A.6.

| | Treated | | | Post | | | Treated * Post | | |
|---|---|---|---|---|---|---|---|---|---|
| **Outcome variable** | **Estimate** | **SE** | **P-value** | **Estimate** | **SE** | **P-value** | **Estimate** | **SE** | **P-value** |
| Durable goods installments | 117.67 | 143.19 | 0.4113 | 364.92*** | 90.60 | 0.0001 | 51.30 | 179.17 | 0.7746 |
| Condominium fees | 92.00 | 134.00 | 0.4918 | -315.00* | 160.00 | 0.0486 | 172.00 | 267.00 | 0.5203 |
| Rent payments | -166.00 | 155.00 | 0.2849 | 533.00 | 331.00 | 0.1076 | 262.00 | 195.00 | 0.1794 |

Table 2.13: Falsification tests. This table reports selected Pooled-DiD estimates for household expenditure categories that are not expected to be directly affected by the lockdown-induced increase in time spent at home. For each outcome, the table reports the coefficients on the treatment indicator, the post-lockdown indicator, and their interaction, together with standard errors and p-values. The full set of controls, month, year, and region fixed effects are included in all specifications. Standard errors are clustered at the survey-wave level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

As an additional robustness check, the Pooled-DiD model was re-estimated using a more restricted subset of ATECO codes, constructed to mirror the sectors available for the subsequent analysis of commercial buildings. Table 2.14 reports this classification. The results confirm the stability of the estimates: the treatment effect remains positive and of comparable magnitude to that obtained in the baseline specification. More specifically, the DID coefficient increases from 0.106 in the full sample to 0.130 under the alternative scenario. Moreover, the confidence intervals associated with the estimates based on the restricted sample substantially overlap with those of the baseline specification, indicating a high degree of statistical consistency across model configurations.

Overall, this evidence suggests that the increase in residential energy consumption associated with remote work during the lockdown does not materially depend on the sectoral composition of ATECO codes in the reference sample, thereby reinforcing the validity of employing narrower sectoral subsets in the subsequent analysis of commercial buildings.

| **Alternative Model** | **Estimate** | **Standard Error** | **P-value** |
|---|---|---|---|
| Treated * post | 0.12 | 0.072 | 0.07 |

Table 2.14: Robustness check: Pooled-DiD estimates using a restricted ATECO sector sample. This table reports pooled-DiD estimates based on the restricted ATECO sector subset described in Table 2.14.

### 2.7.2 Model 2

#### 2.7.2.1 Identification

In Model 2, the dependent variable is the household head's daily commuting time, measured in minutes. The model compares the commuting time of individuals who continued to travel to work with that of treated individuals, whose commuting time is set to zero because they were required to remain at home during the lockdown.

To assess the plausibility of the parallel trends assumption, we implement an event-study specification and report the estimated lead and lag coefficients in Figure 2.7. The coefficients are expressed relative to February 2020 (event time -1), which serves as the baseline period.

The key identifying requirement in a DiD framework concerns the absence of differential pre-treatment trends. In this respect, Figure 2.7 shows that the lead coefficients are small in magnitude and statistically indistinguishable from zero, providing evidence consistent with parallel pre-treatment dynamics between treated and control individuals. This supports the credibility of the identifying assumption that, absent the lockdown, commuting time for the two groups would have evolved similarly. Post-treatment coefficients, however, must be interpreted with caution. During the lockdown months, commuting time for treated individuals is mechanically set to zero, reflecting the institutional prohibition of commuting. By contrast, commuting time for the control group is not directly observed in 2020 but reconstructed through statistical matching from the pre-pandemic time-use survey. Therefore, post-treatment estimates should be interpreted as deviations from a pre-pandemic commuting benchmark rather than as differences in actually observed commuting behavior under lockdown conditions. In this sense, the event-study design provides evidence on the plausibility of parallel trends in the pre-treatment period, while the post-treatment dynamics capture the gap between lockdown-induced zero commuting for treated units and the synthetic counterfactual commuting time for the control group.

The units of observation are the household reference persons of the families included in

the previous analysis, whose characteristics for the two comparison groups were described earlier.

Finally, with regard to SUTVA, the assumption appears plausible in this context. During the lockdown, mobility restrictions and the ban on gatherings substantially limited the possibility of commuting interactions across households, such as car pooling or other forms of shared travel, thereby reducing the scope for interference between units. Moreover, the treatment is not multi-valued, as it corresponds to a single policy regime distinguishing isolated or remote workers from workers remaining on-site. Since commuting time is defined at the individual level and imputed to the household reference person, the potential for spillovers across units is almost impossible. For these reasons, SUTVA is assumed to hold in our setting.

#### 2.7.2.2 Pooled-DiD Estimates

The results of the estimated equation (2.2) are reported in Table 2.15. The key parameter of interest in the Pooled-DiD model is the coefficient on the *treated * post* interaction term, which captures the estimated causal effect of the lockdown on commuting time for the treated group relative to the control group. The estimated coefficient is -28.13, with a standard error of 4.3, and is highly statistically significant ($p < 0.01$).

This implies that, during the lockdown period (March–May 2020), individuals in the treated group experienced, on average, a reduction in commuting time of approximately 28 minutes relative to the control group, conditional on individual, household, and territorial characteristics, as well as weather conditions included in the model. From an interpretative standpoint, this result is consistent with the hypothesis that occupations classified as treated underwent a larger decline in home-to-work mobility during the restriction period, plausibly due to the suspension of certain economic activities or the expansion of remote work arrangements.

Overall, the model yields an adjusted R-squared of 0.064. Although relatively low, this value is typical in regressions based on behavioral microdata, where a substantial portion of individual-level variation remains unobserved.

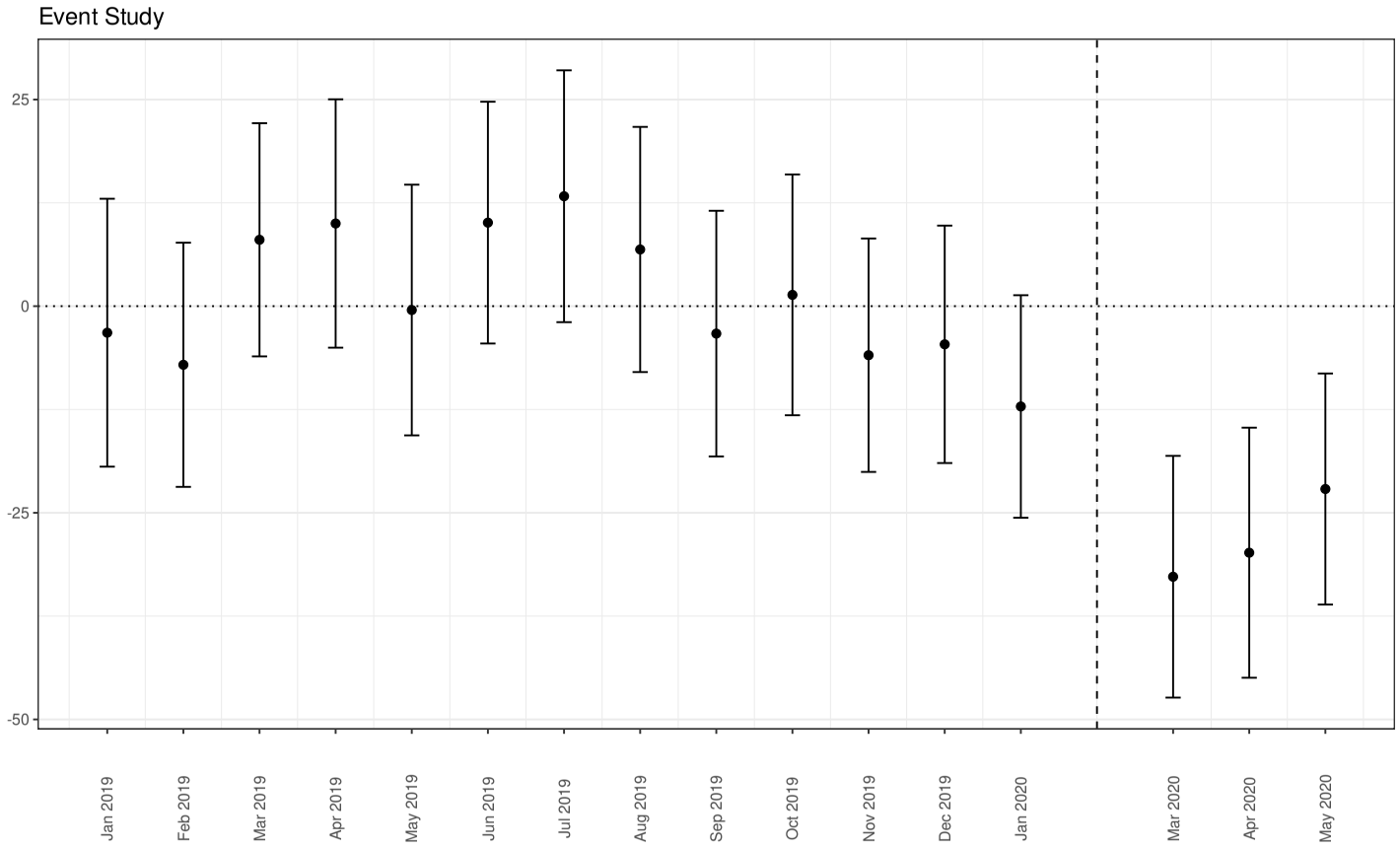



Figure 2.7: Event-study estimates of treatment effects on daily commuting time. This figure reports the differences in daily commuting time between the treatment and control groups relative to the treatment date. Monthly coefficients are shown with 90% confidence intervals.

| Variable | Estimates (SE) |
|---|---|
| Intercept | 24.15 (35.75) |
| Treated | -2.42 (1.98) |
| Post | 4.94 (3.36) |
| **Treated * Post** | **-28.13 (4.3)*** ** |
| February | -0.67 (3.49) |
| March | 5.11 (6.4) |
| April | -2.89 (10.2) |
| May | 0.66 (13.05) |
| June | 2.53 (18.02) |
| July | 14.56 (18.38) |
| August | 3.2 (16.92) |
| September | 6.64 (13.08) |
| October | 7.72 (10.24) |
| November | 1.06 (6.64) |
| December | -0.52 (4.3) |
| Year: 2020 | 1.5 (2.78) |
| Region= Basilicata | -23.42 (6.28)*** |
| Region= Calabria | -2.76 (10.23) |
| Region= Campania | -8.64 (7.65) |
| Region= Emilia-Romagna | -19.87 (5.98)*** |
| Region= Friuli-Venezia Giulia | -26.54 (8.73)*** |
| Region= Lazio | -19.35 (6.08)*** |
| Region= Liguria | -16.07 (6.77)** |
| Region= Lombardia | -19.13 (9)** |
| Region= Marche | -24.68 (8.2)*** |
| Region= Molise | -16.36 (7.34)** |
| Region= Piemonte | -26.02 (6.97)*** |
| Region= Puglia | -20.11 (5.34)*** |
| Region= Sardegna | -20.98 (6.15)*** |
| Region= Sicilia | -16.93 (6.03)*** |
| Region= Toscana | -15.13 (4.16)*** |
| Region= Trentino-Alto Adige | -22.98 (9.97)** |
| Region= Umbria | -23.64 (7.34)*** |
| Region= Valle d'Aosta | -31.16 (11.42)*** |
| Region= Veneto | -18.71 (8.59)** |
| Type of dwelling= apartment in a building with fewer than 10 apartments | 1.23 (2.21) |
| Type of dwelling= apartment in a building with more than 10 apartments | 1.74 (2.01) |
| Type of dwelling= other | -16.18 (10.61) |
| Type of municipality: Metropolitan area suburbs and municipalities with 50,000 inhabitants or more | 0.46 (2.24) |
| Type of municipality: Other municipalities with up to 50,000 inhabitants | 1.53 (2.47) |
| Working area= Intellectual, scientific, and highly specialized professions | 1.68 (8.17) |
| Working area= Technical professions | 3.37 (8.72) |
| Working area= Executive professions in office work | 1.85 (7.92) |
| Working area= Skilled professions in commercial activities and services | 9.99 (8.2) |
| Working area= Craftsmen, skilled workers, and farmers | 2.66 (12.65) |
| Working area= Plant operators, stationary and mobile machinery operators, and vehicle drivers | 16.27 (6.92)** |
| Working area= Unskilled occupations | 7.05 (7.6) |
| Working area= Armed forces | 1.47 (13.06) |
| Source of income= Income from self-employment | -13.83 (7.34)* |
| Second income decile | 2.29 (5.02) |
| Third income decile | 0.62 (4.51) |
| Fourth income decile | -1.42 (4.31) |
| Fifth income decile | -4.53 (4.27) |
| Sixth income decile | 0.29 (3.95) |
| Seventh income decile | -4.11 (4.78) |
| Eighth income decile | 1.44 (3.9) |
| Ninth income decile | 0.82 (6) |
| Tenth income decile | 3.64 (6.3) |
| Log (price) | 2.86 (1.36)** |
| Average maximum temperature | 1.95 (1.35) |
| Average minimum temperature | -3.59 (1.43)** |
| Average wind speed | 1.36 (2) |
| Average rainfall | 0.2 (0.56) |
| Average solar radiation | 0 (0) |
| CDD | 0.01 (0.08) |
| HDD | -0.03 (0.06) |
| Gender of the head of the household = male | -2.11 (2.09) |
| Level of education= primary school diploma | 16.79 (8.24)** |
| Level of education= middle school diploma | 8.07 (6.41) |
| Level of education= two- or three-year vocational diploma | 4.81 (5.22) |
| Level of education= five-year secondary-school diploma | 3.25 (6.13) |
| Level of education= university degree or equivalent | 8.22 (6.04) |
| Level of education= other | 19.38 (4.81)*** |
| Age of the head of the household | 0.11 (0.15) |
| Job position= executive | 10.17 (5.82)* |
| Job position= office worker | 10.23 (6.21)* |
| Job position= factory worker | 2.99 (7.25) |
| Job position= entrepreneur or freelancer | 2.67 (8.56) |
| Ownership= private enterprise or company | 17.27 (10.26)* |
| Internet availability= yes | 1.35 (3.97) |
| Construction period= post-2009 | -3.38 (2.65) |
| Construction period= 2000–2009 | -3.88 (2.31)* |
| Construction period= 1990s | -4.07 (2.51) |
| Number of rooms | -1.17 (1.05) |
| Square meters of living space | 0.02 (0.04) |
| Number of observations | 1935 |
| Adjusted $R^2$ | 0.064 |

Table 2.15: Pooled-DiD regression results for commuting time. This table reports the estimates from regression equation (2.2), where the dependent variable is individual commuting time (in minutes). Standard errors are clustered at the month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The bold coefficient indicates the difference-in-differences estimate of interest, corresponding to the interaction between the treated (staying at home) indicator and the post-lockdown indicator.

Table 2.16 reports the results of the event-study Pooled-DiD analysis. The coefficients for the months preceding the treatment (from event time -14 to -2) are all statistically insignificant and fluctuate around zero. This finding suggests that, prior to the introduction of the lockdown, there were no systematic differences in commuting time between the treated and control groups.

In our dataset, commuting time for the treated group was set to zero during the lockdown months. This implies that, in the months following the introduction of the shock, the estimated variation in the event-study coefficients primarily reflects changes in commuting within the control group, while the treated group remains mechanically near zero. Consequently, differences in the estimated coefficients across post-treatment months should not be interpreted as real changes in the lockdown effect for the treated group. Since treated units are assigned zero commuting time during the lockdown, while control units retain commuting times imputed from pre-pandemic conditions, the post-treatment coefficients mainly reflect the gap between an institutionally imposed zero and a synthetic pre-pandemic commuting benchmark.

Given this construction of the variable, the most informative aspect of the results is the sharp discontinuity observed in the month of the lockdown's introduction, when the coefficient becomes strongly negative and statistically significant. This finding indicates a marked reduction in commuting time for the treated group relative to the control group, consistent with mobility restrictions and the suspension or reorganization of many work activities during the pandemic period.

| Term | Estimate | SE | P-value |
|---|---|---|---|
| $\beta_{-14}$ | -3.21 | 9.85 | 0.74 |
| $\beta_{-13}$ | -7.09 | 8.98 | 0.43 |
| $\beta_{-12}$ | 8.03 | 8.57 | 0.35 |
| $\beta_{-11}$ | 10.00 | 9.13 | 0.27 |
| $\beta_{-10}$ | -0.47 | 9.22 | 0.96 |
| $\beta_{-9}$ | 10.11 | 8.89 | 0.26 |
| $\beta_{-8}$ | 13.30 | 9.26 | 0.15 |
| $\beta_{-7}$ | 6.86 | 9.01 | 0.45 |
| $\beta_{-6}$ | -3.32 | 9.03 | 0.71 |
| $\beta_{-5}$ | 1.37 | 8.85 | 0.88 |
| $\beta_{-4}$ | -5.93 | 8.58 | 0.49 |
| $\beta_{-3}$ | -4.62 | 8.73 | 0.60 |
| $\beta_{-2}$ | -12.14 | 8.18 | 0.14 |
| $\beta_0$ | -32.74 | 8.89 | 0.00 |
| $\beta_1$ | -29.83 | 9.19 | 0.00 |
| $\beta_2$ | -22.12 | 8.49 | 0.01 |

Table 2.16: Event-study estimates of treatment effects on daily commuting time. This table reports the differences in individual daily commuting time between treated and control heads of household relative to the treatment date. Each coefficient corresponds to a specific month before $(t-k)$ or after $(t+k)$ treatment, along with the associated standard errors and p-values.

The estimate, expressed in minutes saved and derived from the econometric model, is subsequently converted into energy terms in order to standardize the analysis and provide an interpretation focused on the energy dimension (Table 2.17 and 2.18). To do so, we used time-use survey data to identify the shares of time devoted to commuting by transport mode, calculating how total commuting time is distributed across the various modes. These shares allow the estimated saving from the Pooled-DiD model, referring to time not spent commuting during the lockdown months, to be allocated while accounting for the fact that not all individuals use the same mode of transport. In this way, we reconstructed a valid estimate that reflects the actual transport modes used in each individual's typical day.

Next, the average commuting time associated with each transport mode was estimated and used as a benchmark for calculating the effective time savings. This makes it possible to assess the extent to which the adoption of smart working can reduce time spent commuting, especially for modes with high energy intensity.

For each transport mode, we estimated an average speed based on the literature, which made it possible to derive the distance travelled and the potential saving for smart workers. Using literature-based data on kWh consumption per kilometre travelled, we calculated the energy use associated with each mode under the two scenarios. Subsequently, since consumption has different weights depending on the share of workers using each mode, we weighted the mode-specific results, both the savings and the average consumption per mode-according to the shares of workers by transport mode.

The estimated saving corresponds to 48% of total consumption for those adopting smart working. Some modes, such as ships or aircraft, are not considered suitable for daily commuting and were therefore excluded (with a consumption value of zero) to avoid distortions in the estimates.

This percentage change cannot be directly compared with changes in residential consumption or commercial building energy use, as it does not derive from the same calculation basis. For this reason, the values are reported at the population level. Specifically, starting

from a working population of 24 million (Istat) and using the shares of workers by transport mode, we distributed the working population according to the mode used for commuting. We then multiplied the individual savings and average consumption values by mode, using the unweighted figures because the weighting is applied when allocating workers across transport modes. Finally, since the estimates from the other two models are on a monthly scale, we multiplied the results by 24 days, corresponding to the number of working days in a month, in order to obtain comparable figures.

| Time savings from commuting in minutes (model estimate) | Mode of Transportation | Time-related incidence by mode of transport | Time saved from commuting in minutes | Average sample time for commuting in minutes | Time saved from commuting in hours | Average sample time for commuting in hours |
|---|---|---|---|---|---|---|
| -28 | Car | 61,76 | -17,29 | 20,38 | -0,288213333 | 0,339705484 |
| | Foot | 15,45 | -4,33 | 13,66 | -0,0721 | 0,227727476 |
| | bus | 6,22 | -1,74 | 30,71 | -0,029026667 | 0,511860175 |
| | Other not specified mode of transportation | 5,17 | -1,45 | 18,31 | -0,024126667 | 0,305238415 |
| | Camion | 3,17 | -0,89 | 24,64 | -0,014793333 | 0,410652921 |
| | Train | 2,46 | -0,69 | 34,26 | -0,01148 | 0,570987654 |
| | Motorbike | 2,34 | -0,66 | 18,75 | -0,01092 | 0,312563323 |
| | Bike | 1,85 | -0,52 | 15,87 | -0,008633333 | 0,264545949 |
| | Tram | 1,14 | -0,32 | 25,73 | -0,00532 | 0,428774929 |
| | Other private means of transportation | 0,1 | -0,03 | 20,37 | -0,000466667 | 0,339506173 |
| | Other public mode of transportation | 0,1 | -0,03 | 44,17 | -0,000466667 | 0,736111111 |
| | Boat | 0,09 | -0,03 | 25,56 | -0,00042 | 0,425925926 |
| | Boat (other categories) | 0,06 | -0,02 | 30,91 | -0,00028 | 0,515151515 |
| | Taxi | 0,04 | -0,01 | 19,17 | -0,000186667 | 0,319444444 |
| | Airplane | 0,04 | -0,01 | 100,00 | -0,000186667 | 1,666666667 |

Table 2.17: Analysis of changes in commuting time due to the lockdown in terms of energy consumption. The table reports the conversion of time savings from reduced commuting-observed for the treatment group relative to the control group-into energy consumption by transport mode. First, the estimated reduction in commuting time was allocated across transportation modes according to each mode's share of total daily commuting time, as reported in the survey. Subsequently, the average daily commuting time per mode was calculated based on survey responses. These time estimates were then translated into energy consumption values using data from the literature on average travel speeds by transport mode in urban and suburban contexts, along with mode-specific energy consumption expressed in Mtoe per unit of distance traveled (later converted into kWh). In addition, the estimates were weighted by the proportion of workers using each transportation mode within the survey sample. The resulting figures were then extrapolated to the entire Italian workforce (approximately 24 million workers) and scaled to a representative commuting month (24 working days). Energy consumption for non-motorized modes (walking and cycling) was set to zero. Similarly, transportation modes identified as outliers in daily commuting patterns (e.g., air and maritime transport) were excluded from the calculations.

| Means of Transportation | Average speed by mode of transport (km/h) | Average distance saved (km) | Average distance travelled by the sample during their commute (km) | Energy intensity (toe/km) | Incidence of workers by mode of transport | Energy saved from commuting (toe), weighted by the proportion of workers | Average consumption related to commuting by sample workers (kWh), weighted by the proportion of workers | Italian workforce by mode (according to sample incidence) | Average fuel savings from commuting among the working population (daily) | Average fuel consumption for commuting among the working population (daily) | Average fuel savings from commuting among the working population (monthly; 24 working days) | Average fuel consumption for commuting among the working population (monthly; 24 working days) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Car | 21.5 | -0.1040464067 | 7.3946467067 | 0.147 | 0.580 | -2.1421 | 3.4905 | 14.328.966 | -5.0.09.443 | 3.978.234 | -1.216.309.457 | 31.949.607 |
| Foot | 5 | 0 | 0 | 0.000 | 0.2.317 | 0.0000 | 0.0000 | 5.272.440 | 0 | 0 | 0 | 0 |
| bus | 18.5 | -0.5240993333 | 9.4696 12.213 | 2.6.0 | 0.0393 | -60.023 | 0.9713 | 94.5.190 | -250.239 | 2.53.11.3.47 | -7.019.314 | 1046732.57.3 |
| Other not specified means of transportation | 21.5 | -0.5147.23.33.3 | 6.30.26.25.92.3 | 0.579 | 0.0.0.19 | -60.9.5 | 0.2.0.6 | 1.1.57.4.00 | -0.0.7.29 | 5.0.0.6.3.6.4 | -5.40.7.40.7 | 1.0.1.0.7.1.4.4.6 |
| Cruises | 20 | -0.2.9.9.4.0.6.6.7 | 6.23.3.9.0.4.1.9 | 1.4.20 | 0.0.35 | -0.0.6.4.3 | 0.7.3.2.2 | 60.6.6.0.0 | -1.0.2.7.9.4 | 1.6.6.5.3.9.6 | -2.4.6.6.1.0.8 | 4.0.4.3.7.2.0.1 |
| Trains | 80 | -0.9.34 | 4.54.7.9.4.2.2.5 | 0.0.0.0 | 0.0.1.1.9 | -0.0.5.7.4 | 0.0.9.1 | 3.5.1.4.0.0 | -1.7.7.1.9.8 | 9.4.1.2.1.1 | -4.2.5.7.4.2.2 | 2.1.9.1.0.1.6.5.7 |
| Motorbike | 26 | -0.2.9.9.2 | 8.12.6.6.4.0.3 | 0.2.9.1 | 0.2.3.1.2 | -0.0.4.1.0 | 0.0.7.2 | 3.0.4.6.0 | -0.5.4.7.8 | 1.2.7.3.3.0.7 | -2.2.9.1.4.6.1 | 3.2.9.4.1.7.1.2.2 |
| Car | 21.5 | 0 | 0 | 0.147 | 0.580 | 0.0000 | 0.0000 | 14.328.966 | 0 | 0 | 0 | 0 |
| Train | 80 | -0.9.9.5.1.2 | 6.46.0.9.9.6 | 0.1.0.0 | 0.0.0.1.6 | -0.0.6.0.4 | 0.0.6.0.3 | 2.6.4.4.0.0 | -1.0.1.7.2 | 1.0.1.3.0.9 | -1.0.4.1.2.0.6 | 3.2.9.3.6.7.1.7.9 |
| Other private means of transportation | 21.5 | -0.1.0.1.0.3.2.3.3 | 7.2.9.1.0.7.1.6 | 0.5.7.9 | 0.0.0.1 | 0.0.0.0.0 | 0.0.4.4.2 | 3.1.0.0.6 | -1.9.9 | 1.0.1.4.1.3 | -3.3.4.6 | 3.4.3.4.7.5.1.3.3. |
| Other public means of transportation | 21.5 | -0.1.0.1.0.3.2.3.3 | 21.4.2.0.2.9.0.0 | 0.0.9.6 | 0.0.0.1.4 | 0.0.0.0.0 | 0.0.0.0.3 | 9.6.0.0 | -5.6 | 1.1.1.5 | -1.2.0.6 | 29.17.2. |
| Boat | 11 | -0.1.0.6.2 | 4.0.5.1.0.3.5 | 0.1.9.0 | 0 | 0.0.0.0.0 | 0.0.0.0.0 | 0 | 0 | 0 | 0 | 0 |
| Road 2 | 11 | -0.1.0.3.0.6 | 5.0.0.0.4.0.6.7 | 0.4.9.0 | 0 | 0.0.0.0.0 | 0.0.0.0.0 | 0 | 0 | 0 | 0 | 0 |
| Taxi | 20.8 | -0.9.9.9.2.9.6.7 | 6.4.4.1.4.4.4.1.4 | 0.5.7.9 | 0 | 0.0.0.0.0 | 0.0.0.0.0 | 0 | 0 | 0 | 0 | 0 |
| Airplane | 99.9 | -0.1.6.2.9.9.6.7 | 1.9.0.4.0.9.6.6.7 | 0.5.2.0 | 0 | 0.0.0.0.0 | 0.0.0.0.0 | 0 | 0 | 0 | 0 | 0 |
| Total | | | | -5.1.9.9.4.9.9.9 | | 4.4.7.7.9.4.4.8 | | | | | -1.2.4.1.3.9.9.4.7.9 | 3.4.7.9.9.5.7.7.3 |
| N | | | | | | 48.5 | | | | | 4.85 | |

Table 2.18: Analysis of changes in commuting time due to the lockdown in terms of energy consumption. The table reports the conversion of time savings from reduced commuting-observed for the treatment group relative to the control group-into energy consumption by transport mode. First, the estimated reduction in commuting time was allocated across transportation modes according to each mode's share of total daily commuting time, as reported in the survey. Subsequently, the average daily commuting time per mode was calculated based on survey responses. These time estimates were then translated into energy consumption values using data from the literature on average travel speeds by transport mode in urban and suburban contexts, along with mode-specific energy consumption expressed in Mtoe per unit of distance traveled (later converted into kWh). In addition, the estimates were weighted by the proportion of workers using each transportation mode within the survey sample. The resulting figures were then extrapolated to the entire Italian workforce (approximately 24 million workers) and scaled to a representative commuting month (24 working days). Energy consumption for non-motorized modes (walking and cycling) was set to zero. Similarly, transportation modes identified as outliers in daily commuting patterns (e.g., air and maritime transport) were excluded from the calculations.

#### 2.7.2.3 Robustness Check

Finally, as a robustness check, we conducted placebo tests using an event-study regression with the baseline set to February 2019, in order to verify that the protocol does not produce spurious effects when the treatment did not actually occur. As shown in Figure 2.8, even when the baseline is shifted to February 2019, none of the estimates exhibit confidence intervals indicating statistical significance for the monthly differences between the two groups analyzed.

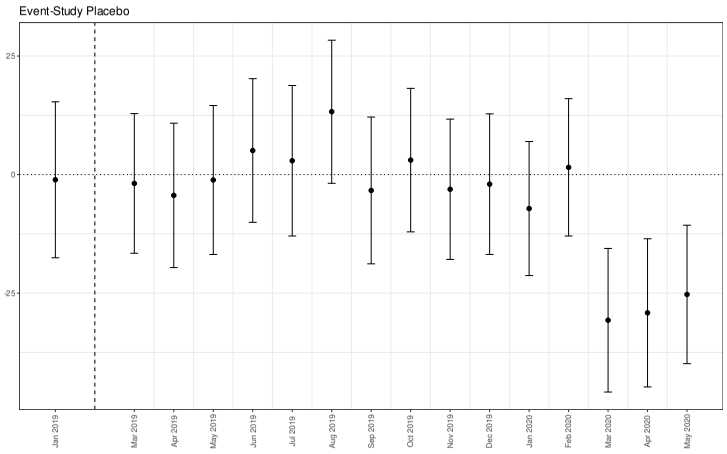



Figure 2.8: Placebo event-study estimates of treatment effects on daily commuting time. This figure reports differences in individual daily commuting time between the treatment and control groups using a placebo specification with the baseline shifted to January 2019. Monthly coefficients are shown with 90% confidence intervals.

### 2.7.3 Model 3

#### 2.7.3.1 Identification

In Model 3, the objective is to estimate the impact of the lockdown on energy consumption within a selected group of service sub-sectors. This restriction is motivated by two main reasons. First, data for other sectors are not available. Second, our focus is on assessing the extent to which the lockdown-used here as a proxy for the widespread adoption of remote work-may have affected electricity consumption in commercial buildings where workers in these sectors typically operate. Concentrating on service sub-sectors is particularly appropriate, as the vast majority of energy consumption in these activities is attributable to the operation of commercial buildings and the activities carried out within them.

The dependent variable is the monthly energy consumption of each sub-sector belonging to either the treated or the control group. The set of regressors mirrors that used in Models 1 and 2, with the addition of variables capturing COVID-19 cases and hospitalizations, both lagged by one month.

As a preliminary step, we tested the parallel trends assumption. Figure 2.9 indicates that the assumption holds. We anticipate that this result is further confirmed when estimating the coefficients and confidence intervals of the leads in the event-study specification of Equation (2.3) (Figure 2.10).

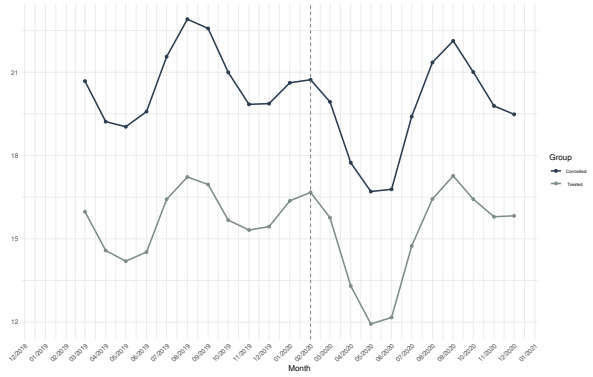



Figure 2.9: Parallel trends in sectoral electricity consumption: treatment vs. control groups. This figure shows the monthly trend in average sectoral electricity consumption (GWh) for the treatment and control groups. The dotted vertical line indicates the onset of the lockdown associated with the SARS-CoV-2 pandemic.

#### 2.7.3.2 DID Estimates

Table 2.19 reports the DiD results. The coefficient on the treatment * post interaction, equal to -0.60 (-45%) and highly statistically significant, represents the estimated causal effect of the lockdown on the treated sectors relative to the control sectors. Since the model is specified in log-level form, the coefficient must be interpreted in percentage terms. Specifically, holding other factors constant, sectors characterized by workers remaining at home experienced an additional reduction in energy consumption of approximately 45% relative to untreated sectors in the post-lockdown period. The effect is therefore not only statistically robust but also economically substantial, pointing to a marked differential impact of the containment measures, consistent with the notion that restrictions on mobility and physical presence disproportionately affected the most exposed sectors. With regard to the adjusted $R^2$, the value of 0.418 indicates that the model explains approximately 41.8% of the total observed variation in energy consumption. This represents a reasonably strong result for a regression model applied to economic data, particularly in a panel setting characterized by substantial cross-sectional and temporal heterogeneity. Turning to the event-study approach, we observe that the estimated coefficients are not statistically significant at the 90% confidence level (Figure 2.10). This may be attributable to the fact that, once the analysis is disaggregated at the monthly level, the number of observations per month and per group becomes very small, leading to large standard errors and consequently wide confidence intervals.

| Variable | Estimate (SE) |
|---|---|
| *Intercept* | 1.53 (3.41) |
| *treated* | -3.59 (0.21)*** |
| *Post* | -0.21 (0.24) |
| ***Treated * Post*** | **-0.60 (0.22)*** ** |
| *Region= Basilicata* | -4.08 (0.54)*** |
| *Region= Calabria* | -0.63 (0.41) |
| *Region= Campania* | 0.99 (0.27)*** |
| *Region= Emilia-Romagna* | 1.42 (0.18)*** |
| *Region= Friuli-Venezia Giulia* | 0.36 (0.36) |
| *Region= Lazio* | 2.11 (0.12)*** |
| *Region= Liguria* | 0.07 (0.13) |
| *Region= Lombardia* | 2.7 (0.25)*** |
| *Region= Marche* | -0.1 (0.12) |
| *Region= Molise* | -9.6 (0.53)*** |
| *Region= Piemonte* | 1.17 (0.26)*** |
| *Region= Puglia* | 0.59 (0.18)*** |
| *Region= Sardegna* | -0.41 (0.3) |
| *Region= Sicilia* | 0.68 (0.38)* |
| *Region= Toscana* | 1.38 (0.17)*** |
| *Region= Trentino-Alto Adige* | -5.87 (0.6)*** |
| *Region= Umbria* | -0.56 (0.21)*** |
| *Region= Valle d'Aosta* | -10.19 (0.5)*** |
| *Region= Veneto* | 1.44 (0.27)*** |
| *Year: 2020* | 0.15 (0.13) |
| *April* | -0.63 (0.57) |
| *December* | 0.65 (1.28) |
| *February* | 0.32 (1.12) |
| *January* | 1 (1.31) |
| *June* | -0.68 (0.3)** |
| *July* | -0.15 (0.24) |
| *May* | -0.94 (0.47)** |
| *March* | -0.07 (0.84) |
| *November* | 0 (1.03) |
| *October* | 0.37 (0.72) |
| *September* | -0.11 (0.38) |
| *Industry: Professional, scientific and technical activitie* | 3.79 (0.15)*** |
| *Industry: Financial and insurance activities* | -2.99 (0.13)*** |
| *Industry: Real Estate* | 1.3 (0.26)*** |
| *Industry: Information and communication services* | 0.54 (0.13)*** |
| *Industry: Human health and social work activitie* | 0.37 (0.13)*** |
| *Industry: Transportation and storage* | 1.11 (0.15)*** |
| *Average maximum temperature* | -0.11 (0.13) |
| *Average minimum temperature* | 0.15 (0.1) |
| *Average wind speed* | 0.19 (0.18) |
| *Average rainfall* | 0.04 (0.03) |
| *Average solar radiation* | 0 (0) |
| *log (Pun price)* | -0.26 (0.47) |
| *CDD* | 0 (0) |
| *HDD* | 0 (0) |
| *1-month lagged new COVID-19 cases per 100k residents* | 0.01 (0.01) |
| *1-month lagged Covid-19 intensive care hospitalized patients per 100k residents* | -0.02 (0.12) |
| *1-month lagged hospitalized with symptoms per 100k residents* | 0 (0.01) |
| | |
| *Adjusted $R^2$* | 0.4177 |
| *Observations* | 2720 |

Table 2.19: Difference-in-differences regression results for sectoral energy consumption. This table reports the estimates from regression equation (2.3), where the dependent variable is monthly sectoral energy consumption. Standard errors are clustered at the month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The bold coefficient indicates the difference-in-differences estimate of interest, corresponding to the interaction between the treated sectors (those whose employees shifted to remote work / were subject to home-confinement restrictions) and the post-lockdown indicator.

#### 2.7.3.3 Robustness Check

Subsequently, we conducted a robustness check in the form of a placebo test, shifting the timing of the intervention to March 2019. Figure 2.11 clearly shows that altering the intervention date in this way does not produce any significant effect, confirming that the main results are not driven by spurious timing patterns.

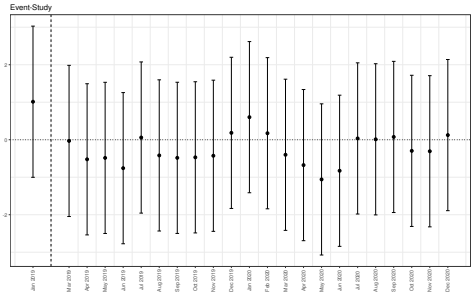



Figure 2.11: Placebo event-study estimates of treatment effects on sectoral monthly energy consumption. This figure reports differences in sectoral monthly energy consumption between the treatment and control groups using a placebo specification with the baseline shifted to January 2019. Monthly coefficients are shown with 90% confidence intervals.

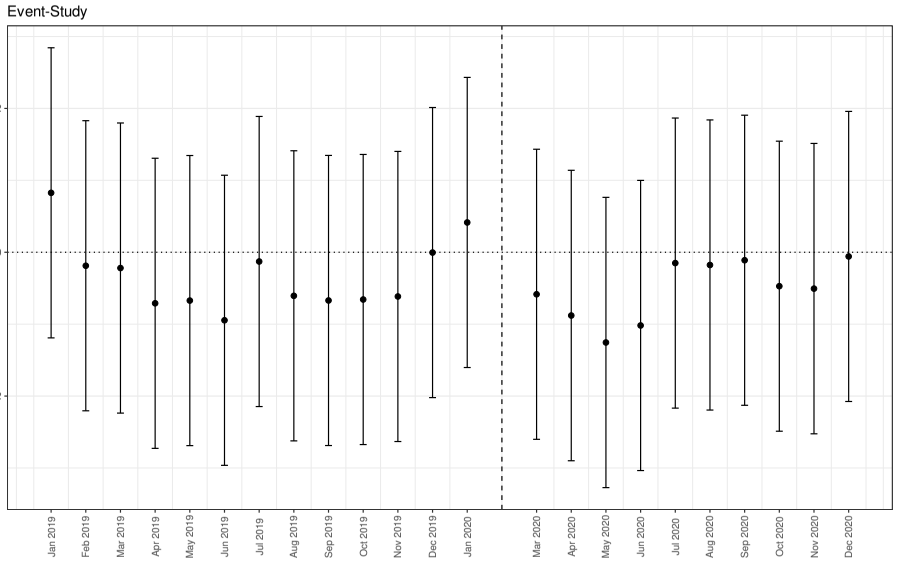



Figure 2.10: Event-study estimates of treatment effects on sectoral monthly energy consumption. This figure reports the differences in sectoral monthly energy consumption (kWh) between the treatment and control groups relative to the treatment date. Monthly coefficients are shown with 90% confidence intervals.

## 2.8 Further Analysis: the Net Effect of 'Stay at Home' Mandate

The final objective of this study is to compute the net energy impact of smart working by combining the three dimensions analyzed in the previous sections: residential electricity consumption, commuting-related energy use, and electricity consumption in the service sector. Let $\bar{Y}_{R0}$, $\bar{Y}_{P0}$, and $\bar{Y}_{S0}$ denote the average of total monthly residential consumption in the pre-treatment period (using sampling weights to recover population aggregates), the average total monthly commuting-related energy consumption, and the average of the total monthly service-sector components, respectively. These averages are computed over the pre-treatment months available in the sample and are intended to represent the baseline monthly level of each component in the population of interest.

The variation associated with the residential component is obtained from the estimated coefficient of Model 1. Since the dependent variable is expressed in logarithms, the effect in levels is given by:

$$\Delta R = \left(e^{\hat{\beta}_1} - 1\right) \bar{Y}_{R0}.$$

Likewise, the effect on the service-sector component is derived from the estimated coefficient of Model 3 and translated into levels as follows:

$$\Delta S = \left(e^{\hat{\beta}_3} - 1\right) \bar{Y}_{S0}.$$

The commuting component is different, because Model 2 estimates the effect of smart working on commuting time, expressed in minutes saved, rather than directly in energy units. For this reason, the estimated coefficient from Model 2 is converted into energy terms through the procedure described in the previous section. Let $\Phi(\hat{\beta}_2)$ denote the full time-to-energy conversion function, which incorporates the allocation of commuting time across transport modes, the average speed associated with each mode, the corresponding energy intensity per kilometre, and the number of working days in a month. The

commuting-related variation is therefore written as:

$$\Delta P = \Phi(\hat{\beta}_2).$$

The net effect of the lockdown mandate in absolute energy terms is then defined as:

$$\Delta Net = \Delta R + \Delta P + \Delta S.$$

To express this impact in percentage terms, the total variation is divided by the sum of the three baseline components:

$$\%\Delta Net = \frac{\Delta R + \Delta P + \Delta S}{\bar{Y}_{R0} + \bar{Y}_{P0} + \bar{Y}_{S0}} \times 100.$$

This measure captures the aggregate energy impact of smart working across the three channels considered in the analysis. It should be interpreted as a harmonized accounting measure, combining effects that are originally estimated using different data structures and units of observation.

The results are reported in Table 2.20 and indicate that the lockdown, interpreted as a proxy for large-scale adoption of smart working, generated heterogeneous effects across the three energy dimensions: residential electricity consumption increased by 12%, reflecting greater time spent at home, while both commuting-related energy use and service-sector electricity consumption experienced substantial reductions, equal to 48% and 45%, respectively; in absolute terms, the reduction in commuting energy consumption represents the largest component of the overall effect, followed by the decline in service-sector consumption, and these two channels more than compensate for the increase in residential demand, resulting in a net decrease in total energy consumption of approximately 47% relative to the pre-treatment baseline.

| Impact of the Lockdown on Energy Dimensions | | |
|---|---|---|
| **Residential (A)** | **Services (B)** | **Commuting (C)** |
| Total average monthly residential electricity consumption before treatment | Total average monthly pre-treatment consumption in the services sector | Total average monthly commuting fuel consumption before treatment |
| 62,919,817 kWh | 150,633,333 kWh | 2,579,095,573 kWh |
| ATET on residential consumption | ATET on sectoral consumption | ATET on commuting fuel consumption |
| +0.12 | -0.45 | -0.48 |
| Impact on residential consumption | Impact on sectoral consumption | Impact on commuting fuel consumption |
| 7,021,851.58 kWh | -67,965,759.85 kWh | -1,242,399,679.45 kWh |
| **Net Effect of the Lockdown (a proxy for remote work)** | | |
| **Consumption Change** | | |
| -1,303,343,587.72 kWh | | |
| **Baseline Consumption (A+B+C)** | | |
| 2,792,648,723 kWh | | |
| **Net effect (as a share)** | | |
| -0.47 | | |

Table 2.20: Net effects of the lockdown on the three dimensions of energy consumption: residential consumption, service-sector consumption, and commuting-related consumption across the relevant populations. Energy consumption is measured in kWh. Baseline consumption refers to total pre-treatment consumption under standard conditions. The reported changes represent total consumption in the counterfactual scenario induced by the lockdown, interpreted as a context of widespread remote work adoption. The analysis is conducted at the monthly level.

The construction of the net effect is subject to several limitations. First, the residential component does not identify smart working in the strict sense, but rather home confinement during the lockdown. The treated group is composed of households that were forced to remain at home instead of working on site, and therefore the estimated residential effect may reflect not only remote work, but also all other activities carried out at home during the lockdown period, such as increased residential presence, caregiving, meal preparation, and more intensive use of household appliances. For this reason, the residential estimate should be interpreted as a proxy for the impact of smart working on home electricity

consumption, rather than as a clean measure of remote work alone. At the same time, because lockdown home confinement was more restrictive than standard teleworking arrangements, the estimated effect may represent an upper bound of the typical smart working effect on residential energy use.

Second, the service-sector component is measured only for service industries and therefore does not cover the whole economy. Moreover, the estimated differential change between treated and control sectors may reflect not only the lower physical presence of workers in commercial buildings, but also the contraction in economic activity, changes in operating hours, demand reductions, and other effects induced by the pandemic and the lockdown. As a consequence, the coefficient from Model 3 should be interpreted as the observed differential reduction in electricity consumption in the treated service sectors, rather than as a purely isolated smart working effect.

Third, the commuting component depends on statistical matching and on a sequence of assumptions used to convert time savings into energy savings. In particular, the construction of the commuting variable may be affected by measurement error, especially because missing values in the donor dataset were recoded as zero before the matching procedure. This may blur the distinction between genuine zero commuting time and missing information treated as zero. In addition, the conversion from commuting time to energy consumption relies on average speeds, mode-specific energy intensities, and the assumed monthly number of working days. These assumptions are necessary for comparability, but they also introduce uncertainty and potential bias.

Finally, the three components are not estimated at the same microeconomic level. The residential effect refers to households, the commuting effect refers to individuals, and the service-sector effect refers to sector-region units. Therefore, the aggregate net effect should be understood as an energy-accounting exercise that combines heterogeneous sources of variation, rather than as a fully homogeneous individual-level causal estimate. Despite this limitation, the resulting measure provides a useful approximation of the overall electricity impact associated with the large-scale adoption of smart working.

## 2.9 Discussion and Policy Implications

This chapter has examined the energy-demand implications of lockdown-induced home confinement in Italy, interpreted as a large-scale and exogenously imposed proxy for the adoption of remote work arrangements. The central objective was to move beyond a partial assessment of telework effects and to evaluate how energy demand was reallocated across three interconnected domains: residential electricity consumption, commuting-related energy use, and electricity consumption in service-sector workplaces. This integrated perspective is particularly relevant because the literature has repeatedly emphasized that telework does not necessarily reduce energy consumption in a mechanical way. Rather, it changes where, when, and by whom energy is consumed, generating potential savings in commuting and office buildings but also higher demand within dwellings and possible rebound effects in mobility and household behaviour (Mokhtarian and Salomon, 1997; Sorrell, 2015; O'Brien and Aliabadi, 2020).

The empirical setting exploited in this chapter is the first Italian COVID-19 lockdown. The institutional classification of economic activities through ATECO codes created a quasi-experimental environment in which some workers were required to remain at home, while others continued working on site. This exogenous policy shock makes it possible to compare treated and control groups in a difference-in-differences framework, reducing the self-selection problems that typically affect studies of telework. The analysis combines several data sources: Istat Household Budget Survey for household electricity expenditure and socio-economic characteristics; Eurostat electricity prices and meteorological data to reconstruct and control for residential electricity consumption; Istat Time Use Survey, matched to household data, to estimate commuting time; and Terna's IMSER dataset to analyse monthly electricity consumption in service-sector activities at the regional-sector level. The empirical design therefore combines household-level, individual-level, and sector-region-level evidence in order to approximate the overall energy balance associated with the shift from on-site to home-based work.

The first result concerns the residential dimension. The estimates indicate that

households forced to stay home increased their electricity consumption by approximately 12 percent relative to comparable households whose members continued working on site. This result is consistent with the expectation that spending more time at home increases the use of lighting, appliances, ICT devices, cooking equipment, heating, cooling, and other domestic services. The event-study evidence suggests that the effect was concentrated in the early phase of the lockdown, particularly in March and April 2020, while it became statistically weaker in May, when restrictions were gradually relaxed. This temporal pattern is important because it suggests that the residential energy impact of remote work was not necessarily a permanent structural shift, but rather a short-run response to an abrupt relocation of work and daily routines into the home. The quantile-regression evidence further shows that the increase was most clearly visible around the middle of the consumption distribution, while low- and high-consumption households did not display equally significant changes. This heterogeneity reinforces the view that the residential energy effect of telework depends on household characteristics, dwelling type, income, work tasks, and the baseline level of residential energy use.

The second result concerns commuting. The estimated effect of the lockdown on commuting time is large and statistically significant: treated workers experienced an average reduction of approximately 28 minutes of daily commuting relative to the control group. When translated into energy terms using information on transport modes, average speeds, mode-specific energy intensity, and the number of working days, this corresponds to a reduction of roughly 48 percent in commuting-related energy consumption for the relevant population. This is the largest component of the total energy saving identified in the chapter. The result is aligned with the literature that identifies the reduction of commuting as the most direct and potentially strongest energy-saving channel of telework (Mokhtarian, 2009; O'Brien and Aliabadi, 2020; Sorrell, 2015). At the same time, the interpretation requires caution. The commuting variable is imputed through statistical matching, and commuting time for treated individuals during lockdown is mechanically set to zero. Therefore, the estimate should be interpreted as the reduction relative to a pre-pandemic commuting benchmark rather than as a direct observation of actual travel

behaviour during the lockdown. Nevertheless, the evidence clearly indicates that avoided commuting is the main channel through which remote work can reduce energy use.

The third result concerns electricity consumption in service-sector workplaces. The estimates show that treated service sectors experienced a substantial reduction in electricity consumption relative to sectors that continued operating on site, with an estimated effect of approximately -45 percent. This finding suggests that the relocation of workers away from offices and other service buildings can generate sizeable reductions in workplace electricity demand. However, the result should not be interpreted as a pure measure of remote work alone. Sector-level electricity consumption during the lockdown may also reflect changes in opening hours, reduced demand for services, lower business intensity, and other pandemic-related disruptions. Even with this caveat, the result remains informative because it reveals the magnitude of electricity demand that is associated with the physical presence of workers and users in service-sector buildings. It is also consistent with the literature showing that commercial-building energy consumption is only partially elastic to occupancy, because offices and service buildings retain base loads related to HVAC systems, lighting, servers, equipment, ventilation, maintenance, and common areas (Cortiços and Duarte, 2022b; Cai and Gou, 2024; Tavakoli et al., 2023).

Taken together, the three components reveal a clear pattern. The lockdown did not simply reduce energy demand; it reallocated energy demand across sectors and spaces. Residential electricity consumption increased, but this increase was more than offset by reductions in commuting-related energy use and service-sector electricity consumption. The accounting exercise conducted in the chapter suggests a net reduction of approximately 47 percent relative to the pre-treatment baseline across the three considered components. The largest contribution came from commuting, followed by service-sector buildings, while the residential increase represented a partial offset. This result confirms that the net energy effect of remote work is context-dependent and depends on the balance between three margins: the transport modes avoided, the degree to which workplace energy use actually falls, and the additional energy consumed at home.

Several limitations should be acknowledged. First, the treatment does not identify voluntary or ordinary smart working, but forced home confinement during an emergency. The residential estimate may therefore represent an upper bound of the effect of standard remote work, because lockdown conditions involved not only working from home but also school closures, restrictions on leisure activities, increased domestic presence, and broader behavioural changes. Second, the service-sector estimate refers only to selected service activities and cannot be generalized to the entire economy. Third, the commuting-energy conversion relies on assumptions about speeds, transport modes, energy intensity, and working days. Finally, the net effect combines estimates obtained at different levels of observation: households, individuals, and sector-region units. For this reason, the final aggregate estimate should be understood as a harmonized energy-accounting exercise rather than as a single homogeneous causal parameter.

Despite these limitations, the chapter provides three important contributions. First, it offers causal evidence for Italy on the energy implications of lockdown-induced remote work, exploiting an institutional shock rather than voluntary telework adoption, at a highly disaggregated level. Second, it shows that analysing only one dimension of telework can be misleading: the residential increase alone would suggest higher electricity demand, while the commuting and workplace effects point in the opposite direction. Third, it demonstrates that the environmental potential of remote work is not automatic. It depends on whether mobility reductions are real and persistent, whether office buildings are actively adapted to lower occupancy, and whether the additional burden placed on households is managed in an efficient and equitable way.

The findings of this chapter have important policy implications (Figure 2.12):

- The first and most general implication is that remote work should not be regarded solely as a labour-market practice or as an internal organisational choice made by firms. Rather, it should be understood more broadly as an instrument of energy-demand policy. The evidence presented here shows that the reorganisation of work simultaneously affects residential electricity consumption, energy use in transport,

and energy demand in commercial buildings. This interpretation is consistent with recent literature showing that the pandemic did not simply reduce aggregate energy consumption, but redistributed it across sectors, places, and times of day (Branchetti et al., 2021; Zapata-Webborn et al., 2023). Therefore, policies should not assess smart working only in terms of productivity, flexibility, or work–life balance, but also in relation to energy efficiency, emissions reduction, electricity-grid management, urban mobility, building quality, distributive equity, and the resilience of the energy system.

- With regard to commuting, the results of this chapter indicate that remote work generates the greatest energy savings when it replaces long and energy-intensive home–work trips, especially those made by car. Policies should therefore focus on workers, firms, and territories where commuting is longer, more car-dependent, and less easily replaceable by public transport or active mobility. In this respect, the literature shows that workers with longer commuting times are among those most likely to continue working remotely, and that an increase in teleworking can reduce car use for work-related purposes (Mohammadi et al., 2023; Kalter et al., 2021). A targeted approach therefore appears more effective than a generalised and undifferentiated promotion of smart working. The territorial dimension is central and calls for place-based policies. These may include, for example, the creation of telework hubs and coworking spaces in peripheral or rural areas, as in the French experience of tiers-lieux, or the integration of remote work into broader territorial development strategies, as in the case of the Autonomous Province of Trento. Such policies are relevant because they can reduce long and car-dependent commuting while limiting the risk that work-related energy demand is simply shifted to private dwellings. Targeted investment in digital connectivity and the coordination of remote work with local mobility services can further increase the effectiveness of these measures. Energy benefits tend to be greater in peripheral areas, car-dependent areas, or areas characterised by long commuting distances, but they may be reduced where dwellings are inefficient, where climate conditions increase household energy

consumption, or where digital connectivity is limited. Moreover, mobility responses vary according to the characteristics of local labour markets, such as the availability of flexible work, exposure to health risks, and the prevalence of precarious contracts (Caselli et al., 2022). Smart working should also be integrated into the management of urban time schedules. Commuting concentrates flows in specific time slots and around major transport nodes, producing congestion and overcrowding (Ghisalberti, 2021). To prevent the benefits from diminishing, hybrid work should be accompanied by staggered starting times, coordinated in-office days, peak spreading, and dynamic demand management. If workers return to the office on the same days or at the same times, the positive effects on traffic, public transport, and energy consumption risk being weakened.

These policies must, however, take account of unequal access to telework. The possibility of working remotely varies by sector, education, income, and type of occupation; many workers remain excluded from this option, and the pandemic expanded this practice in an uneven way (Salon et al., 2022; Reiffer et al., 2023). For this reason, remote work can help reduce mobility demand, but it must not replace investment in public transport, safety, sustainable mobility, and protections for those who must physically travel to work. Policies that increase the cost of commuting would in fact risk penalising precisely those workers who have fewer choices.

Finally, remote work must be accompanied by measures to counter rebound effects. A reduction in home–work trips does not automatically imply an equivalent reduction in kilometres travelled or in energy consumption: the time saved may be reallocated to other trips, to longer occasional journeys, or to residential choices farther from workplaces (Campisi et al., 2022; Liang et al., 2023). To preserve its benefits, hybrid work should be linked to sustainable mobility strategies, such as flexible public transport, cycling infrastructure, walkability, parking management, low-emission zones, and company mobility plans. At the same time, since smart working may

also reduce daily active mobility, cities should strengthen proximity services, local coworking spaces, and compact, multimodal urban models, preventing hybrid work from encouraging urban sprawl, sedentary lifestyles, and greater car dependence.

- With regard to reducing electricity consumption in the service sector, the results show that energy savings depend primarily on the active management of buildings. Lower worker presence does not automatically lead to lower consumption, since many buildings maintain high baseloads: heating and cooling, lighting, lifts, servers, ventilation, security systems, and specialised equipment may continue to operate even with reduced occupancy (Branchetti et al., 2021; Tavakoli et al., 2023).

  To make the benefits of remote work effective, buildings must therefore be adapted to variable occupancy levels. Policies should incentivise firms and public administrations to introduce occupancy-sensitive systems, such as smart lighting, zoned heating and cooling, demand-controlled ventilation, real-time monitoring, advanced building management systems, and automatic shutdown protocols for floors or areas that are little used.

  The organisation of hybrid work is also crucial. Randomly distributed remote-working days have limited effects on office energy consumption, whereas coordinated scheduling by team, floor, or department makes it possible to close, downscale, or concentrate the use of specific areas. If hybrid work leads to a stable reduction in average occupancy, firms may require less space; however, energy savings materialise only if this reduction is translated into the actual concentration, retrofitting, or conversion of buildings. Otherwise, underused offices continue to consume significant amounts of energy.

  Policies should therefore promote the rationalisation of space, particularly in the public sector. Public administrations could conduct audits of occupancy rates, energy consumption, and property use, concentrating activities in more efficient buildings and reallocating vacated or underused premises to new functions, such as social housing, public services, or local work hubs. In this way, smart working

would become part of a broader strategy of energy efficiency, building renovation, and urban regeneration.

- With regard to residential electricity consumption, the results highlight an important distributive issue: remote work may transfer part of the energy costs of production from firms to households. Spending more time at home tends to increase household consumption, but with heterogeneous effects depending on income, household composition, employment status, region, dwelling efficiency, and the presence of children or employed adults (Abdeen et al., 2021; Zapata-Webborn et al., 2023; Mayr and Agnolucci, 2024). This issue is particularly critical for low-income households, tenants, workers living in inefficient dwellings, and households with limited capacity to invest in energy-saving technologies.

  Policies should therefore recognise that when the home becomes a workplace, it generates additional costs for electricity, heating, cooling, internet connectivity, and equipment. One possible response consists of targeted compensation, avoiding flat-rate reimbursements that may be inequitable and inefficient. It would be preferable to combine partial contributions with incentives for energy-efficient technologies and improvements, such as efficient ICT devices, LED lighting, smart thermostats, insulation, and more efficient heating or cooling systems. In this way, smart working can be integrated into residential energy-renovation policies.

  It is also necessary to distinguish between increased consumption and hidden energy poverty. High consumption may reflect greater time spent at home, higher comfort levels, or inefficient housing; low consumption, by contrast, may indicate deprivation and the curtailment of heating or cooling rather than efficiency (Zapata-Webborn et al., 2023). Differentiated responses are therefore needed: retrofitting for inefficient dwellings, social protection for those who reduce consumption for economic reasons, and dedicated tariffs or technologies for those who work from home on a regular basis. In the Italian context, these measures should be coordinated with policies against energy poverty, social energy bonuses, energy communities, and condominium- or

neighbourhood-level interventions (Balest et al., 2021).

Smart working also affects electricity-grid load profiles by shifting part of residential demand towards daytime hours. The effects depend on climate, housing type, the diffusion of electric cooling, and local conditions: in some contexts, demand becomes more evenly distributed across the day, while in others new peaks may emerge (Bielecki et al., 2021; Abdeen et al., 2021; Ferrando et al., 2023). Policies should therefore integrate remote work into demand-response and distributed-energy strategies through time-of-use tariffs, smart meters, household batteries, controllable heat pumps, and the management of electric-vehicle charging, while ensuring adequate protections for vulnerable consumers.

Finally, household energy consumption depends not only on physical presence at home, but also on everyday practices such as care work, cooking, cleaning, device use, and the organisation of family time, all of which are influenced by housing quality, energy poverty, and access to technologies (Balest et al., 2021; Balest and Stawinoga, 2022). Domestic energy management also has a gender dimension: energy-efficiency and smart-working policies must avoid increasing women's invisible labour and should involve the entire household in responsibility for energy saving (Matsumoto et al., 2024).

- Among the relevant public policies, particular attention should be devoted to coworking spaces and local work hubs. Working from home is not the only alternative to commuting to a central office. Local coworking hubs can reduce long-distance commuting while avoiding some of the domestic energy costs associated with working entirely from home. If such spaces are energy-efficient, accessible on foot, by bicycle, or by public transport, and shared by several workers, they can offer an intermediate solution between the home and the traditional office. This is particularly relevant for those living in small or inefficient dwellings, for households with limited space, or for areas where heating or cooling individual homes throughout the working day is inefficient. Policies could support these hubs through urban-regeneration

programmes, public libraries, municipal buildings, or underused public spaces, provided that their energy performance is monitored.

- Another fundamental element is that the results suggest that remote work can become a useful component of energy-security and crisis-management policies. The pandemic showed that the organisation of work can rapidly influence aggregate demand. During periods of energy scarcity, rising fuel prices, transport disruptions, heatwaves, or grid stress, temporary and targeted remote-working measures could reduce energy demand linked to commuting and ease pressure on transport systems. Indeed, in response to the crisis linked to the war in Iran, European institutions have envisaged a series of measures aimed at implementing an 'energy lockdown', including an obligation for employers to introduce remote-working days in order to prevent workers from commuting.

- Policy evaluation requires more integrated and high-frequency data. Uncertainty about the energy effects of teleworking stems from the difficulty of linking household consumption, mobility, office consumption, work characteristics, housing, and household composition. The literature shows the usefulness of counterfactual methods, machine learning, and the integration of energy, weather, and behavioural data (Zapata-Webborn et al., 2023; Scarabaggio et al., 2020). Policies should therefore promote, while respecting privacy, observatories based on anonymised smart-meter data, mobility and time-use surveys, energy audits, and firm-level data on hybrid work, in order to distinguish genuine savings, reallocations of demand, rebound effects, and distributive impacts.

In conclusion, the results suggest that remote work should be regarded as a conditional instrument of climate policy, not as an automatic solution. The evidence indicates the potential for a significant net reduction in energy consumption, but this outcome depends on specific conditions: commuting must actually decrease; workplace energy systems must adapt to lower occupancy; households must not bear excessive or inefficient additional consumption; rebound effects must be contained; and the quality of remote work must

be socially sustainable. In policy terms, the objective should not be to maximise remote work per se, but to maximise energy-efficient, equitable, and well-coordinated remote work. Smart working can contribute to decarbonisation when it is embedded in a broader policy package that includes sustainable transport, building efficiency, household energy support, digital infrastructure, demand-side flexibility, distributed photovoltaics, energy communities, protection of indoor environmental quality, the right to disconnect, gender policies, and rigorous monitoring.

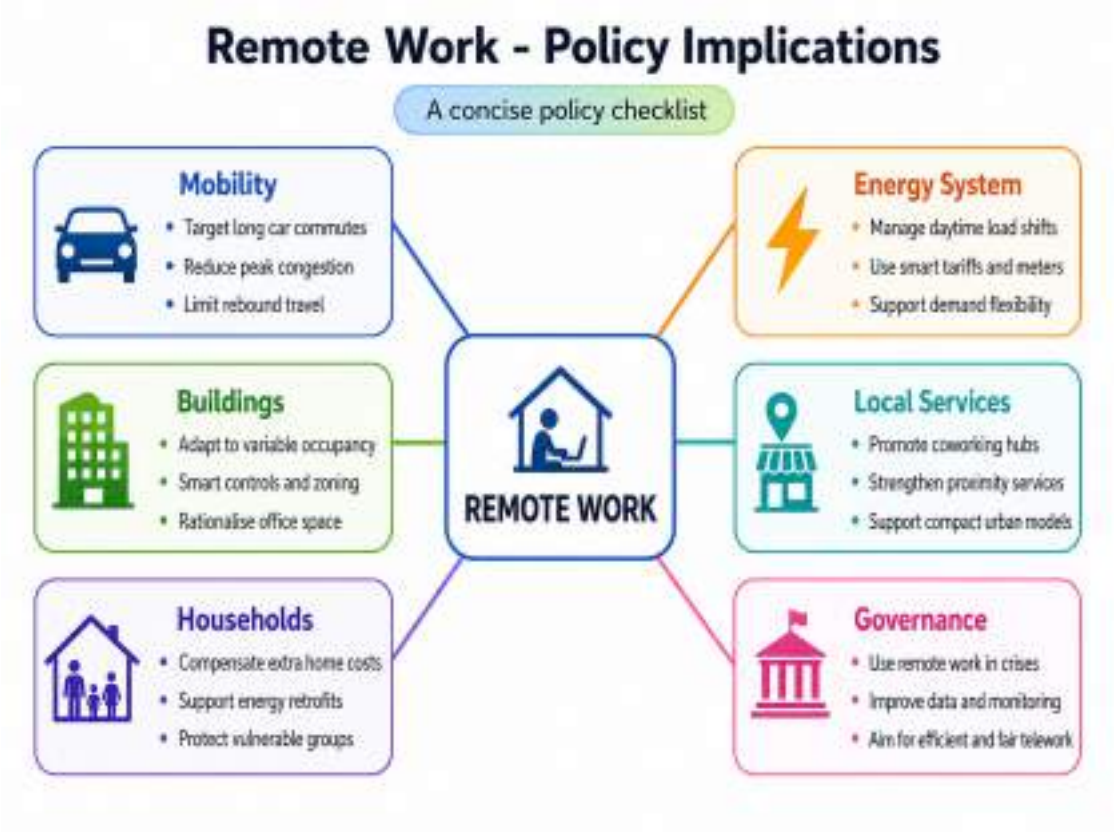



Figure 2.12: Policy implications checklist for the adoption of remote work.

# Appendix

## 2.A.1 Household Budget Survey

Harmonized with Eurostat standards, the survey employs the COICOP classification[8], ensuring comparability at the European level. The unit of observation is the 'de facto household', defined as a group of cohabiting individuals bound by affection, marriage, kinship, affinity, adoption, or guardianship; institutional living arrangements (e.g., barracks, hospitals, religious institutions) and households with permanent members residing abroad are excluded. Data collection is carried out through face-to-face interviews using Computer-Assisted Personal Interviewing (CAPI). The two-stage sampling design first selects municipalities-stratified by region, municipality type, and population size-distinguishing between self-representative municipalities, which are included with certainty if their population exceeds a predefined threshold, and non-self-representative municipalities, which undergo further stratification. In the second stage, households are randomly drawn from each selected municipality; these households constitute the final sampling units. The survey is continuous and conducted on a quarterly basis: approximately 7,000 households are interviewed each quarter (28,000 per year), with monthly stratification to ensure an even distribution of interviews over the three months. The same sampling protocol is replicated in each quarter, thereby producing a sample that is representative across geographic, demographic, and temporal dimensions and enabling the comparability of consumption data throughout the year.

[8]Classification of Individual Consumption by Purpose.

### 2.A.2 Price Endogeneity and the Reconstruction of Electricity Consumption

This reconstruction of electricity consumption imposes a mechanical relationship between expenditure, price, and estimated consumption. Let $E$, $P$, and $Q$ denote, respectively, monthly electricity expenditure in euros, the electricity price in euros per kWh, and monthly electricity consumption in kWh. Since consumption is not directly observed in the HBS, it is reconstructed as:

$$Q = \frac{E}{P}.$$

Taking logarithms gives:

$$\log(Q) = \log(E) - \log(P).$$

This identity implies that variations in the constructed consumption variable are mechanically linked to variations in the price used in the reconstruction. In particular, if electricity expenditure remains constant, or increases only slightly, an increase in the assigned price mechanically reduces the estimated quantity consumed. Therefore, part of the negative relationship between $\log(Q)$ and $\log(P)$ may arise by construction, rather than reflecting a pure behavioural response of households to price changes.

| Year-month | N° of observation | Mean log E | Mean log P | Change Log E | Change Log P | Scenario |
|---|---|---|---|---|---|---|
| 2019-02 | 121 | 3,38 | -0,68 | 0,03 | -0,01 | $\sigma > 0$ ($\lvert\Delta E\rvert > \lvert\Delta P\rvert$, $\Delta E > 0$) |
| 2019-03 | 134 | 3,48 | -0,72 | 0,10 | -0,04 | $\sigma > 0$ ($\lvert\Delta E\rvert > \lvert\Delta P\rvert$, $\Delta E > 0$) |
| 2019-04 | 145 | 3,59 | -0,87 | 0,11 | -0,15 | $\sigma < 0$ ($\lvert\Delta E\rvert < \lvert\Delta P\rvert$, $\Delta E > 0$) |
| 2019-05 | 110 | 3,39 | -0,69 | -0,20 | 0,18 | $\sigma < -2$ ($\lvert\Delta E\rvert > \lvert\Delta P\rvert$, $\Delta E < 0$) |
| 2019-06 | 127 | 3,37 | -0,66 | -0,02 | 0,03 | $\sigma < -1$ ($\lvert\Delta E\rvert < \lvert\Delta P\rvert$, $\Delta E < 0$) |
| 2019-07 | 107 | 3,43 | -0,83 | 0,06 | -0,17 | $\sigma < 0$ ($\lvert\Delta E\rvert < \lvert\Delta P\rvert$, $\Delta E > 0$) |
| 2019-08 | 121 | 3,41 | -0,85 | -0,02 | -0,01 | $\sigma < -2$ ($\lvert\Delta E\rvert > \lvert\Delta P\rvert$, $\Delta E < 0$) |
| 2019-09 | 120 | 3,44 | -0,82 | 0,03 | 0,03 | $\sigma > 0$ ($\lvert\Delta E\rvert > \lvert\Delta P\rvert$, $\Delta E > 0$) |
| 2019-10 | 141 | 3,48 | -0,84 | 0,04 | -0,02 | $\sigma > 0$ ($\lvert\Delta E\rvert > \lvert\Delta P\rvert$, $\Delta E > 0$) |
| 2019-11 | 132 | 3,32 | -0,81 | -0,16 | 0,04 | $\sigma < -2$ ($\lvert\Delta E\rvert > \lvert\Delta P\rvert$, $\Delta E < 0$) |
| 2019-12 | 134 | 3,38 | -0,82 | 0,06 | -0,02 | $\sigma > 0$ ($\lvert\Delta E\rvert > \lvert\Delta P\rvert$, $\Delta E > 0$) |
| 2020-01 | 164 | 3,40 | -0,71 | 0,02 | 0,12 | $\sigma < 0$ ($\lvert\Delta E\rvert < \lvert\Delta P\rvert$, $\Delta E > 0$) |
| 2020-02 | 148 | 3,45 | -0,72 | 0,05 | -0,01 | $\sigma > 0$ ($\lvert\Delta E\rvert > \lvert\Delta P\rvert$, $\Delta E > 0$) |
| 2020-03 | 140 | 3,62 | -0,93 | 0,17 | -0,21 | $\sigma < 0$ ($\lvert\Delta E\rvert < \lvert\Delta P\rvert$, $\Delta E > 0$) |
| 2020-04 | 133 | 3,64 | -0,98 | 0,03 | -0,05 | $\sigma < 0$ ($\lvert\Delta E\rvert < \lvert\Delta P\rvert$, $\Delta E > 0$) |
| 2020-05 | 183 | 3,64 | -0,97 | 0,00 | 0,00 | $\sigma < -1$ ($\lvert\Delta E\rvert < \lvert\Delta P\rvert$, $\Delta E < 0$) |

Table 2.21: Monthly dynamics of expenditure, prices, and implied demand elasticity. This table reports the number of observations, the average monthly log-expenditure and log-price, their month-to-month changes, and the corresponding implied elasticity scenario. The final column classifies the economic scenario based on the direction and magnitude of changes in expenditure and prices.

Table 2.21 illustrates this issue by reporting the month-to-month changes in average log expenditure and average log price. Since constructed consumption satisfies $\log(Q) = \log(E) - \log(P)$, the implied change in log consumption is given by:

$$\Delta \log(Q) = \Delta \log(E) - \Delta \log(P).$$

Accordingly, when expenditure changes little while price increases, the constructed quantity decreases mechanically. Conversely, when price decreases, constructed consumption may increase even in the absence of a proportional increase in expenditure. This mechanical relationship can generate large negative implied elasticities. For example, if $\Delta \log(P) > 0$ and $\Delta \log(E)$ is small or negative, the implied change in consumption becomes strongly negative, leading to an estimated elasticity below $-1$, or even below $-2$ in some cases.

For this reason, the estimated coefficient on $\log(P)$ should not be interpreted exclusively as the behavioural price elasticity of residential electricity demand. It partly reflects the way in which the dependent variable is constructed from expenditure and price. In other words, households do not necessarily reduce their actual electricity use as strongly as the estimated elasticity might suggest; rather, the expenditure-to-consumption conversion may

amplify the observed negative association between price and constructed consumption.

Formally, by definition:

$$E = P \times Q,$$

where $E$ is expenditure, $P$ is price, and $Q$ is quantity consumed. Taking logarithms yields:

$$\log(E) = \log(P) + \log(Q).$$

Since quantity is reconstructed as $Q = E/P$, we equivalently have:

$$\log(Q) = \log(E) - \log(P).$$

Considering two consecutive months, indexed by 1 and 2, the change in constructed log consumption is:

$$\Delta \log(Q) = \Delta \log(E) - \Delta \log(P),$$

where:

$$\Delta \log(E) = \log(E_2) - \log(E_1),$$

$$\Delta \log(P) = \log(P_2) - \log(P_1),$$

and:

$$\Delta \log(Q) = \log(Q_2) - \log(Q_1).$$

The implied price elasticity of constructed consumption can therefore be written as:

$$\sigma = \frac{\Delta \log(Q)}{\Delta \log(P)} = \frac{\Delta \log(E) - \Delta \log(P)}{\Delta \log(P)} = \frac{\Delta \log(E)}{\Delta \log(P)} - 1.$$

This expression clarifies why large negative elasticities can arise in this setting. If expenditure varies less than price, or moves in the opposite direction, the constructed change in consumption may be strongly negative. In particular, when $\Delta \log(P) > 0$ and $\Delta \log(E)$ is small, zero, or negative, the implied elasticity is mechanically negative and may be lower than $-1$.

Therefore, the coefficient on price in the regression should be interpreted with caution. While the first two issues discussed above—simultaneity and measurement error in the assigned price—could in principle be mitigated through instrumental variables or more detailed tariff data, the third issue is structural. It stems from the fact that electricity consumption in kWh is not directly observed but constructed using the same price variable included among the regressors. This creates a mechanical link between the dependent variable and the price variable, which may distort the estimated elasticity relative to the true behavioural response of households.

## 2.A.3 ATECO codes according to the Prime Ministerial Decree of march 9, 2020

| ATECO 1 digit | Italian description of ATECO codes | English sector description | Treatement status |
|---|---|---|---|
| 1 | Agricoltura, silvicoltura e pesca | Agriculture, forestry and fishing | Ambiguous |
| 2 | Estrazione di minerali da cave e miniere | Mining and quarrying | Ambiguous |
| 3 | Attività manifatturiere | Manufacturing | Ambiguous |
| 4 | Fornitura di energia elettrica, gas, vapore e aria condizionata | Electricity, gas, steam and air conditioning supply | Controlled |
| 5 | Fornitura di acqua; reti fognarie, attività di gestione dei rifiuti e risanamento | Water supply; sewerage, waste management and remediation activities | Controlled |
| 6 | Costruzioni | Construction | Ambiguous |
| 7 | Commercio all'ingrosso e al dettaglio; riparazione di autoveicoli e motocicli | Wholesale and retail trade; repair of motor vehicles and motorcycles | Ambiguous |
| 8 | Trasporto e magazzinaggio | Transportation and storage | Controlled |
| 9 | Attività dei servizi di alloggio e di ristorazione | Accommodation and food service activities | Ambiguous |
| 10 | Servizi di informazione e comunicazione | Information and communication services | Controlled |
| 11 | Attività finanziarie e assicurative | Financial and insurance activities | Controlled |
| 12 | Attività immobiliari | Real estate activities | Treated |
| 13 | Attività professionali, scientifiche e tecniche | Professional, scientific and technical activities | Treated |
| 14 | Noleggio, agenzie di viaggio, servizi di supporto alle imprese | Rental, travel agencies and business support services | Ambiguous |
| 15 | Amministrazione pubblica e difesa; assicurazione sociale obbligatoria | Public administration and defense; compulsory social security | Controlled |
| 16 | Istruzione | Education | Treated |
| 17 | Sanità e assistenza sociale | Human health and social work activities | Controlled |
| 18 | Attività artistiche, sportive, di intrattenimento e divertimento | Arts, entertainment and recreation activities | Treated |
| 19 | Altre attività di servizi | Other service activities | Ambiguous |
| 20 | Attività di famiglie e convivenze come datori di lavoro per personale domestico; produzione di beni e servizi indifferenziati per uso proprio da parte di famiglie e convivenze | Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use | Treated |
| 21 | Organizzazioni ed organismi extraterritoriali | Extraterritorial organizations and bodies | Treated |

Table 2.22: Description of 1-digit ATECO codes and corresponding classification in the treated and control group according to the Prime Ministerial Decree of march 9, 2020.

## 2.A.4 Consumption and electricity data

| Annuality | Band 1 | Band 2 | Band 3 | Band 4 | Band 5 |
|---|---|---|---|---|---|
| 2018-S1-S2 | € <26,4 | 26,4 <€ <47 | 47 <€ <88,06 | 88,06<€ <265,04 | €>265,04 |
| 2019-S1-S2 | € <42,6 | 42,6 <€ <51,56 | 51,56 <€ <96,69 | 96,69<€ <288,35 | €>280,35 |
| 2020-S1-S2 | € <42 | 42<€ <51,42 | 51,42 <€ <91,21 | 91,21 <€ <259,1 | € >259,10 |
| 2021-S1-S2 | € <41,87 | 41,87 <€ <54,46 | 54,46 <€ <96,21 | 96,21 <€ <270,73 | €>270,73 |
| 2022-S1-S2 | € <47,11 | 47,11 <€ <76,87 | 76,87 <€ <140,72 | 140,72<€ <399,16 | €>399,16 |

Table 2.23: Monthly spending ranges divided by year. Based on the spending for a given month, it is possible to identify the range to which the price should be assigned (see table below).

| Semester | Band 1 | Band 2 | Band 3 | Band 4 | Band 5 |
|---|---|---|---|---|---|
| 2018-S1 | 0,31 | 0,22 | 0,21 | 0,21 | 0,20 |
| 2018-S2 | 0,33 | 0,23 | 0,22 | 0,22 | 0,21 |
| 2019-S1 | 0,56 | 0,24 | 0,23 | 0,23 | 0,22 |
| 2019-S2 | 0,47 | 0,25 | 0,23 | 0,23 | 0,23 |
| 2020-S1 | 0,55 | 0,25 | 0,22 | 0,21 | 0,19 |
| 2020-S2 | 0,46 | 0,25 | 0,22 | 0,20 | 0,18 |
| 2021-S1 | 0,56 | 0,26 | 0,23 | 0,21 | 0,20 |
| 2021-S2 | 0,44 | 0,27 | 0,24 | 0,22 | 0,21 |
| 2022-S1 | 0,55 | 0,34 | 0,31 | 0,29 | 0,29 |
| 2022-S2 | 0,58 | 0,40 | 0,36 | 0,35 | 0,36 |

Table 2.24: Half-yearly prices by expenditure bands.

## 2.A.5 Results from quantile regressions

| | Estimate | SE | P-value |
|---|---|---|---|
| Intercept | 2.58 | 763.53 | 0.99760 |
| Treated | -0.07399 | 0.03452 | 0.03216 |
| Post | 0.00454 | 0.06595 | 0.94511 |
| **Treated * Post** | **0.06822** | **0.06776** | **0.31406** |
| February | -0.08619 | 0.07237 | 0.23372 |
| March | -0.14080 | 0.12073 | 0.24360 |
| April | -0.19781 | 0.19402 | 0.30801 |
| May | -0.34044 | 0.22396 | 0.12857 |
| June | -0.57532 | 0.28579 | 0.04418 |
| July | -0.65662 | 0.28190 | 0.01990 |
| August | -0.60390 | 0.24685 | 0.01448 |
| September | -0.37767 | 0.17415 | 0.03017 |
| October | -0.18988 | 0.10454 | 0.06939 |
| November | -0.16485 | 0.06622 | 0.01284 |
| December | -0.10966 | 0.04167 | 0.00853 |
| Year: 2020 | 0.04393 | 0.02388 | 0.06594 |
| Region= Basilicata | -0.12449 | 0.11255 | 0.26875 |
| Region= Calabria | -0.17586 | 0.10472 | 0.09316 |
| Region= Campania | -0.10978 | 0.07833 | 0.16115 |
| Region= Emilia-Romagna | -0.19789 | 0.09635 | 0.04006 |
| Region= Friuli-Venezia Giulia | 0.03530 | 0.12731 | 0.78158 |
| Region= Lazio | -0.04198 | 0.09114 | 0.64508 |
| Region= Liguria | -0.28164 | 0.09955 | 0.00469 |
| Region= Lombardia | -0.01537 | 0.12993 | 0.90586 |
| Region= Marche | 0.04967 | 0.09429 | 0.59837 |
| Region= Molise | -0.11206 | 0.06772 | 0.09806 |
| Region= Piemonte | -0.08232 | 0.12846 | 0.52170 |
| Region= Puglia | -0.06717 | 0.09573 | 0.48293 |
| Region= Sardegna | -0.05427 | 0.11997 | 0.65100 |
| Region= Sicilia | -0.16989 | 0.10062 | 0.09144 |
| Region= Toscana | -0.05297 | 0.08409 | 0.52879 |
| Region= Trentino-Alto Adige | -0.10263 | 0.15377 | 0.50456 |
| Region= Umbria | -0.05039 | 0.10216 | 0.62189 |
| Region= Valle d'Aosta | -0.08988 | 0.15450 | 0.56078 |
| Region= Veneto | -0.04755 | 0.13796 | 0.73040 |
| Type of dwelling= apartment in a building with fewer than 10 apartments | 0.12396 | 0.02423 | 0.00000 |
| Type of dwelling= apartment in a building with more than 10 apartments | 0.01683 | 0.02770 | 0.54349 |
| Type of dwelling= other | -0.19107 | 1548.08 | 0.99991 |
| Type of municipality: Metropolitan area suburbs and municipalities with 50,000 inhabitants or more | 0.05164 | 0.03018 | 0.08715 |
| Type of municipality: Other municipalities with up to 50,000 inhabitants | 0.00738 | 0.03406 | 0.82860 |
| Working area= Intellectual, scientific, and highly specialized professions | 0.10082 | 0.06803 | 0.13840 |
| Working area= Technical professions | 0.06723 | 0.06348 | 0.28963 |
| Working area= Executive professions in office work | 0.02914 | 0.07606 | 0.70164 |
| Working area= Skilled professions in commercial activities and services | -0.08966 | 0.08729 | 0.30441 |
| Working area= Craftsmen, skilled workers, and farmers | 0.17229 | 0.12184 | 0.15745 |
| Working area= Plant operators, stationary and mobile machinery operators, and vehicle drivers | 0.06941 | 0.11462 | 0.54485 |
| Working area= Unskilled occupations | -0.06743 | 0.10791 | 0.53210 |
| Working area= Armed forces | 0.03955 | 0.09825 | 0.68732 |
| Source of income= Income from self-employment | 0.04752 | 0.06812 | 0.48550 |
| Second income decile | -0.07439 | 0.03466 | 0.03189 |
| Third income decile | -0.00345 | 0.05034 | 0.94540 |
| Fourth income decile | -0.08992 | 0.04524 | 0.04695 |
| Fifth income decile | -0.08839 | 0.03784 | 0.01954 |
| Sixth income decile | -0.12268 | 0.04777 | 0.01026 |
| Seventh income decile | -0.21581 | 0.04711 | 0.00000 |
| Eighth income decile | -0.58571 | 0.03917 | 0.00000 |
| Ninth income decile | -0.67082 | 0.04053 | 0.00000 |
| Tenth income decile | -0.75503 | 0.05715 | 0.00000 |
| Log (price) | -1.34 | 0.06749 | 0.00000 |
| Average maximum temperature | -0.02228 | 0.02874 | 0.43831 |
| Average minimum temperature | 0.04512 | 0.02562 | 0.07828 |
| Average wind speed | -0.02952 | 0.04948 | 0.55086 |
| Average rainfall | 0.00604 | 0.01230 | 0.62349 |
| Average solar radiation | 0.00003 | 0.00002 | 0.08202 |
| CDD | -0.00068 | 0.00126 | 0.59252 |
| HDD | 0.00063 | 0.00100 | 0.52947 |
| Gender of the head of the household = male | 0.09965 | 0.02223 | 0.00001 |
| Level of education= primary school diploma | -0.12040 | 763.54 | 0.99989 |
| Level of education= middle school diploma | 0.03812 | 763.54 | 0.99996 |
| Level of education= two- or three-year vocational diploma | -0.02233 | 763.54 | 0.99998 |
| Level of education= five-year secondary-school diploma | 0.00066 | 763.54 | 1.0 |
| Level of education= university degree or equivalent | 0.02514 | 763.54 | 0.99998 |
| Level of education= other | 0.05762 | 763.54 | 0.99995 |
| Age of the head of the household | 0.00265 | 0.00113 | 0.01895 |
| Job position= executive | -0.20204 | 0.07781 | 0.00945 |
| Job position= office worker | -0.20417 | 0.10237 | 0.04618 |
| Job position= factory worker | -0.26223 | 0.11406 | 0.02157 |
| Job position= apprentice | 0.42799 | 5771.60 | 0.99994 |
| Job position= entrepreneur or freelancer | -0.25380 | 0.10505 | 0.01574 |
| Ownership= private enterprise or company | 0.00976 | 0.08449 | 0.90802 |
| Internet availability= yes | 0.05009 | 0.02653 | 0.05908 |
| Construction period= post-2009 | -0.05757 | 0.05763 | 0.31790 |
| Construction period= 2000–2009 | -0.07030 | 0.04546 | 0.12214 |
| Construction period= 1990s | -0.06842 | 0.03610 | 0.05816 |
| Number of rooms | 0.00179 | 0.01130 | 0.87444 |
| Square meters of living space | 0.00091 | 0.00038 | 0.01528 |

Table 2.25: Quantile regression results at the 25th percentile ($\tau = 0.25$) for equation (2.1). The dependent variable is the logarithm of household electricity consumption (kWh). Standard errors are clustered at the month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

| | Estimate | SE | P-value |
|---|---|---|---|
| Intercept | 3.04 | 0.45 | 0.00 |
| Treated | -0.02475 | 0.01992 | 0.21433 |
| Post | 0.05821 | 0.06153 | 0.34418 |
| **Treated * Post** | **0.09242** | **0.04200** | **0.02782** |
| February | 0.09434 | 0.04582 | 0.03956 |
| March | 0.19794 | 0.10855 | 0.06830 |
| April | 0.32882 | 0.15513 | 0.03411 |
| May | 0.30673 | 0.21440 | 0.15263 |
| June | 0.26808 | 0.25349 | 0.29032 |
| July | 0.17326 | 0.27601 | 0.53024 |
| August | 0.11497 | 0.26774 | 0.66765 |
| September | 0.11544 | 0.19839 | 0.56067 |
| October | 0.01622 | 0.11552 | 0.88835 |
| November | -0.02100 | 0.07758 | 0.78665 |
| December | -0.04011 | 0.04370 | 0.35871 |
| Year: 2020 | 0.02142 | 0.01850 | 0.24695 |
| Region= Basilicata | 0.07824 | 0.11690 | 0.50338 |
| Region= Calabria | 0.15198 | 0.11372 | 0.18150 |
| Region= Campania | 0.02943 | 0.08294 | 0.72270 |
| Region= Emilia-Romagna | -0.02407 | 0.08121 | 0.76698 |
| Region= Friuli-Venezia Giulia | 0.06203 | 0.78200 | 0.43427 |
| Region= Lazio | 0.03415 | 0.05883 | 0.56162 |
| Region= Liguria | -0.04926 | 0.09161 | 0.59079 |
| Region= Lombardia | 0.05363 | 0.07204 | 0.45668 |
| Region= Marche | 0.03988 | 0.06231 | 0.52223 |
| Region= Molise | -0.00624 | 0.07802 | 0.93624 |
| Region= Piemonte | 0.00038 | 0.07205 | 0.99581 |
| Region= Puglia | 0.02330 | 0.07586 | 0.75878 |
| Region= Sardegna | 0.09190 | 0.10495 | 0.38129 |
| Region= Sicilia | 0.11251 | 0.09137 | 0.21825 |
| Region= Toscana | 0.01829 | 0.06793 | 0.78778 |
| Region= Trentino-Alto Adige | 0.04034 | 0.28520 | 0.77551 |
| Region= Umbria | -0.00409 | 0.10367 | 0.96855 |
| Region= Valle d'Aosta | d'Aosta | 0.07409 | 0.45948 |
| Region= Veneto | 0.01008 | 0.07232 | 0.88920 |
| Type of dwelling= apartment in a building with fewer than 10 apartments | 0.01690 | 0.02347 | 0.47150 |
| Type of dwelling= apartment in a building with more than 10 apartments | -0.04195 | 0.02161 | 0.05234 |
| Type of dwelling= other | -0.18026 | 862.49 | 0.99978 |
| Type of municipality: Metropolitan area suburbs and municipalities with 50,000 inhabitants or more | -0.00514 | 0.02256 | 0.81983 |
| Type of municipality: Other municipalities with up to 50,000 inhabitants | -0.04216 | 0.02814 | 0.13417 |
| Working area= Intellectual, scientific, and highly specialized professions | 0.06155 | 0.09566 | 0.51997 |
| Working area= Technical professions | 0.05674 | 0.07952 | 0.47561 |
| Working area= Executive professions in office work | 0.03824 | 0.09260 | 0.67963 |
| Working area= Skilled professions in commercial activities and services | -0.06403 | 0.09497 | 0.50021 |
| Working area= Craftsmen, skilled workers, and farmers | 0.11967 | 0.10935 | 0.27385 |
| Working area= Plant operators, stationary and mobile machinery operators, and vehicle drivers | -0.01633 | 0.09876 | 0.86870 |
| Working area= Unskilled occupations | -0.04432 | 0.11242 | 0.69346 |
| Working area= Armed forces | 0.03550 | 0.09712 | 0.71474 |
| Source of income= Income from self-employment | 0.13791 | 0.06106 | 0.02397 |
| Second income decile | -0.04477 | 0.03037 | 0.14049 |
| Third income decile | 0.01711 | 0.03796 | 0.65222 |
| Fourth income decile | -0.02741 | 0.04440 | 0.53701 |
| Fifth income decile | -0.02776 | 0.05228 | 0.59550 |
| Sixth income decile | -0.03193 | 0.03973 | 0.42164 |
| Seventh income decile | -0.03207 | 0.04336 | 0.45960 |
| Eighth income decile | -0.52945 | 0.07840 | 0.00000 |
| Ninth income decile | -0.68163 | 0.05279 | 0.00000 |
| Tenth income decile | -0.70920 | 0.06636 | 0.00000 |
| Log (price) | -1.33 | 0.08958 | 0.00000 |
| Average maximum temperature | 0.01472 | 0.02012 | 0.46455 |
| Average minimum temperature | 0.00597 | 0.02320 | 0.79699 |
| Average wind speed | 0.00477 | 0.03082 | 0.87710 |
| Average rainfall | -0.00288 | 0.00589 | 0.62467 |
| Average solar radiation | -0.00002 | 0.00001 | 0.14535 |
| CDD | -0.00034 | 0.00070 | 0.62775 |
| HDD | 0.00041 | 0.00063 | 0.51667 |
| Gender of the head of the household = male | 0.04211 | 0.01620 | 0.00940 |
| Level of education= primary school diploma | -0.03554 | 0.16511 | 0.82960 |
| Level of education= middle school diploma | 0.01130 | 0.13293 | 0.93226 |
| Level of education= two- or three-year vocational diploma | -0.06888 | 0.13830 | 0.61851 |
| Level of education= five-year secondary-school diploma | -0.09146 | 0.13638 | 0.50251 |
| Level of education= university degree or equivalent | -0.07325 | 0.14142 | 0.60453 |
| Level of education= other | -0.08602 | 0.18717 | 0.64585 |
| Age of the head of the household | 0.00198 | 0.00101 | 0.04899 |
| Job position= executive | -0.29732 | 0.07869 | 0.00016 |
| Job position= office worker | -0.26586 | 0.06777 | 0.00009 |
| Job position= factory worker | -0.26165 | 0.06826 | 0.00013 |
| Job position= apprentice | -0.18781 | 7944.18 | 0.99998 |
| Job position= entrepreneur or freelancer | -0.34815 | 0.08866 | 0.00009 |
| Ownership= private enterprise or company | 0.03576 | 0.03687 | 0.33217 |
| Internet availability= yes | -0.00203 | 0.01746 | 0.90739 |
| Construction period= post-2009 | -0.01819 | 0.06284 | 0.77230 |
| Construction period= 2000–2009 | -0.03472 | 0.05077 | 0.49412 |
| Construction period= 1990s | -0.02003 | 0.05195 | 0.69987 |
| Number of rooms | -0.00558 | 0.00956 | 0.55961 |
| Square meters of living space | 0.00058 | 0.00037 | 0.11031 |

Table 2.26: Quantile regression results at the median ($\tau = 0.50$) for equation (2.1). The dependent variable is the logarithm of household electricity consumption (kWh). Standard errors are clustered at the month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

| | Estimate | SE | P-value |
|---|---|---|---|
| Intercept | 3.52 | 0.51 | 0.00 |
| Treated | -0.01261 | 0.01835 | 0.49223 |
| Post | 0.07277 | 0.09634 | 0.45009 |
| **Treated * Post** | **0.05913** | **0.08029** | **0.46153** |
| February | 0.11185 | 0.03467 | 0.00126 |
| March | 0.24833 | 0.08775 | 0.00468 |
| April | 0.32636 | 0.12969 | 0.01190 |
| May | 0.33269 | 0.15804 | 0.03535 |
| June | 0.30662 | 0.18688 | 0.10095 |
| July | 0.30523 | 0.20833 | 0.14298 |
| August | 0.30159 | 0.19031 | 0.11312 |
| September | 0.26032 | 0.15497 | 0.09308 |
| October | 0.11569 | 0.09119 | 0.20464 |
| November | 0.04639 | 0.06272 | 0.45953 |
| December | 0.04243 | 0.05038 | 0.39975 |
| Year: 2020 | 0.00479 | 0.01424 | 0.73635 |
| Region= Basilicata | -0.05447 | 0.11376 | 0.63210 |
| Region= Calabria | 0.02840 | 0.07387 | 0.70072 |
| Region= Campania | 0.01283 | 0.05336 | 0.80998 |
| Region= Emilia-Romagna | -0.12842 | 0.06674 | 0.05441 |
| Region= Friuli-Venezia Giulia | -0.02353 | -0.29368 | 0.76902 |
| Region= Lazio | 0.01359 | 0.04108 | 0.74076 |
| Region= Liguria | -0.07461 | 0.06626 | 0.26021 |
| Region= Lombardia | -0.10007 | 0.06020 | 0.09655 |
| Region= Marche | -0.10274 | 0.05559 | 0.06466 |
| Region= Molise | -0.03868 | 0.04839 | 0.42413 |
| Region= Piemonte | -0.14467 | 0.06543 | 0.02709 |
| Region= Puglia | -0.02052 | 0.05942 | 0.72984 |
| Region= Sardegna | 0.02448 | 0.06849 | 0.72079 |
| Region= Sicilia | 0.03474 | 0.06628 | 0.60025 |
| Region= Toscana | -0.06229 | 0.04572 | 0.17312 |
| Region= Trentino-Alto Adige | -0.15290 | 0.11 | 0.17506 |
| Region= Umbria | -0.02366 | 0.08379 | 0.77766 |
| Region= Valle d'Aosta | -0.18196 | 0.15 | 0.23870 |
| Region= Veneto | -0.06886 | 0.06092 | 0.25838 |
| Type of dwelling= apartment in a building with fewer than 10 apartments | 0.01679 | 0.01376 | 0.22249 |
| Type of dwelling= apartment in a building with more than 10 apartments | -0.03019 | 0.01640 | 0.06572 |
| Type of dwelling= other | 0.11379 | 3640.94 | 0.99997 |
| Type of municipality: Metropolitan area suburbs and municipalities with 50,000 inhabitants or more | 0.00036 | 0.01383 | 0.97906 |
| Type of municipality: Other municipalities with up to 50,000 inhabitants | -0.01538 | 0.01572 | 0.32787 |
| Working area= Intellectual, scientific, and highly specialized professions | -0.00397 | 0.08632 | 0.96335 |
| Working area= Technical professions | 0.02972 | 0.08633 | 0.73066 |
| Working area= Executive professions in office work | 0.03701 | 0.08059 | 0.64609 |
| Working area= Skilled professions in commercial activities and services | 0.00553 | 0.09560 | 0.95391 |
| Working area= Craftsmen, skilled workers, and farmers | 0.03470 | 0.08001 | 0.66450 |
| Working area= Plant operators, stationary and mobile machinery operators, and vehicle drivers | 0.00738 | 0.09713 | 0.93945 |
| Working area= Unskilled occupations | -0.01049 | 0.08536 | 0.90218 |
| Working area= Armed forces | -0.00459 | 0.09463 | 0.96130 |
| Source of income= Income from self-employment | 0.07897 | 0.05188 | 0.12806 |
| Second income decile | -0.00296 | 0.02590 | 0.90914 |
| Third income decile | 0.01773 | 0.03411 | 0.60319 |
| Fourth income decile | 0.00917 | 0.03660 | 0.80208 |
| Fifth income decile | 0.00730 | 0.03281 | 0.82386 |
| Sixth income decile | 0.01289 | 0.02950 | 0.66207 |
| Seventh income decile | 0.05242 | 0.02975 | 0.07810 |
| Eighth income decile | -0.12811 | 0.05036 | 0.01100 |
| Ninth income decile | -0.21720 | 0.08458 | 0.01027 |
| Tenth income decile | -0.37060 | 0.10527 | 0.00044 |
| Log (price) | -1.26 | 0.13824 | 0.00000 |
| Average maximum temperature | -0.00370 | 0.01868 | 0.84287 |
| Average minimum temperature | -0.00680 | 0.01687 | 0.68713 |
| Average wind speed | -0.01278 | 0.01938 | 0.50982 |
| Average rainfall | -0.00259 | 0.00379 | 0.49417 |
| Average solar radiation | -0.00001 | 0.00001 | 0.33494 |
| CDD | -0.00012 | 0.00079 | 0.87701 |
| HDD | -0.00030 | 0.00060 | 0.61353 |
| Gender of the head of the household = male | 0.05823 | 0.01535 | 0.00015 |
| Level of education= primary school diploma | 0.13738 | 0.10 | 0.99988 |
| Level of education= middle school diploma | 0.13062 | 0.09 | 0.99988 |
| Level of education= two- or three-year vocational diploma | 0.09376 | 0.09 | 0.99992 |
| Level of education= five-year secondary-school diploma | 0.06360 | 0.091 | 0.99994 |
| Level of education= university degree or equivalent | 0.11469 | 0.91 | 0.99990 |
| Level of education= other | 0.08565 | 0.91 | 0.99992 |
| Age of the head of the household | 0.00124 | 0.00073 | 0.08894 |
| Job position= executive | -0.25302 | 0.08812 | 0.00411 |
| Job position= office worker | -0.19829 | 0.08280 | 0.01668 |
| Job position= factory worker | -0.18606 | 0.07734 | 0.01619 |
| Job position= apprentice | -0.38809 | 20096.39 | 0.99999 |
| Job position= entrepreneur or freelancer | -0.24968 | 0.07694 | 0.00119 |
| Ownership= private enterprise or company | -0.01400 | 0.02226 | 0.52951 |
| Internet availability= yes | -0.02413 | 0.01603 | 0.13239 |
| Construction period= post-2009 | -0.04201 | 0.04239 | 0.32170 |
| Construction period= 2000–2009 | -0.01548 | 0.04462 | 0.72868 |
| Construction period= 1990s | -0.00754 | 0.03329 | 0.82087 |
| Number of rooms | -0.00243 | 0.00712 | 0.73244 |
| Square meters of living space | 0.00066 | 0.00044 | 0.12973 |

Table 2.27: Quantile regression results at the 75th percentile ($\tau = 0.75$) for equation (2.1). The dependent variable is the logarithm of household electricity consumption (kWh). Standard errors are clustered at the month level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

## 2.A.6 Results from falsification tests

| | Estimate | SE | P-value | |
|---|---|---|---|---|
| **Expenses for installments on durable goods** | | | | |
| *Intercept* | 5630,60 | 1648,00 | 0.0006457 | *** |
| *Treated* | 117,67 | 143,19 | 0.4113176 | |
| *post* | 364,92 | 90,60 | 0,06 | *** |
| ***Treated * post*** | **51,30** | 179,17 | 0.7746488 | |
| *February* | 135,77 | 184,75 | 0.4625127 | |
| *March* | -209,94 | 301,48 | 0.4862685 | |
| *April* | -373,38 | 505,72 | 0.4604093 | |
| *May* | -618,33 | 752,98 | 0.4116344 | |
| *June* | -1078,30 | 1011,40 | 0.2864822 | |
| *July* | -946,06 | 1096,60 | 0.3883814 | |
| *August* | -1092,40 | 1077,10 | 0.3105800 | |
| *September* | -452,30 | 794,66 | 0.5692978 | |
| *October* | -337,80 | 698,40 | 0.6286603 | |
| *November* | -154,59 | 743,12 | 0.8352268 | |
| *December* | -256,76 | 327,40 | 0.4329843 | |
| *Year: 2020* | -203,30 | 84,85 | 0.0166627 | * |
| *Region= Basilicata* | -195,65 | 429,07 | 0.6484493 | |
| *Region= Calabria* | -419,56 | 444,47 | 0.3452924 | |
| *Region= Campania* | -251,97 | 355,10 | 0.4780521 | |
| *Region= Emilia-Romagna* | -270,25 | 470,59 | 0.5658396 | |
| *Region= Friuli-Venezia Giulia* | -200,93 | -0.3221 | 0.7474084 | |
| *Region= Lazio* | -417,38 | 450,93 | 0.3547633 | |
| *Region= Liguria* | -693,70 | 344,42 | 0.0441198 | * |
| *Region= Lombardia* | -619,08 | 477,88 | 0.1952902 | |
| *Region= Marche* | 44,01 | 346,29 | 0.8988796 | |
| *Region= Molise* | -162,30 | 416,51 | 0.6968193 | |
| *Region= Piemonte* | -624,26 | 517,57 | 0.2278897 | |
| *Region= Puglia* | -319,13 | 470,81 | 0.4979537 | |
| *Region= Sardegna* | -912,27 | 652,78 | 0.1624000 | |
| *Region= Sicilia* | -566,60 | 466,03 | 0.2241931 | |
| *Region= Toscana* | -463,65 | 645,78 | 0.4728521 | |
| *Region= Trentino-Alto Adige* | 359,53 | 0.5606 | 0.5751532 | |
| *Region= Umbria* | -406,36 | 628,69 | 0.5181190 | |
| *Region= Valle d'Aosta* | -23,16 | -0.0291 | 0.9767584 | |
| *Region= Veneto* | -416,71 | 532,94 | 0.4343466 | |
| *Type of dwelling= apartment in a building with fewer than 10 apartments* | -70,34 | 130,36 | 0.5895430 | |
| *Type of dwelling= apartment in a building with more than 10 apartments* | -50,04 | 131,75 | 0.7041058 | |
| *Type of dwelling= other* | -238,17 | 469,25 | 0.6118077 | |
| *Type of municipality: Metropolitan area suburbs and municipalities with 50,000 inhabitants or more* | -99,32 | 134,97 | 0.4619119 | |
| *Type of municipality: Other municipalities with up to 50,000 inhabitants* | -68,37 | 125,83 | 0.5869717 | |
| *Working area= Intellectual, scientific, and highly specialized professions* | 180,21 | 481,24 | 0.7080875 | |
| *Working area= Technical professions* | 90,03 | 409,13 | 0.8258543 | |
| *Working area= Executive professions in office work* | 30,88 | 454,53 | 0.9458377 | |
| *Working area= Skilled professions in commercial activities and services* | 81,81 | 503,73 | 0.8709992 | |
| *Working area= Craftsmen, skilled workers, and farmers* | -491,85 | 974,40 | 0.6137686 | |
| *Working area= Plant operators, stationary and mobile machinery operators, and vehicle drivers* | -133,10 | 510,94 | 0.7944969 | |
| *Working area= Unskilled occupations* | -288,56 | 566,36 | 0.6104587 | |
| *Working area= Armed forces* | 139,21 | 688,22 | 0.8397208 | |
| *Source of income= Income from self-employment* | 383,24 | 268,81 | 0.1541046 | |
| *Second income decile* | 197,96 | 161,03 | 0.2190885 | |
| *Third income decile* | -256,89 | 193,77 | 0.1850762 | |
| *Fourth income decile* | -212,29 | 159,30 | 0.1827813 | |
| *Fifth income decile* | -213,53 | 124,98 | 0.0876740 | . |
| *Sixth income decile* | -244,35 | 163,24 | 0.1345788 | |
| *Seventh income decile* | -383,54 | 235,67 | 0.1037795 | |
| *Eighth income decile* | -153,20 | 126,61 | 0.2264044 | |
| *Ninth income decile* | -215,63 | 257,52 | 0.4025092 | |
| *Tenth income decile* | -490,37 | 359,21 | 0.1723553 | |
| *Log (price)* | -80,43 | 160,31 | 0.6159083 | |
| *Average maximum temperature* | 44,27 | 89,44 | 0.6207072 | |
| *Average minimum temperature* | 22,00 | 117,55 | 0.8515407 | |
| *Average wind speed* | 62,94 | 159,97 | 0.6940086 | |
| *Average rainfall* | 18,84 | 41,10 | 0.6468365 | |
| *Average solar radiation* | 0,00 | 0,05 | 0.9256611 | |
| *CDD* | -0,60 | 4,87 | 0.9017420 | |
| *HDD* | 0,57 | 3,48 | 0.8695188 | |
| *Gender of the head of the household = male* | 0,98 | 133,91 | 0.9941412 | |
| *Level of education= primary school diploma* | -181,20 | 473,23 | 0.7018393 | |
| *Level of education= middle school diploma* | -52,62 | 224,31 | 0.8145504 | |
| *Level of education= two- or three-year vocational diploma* | -37,78 | 282,18 | 0.8935096 | |
| *Level of education= five-year secondary-school diploma* | -327,01 | 258,79 | 0.2064980 | |
| *Level of education= university degree or equivalent* | -42,93 | 264,42 | 0.8710471 | |
| *Level of education= other* | -136,32 | 454,16 | 0.7640943 | |
| *Age of the head of the household* | 5,57 | 5,70 | 0.3289328 | |
| *Job position= executive* | -314,30 | 356,04 | 0.3774506 | |
| *Job position= office worker* | -250,94 | 242,93 | 0.3017303 | |
| *Job position= factory worker* | 29,87 | 349,07 | 0.9318093 | |
| *Job position= entrepreneur or freelancer* | -519,17 | 347,97 | 0.1358437 | |
| *Ownership= private enterprise or company* | 174,36 | 302,40 | 0.5642745 | |
| *Internet availability= yes* | 256,23 | 125,12 | 0.0406975 | * |
| *Construction period= post-2009* | -32,86 | 240,92 | 0.8915375 | |
| *Construction period= 2000–2009* | -38,88 | 306,03 | 0.8989070 | |
| *Construction period= 1990s* | 203,33 | 265,98 | 0.4446676 | |
| *Number of rooms* | 34,22 | 52,37 | 0.5135335 | |
| *Square meters of living space* | 0,87 | 1,50 | 0.5599172 | |

Table 2.28: Falsification test 1. Pooled-DiD estimates of the effect of the treatment on household expenditures for durable goods installments. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

| | Estimate | SE | P-value | |
|---|---|---|---|---|
| **Condominium fees** | | | | |
| *Intercept* | 61544 | 3037 | 0.00 | *** |
| *Treated* | 92 | 134 | 0.4917801 | |
| *Post* | -315 | 160 | 0.0486201 | * |
| ***Treated * post*** | **172** | **267** | **0.5202683** | |
| *February* | 102 | 244 | 0.6758262 | |
| *March* | -28 | 533 | 0.9582673 | |
| *April* | -96 | 879 | 0.9135020 | |
| *May* | 403 | 1096 | 0.7129544 | |
| *June* | 472 | 1280 | 0.7125704 | |
| *July* | 1128 | 1232 | 0.3600460 | |
| *August* | 2053 | 1064 | 0.0537073 | . |
| *September* | 1633 | 814 | 0.0450201 | * |
| *October* | 1014 | 725 | 0.1618792 | |
| *November* | 374 | 745 | 0.6150935 | |
| *December* | 406 | 325 | 0.2108829 | |
| *Year: 2020* | 303 | 159 | 0.0568101 | . |
| *Region= Basilicata* | 1159 | 486 | 0.0172366 | * |
| *Region= Calabria* | 272 | 443 | 0.5398678 | |
| *Region= Campania* | -601 | 342 | 0.0792155 | . |
| *Region= Emilia-Romagna* | -666 | 427 | 0.1186374 | |
| *Region= Friuli-Venezia Giulia* | -1223 | -19853 | 0.0472338 | * |
| *Region= Lazio* | -74 | 363 | 0.8396296 | |
| *Region= Liguria* | 2 | 393 | 0.9965752 | |
| *Region= Lombardia* | -383 | 416 | 0.3574748 | |
| *Region= Marche* | -350 | 316 | 0.2684126 | |
| *Region= Molise* | 148 | 319 | 0.6434074 | |
| *Region= Piemonte* | -1145 | 350 | 0.0010989 | ** |
| *Region= Puglia* | 139 | 376 | 0.7127152 | |
| *Region= Sardegna* | 483 | 539 | 0.3704930 | |
| *Region= Sicilia* | 217 | 675 | 0.7474812 | |
| *Region= Toscana* | -71 | 335 | 0.8324389 | |
| *Region= Trentino-Alto Adige* | -472 | -0.9443 | 0.3451204 | |
| *Region= Umbria* | -310 | 381 | 0.4157166 | |
| *Region= Valle d'Aosta* | -1385 | -23962 | 0.0166496 | * |
| *Region= Veneto* | -446 | 408 | 0.2746139 | |
| *Type of dwelling= apartment in a building with fewer than 10 apartments* | -276 | 170 | 0.1052518 | |
| *Type of dwelling= apartment in a building with more than 10 apartments* | 60 | 119 | 0.6143991 | |
| *Type of dwelling= other* | -1713 | 1674 | 0.3065111 | |
| *Type of municipality: Metropolitan area suburbs and municipalities with 50,000 inhabitants or more* | -570 | 237 | 0.0161603 | * |
| *Type of municipality: Other municipalities with up to 50,000 inhabitants* | -902 | 293 | 0.0020734 | ** |
| *Working area= Intellectual, scientific, and highly specialized professions* | 146 | 221 | 0.5084525 | |
| *Working area= Technical professions* | 473 | 297 | 0.1118266 | |
| *Working area= Executive professions in office work* | 430 | 305 | 0.1590472 | |
| *Working area= Skilled professions in commercial activities and services* | 307 | 306 | 0.3156662 | |
| *Working area= Craftsmen, skilled workers, and farmers* | 980 | 463 | 0.0342581 | * |
| *Working area= Plant operators, stationary and mobile machinery operators, and vehicle drivers* | 104 | 411 | 0.8000588 | |
| *Working area= Unskilled occupations* | 342 | 490 | 0.4856532 | |
| *Working area= Armed forces* | 253 | 439 | 0.5638218 | |
| *Source of income= Income from self-employment* | 199 | 343 | 0.5613694 | |
| *Second income decile* | 1474 | 433 | 0.0006796 | *** |
| *Third income decile* | 1660 | 506 | 0.0010563 | ** |
| *Fourth income decile* | 1882 | 418 | 0 | *** |
| *Fifth income decile* | 1578 | 422 | 0.0001927 | *** |
| *Sixth income decile* | 1377 | 349 | 0 | *** |
| *Seventh income decile* | 1848 | 454 | 0 | *** |
| *Eighth income decile* | 1641 | 457 | 0.0003356 | *** |
| *Ninth income decile* | 1459 | 421 | 0.0005378 | *** |
| *Tenth income decile* | 1967 | 450 | 0 | *** |
| *Log (price)* | -66 | 160 | 0.6781489 | |
| *Average maximum temperature* | -50 | 127 | 0.6939716 | |
| *Average minimum temperature* | -163 | 80 | 0.0417948 | * |
| *Average wind speed* | -357 | 200 | 0.0738544 | . |
| *Average rainfall* | 94 | 42 | 0.0267658 | * |
| *Average solar radiation* | 0 | 0 | 0.4093110 | |
| *CDD* | 1 | 7 | 0.8902146 | |
| *HDD* | -3 | 5 | 0.4814587 | |
| *Gender of the head of the household = male* | 77 | 117 | 0.5136687 | |
| *Level of education= primary school diploma* | -625 | 2314 | 0.7870019 | |
| *Level of education= middle school diploma* | -114 | 2207 | 0.9586631 | |
| *Level of education= two- or three-year vocational diploma* | 18 | 2136 | 0.9933037 | |
| *Level of education= five-year secondary-school diploma* | 76 | 2188 | 0.9722319 | |
| *Level of education= university degree or equivalent* | 29 | 2237 | 0.9896550 | |
| *Level of education= other* | -168 | 2238 | 0.9399915 | |
| *Age of the head of the household* | 4 | 5 | 0.3789038 | |
| *Job position= executive* | 160 | 384 | 0.6769304 | |
| *Job position= office worker* | -253 | 372 | 0.4957143 | |
| *Job position= factory worker* | -538 | 383 | 0.1602407 | |
| *Job position= entrepreneur or freelancer* | -95 | 545 | 0.8622375 | |
| *Ownership= private enterprise or company* | -5819 | 943 | 0 | *** |
| *Internet availability= yes* | 14 | 141 | 0.9192903 | |
| *Construction period= post-2009* | -68 | 252 | 0.7883455 | |
| *Construction period= 2000–2009* | 186 | 335 | 0.5785476 | |
| *Construction period= 1990s* | -60 | 231 | 0.7948994 | |
| *Number of rooms* | 51 | 63 | 0.4219031 | |
| *Square meters of living space* | 3 | 2 | 0.0783604 | . |

Table 2.29: Falsification test 2. Pooled-DiD estimates of the effect of the treatment on household conodominium fees. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

| | Estimate | SE | P-value | |
|---|---|---|---|---|
| **Rent payments** | | | | |
| *Intercept* | -277810 | 4864 | 2.2e-16 | *** |
| *Treated* | -166 | 155 | 0.2849102 | |
| *Post* | 533 | 331 | 0.1076227 | |
| ***Treated * post*** | **262** | **195** | **0.1794387** | |
| *February* | -595 | 318 | 0.0613178 | . |
| *March* | -1096 | 603 | 0.0695502 | . |
| *April* | -1703 | 997 | 0.0878581 | . |
| *May* | -2821 | 1312 | 0.0316132 | * |
| *June* | -3195 | 1770 | 0.0712916 | . |
| *July* | -3606 | 1886 | 0.0559158 | . |
| *August* | -4002 | 1885 | 0.0338265 | * |
| *September* | -3146 | 1549 | 0.0424004 | * |
| *October* | -2875 | 1218 | 0.0183601 | * |
| *November* | -915 | 934 | 0.3273212 | |
| *December* | -729 | 507 | 0.1502983 | |
| *Year: 2020* | -471 | 336 | 0.1610921 | |
| *Region= Basilicata* | -4544 | 731 | 0 | *** |
| *Region= Calabria* | -3199 | 779 | 0 | *** |
| *Region= Campania* | -1001 | 543 | 0.0652933 | . |
| *Region= Emilia-Romagna* | 764 | 632 | 0.2273270 | |
| *Region= Friuli-Venezia Giulia* | 1021 | 13261 | 0.1849491 | |
| *Region= Lazio* | 1622 | 733 | 0.0270606 | * |
| *Region= Liguria* | -910 | 599 | 0.1288712 | |
| *Region= Lombardia* | 1564 | 932 | 0.0933720 | . |
| *Region= Marche* | 793 | 655 | 0.2264676 | |
| *Region= Molise* | -1520 | 540 | 0.0049020 | ** |
| *Region= Piemonte* | 687 | 733 | 0.3491543 | |
| *Region= Puglia* | -1789 | 563 | 0.0015018 | ** |
| *Region= Sardegna* | -1155 | 696 | 0.0973180 | . |
| *Region= Sicilia* | -3088 | 765 | 0 | *** |
| *Region= Toscana* | 1660 | 707 | 0.0190240 | * |
| *Region= Trentino-Alto Adige* | 3378 | 28885 | 0.0039087 | ** |
| *Region= Umbria* | -914 | 699 | 0.1916060 | |
| *Region= Valle d'Aosta* | 2466 | 19264 | 0.0541890 | . |
| *Region= Veneto* | 949 | 789 | 0.2292361 | |
| *Type of dwelling= apartment in a building with fewer than 10 apartments* | 687 | 189 | 0.0002825 | *** |
| *Type of dwelling= apartment in a building with more than 10 apartments* | 836 | 83 | 2.2e-16 | *** |
| *Type of dwelling= other* | 1112 | 1939 | 0.5663245 | |
| *Type of municipality: Metropolitan area suburbs and municipalities with 50,000 inhabitants or more* | -2145 | 142 | 2.2e-16 | *** |
| *Type of municipality: Other municipalities with up to 50,000 inhabitants* | -3263 | 297 | 2.2e-16 | *** |
| *Working area= Intellectual, scientific, and highly specialized professions* | 403 | 505 | 0.4243815 | |
| *Working area= Technical professions* | -225 | 633 | 0.7227463 | |
| *Working area= Executive professions in office work* | 269 | 664 | 0.6848179 | |
| *Working area= Skilled professions in commercial activities and services* | -55 | 743 | 0.9407361 | |
| *Working area= Craftsmen, skilled workers, and farmers* | -299 | 653 | 0.6475553 | |
| *Working area= Plant operators, stationary and mobile machinery operators, and vehicle drivers* | 414 | 650 | 0.5238495 | |
| *Working area= Unskilled occupations* | -21 | 527 | 0.9680425 | |
| *Working area= Armed forces* | -142 | 702 | 0.8393525 | |
| *Source of income= Income from self-employment* | -229 | 531 | 0.6669583 | |
| *Second income decile* | -148 | 485 | 0.7595387 | |
| *Third income decile* | 212 | 376 | 0.5725999 | |
| *Fourth income decile* | -292 | 377 | 0.4391139 | |
| *Fifth income decile* | 273 | 401 | 0.4957127 | |
| *Sixth income decile* | 189 | 330 | 0.5679135 | |
| *Seventh income decile* | 296 | 428 | 0.4897662 | |
| *Eighth income decile* | 863 | 435 | 0.0474107 | * |
| *Ninth income decile* | 1209 | 361 | 0.0008250 | *** |
| *Tenth income decile* | 1243 | 463 | 0.0073805 | ** |
| *Log (price)* | -265 | 191 | 0.1641201 | |
| *Average maximum temperature* | -103 | 206 | 0.6187318 | |
| *Average minimum temperature* | 279 | 197 | 0.1569265 | |
| *Average wind speed* | -15 | 247 | 0.9521484 | |
| *Average rainfall* | -61 | 43 | 0.1601889 | |
| *Average solar radiation* | 0 | 0 | 0.6769322 | |
| *CDD* | -2 | 9 | 0.8173992 | |
| *HDD* | 1 | 7 | 0.8654453 | |
| *Gender of the head of the household = male* | 11 | 145 | 0.9397677 | |
| *Level of education= primary school diploma* | 598 | 853 | 0.4832207 | |
| *Level of education= middle school diploma* | 541 | 770 | 0.4823626 | |
| *Level of education= two- or three-year vocational diploma* | 462 | 901 | 0.6077090 | |
| *Level of education= five-year secondary-school diploma* | 552 | 733 | 0.4510734 | |
| *Level of education= university degree or equivalent* | 882 | 778 | 0.2570357 | |
| *Level of education= other* | 1264 | 1124 | 0.2612027 | |
| *Age of the head of the household* | 0 | 9 | 0.9604456 | |
| *Job position= executive* | 169 | 528 | 0.7484365 | |
| *Job position= office worker* | -156 | 468 | 0.7390663 | |
| *Job position= factory worker* | -303 | 456 | 0.5068855 | |
| *Job position= entrepreneur or freelancer* | 421 | 572 | 0.4615028 | |
| *Ownership= private enterprise or company* | -193 | 225 | 0.3908856 | |
| *Internet availability= yes* | -738 | 125 | 0 | *** |
| *Construction period= post-2009* | -243 | 361 | 0.5016646 | |
| *Construction period= 2000–2009* | -516 | 614 | 0.4010846 | |
| *Construction period= 1990s* | -569 | 347 | 0.1013218 | |
| *Number of rooms* | 338 | 128 | 0.0080448 | ** |
| *Square meters of living space* | 22 | 6 | 0.0002048 | *** |

Table 2.30: Falsification test 3. Pooled-DiD estimates of the effect of the treatment on rent fees. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

### 2.A.7 Statistical matching between the 2019 and 2020 HBS and the 2013 Time Use Survey

Statistical matching techniques (or data fusion) make it possible to integrate two or more data sources referring to the same target population, provided that they share a common set of variables. In practice, one has a donor dataset (or control group), which contains the additional information-and typically a larger number of units-and a recipient dataset (or treatment group), for which those variables are missing. Matching combines the information observed in the donor with the units in the recipient, imputing the absent variables so as to obtain a synthetic dataset with complete information on all variables of interest (Rubin and Schenker (1986); D'Orazio et al. (2006); Masterson (2014); Tedeschi and Pisano (2013); Chiara et al. (2019)).

Let A and B be two independent samples, of sizes $n_A$ and $n_B$ respectively, drawn from the same population. Variables Y are observed only in A, whereas variables Z are observed only in B; a set of variables X, collected in both samples and correlated with both Y and Z, serves as a bridge for imputation. The main objective is to estimate the joint distribution of (Y,Z,X) or, at least, of the pairs (Y,Z) not simultaneously observed. By applying imputation techniques, values of Y derived from 'similar' units in A are assigned to the units in B, based on the X–Y and X–Z relationships, thus obtaining a synthetic microdataset representative of the population of interest (Rässler (2002); D'Orazio et al. (2006)).

The need for such approaches arises from situations in which no single survey contains all the information required for in-depth analyses, while the collection of new data would be costly and time-consuming. Statistical matching therefore exploits already available data, preserving the distributional features of the individual surveys under the assumption that both represent the same population (Singh et al., 1990).

In the literature, two main approaches have been identified to address this problem:

- Point imputation (data fusion), which aims to create a synthetic dataset by filling in

missing values with plausible values, record by record, and which can then be used for subsequent micro-level inference (Romano (2008); Kroese and Renssen (2000)).

- Direct estimation of parameters through calibration estimators, which do not produce a complete dataset but allow interest functions to be estimated directly ((Singh et al. (1990); Kroese and Renssen (2000)).

In the context of interest, the focus is on imputation techniques. These allow information from two independent surveys to be assembled into a single microdataset, in which each unit represents, for example, a household and has values for X, Y, and Z (Tedeschi and Pisano (2013); Donatiello et al. (2014)).

Statistical matching methods are classified into three main categories (D'Orazio et al., 2006). Nonparametric methods, known as hot deck, replace missing values with values actually observed in a donor similar according to the common variables. Among the most widely used versions are random hot deck, which selects the donor at random within imputation classes defined on X; nearest neighbor hot deck, which chooses the donor with the minimum distance (e.g., Mahalanobis or Euclidean) with respect to the recipient unit; and rank hot deck, which matches the percentiles of A and B based on the distributions of X (D'Orazio et al., 2006). Constrained hot deck additionally imposes that each donor be used only once, avoiding repetitions and ensuring the use of values actually present in the database (Masterson, 2014), whereas unconstrained hot deck allows repetitions and selects the best match according to distance criteria, often simplified through a balancing score such as the propensity score (Mittag (2013); Andridge and Little (2010).

Parametric methods, instead, rely on the estimation of a model, typically an OLS linear regression, to predict Z from X in the donor dataset and then transfer the estimated coefficients to impute missing values in the recipient. This procedure may include the addition of a random error term to preserve the natural variability of the data ((D'Orazio et al., 2006)).

Mixed methods, finally, articulate a combined approach in two stages: a parametric model identifies a subset of plausible donors, on which a hot deck is then applied. Among

these, predictive mean matching (PMM) and propensity score matching (PSM) reduce the *curse of dimensionality* by condensing the information in X into a single score that simplifies the search for robust matches (Masterson (2014); Leulescu and Agafitei (2013)). A parametric approach requires the explicit adoption of a model for (X,Y,Z); its reliability therefore depends on correct model specification. By contrast, the nonparametric approach is more flexible in handling complex situations, especially when variables are of mixed types.

The validity of a matching technique with respect to preserving the true association between variables that are never jointly observed depends on the explanatory power of the common variables (Rässler (2002); Rässler and Kiesl (2009)). Given this set of common variables, the variables not jointly observed may be more or less independent after statistical matching.

The conditional independence assumption constitutes a key premise in the earliest applications of statistical matching and states that, given the common covariates X, the two variables of interest that are never jointly observed (Y in A and Z in B) are independent of each other. Mathematically, it is expressed as:

$$f(x, y, z) = f_{Y|X}(y|x) \times f_{Z|X}(z|x) \times f_X(x)$$

where $f_{Y|X}$ and $f_{Z|X}$ are respectively the conditional densities of Y and Z given X, and $f_X$ is the marginal density of X (D'Orazio et al., 2006). However, such independence occurs very rarely in reality, and, having only samples A and B, it is not possible to test the hypothesis empirically. To overcome its limitations, contemporary applications resort, where available, to auxiliary data sources that make it possible to inform the joint relationship between Y and Z outside the conditional independence assumption (Donatiello et al., 2014) and to quantify the uncertainty caused by the absence of joint observations, for example through sensitivity analysis procedures or imputation error estimation (Conti et al., 2017).

The matching process involves a series of well-defined steps in the literature. We will specify when a given step pertains to the specific use of an algorithm.

**1. Harmonisation and consistency of the datasets used**

Before implementing any statistical matching technique, it is essential to conduct a thorough pre-processing phase to ensure the compatibility and comparability of the two (or more) data sources to be integrated. This process essentially consists of two closely interconnected stages: verification of the overlap between the reference populations and harmonization of the common variables.

First, the comparability of the sampled populations must be assessed. The two surveys should approximately represent the same target population, both in terms of demographic structure and statistical weights. If discrepancies emerge-for example, due to different data collection periods or non-fully comparable sampling designs-survey design weights are adjusted by reallocating them so as to align, for instance by demographic strata or household composition, the structure of the donor with that of the recipient. Only after achieving a satisfactory degree of overlap between the weighted distributions of the two datasets can one proceed to the subsequent step (Augurzky and Schmidt, 2001).

Second, harmonization of the common variables is undertaken. This involves a detailed examination of the definitions, classifications, and data collection conditions adopted in the different surveys, in order to render them homogeneous. Variables that appear analogous-such as *education of the household head* or *employment status*-may conceal differences in measurement or in category definitions; in such cases, agreed recoding procedures are applied or, if alignment proves impossible, non-harmonizable variables are excluded (Scanu (2008); D'Orazio (2017)).

Consistent harmonization is subsequently reflected in the examination of the marginal and joint distributions of the common variables: these should be substantially overlapping if the two samples are representative of the same population, otherwise the matching procedure may introduce bias (Black and Smith (2004); Caliendo and Kopeinig (2008)).

**2. The selection of variables for matching**

The selection of the matching variables, here denoted as $X_M$, represents a crucial step

in statistical matching, as it directly affects both compliance with the common support condition (in the case of mixed methods using the propensity score matching approach) and the plausibility of the conditional independence assumption $Y \perp Z \mid X$. An overly parsimonious specification may favor the area of overlap between donor and recipient, but at the risk of omitting covariates that are relevant for conditional independence; conversely, including a broad set of variables enhances the credibility of this assumption, albeit at the potential cost of reducing the region of common support (Caliendo and Kopeinig (2008); Augurzky and Schmidt (2001)).

To ensure that the selected common variables are not inherently linked to the sampling structure, their marginal and joint distributions are compared across the two datasets prior to matching. For this purpose, distance measures such as the Hellinger distance and Cramer's V association coefficient are commonly computed, assessing both the similarity of frequencies and the strength of association between the two distributions. Both indices range between 0 and 1, with values close to 0 indicating a weak relationship: in the case of Cramer's V, a value below 0.15 is generally considered an acceptable threshold for 'weak association' (Sisto (2006); Leulescu and Agafitei (2013); Masterson (2010)).

The construction of $X_M$ may follow two strategies-starting from the subset of variables that best explain Y ($X_Y$) and/or Z ($X_Z$)-and combining them through either the union ($X_Y \vee X_Z$) or the intersection ($X_Y \wedge X_Z$) of their respective importance rankings (Cohen (1991); D'Orazio (2017)). The relationship between each common variable and the variable of interest is assessed through appropriate measures of association: for pairs of categorical variables, chi-square tests with Cramer's coefficients or measures of variance reduction are employed; when the response variable is continuous, Pearson or Spearman rank correlations are examined, supported by the analysis of adjusted $R^2$ to detect potential nonlinear relationships. In the mixed case of categorical predictors and a continuous response, the coefficient $\eta^2$ derived from an ANOVA provides an excellent measure of effect strength.

**3. Use the matching algorithm**

Once the common variables to be used in the two datasets have been identified, the

chosen algorithm can be implemented. With regard to the application of non-parametric techniques, once these have been carried out, one may proceed directly to step 4), which concerns the evaluation of matching quality.

By contrast, when adopting a mixed approach based on propensity score matching, several intermediate assessments are required before performing the actual matching algorithm. Specifically, it is necessary to evaluate the outcome of the propensity score estimation, verifying adequate covariate balance and sufficient overlap in the score distributions. Only after confirming satisfactory balancing of covariates and an adequate region of common support does one proceed to the actual matching step, whereby each individual in the recipient dataset is paired with a donor whose propensity score is as close as possible. In this way, a sample balanced on X is obtained, reducing selection bias and enhancing the credibility of the estimated effects of interest.

The choice of matching algorithm also differs according to whether or not replacement of donor units is allowed when matching to recipient units. Unconstrained matching permits the same donor to be used multiple times (sampling with replacement). This approach favors the closest possible match for each recipient, thereby reducing bias, but it may increase the variance of the estimators and lead the distribution of imputed variables to more closely reflect the empirical marginal distribution of the recipient rather than that of the original donor (Rodgers (1984); Rässler (2002); Masterson (2010)).

Constrained matching, in contrast, imposes that each donor be used only once (sampling without replacement). As a result, the average distance between recipients and donors tends to increase-with a possible rise in bias-although it remains possible to weight records so that a single donor can effectively represent multiple recipients (by using sampling weights). This method is computationally more demanding.

Among the principal algorithms employed in the literature are Nearest Neighbor matching (with or without caliper), Caliper or radius matching (distance threshold), Stratification or interval matching, Kernel and local linear matching, and Weighting (assignment of weights based on the propensity score). The choice among these methods

depends on the well-known bias–variance trade-off: with large samples, all methods tend to converge to similar results, whereas with small samples the distinction between matching with and without replacement (as well as the number of controls used) becomes crucial (Dehejia and Wahba (2002); Caliendo and Kopeinig (2008)).

### 3.1 Evaluation of propensity score matching

Propensity score matching consists in calculating, for each unit in the recipient and donor samples, the propensity score, that is, the probability of belonging to the recipient group given the combination of matching covariates (X). These covariates may vary depending on the specific pairwise matching to be performed, but the objective remains to condense into a single synthetic indicator all the information necessary to balance the distributions of (X) between the two groups. Once the propensity score has been estimated-usually by means of a logistic regression-it is essential to validate its specification through two main assessments. The covariate balance test. To verify that, after matching, the distributions of each common variable are effectively balanced, several types of tests are employed (Lee, 2013) including standardized differences (the difference between the means of a common variable in the two groups divided by the square root of the average of their variances; values above 20% indicate insufficient balance (Rosenbaum and Rubin, 1985), the univariate t-test (which compares the mean of each common variable between recipient and donor, both before and after matching, assessing the statistical significance of the differences (Rosenbaum and Rubin, 1985), the stratification test (the sample is divided into homogeneous strata of propensity score in which the mean score does not differ between groups; within each stratum the t-test on the covariates is repeated, ensuring that none yields a significant result (Dehejia and Wahba (2002); Caliendo and Kopeinig (2008)) and Hotelling's test (which jointly verifies the equality of the multivariate means of all covariates; it is the multivariate generalization of the t-test and rejects the specification if significant (Smith and Todd, 2005). The second test necessary for the validation of PSM is the verification of overlap (*common support*). For matching to be valid, every value of the propensity score observed in the recipient group must find a corresponding donor unit

with a similar score. The region of overlap between the two score distributions is therefore examined and, in particular, the propensity score densities are graphically inspected in order to highlight any areas not covered by the donor sample (Lechner (2008); Caliendo and Kopeinig (2008)).

**4. Assessment of the quality of statistical matching**

The evaluation of the quality of a statistical matching procedure represents the final and crucial stage in which it is assessed whether the resulting synthetic dataset is effectively capable of reproducing the characteristics of the donor dataset and, more generally, of the reference population. In the literature (D'Orazio et al. (2006); Rässler (2002)), four levels of validity are identified, from the most stringent to the weakest: preservation of the individual imputed values, preservation of the joint distribution of X,Y,Z, maintenance of the correlation structure among the variables, and, finally, mere preservation of the marginal and joint distributions of the common covariates and the imputed values. Since in real applications the true unobserved values are rarely available for direct verification, attention is typically focused on the two less stringent levels, namely marginal/joint distributions and correlations (Conti et al. (2016, 2017)).

A pragmatic approach to this issue first involves:

a) The graphical inspection of the distributions of the imputed variables, comparing the density functions or histograms of the imputed values with the original ones. When the probability densities of a continuous variable-for example, household disposable income-appear nearly overlapping in the donor and in the synthetic dataset, it can reasonably be concluded that the marginal distribution is well preserved (Masterson (2010); Webber and Tonkin (2013));

b) In parallel, the central tendency of the imputed values is assessed in relation to the covariates (X) used for matching, by calculating the ratio between means (or medians) in the two datasets. This ratio, ideally equal to 100, indicates the percentage distance between the location statistics: the closer it is to 100, the greater the similarity between donor and recipient. Although no universally accepted thresholds exist, a confidence interval

between 80% and 120% is often considered indicative of good matching performance when analyzing means or percentiles within groups defined by demographic or socio-economic characteristics (Rässler (2002); Lechner (2008));

c) Moreover, it is common practice to determine and compare the conditional distributions of the imputed variables with respect to the variables employed in matching, by examining means, medians, quartiles, minima, and maxima within each class of the categorical variables.

d) Finally, in order to more rigorously quantify the uncertainty arising from the conditional independence assumption-that is, from the impossibility of observing (Y) and (Z) simultaneously-researchers resort to the computation of Fréchet bounds. These intervals operationalize the maximum and minimum extent of correlation compatible with the known marginals, thereby providing a measure of the possible deviations from the true joint distribution (Conti et al. (2016, 2017)).

## Statistical matching procedure applied in this paper

In order to enrich the analysis of changes in energy consumption due to the lockdown, we decided to also consider the impact on home-to-work commuting. Since the HBS does not report this information, we adopted a statistical matching strategy: from the TUS (Time Use Survey) dataset we extract each individual's commuting time and associate it with the corresponding cases in the HBS. The operation is structured in two stages: in the first matching, we link HBS 2019 with TUS 2013; in the second, we repeat the procedure between HBS 2020 and TUS 2013, applying different matching techniques to ensure the robustness of the results.

In this process, the donor dataset is TUS 2013. The microdata from the *Indagine Multiscopo sulle Famiglie: Uso del Tempo* conducted by Istat collect, in diary form, the activities performed by approximately 20,000 households and 50,000 individuals in Italy. Thanks to daily diaries organized into 144 ten-minute intervals, it is possible to reconstruct precisely the 24-hour schedule-from commuting to work, to study, to leisure-thereby avoiding the over- or underestimation biases typical of direct questions on activity duration (Chenu and Lesnard, 2006). We use the most recent available dataset, referring to 2013, in which each recorded event reports start and end time, location, type of activity, and co-presence, while 269 variables describe individual characteristics such as age, gender, educational attainment, income, and type of employment. The survey includes three distinct diaries-daily, individual, and weekly-which respectively cover main and secondary activities with detailed time data, the socio-demographic profile, and working hours distributed in 15-minute intervals over the week. Integration between the daily and individual diaries is ensured through unique identifiers relating to individual and household progressive numbers. From this dataset it is possible to derive, for each individual, the time devoted to commuting (when present), which constitutes our variable of interest. Leisure activities were reclassified and aggregated according to the classification reported in Table 2.31.

| Istat Codes for Individual Activities (Working and Leisure Time) | Description of the Activity Undertaken | Classification of the Individual Activity into Its Category |
|---|---|---|
| 11 | Dormire | personal need |
| 12 | Stare a letto malato | personal need |
| 21 | Mangiare, bere | personal need |
| 31 | Lavarsi, vestirsi, pettinarsi | personal need |
| 39 | Altre cure specificate e non specificate legate alla cura della propria persona, cure mediche | personal need |
| 90 | Spostamenti senza finalità | non-work travel |
| 111 | Lavoro principale, formazione sul lavoro, altre attivita' svolte per lavoro | paid work |
| 112 | Pausa caffè/brevi pause sul lavoro principale | personal need |
| 113 | Spostamenti durante il lavoro principale | commuting to work |
| 121 | Secondo lavoro | paid work |
| 122 | Pausa caffè/brevi pause durante il secondo lavoro | personal need |
| 123 | Spostamenti durante il secondo lavoro | commuting to work |
| 132 | Attivita' svolte per lavoro, fuori dell orario di lavoro | paid work |
| 139 | Altre attivita' legate al lavoro, ricerca di lavoro | paid work |
| 211 | Corsi, lezioni, esami | education |
| 212 | Studio a casa (compiti), in biblioteca o altrove | education |
| 219 | Altre attivita' legate alla scuola o all universita' | education |
| 221 | Studi e corsi espressivo-artistici | leisure |
| 222 | Studi e corsi di lingue | education |
| 223 | Studi e corsi per l uso del computer | education |
| 224 | Studi e corsi tecnico-operativi | education |
| 229 | Altre attivita' specificate e non specificate legate a studi e corsi | education |
| 311 | Preparare i pasti | housework |
| 312 | Lavare le stoviglie, apparecchiare e sparecchiare la tavola | housework |
| 319 | Altre attivita' specificate e non legate alla preparazione dei pasti | housework |
| 321 | Pulizia e riordino dell'abitazione e parti dell'edificio abitativo | housework |
| 322 | Pulizia delle parti esterne della casa | housework |
| 323 | Approvvigionamento di materiale per riscaldamento e acqua | housework |
| 324 | Sistemazione di oggetti e beni della propria famiglia | housework |
| 329 | Altre attivita' specificate e non legate alla cura della casa | housework |
| 331 | Lavare, stendere e ritirare il bucato | housework |
| 332 | Stiratura | housework |
| 333 | Produzione di capi di abbigliamento, biancheria, calzature (non per lavoro) | personal need |
| 339 | Altre attivita' specificate e non legate alla produzione, riparazione e cura di abiti, biancheria, calzature | personal need |
| 341 | Cura delle piante | housework |
| 342 | Cura degli animali da cortile/allevamento | housework |
| 343 | Cura degli animali domestici | housework |
| 344 | Portare a passeggio il cane | housework |
| 349 | Altre attivita' specificate e non legate al giardinaggio e alla cura di animali | housework |
| 351 | Costruzione e ristrutturazione della propria abitazione | housework |
| 352 | Riparazioni nella propria abitazione:pitturare pareti, riparare impianti, ecc. | housework |
| 353 | Costruzione, riparazione e cura di mobili o altri beni della propria abitazione | housework |
| 354 | Manutenzione e riparazione di veicoli | housework |
| 359 | Altre attivita' specificate e non legate alla costruzione e riparazione abitazione, altri beni e veicoli | housework |
| 361 | Acquisto di beni, spesa quotidiana | housework |
| 362 | Acquisto di servizi commerciali per la casa e la famiglia | housework |
| 363 | Acquisto di servizi amministrativi per la casa e la famiglia | housework |
| 364 | Servizi medici, altri servizi personali a pagamento | personal need |
| 365 | Servizi veterinari per animali domestici o da cortile, allevamento | housework |
| 369 | Altre attivita' specificate e non legate agli acquisti di beni e servizi | housework |
| 371 | Gestione della vita familiare | housework |
| 372 | Gestione della vita familiare con l uso del PC o di internet | housework |
| 381 | Cure fisiche e sorveglianza | time care |
| 382 | Aiutare i bambini/ragazzi a fare i compiti | time care |
| 383 | Giocare, leggere e parlare con bambini/ragazzi della famiglia | time care |
| 384 | Accompagnare i bambini/ragazzi | time care |
| 389 | Altre attivita' specificate e non legate alla cura di bambini/ragazzi | time care |
| 391 | Cure fisiche ad adulti della famiglia | time care |
| 392 | Prestazioni sanitarie ad adulti disabili o malati della famiglia | time care |
| 393 | Compagnia, accompagnare adulti della famiglia | time care |
| 394 | Aiuto prestato ad adulti della famiglia nello svolgimento di attivita' varie: lavoro extradomestico, studio, ecc. | time care |
| 399 | Altre attivita' specificate e non di cura o aiuto ad adulti famiglia | time care |
| 411 | Attivita' di volontariato svolta nell ambito di un gruppo/associazione | social partecipation |
| 421 | Cucinare come aiuto | social partecipation |
| 422 | Pulizia e riordino della casa come aiuto | social partecipation |
| 423 | Cura dei propri figli non conviventi | time care |
| 424 | Costruzioni e riparazioni come aiuto | social partecipation |
| 425 | Acquisti di beni e servizi come aiuto | social partecipation |
| 426 | Aiuto nel lavoro extradomestico | social partecipation |
| 427 | Cura di bambini/ragazzi di altre famiglie come aiuto | social partecipation |
| 428 | Cura di adulti come aiuto | social partecipation |
| 429 | Altre attivita' specificate e non legate agli aiuti gratuiti a persone di altre famiglie | social partecipation |
| 431 | Partecipazione in incontri/riunioni | leisure |
| 432 | Partecipazione religiosa | social partecipation |
| 439 | Altre attivita' specificate e non legate alla partecipazione sociale religiosa | social partecipation |
| 511 | Socializzare con la propria famiglia | housework |
| 512 | Fare e ricevere visite | leisure |
| 513 | Festeggiamenti | leisure |
| 514 | Conversazioni telefoniche | leisure |
| 515 | Attivita' di socializzazione dei bambini/ragazzi non meglio specificate | leisure |
| 516 | Parlare fuori casa con persone non conviventi | leisure |
| 517 | Altre attivita' di vita sociale svolte fuori casa | leisure |
| 519 | Altre attivita' specificate e non legate alla vita sociale | leisure |
| 521 | Cinema | leisure |
| 522 | Teatro, concerto | leisure |
| 523 | Mostre, musei | leisure |
| 524 | Biblioteca (non per studio) | leisure |
| 525 | Manifestazioni sportive come spettatore | leisure |
| 529 | Escursioni, gite ed altre attivita' specificate e non legate al divertimento/cultura | leisure |
| 531 | Riposo, pausa, non fare niente | leisure |
| 611 | Camminare, passeggiare, guardare le vetrine, fare escursioni a piedi, | leisure |
| 612 | Jogging, corsa | leisure |
| 613 | Ciclismo, sci, pattinaggio | leisure |
| 614 | Giochi con la palla | leisure |
| 615 | Ginnastica, fitness | leisure |
| 616 | Sport acquatici, sport nautici | leisure |
| 617 | Danza classica, moderna, jazz, ecc. (come sport) | leisure |
| 619 | Altri sport specificati e non specificati | leisure |
| 621 | Caccia, pesca, raccolta di funghi, piante, bacche selvatiche e altre attivita' svolte per procurarsi prodotti della natura | personal need |
| 631 | Altre attivita' legate allo sport e alle attivita' all aperto | leisure |
| 711 | Attivita' artistico-espressive (pittura, scultura, fotografia, video, musica, teatro, cinema, prosa e poesia) | leisure |
| 712 | Collezioni | leisure |
| 713 | Corrispondenza | leisure |
| 714 | Ascoltare una favola (per rispondenti fino a 17 anni) | time care |
| 719 | Altri passatempi specificati e non | leisure |
| 721 | Informatica, programmazione | leisure |
| 722 | Accesso alle informazioni tramite il computer: internet, CD-rom, DVD | leisure |
| 723 | Posta elettronica, chat, messaggistica mobile | leisure |
| 729 | Altri utilizzi specificati e non specificati del pc | leisure |
| 731 | Giocare da soli, giochi d'azzardo | leisure |
| 732 | Giocare con altri, giochi di societa' | leisure |
| 733 | Giochi con il computer, videogiochi | leisure |
| 734 | Giochi con animali | housework |
| 735 | Giochi creativi, artistici dei bambini: colorare, disegnare, scrivere, ecc. (per rispondenti fino a 17 anni) | time care |
| 736 | Giochi di movimento dei bambini: correre, giochi con la palla, la bicicletta, il triciclo, ecc. (per rispondenti fino a 17 anni) | time care |
| 739 | Altri giochi specificati e non specificati | leisure |
| 811 | Lettura di quotidiani | leisure |
| 812 | Lettura di riviste periodiche | leisure |
| 813 | Lettura di libri | leisure |
| 814 | Leggere fumetti, giornalini, per bambini/ragazzi (per rispondenti fino a 17 anni) | leisure |
| 819 | Altre letture specificate e non specificate | leisure |
| 821 | Guardare la televisione o registrare videocassette, dvd, dvx | leisure |
| 822 | Guardare programmi televisivi, film, video su PC o internet | leisure |
| 831 | Ascoltare musica | leisure |
| 832 | Ascoltare musica o radio su pc o internet | leisure |
| 900 | Spostamenti per la cura della propria persona | non-work travel |
| 910 | Spostamenti per lavoro | commuting to work |
| 921 | Spostamenti per scuola, universita' | non-work travel |
| 922 | Spostamenti legati ad altri studi o corsi | non-work travel |
| 931 | Spostamenti per la cura della propria casa | non-work travel |
| 936 | Spostamenti per acquisti beni/servizi, gestione della famiglia | non-work travel |
| 938 | Spostamenti per la cura di bambini della famiglia | non-work travel |
| 939 | Spostamenti per la cura di adulti della famiglia | non-work travel |
| 941 | Spostamenti legati ad attivita' di volontariato | non-work travel |
| 942 | Spostamenti legati ad aiuti gratuiti ad altre famiglie | non-work travel |
| 943 | Spostamenti legati alla partecipazione sociale e religiosa | non-work travel |
| 951 | Spostamenti legati alla vita sociale | non-work travel |
| 960 | Spostamenti legati ad altre attivita' del proprio tempo libero | non-work travel |
| 971 | Spostamenti legati al cambio di localita' | Long-distance travel |
| 972 | Spostamenti per svago | non-work travel |
| 981 | Spostamenti di bambini con entrambi i genitori (per rispondenti fino a 17 anni) | non-work travel |
| 982 | Spostamenti di bambini con il padre (anche non convivente) (per rispondenti fino a 17 anni) | non-work travel |
| 983 | Spostamenti di bambini con la madre (anche non convivente) (per rispondenti fino a 17 anni) | non-work travel |
| 989 | Spostamenti di bambini con altre persone (per rispondenti fino a 17 anni) | non-work travel |
| 995 | Compilare il diario sull'Uso del Tempo Istat | leisure |
| 997 | Frase che non descrive attivita' o utilizzo improprio delle caselle del diario | leisure |

Table 2.31: Original activities and categorizations from the Italian National Institute of Statistics (Istat) dataset. The first column contains the identification codes for free time, commuting to work and work activities, whereas the second column provides their descriptions according to the Istat classification. In the third column, each free time activity is assigned to a corresponding free time macro-category according to the authors' classification.

Recalling point 1) of the procedure required to conduct sound statistical matching, the comparison between TUS and HBS reveals substantial consistency in the reference populations and in the methodological framework, alongside some differences in detail that require prior harmonization of sampling weights. In both cases, the reference population is defined as the set of 'de facto' households residing in Italy and the individuals composing them, explicitly excluding institutionalized populations (barracks, hospitals, religious institutions, or similar settings). This semantic coincidence ensures full overlap in inclusion criteria, so that neither survey introduces structural bias in defining the statistical universe.

The sampling design in both surveys follows a two-stage cluster model: municipalities, classified as 'self-representative' (AR) and 'non-self-representative' (NAR), and households within them. In AR municipalities, inclusion is certain; in NAR municipalities, selection occurs with probability proportional to population size and without replacement, while households within each municipality are selected systematically or randomly with equal probability. This shared framework ensures comparable variance structures and allows the two samples to be combined without introducing design heterogeneity.

Differences mainly concern temporal articulation and the definition of municipal classes. In TUS, temporal stratification involves monthly subdivision over twelve months and assignment of day type (weekday, pre-holiday, holiday), whereas in HBS the design is replicated quarterly with monthly stratification and two fourteen-day windows per month. Regarding municipal typologies, TUS distinguishes six categories based on a more detailed socio-demographic grid, whereas HBS uses three categories grouping municipalities into metropolitan centers, intermediate aggregates, and the rest of the territory. Although this diversity does not compromise overall design coherence, it requires recoding or aggregation of municipal classes to obtain a homogeneous basis for comparison. Concerning sampling weights, both surveys employ calibration estimators articulated in sequential stages: calculation of the base weight (inverse of the inclusion probability), correction for non-response, and final adjustment through calibration on known totals of auxiliary variables (distribution by sex and age, municipal typology, geographical area,

etc.). TUS introduces additional complexity by assigning distinct weights to the three day types and defining a weight for the 'average week day' as a weighted combination of sub-samples. HBS, by contrast, adopts a single set of weights referring to the entire year, replicated quarterly. Although both share the same calibration principle and similar constraint sets, differences in temporal granularity and weight structure require adjustment to ensure direct comparability. In conclusion, TUS 2013 and HBS 2019 do not present substantial inconsistencies in the reference population or in the two-stage AR/NAR design and share the same philosophy of weight calibration. The discrepancies concern only temporal-spatial stratification and municipal classification, which can be resolved through appropriate recoding of territorial classes and recalibration of weights on a shared set of auxiliary margins and total weight sums. Only in this way can statistical matching be conducted without artifacts and allow for rigorous comparative analysis of the two datasets.

In TUS, each observation corresponds to a single individual; consequently, dataset columns represent individual characteristics. HBS adopts a different structure: each row reports all information concerning the members of a household. For example, if a household consists of three individuals, the observation includes the variables of all three members. This structural difference requires careful consideration in designing the statistical matching procedure between the two datasets. A crucial element is that, in HBS, the first individual 'slot' in each row identifies the reference person-that is, the individual to whom the survey was actually administered. This person can be considered the household representative and constitutes an ideal candidate for comparison with those TUS observations identified as reference persons according to the variable 'relparm'. In practice, by selecting the household head or 'reference individual' in HBS, we obtain a set of variables perfectly alignable with the observational units of TUS, thereby facilitating the statistical matching process.

Recalling points 1) and 2), we subsequently identified all common variables in the datasets and, irrespective of the technique employed, selected a set of eighteen covariates

when matching HBS 2019 with TUS 2013. When matching HBS 2020 with TUS 2013, we considered sixteen covariates, excluding the variables 'education' and 'mobile phone' based on an ex-ante evaluation of their marginal distributions. Furthermore, a harmonization procedure was required for the common variables used in these applications. Table 2.32 reports the variables employed in the two statistical matching processes, indicating in which process they were used and the harmonization performed (where necessary). All variables considered are categorical.

Referring again to points 1) and 2), we conducted an ex-ante assessment on the HBS 2019 and 2020 datasets and the TUS 2013 dataset. It should be noted that, since our target population for the analysis concerns workers, we excluded observations that do not fall within this category. Moreover, in this ex-ante evaluation, some variables were considered that were not subsequently used among the common variables. The preliminary checks included: i) calculating and reporting absolute and relative frequency tables for each variable, both in the TUS and in the HBS; ii) measuring the relative or percentage difference between the TUS and HBS distributions, category by category; and iii) applying global association tests (Cramer's V) and distance measures (Hellinger) for each common variable, in order to quantify the extent to which the two groups differ.

**Ex-ante Assessment HBS 2019 and TUS 2013**

Overall, the analysis highlights good comparability between the two surveys on a substantial number of socio-demographic and economic variables (Tables 2.33 and 2.35). Variables such as gender, marital status, household composition (ncomp), citizenship, geographic area, number of children, car ownership, working hours, and ownership of digital devices (PC, mobile phone, internet) show minor differences, with Cramér's V values generally below 0.05 and Hellinger distances well below the threshold of concern (0.075), suggesting good overlap of the distributions (Table 2.36). Other covariates, however, display moderate heterogeneity between the two samples. Perceptions of available economic resources, education level, main source of income, and occupational position show notable but still acceptable deviations, with Cramér's V values ranging from 0.07 to 0.10 and

| Variables | Description | Use in Statistical Matching | Harmonization (if necessary) |
|---|---|---|---|
| Household's components | Indicates the number of people composing the household | 2019; 2020 | All values 9 are recoded as 9 |
| Quarter | Indicates the quarter to which the observation refers | 2019; 2020 | Grouping of months into four quarters (1 = Jan–Mar ... 4 = Oct–Dec) |
| Gender | Indicates the gender of the individual | 2019; 2020 | None |
| Geographic Area | Indicates the geographic area of the observation: North-East, Center, South, and Islands | 2019; 2020 | None |
| Marital Status | Indicates the civil status of the observed individual | 2019; 2020 | Unified into 4 categories: single; married/cohabiting; separated/divorced; widowed |
| Age | Indicates the age range of the observation | 2019; 2020 | 7 age groups: 15–24; 25–34; ...; 75+ |
| Professional Code | Indicates the occupation of the observation. Classification includes nine categories: 1) legislators, entrepreneurs, and top executives; 2) intellectual, scientific, and highly specialized professions; 3) technical professions; 4) office clerical professions; 5) skilled professions in commerce and services; 6) artisans, skilled workers, and farmers; 7) plant operators, machinery operators, and vehicle drivers; 8) unskilled professions; 9) armed forces | 2019; 2020 | None |
| Citizenship | Indicates whether the individual is Italian or foreign | 2019; 2020 | None |
| Education | Indicates the education level of the individual | 2019 | Recoding: 1 = Bachelor's or postgraduate degree; 7 = High school diploma; 9 = Middle school certificate; 10 = Elementary school certificate; 11 = No qualification |
| Mobile Phone | Indicates ownership of a mobile phone | 2019 | None |
| Number of Children | Indicates the number of children of the individual | 2019; 2020 | None |
| Number of Children under 15 | Indicates the number of children under 15 | 2019; 2020 | None |
| Source of Income | Indicates the source of individual income | 2019; 2020 | 5 ordered categories: employee; self-employed; pension; assets/allowances/rent/securities; family support |
| Contract Type | Indicates whether the employment contract is full-time or part-time | 2019; 2020 | None |
| Computer | Indicates ownership of a computer | 2019; 2020 | None |
| Internet Access | Indicates whether the individual has an internet connection at home | 2019; 2020 | None |
| Car | Indicates ownership of a car | 2019; 2020 | None |
| Economic Resources | Self-assessed level of available economic resources | 2019; 2020 | Recoded into 4 ordered levels: excellent; adequate; scarce; completely insufficient |

Table 2.32: Common variables used in the statistical matching process for the TUS and HBS surveys.

Hellinger distances between 0.10 and 0.14. The variable capturing the sector of activity records the largest differences, with a Cramér's V above 0.10 and a Hellinger distance exceeding 0.15.

| Variable | Class | Tus (absolute and relative frequency (%)) | Hbs 2019 (absolute and relative frequency (%)) |
|---|---|---|---|
| Internet access | | | |
| | No | 1455 (15.9%) | 1390 (15.3%) |
| | Yes | 7719 (84.1%) | 7684 (84.7%) |
| ATECO code (industrial sector code) | | | |
| | Agriculture, forestry, hunting, and fishing | 540 (5.9%) | 221 (2.4%) |
| | Construction | 900 (9.8%) | 620 (6.8%) |
| | Industry (excluding construction) | 1364 (14.9%) | 1689 (18.6%) |
| | Services | 6370 (69.4%) | 6325 (69.7%) |
| Car ownership | | | |
| | No | 951 (10.4%) | 832 (9.2%) |
| | Yes | 8223 (89.6%) | 8242 (90.8%) |
| Domestic origin | | | |
| | Foregin | 1029 (11.2%) | 855 (9.4%) |
| | Italian | 8145 (88.8%) | 8219 (90.6%) |
| Age range | | | |
| | 15-24 | 36 (0.4%) | 62 (0.7%) |
| | 25-34 | 1069 (11.7%) | 904 (10%) |
| | 35-44 | 2626 (28.6%) | 2192 (24.2%) |
| | 45-54 | 3208 (35%) | 3166 (34.9%) |
| | 55-64 | 1892 (20.6%) | 2322 (25.6%) |
| | 65-74 | 276 (3%) | 367 (4%) |
| | 75 and higher | 67 (0.7%) | 61 (0.7%) |
| Job code | | | |
| | Legislators, entrepreneurs, and senior management | 453 (4.9%) | 351 (3.9%) |
| | Intellectual, scientific, and highly specialized professions | 1203 (13.1%) | 1378 (15.2%) |
| | Technical professions | 1392 (15.2%) | 1570 (17.3%) |
| | Clerical support workers | 981 (10.7%) | 963 (10.6%) |
| | Skilled workers in commercial activities and services | 1513 (16.5%) | 1478 (16.3%) |
| | Craftsmen, skilled workers, and farmers | 1807 (19.7%) | 1464 (16.1%) |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | 717 (7.8%) | 803 (8.8%) |
| | Elementary occupations | 909 (9.9%) | 921 (10.1%) |
| | Armed forces | 122 (1.3%) | 139 (1.5%) |
| Working condition | | | |
| | Employed | 9174 (100%) | 9074 (100%) |
| Source of income | | | |
| | Self-employed | 2363 (25.8%) | 2178 (24%) |
| | Employee (or Salaried worker) | 6545 (71.3%) | 6808 (75%) |
| | Family support | 57 (0.6%) | 15 (0.2%) |
| | Capital income / Allowances / Rents / Securities | 80 (0.9%) | 23 (0.3%) |
| | Pension (or Retirement income) | 129 (1.4%) | 50 (0.6%) |
| Level of education | | | |
| | High school diploma | 4026 (43.9%) | 4286 (47.2%) |
| | Bachelor diploma or higher | 1817 (19.8%) | 1974 (21.8%) |
| | Elementary school diploma | 422 (4.6%) | 231 (2.5%) |
| | Middle school diploma | 2856 (31.1%) | 2544 (28%) |
| | No formal education | 53 (0.6%) | 39 (0.4%) |
| Type of working contract | | | |
| | Fixed-term | 841 (9.2%) | 675 (7.4%) |
| | Open-ended | 5525 (60.2%) | 6159 (67.9%) |
| Quarter | | | |
| | 1 | 2431 (26.5%) | 2207 (24.3%) |
| | 2 | 2326 (25.4%) | 2255 (24.9%) |
| | 3 | 2227 (24.3%) | 2297 (25.3%) |
| | 4 | 2190 (23.9%) | 2315 (25.5%) |
| Number of household's components | | | |
| | 1 | 2425 (26.4%) | 2291 (25.2%) |
| | 2 | 1681 (18.3%) | 2047 (22.6%) |
| | 3 | 2232 (24.3%) | 2089 (23%) |
| | 4 | 2213 (24.1%) | 2032 (22.4%) |
| | 5 | 497 (5.4%) | 496 (5.5%) |
| | 6 | 89 (1%) | 93 (1%) |
| | 7 | 24 (0.3%) | 16 (0.2%) |
| | 8 | 6 (0.1%) | 6 (0.1%) |
| | >=9 | 7 (0.1%) | 4 (0%) |
| Number of children | | | |
| | 0 | 4339 (47.3%) | 4005 (44.1%) |
| | 1 | 2314 (25.2%) | 2308 (25.4%) |
| | 2 | 2086 (22.7%) | 2207 (24.3%) |
| | 3 | 372 (4.1%) | 477 (5.3%) |
| | 4 | 55 (0.6%) | 70 (0.8%) |
| | 5 | 6 (0.1%) | 5 (0.1%) |
| Number of children under 15 | | | |
| | 0 | 6541 (71.3%) | 6227 (68.6%) |
| | 1 | 1654 (18%) | 1634 (18%) |
| | 2 | 856 (9.3%) | 1025 (11.3%) |
| | 3 | 111 (1.2%) | 164 (1.8%) |
| | 4 | 11 (0.1%) | 20 (0.2%) |
| | 5 | 1 (0%) | 4 (0%) |
| Computer ownership | | | |
| | No | 1253 (13.7%) | 1607 (17.7%) |
| | Yes | 7921 (86.3%) | 7467 (82.3%) |
| Geographical distribution | | | |
| | North-west | 2200 (24%) | 2421 (26.7%) |
| | North-east | 2141 (23.3%) | 2164 (23.8%) |
| | Centre | 1734 (18.9%) | 1855 (20.4%) |
| | South | 2252 (24.5%) | 1916 (21.1%) |
| | Islands | 833 (9.1%) | 718 (7.9%) |
| Economic resources | | 14 (0.2%) | 0 (0%) |
| | Adequate | 5571 (60.7%) | 6142 (67.7%) |
| | Absolutely insufficient | 533 (5.8%) | 313 (3.4%) |
| | Excellent | 189 (2.1%) | 309 (3.4%) |
| | Poor | 2881 (31.4%) | 2310 (25.5%) |
| Gender | | | |
| | Male | 6703 (73.1%) | 6354 (70%) |
| | Female | 2471 (26.9%) | 2720 (30%) |
| Marital status | | | |
| | Single | 2203 (24%) | 2446 (27%) |
| | Married | 5125 (55.9%) | 4927 (54.3%) |
| | Separated/divorced | 1593 (17.4%) | 1472 (16.2%) |
| | Widow/widower | 253 (2.8%) | 229 (2.5%) |
| Mobile phone ownership | | | |
| | No | 73 (0.8%) | 194 (2.1%) |
| | Yes | 9101 (99.2%) | 8880 (97.9%) |
| Type of working schedule | | | |
| | Full-time | 8076 (88%) | 6082 (67%) |
| | Part-time | 1098 (12%) | 752 (8.3%) |

Table 2.33: Absolute and relative frequencies of covariates in TUS 2013 vs. HBS 2019. This table shows, for each categorical variable, the absolute frequencies (N) and relative frequencies (percentage) in both the TUS sample and the HBS sample.

**Ex-ante Assessment HBS 2020 and TUS 2013**

Compared to the comparison between TUS 2013 and HBS 2019, the preliminary analysis between TUS 2013 and HBS 2020 shows slightly more pronounced misalignments in the distributions of socio-demographic covariates, but still within limits that allow the application of matching techniques (Tables 2.34 and 2.35). The percentage differences by category, calculated between the two sources, reveal wider deviations in some key variables such as age, education, sector of activity, and perceived resources, while for many other variables the distributions are similar or only moderately divergent. Synthetic tests based on Cramér's V and Hellinger distance (Table 2.36)-used to measure the overall degree of distributional inequality between the two datasets-return values that on average remain below the thresholds commonly adopted in the literature to define good overlap (0.10 for Cramér and 0.15 for Hellinger). However, compared to the combination with HBS 2019, there is a higher concentration of variables approaching or exceeding these thresholds.

**Matching Strategy**

For the matching operation, two different approaches were employed: the mixed approach, which involves the use of propensity score matching (PSM) followed by techniques to pair observations from the donor and recipient samples (Wolff and Zacharias (2003); Masterson (2010); Zacharias et al. (2014); Chiara et al. (2019)), and the non-parametric approach, which utilized various hot deck strategies, ranging from more 'deterministic' to more 'random' imputation, with or without the use of predefined donor groups.

In the application of the first method (PSM), when the terms 'treated' and 'control' are used, the treated group refers to the recipient dataset and the control group to the donor dataset. This analogy implies that the treated group is the recipient of the 'treatment', that is, of the additional information coming from the control (donor) dataset, which 'treats' (provides) information to the recipient. The main assumptions underlying this statistical matching procedure, particularly when using PSM-that is, the conditions without which the imputation of missing data risks producing biased or unidentified results—are the following (Chiara et al., 2019): i) Missing Completely At Random (MCAR): this

assumption states that the probability of encountering a missing value does not depend on either observed or unobserved values, but is simply due to a sampling process or random error. In other words, missing cases are distributed 'randomly' across the dataset and are not correlated with any unit characteristics. If this assumption holds, we can ignore their presence without introducing bias; and ii) Ignorability: when referring to ignorability, the concept of MCAR is extended to the fact that, once conditioned on the observed covariates, any unobserved confounding factors or missing data do not affect the estimation of the effect of interest. In practice, we assume that everything that matters in explaining the occurrence of missing values is already included in the variables we have measured. Rosenbaum and Rubin (1983) define strong ignorability as the combination of the conditional independence assumption and common support. Only if both requirements are satisfied can we hope to credibly reconstruct missing values using matching.

In the practice of statistical matching, however, we never have joint observations of Y and Z, and thus it is impossible to verify MCAR, ignorability, or conditional independence; the common data X serve only as a bridge for imputation. This lack of joint information makes the true relationship between Y and Z unidentifiable: we cannot know whether the pairing we impose truly reflects the statistical structure of the phenomenon or is the result of our assumptions.

Regarding the matching algorithm using PSM, we tested several approaches: Nearest Neighbor with and without replacement, and with and without caliper. For each result, we calculated the absolute standardized bias (ABS) for the common variables used to determine the propensity score, both before and after matching. Good matching quality is achieved when individual covariates present an ABS below 0.1 in absolute value and below 0.6 on average. Furthermore, we verified that the common support assumption holds by comparing the distribution of propensity scores for donor and recipient observations.

In light of the properties of the various matching schemes and the specific requirements of our study—particularly the need to preserve as many treated units as possible, given the limited sample size—we chose to adopt a nearest neighbor approach with replacement

and a 1:1 ratio. This method ensures that each treated unit always receives a match, avoiding the exclusion of treated units that would not find donors under a fixed caliper or the discarding of 'excess' controls as occurs in deterministic matching without replacement. The possibility of replacement also allows us to use the most similar controls multiple times, increasing the stability of estimates while maintaining the number of treated observations intact, an essential condition to ensure the statistical power of our econometric analyses.

In the application of the second method, we repeatedly adopted the hot deck matching technique (D'Orazio (2017); D'Orazio et al. (2006)), articulating it into two main families of approaches—one 'deterministic'(Nearest Neighbor) and one 'randomized'(Singh et al., 1990)—and repeatedly varying the donor class constraints (the so-called donor classes). Initially, in version 0, we applied the 'pure' nearest-neighbor hot deck method, that is, without any donor class restriction. In practice, for each recipient unit, the StatMatch package computes the Gower distance (Gower, 1971) with respect to a set of variables[9] and identifies the most similar donor—the nearest neighbor—within the entire pool of donor individuals. At that point, the values of the variables of interest—here, commuting time—are transferred from the selected donor to the recipient. This approach is fully deterministic, because for each recipient there is always a single donor chosen on the basis of the minimum distance.

Subsequently, we introduced the concept of donor class: the idea is to restrict the search for the nearest neighbor to donors belonging to the same sociodemographic 'category' (or group) as the recipient. In this way, we reduce the possibility of 'mixing' individuals who are very different from one another. We therefore constructed nine successive versions, each based on a different class criterion:

- Gender. Only donors of the same sex as the recipient may be considered;
- Geographical distribution. The nearest-neighbor search is restricted to the same

[9]These variables are: Number of household members, quarter, geographical area, gender, marital status, age range, occupational code, citizenship, education, mobile phone, number of children, number of children under 15, income source, contract type, computer, internet access, car ownership, and economic resources.

macro-geographical areas;

- Age range. Each recipient is matched with donors belonging to the same age group;
- Education. Only individuals with the same educational attainment are compared;
- Gender and geographical distribution. Both sex and geographical area must match;
- Gender and age group;
- Gender and educational level;
- Age group and macro-geographical area;
- Education and geographical distribution. Education and geographical area.

In each of these versions, the package first subsets the donors on the basis of the specified class, then computes Gower distances within that subset, and finally selects the nearest one for imputation.

To introduce a degree of randomness into the matching, we then explored a second approach, referred to as randomized, which does not always assign the closest donor but instead draws randomly from a restricted set of 'nearby' candidates. Here too, we experimented with two subfamilies:

i) Random without matching covariates. In four preliminary versions, we decided not to include any covariates, meaning that the random selection occurs among all donors within a given donor class, without any numerical similarity criterion. The classes considered were: Gender and geographical distribution, Gender and age range, Gender and education, and Age range and geographical distribution. In each version, all recipients were matched with a donor randomly drawn from the same class.

ii) Random with matching covariates + donor classes. We used the same donor classes as in point i) and proceeded as follows: for each recipient, we restricted potential donors to those sharing the same donor class and measured similarity across all pre-specified common variables using the Gower distance. We required that the donor strictly belongs to the selected class, but instead of always choosing the closest one, we randomly

selected one among the first k nearest neighbors (k was adjusted based on the number of potential neighbors available for each case). In this way, we combine the sociodemographic consistency of the class constraint with a random component that mitigates excessive fitting' on the single nearest neighbor. Table 2.37 summarizes the creation of the synthetic datasets using these nonparametric approaches.

Before proceeding to the overall evaluation of matching quality, the first mixed approach, which includes the use of propensity score matching, involves an additional step, namely assessing the quality of the propensity score estimation. As noted, we will present the results of the nearest-neighbor (NN) approach with replacement for both 2019 and 2020.

Regarding the matching between HBS 2019 and TUS 2020, Table 2.38 shows the ABS values before and after the matching process[10]. The comparison of covariates before matching revealed moderate imbalance: although never exceeding the critical threshold of 0.10, some characteristics—such as economic resources, age groups 35–44 and 55–64, and the 'self-employed' status—showed standardized differences between 0.05 and 0.07, indicating that the control and treated samples were not perfectly comparable. After applying the matching, all variables recorded ABS values below 0.02, so that even the covariate with the greatest misalignment ('self-employed', with ABS = 0.0163) is now perfectly balanced.

In conclusion, the matching procedure eliminated any residual imbalance and now ensures a high degree of homogeneity between the two groups, making them comparable without bias from observed characteristics. Overall, the mean ABS pre-matching was 0.025, while post-matching it was 0.004. In the literature, a mean ABS below 5% is typically considered indicative of good matching; in our case, the result is below 0.4%, confirming that the matching was virtually perfect in terms of balancing the common variables.

[10]Before proceeding with the PSM, the two datasets were merged into a single dataset. From there, a treatment variable was constructed, which takes the value 1 if the observation belongs to the recipient dataset and 0 if it belongs to the donor dataset. Subsequently, all the steps listed were carried out.

| Variable | Class | Tus (absolute and relative frequency (%)) | Hbs 2020 (absolute and relative frequency (%)) |
|---|---|---|---|
| Internet access | | | |
| | No | 1455 (15.9%) | 1412 (11.4%) |
| | Yes | 7719 (84.1%) | 11003 (88.6%) |
| ATECO code (industrial sector code) | | | |
| | Agriculture, forestry, hunting, and fishing | 540 (5.9%) | 289 (2.3%) |
| | Construction | 900 (9.8%) | 746 (6%) |
| | Industry (excluding construction) | 1364 (14.9%) | 2258 (18.2%) |
| | Services | 6370 (69.4%) | 8811 (71%) |
| Car ownership | | | |
| | No | 951 (10.4%) | 1111 (8.9%) |
| | Yes | 8223 (89.6%) | 11304 (91.1%) |
| Domestic origin | | | |
| | Foregin | 1029 (11.2%) | 958 (7.7%) |
| | Italian | 8145 (88.8%) | 11457 (92.3%) |
| Age range | | | |
| | 15-24 | 36 (0.4%) | 67 (0.5%) |
| | 25-34 | 1069 (11.7%) | 1219 (9.8%) |
| | 35-44 | 2626 (28.6%) | 2920 (23.5%) |
| | 45-54 | 3208 (35%) | 4318 (34.8%) |
| | 55-64 | 1892 (20.6%) | 3342 (26.9%) |
| | 65-74 | 276 (3%) | 477 (3.8%) |
| | 75 and higher | 67 (0.7%) | 72 (0.6%) |
| Job code | | | |
| | Legislators, entrepreneurs, and senior management | 453 (4.9%) | 448 (3.6%) |
| | Intellectual, scientific, and highly specialized professions | 1203 (13.1%) | 1979 (15.9%) |
| | Technical professions | 1392 (15.2%) | 2314 (18.6%) |
| | Clerical support workers | 981 (10.7%) | 1533 (12.3%) |
| | Skilled workers in commercial activities and services | 1513 (16.5%) | 1983 (16%) |
| | Craftsmen, skilled workers, and farmers | 1807 (19.7%) | 1831 (14.7%) |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | 717 (7.8%) | 1014 (8.2%) |
| | Elementary occupations | 909 (9.9%) | 1162 (9.4%) |
| | Armed forces | 122 (1.3%) | 150 (1.2%) |
| Working condition | | | |
| | Employed | 9174 (100%) | 12415 (100%) |
| Source of income | | | |
| | Self-employed | 2363 (25.8%) | 2942 (23.7%) |
| | Employee (or Salaried worker) | 6545 (71.3%) | 9338 (75.2%) |
| | Family support | 57 (0.6%) | 14 (0.1%) |
| | Capital income / Allowances / Rents / Securities | 80 (0.9%) | 65 (0.5%) |
| | Pension (or Retirement income) | 129 (1.4%) | 56 (0.5%) |
| Level of education | | | |
| | High school diploma | 4026 (43.9%) | 5774 (46.5%) |
| | Bachelor diploma or higher | 1817 (19.8%) | 2790 (22.5%) |
| | Elementary school diploma | 422 (4.6%) | 271 (2.2%) |
| | Middle school diploma | 2856 (31.1%) | 3155 (25.4%) |
| | No formal education | 53 (0.6%) | 35 (0.3%) |
| Type of working contract | | | |
| | Fixed-term | 841 (9.2%) | 898 (7.2%) |
| | Open-ended | 5525 (60.2%) | 8484 (68.3%) |
| Quarter | | | |
| | 1 | 2431 (26.5%) | 2680 (21.6%) |
| | 2 | 2326 (25.4%) | 2813 (22.7%) |
| | 3 | 2227 (24.3%) | 3324 (26.8%) |
| | 4 | 2190 (23.9%) | 3598 (29%) |
| Number of household's components | | | |
| | 1 | 2425 (26.4%) | 3174 (25.6%) |
| | 2 | 1681 (18.3%) | 2794 (22.5%) |
| | 3 | 2232 (24.3%) | 2908 (23.4%) |
| | 4 | 2213 (24.1%) | 2825 (22.8%) |
| | 5 | 497 (5.4%) | 577 (4.6%) |
| | 6 | 89 (1%) | 104 (0.8%) |
| | 7 | 24 (0.3%) | 22 (0.2%) |
| | 8 | 6 (0.1%) | 9 (0.1%) |
| | >=9 | 7 (0.1%) | 1 (0%) |
| Number of children | | | |
| | 0 | 4339 (47.3%) | 5504 (44.3%) |
| | 1 | 2314 (25.2%) | 3203 (25.8%) |
| | 2 | 2086 (22.7%) | 3064 (24.7%) |
| | 3 | 372 (4.1%) | 556 (4.5%) |
| | 4 | 55 (0.6%) | 74 (0.6%) |
| | 5 | 6 (0.1%) | 11 (0.1%) |
| | 6 | 1 (0%) | 2 (0%) |
| Number of children under 15 | | | |
| | 0 | 6541 (71.3%) | 8438 (68%) |
| | 1 | 1654 (18%) | 2339 (18.8%) |
| | 2 | 856 (9.3%) | 1419 (11.4%) |
| | 3 | 111 (1.2%) | 198 (1.6%) |
| | 4 | 11 (0.1%) | 17 (0.1%) |
| | 5 | 1 (0%) | 2 (0%) |
| | 6 | 0 (0%) | 2 (0%) |
| Computer ownership | | | |
| | No | 1253 (13.7%) | 1863 (15%) |
| | Yes | 7921 (86.3%) | 10552 (85%) |
| Geographical distribution | | | |
| | North-west | 2200 (24%) | 3366 (27.1%) |
| | North-east | 2141 (23.3%) | 2877 (23.2%) |
| | Centre | 1734 (18.9%) | 2879 (23.2%) |
| | South | 2252 (24.5%) | 2420 (19.5%) |
| | Islands | 833 (9.1%) | 873 (7%) |
| Economic resources | | | |
| | Adequate | 5571 (60.7%) | 8954 (72.1%) |
| | Absolutely insufficient | 533 (5.8%) | 342 (2.8%) |
| | Excellent | 189 (2.1%) | 354 (2.9%) |
| | Poor | 2881 (31.4%) | 2765 (22.3%) |
| Gender | | | |
| | Male | 6703 (73.1%) | 8537 (68.8%) |
| | Female | 2471 (26.9%) | 3878 (31.2%) |
| Marital status | | | |
| | Single | 2203 (24%) | 3515 (28.3%) |
| | Married | 5125 (55.9%) | 6659 (53.6%) |
| | Separated/divorced | 1593 (17.4%) | 1930 (15.5%) |
| | Widow/widower | 253 (2.8%) | 311 (2.5%) |
| Mobile phone ownership | | | |
| | No | 73 (0.8%) | 255 (2.1%) |
| | Yes | 9101 (99.2%) | 12160 (97.9%) |
| Type of working schedule | | | |
| | Full-time | 8076 (88%) | 8392 (67.6%) |
| | Part-time | 1098 (12%) | 990 (8%) |

Table 2.34: Absolute and relative frequencies of covariates in TUS 2013 vs. HBS 2020. This table shows, for each categorical variable, the absolute frequencies (N) and relative frequencies (percentage) in both the TUS sample and the HBS sample.

| Variable | Class | Difference of relative frequency TUS 2013-HBS 2019 (%) | Difference of relative frequency TUS 2013-HBS 2020(%) |
|---|---|---|---|
| Number of household's component | | | |
| | 1 | 1,19 | 0,87 |
| | 2 | 4,24 | 4,18 |
| | 3 | 1,31 | 0,91 |
| | 4 | 1,73 | 1,37 |
| | 5 | 0,05 | 0,77 |
| | 6 | 0,05 | 0,13 |
| | 7 | 0,09 | 0,08 |
| | 8 | 0 | 0,01 |
| | >= 9 | 0,03 | 0,07 |
| Quarter | | | |
| | 1 | 2,18 | 4,91 |
| | 2 | 0,5 | 2,70 |
| | 3 | 1,04 | 2,50 |
| | 4 | 1,64 | 5,11 |
| Gender | | | |
| | Male | 3,04 | 4,30 |
| | Female | 3,04 | 4,30 |
| Marital status | | | |
| | Single | 2,94 | 4,30 |
| | Married | 1,57 | 2,23 |
| | Separated/divorced | 1,14 | 1,82 |
| | Widow/widower | 0,23 | 0,25 |
| Level of education | | | |
| | High school diploma | 3,35 | 3,3 |
| | Bachelor diploma or higher | 1,95 | 2 |
| | Elementary school diploma | 2,05 | 2,1 |
| | Middle school diploma | 3,1 | 3,1 |
| | No formal education | 0,15 | 0,2 |
| Geographical distribution | | | |
| | North-west | 2,66 | 3,09 |
| | North-east | 0,47 | 0,20 |
| | Centre | 1,51 | 4,26 |
| | South | 3,47 | 5,09 |
| | Islands | 1,18 | 2,06 |
| Age range | | | |
| | 15-24 | 0,29 | 0,15 |
| | 25-34 | 1,69 | 1,83 |
| | 35-44 | 4,47 | 5,10 |
| | 45-54 | 0,08 | 0,19 |
| | 55-64 | 4,97 | 6,30 |
| | 65-74 | 1,04 | 0,83 |
| | 75 and higher | 0,06 | 0,15 |
| Working condition | | | |
| | Employed | 0 | 0,00 |
| Job code | | | |
| | Legislators, entrepreneurs, and senior management | 1,11 | 1,37 |
| | Intellectual, scientific, and highly specialized professions | 1,97 | 2,72 |
| | Technical professions | 2,01 | 3,34 |
| | Clerical support workers | 0,16 | 1,57 |
| | Skilled workers in commercial activities and services | 0,33 | 0,66 |
| | Craftsmen, skilled workers, and farmers | 3,72 | 5,11 |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | 0,97 | 0,29 |
| | Elementary occupations | 0,17 | 0,63 |
| | Armed forces | 0,19 | 0,13 |
| Source of income | | | |
| | Self-employed | 1,75 | 2,06 |
| | Employee (or Salaried worker) | 3,68 | 3,87 |
| | Family support | 0,46 | 0,51 |
| | Capital income / Allowances / Rents / Securities | 0,62 | 0,35 |
| | Pension (or Retirement income) | 0,86 | 0,96 |
| Domestic origin | | | |
| | Foregin | 1,79 | 3,50 |
| | Italian | 1,79 | 3,50 |
| ATECO code (industrial sector code) | | | |
| | Agriculture, forestry, hunting, and fishing | 3,39 | 3,50 |
| | Construction | 2,81 | 3,65 |
| | Industry (excluding construction) | 4,21 | 3,79 |
| | Services | 1,99 | 3,36 |
| Type of working schedule | | | |
| | Full-time | 0,96 | 1,42 |
| | Part-time | 0,96 | 1,42 |
| Type of working contract | | | |
| | Fixed-term | 3,33 | 3,64 |
| | Open-ended | 3,33 | 3,64 |
| Computer ownership | | | |
| | No | 4,05 | 1,35 |
| | Yes | 4,05 | 1,35 |
| Internet access | | | |
| | No | 0,54 | 4,49 |
| | Yes | 0,54 | 4,49 |
| Mobile phone ownership | | | |
| | No | 1,34 | 1,26 |
| | Yes | 1,34 | 1,26 |
| Car ownership | | | |
| | No | 1,2 | 1,42 |
| | Yes | 1,2 | 1,42 |
| Economic resources | | | |
| | Adequate | 6,96 | 11,40 |
| | Absolutely insufficient | 2,36 | 3,06 |
| | Excellent | 1,35 | 0,79 |
| | Poor | 5,95 | 9,13 |
| Number of children | | | |
| | 0 | 3,16 | 2,96 |
| | 1 | 0,21 | 0,58 |
| | 2 | 1,58 | 0,01 |
| | 3 | 1,2 | 1,94 |
| | 4 | 0,17 | 0,42 |
| | 5 | 0,01 | 0,00 |
| | 6 | | 0,02 |
| Number of children under 15 | | | |
| | 0 | 2,67 | 3,33 |
| | 1 | 0,02 | 0,81 |
| | 2 | 1,97 | 2,10 |
| | 3 | 0,6 | 0,38 |
| | 4 | 0,1 | 0,02 |
| | 5 | 0,03 | 0,01 |
| | 6 | | 0,02 |

Table 2.35: Percentage difference between TUS and HBS distributions. For each category of every variable, the table calculates the percentage difference between the proportion recorded in TUS and that in HBS. The second column shows the relative percentage differences for the 2019 TUS and HBS samples, whilst the third column shows those for the 2020 TUS and HBS samples.

| Variable | ASB (unadjusted) | ASB (udjusted) |
|---|---|---|
| Number of household's component | | |
| 1 | 0.0119 | 0.0055 |
| 2 | 0.0424 | 0.0017 |
| 3 | 0.0131 | 0.0030 |
| 4 | 0.0173 | 0.0002 |
| 5 | 0.0005 | 0.0030 |
| 6 | 0.0005 | 0.0026 |
| 7 | 0.0009 | 0.0001 |
| 8 | 0.0000 | 0.0007 |
| >= 9 | 0.0003 | 0.0004 |
| Quarter | | |
| 1 | 0.0218 | 0.0007 |
| 2 | 0.0050 | 0.0080 |
| 3 | 0.0104 | 0.0002 |
| 4 | 0.0164 | 0.0072 |
| Geographical distribution | | |
| North-west | 0.0270 | 0.0021 |
| North-east | 0.0051 | 0.0122 |
| Centre | 0.0154 | 0.0109 |
| South | 0.0343 | 0.0014 |
| Islands | 0.0117 | 0.0022 |
| Marital status | | |
| Single | 0.0294 | 0.0018 |
| Married | 0.0157 | 0.0077 |
| Separated/divorced | 0.0114 | 0.0021 |
| Widow/widower | 0.0023 | 0.0039 |
| Age range | | |
| 15-24 | 0.0029 | 0.0001 |
| 25-34 | 0.0169 | 0.0062 |
| 35-44 | 0.0447 | 0.0035 |
| 45-54 | 0.0008 | 0.0090 |
| 55-64 | 0.0497 | 0.0020 |
| 65-74 | 0.0104 | 0.0019 |
| 75 and higher | 0.0006 | 0.0007 |
| Job code | | |
| Legislators, entrepreneurs, and senior management | 0.0107 | 0.0015 |
| Intellectual, scientific, and highly specialized professions | 0.0207 | 0.0015 |
| Technical professions | 0.0213 | 0.0039 |
| Clerical support workers | 0.0008 | 0.0035 |
| Skilled workers in commercial activities and services | 0.0020 | 0.0034 |
| Craftsmen, skilled workers, and farmers | 0.0356 | 0.0116 |
| Plant operators, machine operators (fixed and mobile), and vehicle drivers | 0.0103 | 0.0078 |
| Elementary occupations | 0.0024 | 0.0080 |
| Armed forces | 0.0020 | 0.0006 |
| Level of Education | | |
| High school diploma | 0.0335 | 0.0099 |
| Bachelor diploma or higher | 0.0195 | 0.0002 |
| Elementary school diploma | 0.0205 | 0.0007 |
| Middle school diploma | 0.0310 | 0.0106 |
| No formal education | 0.0015 | 0.0002 |
| Number of children | | |
| 0 | 0.0316 | 0.0087 |
| 1 | 0.0021 | 0.0057 |
| 2 | 0.0158 | 0.0086 |
| 3 | 0.0120 | 0.0029 |
| 4 | 0.0017 | 0.0022 |
| 5 | 0.0001 | 0.0003 |
| Number of children under 15 | | |
| 0 | 0.0267 | 0.0011 |
| 1 | 0.0002 | 0.0057 |
| 2 | 0.0197 | 0.0046 |
| 3 | 0.0060 | 0.0008 |
| 4 | 0.0010 | 0.0003 |
| 5 | 0.0003 | 0.0004 |
| Source of income | | |
| Self-employed | 0.0368 | 0.0163 |
| Employee (or Salaried worker) | 0.0175 | 0.0145 |
| Family support | 0.0062 | 0.0006 |
| Capital income / Allowances / Rents / Securities | 0.0086 | 0.0015 |
| Pension (or Retirement income) | 0.0046 | 0.0008 |
| Economic resources | | |
| Absolutely insufficient | 0.0236 | 0.0024 |
| Poor | 0.0595 | 0.0044 |
| Adequate | 0.0696 | 0.0118 |
| Excellent | 0.0135 | 0.0050 |

Table 2.38: Absolute standardised bias before and after the application of propensity score matching. Columns two and three show, respectively, the values of the absolute standardised bias for each class of the categorical variables used in the matching process, before and after the application of propensity score matching and the corresponding matching for TUS 2013–HBS 2019.

| Variable | Cramers V test (TUS vs HBS 2019) | Hellinger test (TUS vs HBS 2019) | Cramers V test (TUS vs HBS 2020) | Hellinger test (TUS vs HBS 2020) |
|---|---|---|---|---|
| Number of household's component | 0,05 | 0,08 | 0,06 | 0,08 |
| Quarter | 0,03 | 0,04 | 0,08 | 0,11 |
| Gender | 0,03 | 0,05 | 0,05 | 0,07 |
| Marital status | 0,03 | 0,05 | 0,05 | 0,07 |
| Level of education | 0,07 | 0,10 | 0,09 | 0,13 |
| Geographical distribution | 0,05 | 0,07 | 0,09 | 0,12 |
| Age range | 0,08 | 0,11 | 0,09 | 0,13 |
| Job code | 0,07 | 0,09 | 0,09 | 0,13 |
| Source of income | 0,08 | 0,11 | 0,08 | 0,11 |
| Domestic origin | 0,03 | 0,04 | 0,06 | 0,08 |
| ATECO code (industrial sector code) | 0,11 | 0,16 | 0,12 | 0,17 |
| Type of working schedule | 0,01 | 0,02 | 0,02 | 0,03 |
| Type of working contract | 0,05 | 0,07 | 0,06 | 0,08 |
| Computer ownership | 0,06 | 0,08 | 0,02 | 0,03 |
| Internet access | 0,01 | 0,01 | 0,07 | 0,09 |
| Mobile phone ownership | 0,06 | 0,08 | 0,05 | 0,08 |
| Car ownership | 0,02 | 0,03 | 0,02 | 0,03 |
| Economic resources | 0,10 | 0,14 | 0,14 | 0,19 |
| Number of children | 0,04 | 0,06 | 0,03 | 0,05 |
| Number of children under 15 | 0,05 | 0,06 | 0,04 | 0,06 |

Table 2.36: Association indices and distance between TUS and HBS. For each variable, the values of Cramer's V (association test) and Hellinger's index (a measure of distance between distributions) are summarised here. These indices provide an overall measure of how much the two distributions differ.

| Dataset | Apporach | Donor classes | K (neighbors) | Covariate matching |
|---|---|---|---|---|
| 1 | NN hot-deck | No | | Yes |
| 2 | NN hot-deck | Gender | | Yes |
| 3 | NN hot-deck | Geographical distribution | | Yes |
| 4 | NN hot-deck | Age range | | Yes |
| 5 | NN hot-deck | Education | | Yes |
| 6 | NN hot-deck | Gender + Geographical distribution | | Yes |
| 7 | NN hot-deck | Gender + age range | | Yes |
| 8 | NN hot-deck | Gender + education | | Yes |
| 9 | NN hot-deck | Age range + geographical distribution | | Yes |
| 10 | NN hot-deck | Education + geographical distribution | | Yes |
| 11 | NN random hot-deck | Gender + geographical distribution | | No |
| 12 | NN random hot-deck | Gender + age range | | No |
| 13 | NN random hot-deck | Gender + education | | No |
| 14 | NN random hot-deck | Age range + geographical distribution | | No |
| 15 | NN random hot-deck | Gender + geographical distribution | 20 | Yes |
| 16 | NN random hot-deck | Gender + age range | 10 | Yes |
| 17 | NN random hot-deck | Gender + education | 10 | Yes |
| 18 | NN random hot-deck | Age range + geographical distribution | 1 | Yes |

Table 2.37: Overview of synthetic datasets and hot-deck matching approaches

Table 2.39 provides a summary of the number of observations employed. As can be observed, all units in the original HBS dataset are retained, whereas not all units from the TUS dataset are used. Furthermore, Table 9 reports the tests for categorical variables and the proportion tests for binary variables.

| Sample | Control | Treated |
|---|---|---|
| All | 9174 | 9074 |
| Matched (ESS) | 2859.73 | 9074 |
| Matched (Unweighted) | 4532 | 9074 |
| Unmatched | 4642 | 0 |

Table 2.39: Summary of the allocation process using PSM and NN with replacement, for TUS 2013–HBS 2019.

Categorical variables are first transformed into dummy variables, one for each category; for each of these dummies, a standard t-test is performed—both before and after matching—to verify whether the mean (which coincides with the proportion of cases in which the dummy equals 1) differs significantly between treatment and control groups (Table 2.40. For variables that are intrinsically binary, instead of a t-test on means, a test of proportions is applied. This test compares the number of 'successes' (value = 1) and the total number of cases in the two groups, computing a p-value based on Pearson's chi-square statistic (with Yates' continuity correction) to assess the null hypothesis of equality of proportions.

Before matching, many covariates exhibit statistically significant differences between treated and control units: several household-size categories (e.g., '2 members', $p < 0.01$), first quarter ($p < 0.01$), nearly all major geographical areas (North-West, Centre, South with $p < 0.01$), middle and older age groups (35–44, 55–64, 65–74 with $p < 0.01$), a large share of medium- to high-level occupational codes, as well as almost all income types and measures of economic resources ($p < 0.01$). Among the binary variables, gender, citizenship, and ownership of a mobile phone, computer, and car are initially imbalanced ($p \leq 0.01$).

After matching, most of these tests lose statistical significance: almost all categories display $p > 0.05$, indicating that distributional differences between groups are no longer

statistically relevant. A few marginal signals remain—for example, the category '$\geq 9$ members'with $p = 0.05$, and self-employed individuals with $p < 0.01$ both before and after matching—but these represent highly isolated exceptions. Among the binary variables, only internet access, which was already balanced before matching, confirms the absence of differences ($p = 0.95$), while all others lose statistical significance.

In conclusion, the matching procedure substantially reduced the number of covariates that remained significantly different between the treated and control groups, markedly improving the overall balance of observed characteristics.

A visual inspection of Figures 2.13 and 2.14—respectively, the histogram and the density curve of the propensity score distribution—clearly shows that, after the application of matching, the common support condition is fully satisfied: the histograms of the propensity scores for the recipient dataset and the donor dataset coincide exactly, and the two density curves overlap almost perfectly.

| Variable | P-value pre-matching | P-value post-matching |
|---|---|---|
| Categorical | | |
| Number of household's component | | |
| 1 | 0,07 | 0,14 |
| 2 | 0,00 | 0,04 |
| 3 | 0,04 | 0,72 |
| 4 | 0,01 | 0,35 |
| 5 | 0,89 | 0,33 |
| 6 | 0,71 | 0,34 |
| 7 | 0,22 | 1,00 |
| 8 | 0,99 | 0,01 |
| >= 9 | 0,38 | 0,05 |
| Quarter | | |
| 1 | 0,00 | 0,09 |
| 2 | 0,43 | 0,97 |
| 3 | 0,10 | 0,28 |
| 4 | 0,01 | 0,55 |
| Geographical distribution | | |
| North-west | 0,00 | 0,05 |
| North-east | 0,42 | 0,53 |
| Centre | 0,01 | 0,05 |
| South | 0,00 | 0,01 |
| Islands | 0,01 | 0,52 |
| Marital status | | |
| Single | 0,00 | 0,14 |
| Married | 0,03 | 0,51 |
| Separated/divorced | 0,04 | 0,46 |
| Widow/widower | 0,32 | 0,78 |
| Age range | | |
| 15-24 | 0,01 | 0,14 |
| 25-34 | 0,00 | 0,56 |
| 35-44 | 0,00 | 0,04 |
| 45-54 | 0,91 | 0,28 |
| 55-64 | 0,00 | 0,01 |
| 65-74 | 0,00 | 0,02 |
| 75 and higher | 0,64 | 0,82 |
| Job Code | | |
| Legislators, entrepreneurs, and senior management | 0,00 | 0,40 |
| Intellectual, scientific, and highly specialized professions | 0,00 | 0,35 |
| Technical professions | 0,00 | 0,30 |
| Clerical support workers | 0,86 | 0,45 |
| Skilled workers in commercial activities and services | 0,71 | 0,29 |
| Craftsmen, skilled workers, and farmers | 0,00 | 0,00 |
| Plant operators, machine operators (fixed and mobile), and vehicle drivers | 0,01 | 0,24 |
| Elementary occupations | 0,59 | 0,19 |
| Armed forces | 0,25 | 0,33 |
| Level of Education | | |
| High school diploma | 0,00 | 0,82 |
| Bachelor diploma or higher | 0,00 | 0,76 |
| Elementary school diploma | 0,00 | 0,06 |
| Middle school diploma | 0,00 | 0,38 |
| No formal education | 0,16 | 0,78 |
| Number of children | | |
| 0 | 0,00 | 0,40 |
| 1 | 0,74 | 0,68 |
| 2 | 0,01 | 0,58 |
| 3 | 0,00 | 0,12 |
| 4 | 0,16 | 0,09 |
| 5 | 0,78 | 0,78 |
| 6 | 0,56 | 0,16 |
| Number of children under 15 | | |
| 0 | 0,00 | 0,16 |
| 1 | 0,97 | 0,54 |
| 2 | 0,00 | 0,51 |
| 3 | 0,00 | 0,21 |
| 4 | 0,10 | 0,58 |
| 5 | 0,18 | 0,05 |
| Source of income | | |
| Self-employed | 0,00 | 0,00 |
| Employee (or Salaried worker) | 0,01 | 0,02 |
| Family support | 0,00 | 0,90 |
| Capital income / Allowances / Rents / Securities | 0,00 | 0,09 |
| Pension (or Retirement income) | 0,00 | 0,12 |
| Economic resources | | |
| Absolutely insufficient | 0,00 | 0,09 |
| Poor | 0,00 | 0,00 |
| Adequate | 0,00 | 0,01 |
| Excellent | 0,00 | 0,00 |
| Binary | | |
| Gender | 0,00 | 0,02 |
| Domestic origin | 0,00 | 0,56 |
| Mobile phone ownership | 0,00 | 0,00 |
| Computer ownership | 0,00 | 0,00 |
| Internet access | 0,32 | 0,95 |
| Car ownership | 0,01 | 0,60 |



Table 2.40: T-tests for categorical variables and proportion tests for binary variables considered in the statistical matching for TUS 2013–HBS 2019.

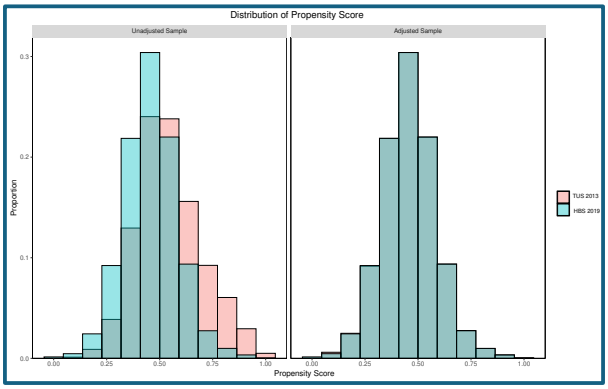



Figure 2.13: Distribution of propensity score across recipient (HBS 2019) and donor (TUS 2013) data sets.

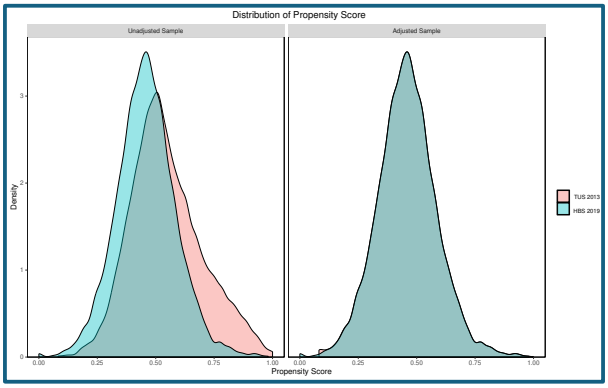



Figure 2.14: Distribution of propensity score across recipient (HBS 2019) and donor (TUS 2013) data sets.

The same assessment was conducted for the matching between TUS 2013 and HBS 2020. Table 2.41 reports the Absolute Standardized Bias (ASB) before and after the application of propensity score matching for the TUS 2013–HBS 2020 match. Prior to matching, the standardized differences ranged from values close to zero up to a maximum of 0.114 for economic conditions ('Poor') and 0.091 for 'Absolutely insufficient'; some covariates therefore exhibited moderate imbalance (ASB $>$ 0.05), particularly in the central age groups (55–64 with ASB = 0.063), certain occupational categories (craftsmen and manual workers with ASB = 0.0495), and in quarters 1 and 4 (ASB around 0.05). After matching, all ASB values fell below 0.02, with the maximum difference reduced to 0.0163 for 'Poor' and a minimum of 0.0000 for several categories, indicating excellent balance across all characteristics, with no variable exceeding an ASB of 0.05. In summary, the matching procedure eliminated any residual imbalance, rendering the treated and control groups perfectly comparable. The mean ASB pre-matching was 0.03, already a

very good value; the mean ASB post-matching was 0.004, a very low value indicating that after matching the variables employed are fully balanced.

Table 2.42 provides a summary of the matched units between TUS 2013 and HBS 2020.

Table 2.43 reports the t-tests for categorical variables and proportion tests for the binary variables considered in the statistical matching for TUS 2013–HBS 2020. Before matching, many covariates exhibited significant differences between treated and control units: in particular, '2 members' ($p < 0.01$), quarters 1–4 (all $p < 0.01$), several geographical regions such as North-West, Centre, and South ($p < 0.01$), age groups 25–34, 35–44, 55–64, and 65–74 ($p < 0.01$), most medium- and high-level occupational codes, as well as all sources of income and economic conditions ($p < 0.01$). Almost all binary variables—gender, citizenship, mobile phone ownership, computer ownership, Internet access, and car ownership—were initially imbalanced ($p < 0.01$), except for 'Computer ownership' ($p = 0.01$) and 'Internet access' ($p = 0.00$).

After matching, the majority of differences lost statistical significance ($p > 0.05$): nearly all household-size categories, quarters 2 and 3, the 'North-East' and 'Islands' regions, marital status categories 'Single', 'Separated/divorced', and 'Married', the extreme age groups, and almost all occupational codes no longer showed significant imbalance. Among binary variables, 'Car ownership', remained perfectly balanced (p = 0.99), while others presented non-significant or borderline p-values ('Domestic origin' $p = 0.01$; 'Employee' $p = 0.01$). A few marginal categories with $p < 0.05$ persisted ('Self-employed' $p = 0.00$; 'Absolutely insufficient' $p = 0.00$; 'Poor' $p = 0.00$; 'Excellent' $p = 0.01$; quarters 1 and 4 $p = 0.00$), but overall the matching drastically reduced the number of significantly different covariates, ensuring excellent balance between the groups. Figures 2.15 and 2.16 again show that the common support condition is fully satisfied.

| Variable | ASB (unadjusted) | ASB (adjusted) |
|---|---|---|
| Number of household's component | | |
| 1 | 0.0087 | 0.0032 |
| 2 | 0.0418 | 0.0058 |
| 3 | 0.0091 | 0.0002 |
| 4 | 0.0137 | 0.0030 |
| 5 | 0.0077 | 0.0037 |
| 6 | 0.0013 | 0.0006 |
| 7 | 0.0008 | 0.0002 |
| 8 | 0.0001 | 0.0007 |
| >= 9 | 0.0007 | 0.0001 |
| Quarter | | |
| 1 | 0.0491 | 0.0089 |
| 2 | 0.0270 | 0.0014 |
| 3 | 0.0250 | 0.0010 |
| 4 | 0.0511 | 0.0086 |
| Geographical distribution | | |
| North-west | 0.0313 | 0.0016 |
| North-east | 0.0016 | 0.0000 |
| Centre | 0.0429 | 0.0035 |
| South | 0.0506 | 0.0072 |
| Islands | 0.0205 | 0.0053 |
| Marital status | | |
| Single | 0.0182 | 0.0011 |
| Married | 0.0430 | 0.0035 |
| Separated/divorced | 0.0223 | 0.0039 |
| Widow/widower | 0.0025 | 0.0007 |
| Age range | | |
| 15-24 | 0.0015 | 0.0016 |
| 25-34 | 0.0183 | 0.0025 |
| 35-44 | 0.0510 | 0.0066 |
| 45-54 | 0.0019 | 0.0002 |
| 55-64 | 0.0630 | 0.0075 |
| 65-74 | 0.0083 | 0.0021 |
| 75 and higher | 0.0015 | 0.0006 |
| Job code | | |
| Legislators, entrepreneurs, and senior management | 0.0133 | 0.0050 |
| Intellectual, scientific, and highly specialized professions | 0.0283 | 0.0005 |
| Technical professions | 0.0347 | 0.0045 |
| Clerical support workers | 0.0165 | 0.0002 |
| Skilled workers in commercial activities and services | 0.0052 | 0.0041 |
| Craftsmen, skilled workers, and farmers | 0.0495 | 0.0075 |
| Plant operators, machine operators (fixed and mobile), and vehicle drivers | 0.0035 | 0.0007 |
| Elementary occupations | 0.0055 | 0.0093 |
| Armed forces | 0.0012 | 0.0019 |
| Number of children | | |
| 0 | 0.0296 | 0.0077 |
| 1 | 0.0058 | 0.0023 |
| 2 | 0.0194 | 0.0163 |
| 3 | 0.0042 | 0.0065 |
| 4 | 0.0000 | 0.0006 |
| 5 | 0.0002 | 0.0002 |
| 6 | 0.0001 | 0.0002 |
| Number of children under 15 | | |
| 0 | 0.0333 | 0.0057 |
| 1 | 0.0081 | 0.0108 |
| 2 | 0.0210 | 0.0048 |
| 3 | 0.0038 | 0.0006 |
| 4 | 0.0002 | 0.0001 |
| 5 | 0.0001 | 0.0002 |
| 6 | 0.0002 | 0.0002 |
| Source of income | | |
| Self-employed | 0.0387 | 0.0075 |
| Employee (or Salaried worker) | 0.0206 | 0.0063 |
| Family support | 0.0096 | 0.0004 |
| Capital income / Allowances / Rents / Securities | 0.0035 | 0.0004 |
| Pension (or Retirement income) | 0.0051 | 0.0004 |
| Economic resources | | |
| Absolutely insufficient | 0.0913 | 0.0050 |
| Poor | 0.1140 | 0.0126 |
| Adequate | 0.0079 | 0.0069 |
| Excellent | 0.0306 | 0.0007 |

Table 2.41: Absolute standardised bias before and after the application of propensity score matching. Columns two and three show, respectively, the values of the absolute standardised bias for each class of the categorical variables used in the matching process, before and after the application of propensity score matching and the corresponding matching for TUS 2013–HBS 2020.

| Sample | Control | Treated |
|---|---|---|
| All | 9174 | 12415 |
| Matched (ESS) | 2948.71 | 12415 |
| Matched (Unweighted) | 4906 | 12415 |
| Unmatched | 4268 | 0 |

Table 2.42: Summary of the allocation process using PSM and NN with replacement, for TUS 2013–HBS 2020.

| Variable | P-value pre-matching | P-value post-matching |
|---|---|---|
| Categorical | | |
| Number of household's component | | |
| 1 | 0,15 | 0,15 |
| 2 | 0,00 | 0,01 |
| 3 | 0,12 | 0,46 |
| 4 | 0,02 | 0,83 |
| 5 | 0,01 | 0,86 |
| 6 | 0,31 | 0,23 |
| 7 | 0,20 | 0,93 |
| 8 | 0,84 | 0,00 |
| >= 9 | 0,02 | 0,32 |
| Quarter | | |
| 1 | 0,00 | 0,00 |
| 2 | 0,00 | 0,15 |
| 3 | 0,00 | 0,11 |
| 4 | 0,00 | 0,00 |
| Geographical distribution | | |
| North-west | 0,00 | 0,10 |
| North-east | 0,78 | 0,55 |
| Centre | 0,00 | 0,00 |
| South | 0,00 | 0,00 |
| Islands | 0,00 | 0,11 |
| Marital status | | |
| Single | 0,00 | 0,46 |
| Married | 0,00 | 0,02 |
| Separated/divorced | 0,00 | 0,16 |
| Widow/widower | 0,25 | 0,81 |
| Age range | | |
| 15-24 | 0,11 | 0,24 |
| 25-34 | 0,00 | 0,10 |
| 35-44 | 0,00 | 0,00 |
| 45-54 | 0,78 | 0,29 |
| 55-64 | 0,00 | 0,00 |
| 65-74 | 0,00 | 0,02 |
| 75 and higher | 0,18 | 0,93 |
| Job Code | | |
| Legislators, entrepreneurs, and senior management | 0,00 | 0,07 |
| Intellectual, scientific, and highly specialized professions | 0,00 | 0,03 |
| Technical professions | 0,00 | 0,00 |
| Clerical support workers | 0,00 | 0,38 |
| Skilled workers in commercial activities and services | 0,31 | 0,26 |
| Craftsmen, skilled workers, and farmers | 0,00 | 0,00 |
| Plant operators, machine operators (fixed and mobile), and vehicle drivers | 0,35 | 0,46 |
| Elementary occupations | 0,18 | 0,86 |
| Armed forces | 0,43 | 0,89 |
| Number of children | | |
| 0 | 0,00 | 0,15 |
| 1 | 0,34 | 0,46 |
| 2 | 0,00 | 0,60 |
| 3 | 0,13 | 0,21 |
| 4 | 0,97 | 0,21 |
| 5 | 0,54 | 0,54 |
| 6 | 0,74 | 0,16 |
| Number of children under 15 | | |
| 0 | 0,00 | 0,04 |
| 1 | 0,13 | 0,45 |
| 2 | 0,00 | 0,07 |
| 3 | 0,02 | 0,41 |
| 4 | 0,73 | 0,93 |
| 5 | 0,74 | 0,16 |
| 6 | 0,16 | 0,16 |
| Source of income | | |
| Self-employed | 0,00 | 0,00 |
| Employee (or Salaried worker) | 0,00 | 0,01 |
| Family support | 0,00 | 0,02 |
| Capital income / Allowances / Rents / Securities | 0,00 | 0,10 |
| Pension (or Retirement income) | 0,00 | 0,09 |
| Economic resources | | |
| Absolutely insufficient | 0,00 | 0,00 |
| Poor | 0,00 | 0,00 |
| Adequate | 0,00 | 0,02 |
| Excellent | 0,00 | 0,01 |
| Binary | | |
| Gender | 0,00 | 0,00 |
| Domestic origin | 0,00 | 0,01 |
| Mobile phone ownership | 0,00 | 0,00 |
| Computer ownership | 0,01 | 0,00 |
| Internet access | 0,00 | 0,00 |
| Car ownership | 0,00 | 0,99 |

Table 2.43: T-tests for categorical variables and proportion tests for binary variables considered in the statistical matching for TUS 2013–HBS 2020.

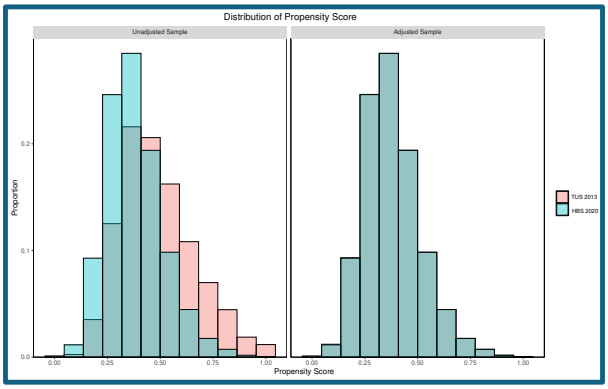



Figure 2.15: Distribution of propensity score across recipient (HBS 2020) and donor (TUS 2013) datasets.

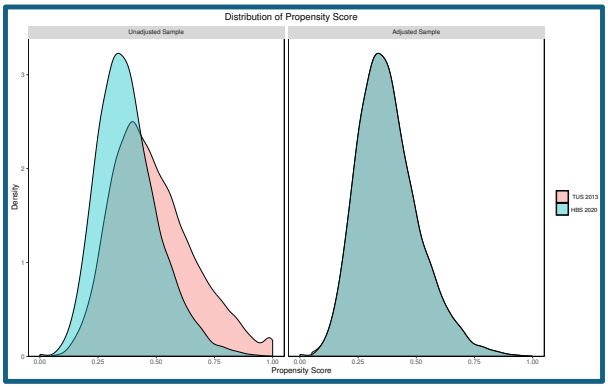



Figure 2.16: Distribution of propensity score across recipient (HBS 2020) and donor (TUS 2013) datasets.

**Assessment of the quality of statistical matching**

We then proceed with the assessment of the statistical matching, whose primary objective is to impute the value of commuting time from the 2013 Time Use survey into the 2019 and 2020 HBS. The first three steps (a–c) concern the evaluation of matching for all types of techniques employed, whereas the last one (d) applies only to the nonparametric techniques:

a) Inspection of marginal distributions

The densities (kernel density plots) of the imputed time variable in the 'merged' database (recipient) are visually compared with those of the original donor dataset; moreover, other time categories such as paid work, travel, domestic time, care time, etc., are used as robustness checks.

b) Analysis of covariate trends

For each common variable used in the matching, we calculate the mean time devoted to commuting in both the donor dataset and the matched dataset. We then compute the ratios of these means. Values equal to 1 indicate a perfect transfer. Finally, all mean ratios are aggregated into a weighted kernel density (we assign to each ratio a weight equal to the number of cases in its category, so that the density estimate reflects the actual statistical importance of each subgroup, avoiding the possibility that very small—and potentially noisier—groups distort the overall picture), in order to verify at a glance how closely the transfers cluster around unity.

c) Verification of stratified marginal distributions

For a set of common variables (not only those used for matching), the values of the distribution of commuting time are compared across the categories of each categorical variable for the two datasets, namely the donor and the synthetic dataset. As a robustness check, this procedure is repeated for other time variables.

We note in advance that the approach ultimately employed for the analysis presented in this paper is propensity score matching. For this reason, we will provide a detailed assessment of the matching quality specifically for this approach. Results for the parametric methods are available upon request. The reason for using multiple techniques lies in the fact that some of the synthetic datasets generated through nonparametric methods were employed as robustness checks for estimating the causal effect of the lockdown on commuting time.

**Ex-post evaluation of matching – propensity score matching (PSM)**

The first assessment concerns the TUS 2013 and HBS 2019 datasets. Figure 2.17 shows the kernel density of the hours devoted to commuting time, comparing the TUS 2013 dataset (gray) and the synthetic 2019 dataset (blue). As can be seen, the two curves are virtually overlapping, indicating that the marginal distribution of commuting time in the donor dataset is preserved in the synthetic dataset. As a robustness check, we examined the marginal distributions of other leisure-time categories (Figure 2.18); these distributions also appear approximately identical in the synthetic dataset. Table

2.44 shows the ratios between the mean commuting time in the synthetic dataset and in the donor survey, calculated for each category of the common variables. For the largest categories, these ratios are concentrated within a narrow interval around unity (between 0.90 and 1.10): for example, l number of household members = 1' yields 0.99, 'quarter 2'0.98, 'age 35–44' 0.99, and 'female' 0.98. This indicates that, at an aggregate level, the matching reproduces the original means very faithfully. The largest deviations are observed mainly in small categories, where within-group variability is greater: for example, '¿= 9 members' (3.50), '6 members' (0.70), '5 children' (1.66), and 'No formal education' (0.68). Some occupational categories and income-source categories also show ratios far from 1, but these are subgroups with few cases.

Overall, the matching ensures a high degree of correspondence between the donor and synthetic means for the main covariates, with limited deviations where sample size is adequate.

The weighted kernel density of the mean ratios (synthetic/donor) shows a single peak centered around 0.9 (Figure 2.19), with a bell-shaped form that is concave downward in the middle and relatively flat tails. This means that, for most covariate categories, the mean commuting time in the synthetic dataset is about 90% of that in the original survey. The flat tails also indicate that only a few classes exhibit extreme deviations, confirming that the matching reproduces the means consistently for the vast majority of subgroups.

Table 2.45 shows that, for covariate classes with adequate sample sizes, the position and dispersion statistics of commuting time—from the minimum to the maximum, including the quartiles—are virtually identical in the two datasets. It should be noted that the donor dataset, and consequently also the recipient dataset, contain many observations with a value of zero for commuting time. This occurs because a large share of observations referring to workers report NA for commuting time, which was conventionally recoded as zero.

The medians and upper quartiles are aligned at the same values (for example, the third quartile is almost always 50 minutes), and the maxima differ only by a few units,

indicating that the distributional structure has been preserved with high fidelity. Only in extremely rare groups, characterized by very few observations, do constant or anomalous values emerge (all quantiles equal to 60 or 170 minutes), due to an insufficient number of donors to ensure variability; however, these isolated cases do not compromise the overall quality of the matching.

As a robustness check, we examined the joint distributions of other time-use categories with respect to both the variables used for matching and those not used. Table 2.46 shows that, for most covariate classes with adequate sample sizes, the quartiles and extremes of the leisure distribution closely coincide between TUS 2013 and Synthetic 2019. The medians and lower and upper quartiles remain at the same reference values (for example, Q2 around 240–250 minutes, Q3 between 360 and 380 minutes), and the maxima differ by only a few dozen minutes, confirming a faithful reproduction of the distributional shape. Only in numerically small classes—such as '6 children', '$\geq$ 9 members', and 'No formal education' in the synthetic dataset—do constant or zero quantiles appear, reflecting the scarcity of donors in those subgroups; nevertheless, these anomalies remain isolated and do not affect the overall quality of the matching.

Table 2.47 confirms once again the high fidelity of the matching: for classes with substantial size, the minimum, quartile, and maximum values of time devoted to l personal needs' are almost identical between TUS 2013 and Synthetic 2019, with the median around 670 minutes and Q1/Q3 consistently at approximately 590 and 760 minutes, respectively. Differences in the extreme values do not exceed a few dozen minutes, indicating that the distributional structure has been accurately preserved. Only in some very small classes—for example, '$\geq$ 9 members' or isolated values in minor categories—do constant or uniform quantiles appear, reflecting the limited number of available donor units; however, these exceptions remain circumscribed and do not compromise the overall quality of the matching. The second assessment concerns the TUS 2013 and HBS 2020 datasets. Figures 2.20 and 2.21 and Tables 2.48 - 2.51 again show that the mixed approach yields very satisfactory matching quality.

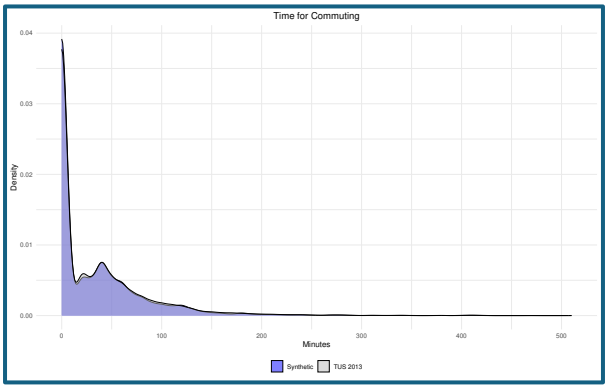
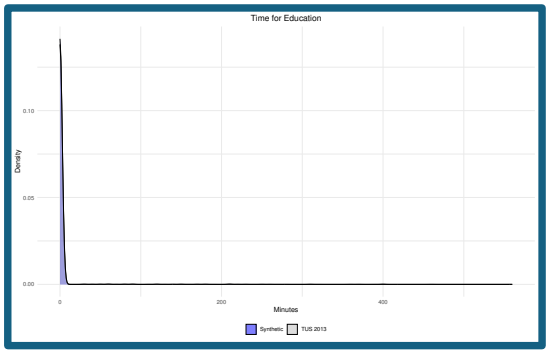


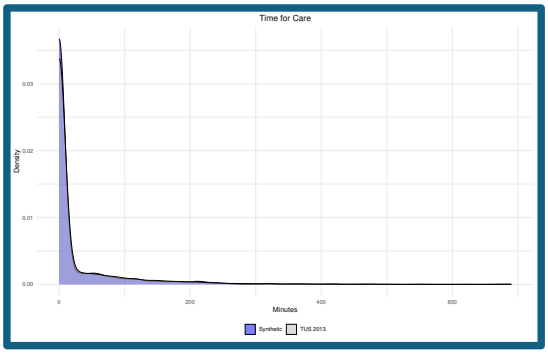

Figure 2.17: Kernel density plot of hours spent on commuting time, comparing the 2013 TUS dataset (grey) and the 2019 synthetic dataset (blue).

| Variable | Class | Mean (Donor Survey) | Mean (Synthetic Survey) | Ratio |
|---|---|---|---|---|
| Number of household's component | | | | |
| | 1 | 32,55 | 32,16 | 0,99 |
| | 2 | 32,25 | 29,63 | 0,92 |
| | 3 | 32,22 | 30,38 | 0,94 |
| | 4 | 32,11 | 28,77 | 0,90 |
| | 5 | 31,87 | 28,08 | 0,88 |
| | 6 | 32,81 | 23,12 | 0,70 |
| | 7 | 21,25 | 33,13 | 1,56 |
| | 8 | 41,67 | 60,00 | 1,44 |
| | >= 9 | 17,14 | 60,00 | 3,50 |
| Quarter | | | | |
| | 1 | 32,53 | 29,99 | 0,92 |
| | 2 | 31,95 | 31,27 | 0,98 |
| | 3 | 33,66 | 29,62 | 0,88 |
| | 4 | 30,79 | 29,71 | 0,96 |
| Geographical distribution | | 32,05 | 29,74 | 0,93 |
| | North-west | 27,10 | 29,66 | 1,09 |
| | North-east | 32,91 | 28,09 | 0,85 |
| | Centre | 36,28 | 32,60 | 0,90 |
| | South | 33,72 | 31,66 | 0,94 |
| | Islands | | | |
| Gender | | | | |
| | Female | 29,22 | 28,73 | 0,98 |
| | Male | 33,35 | 30,74 | 0,92 |
| Marital status | | | | |
| | Single | 31,58 | 31,23 | 0,99 |
| | Married | 32,69 | 29,12 | 0,89 |
| | Separated/divorced | 32,50 | 31,81 | 0,98 |
| | Widow/widower | 27,15 | 29,69 | 1,09 |
| Age range | | | | |
| | 15-24 | 30,00 | 32,42 | 1,08 |
| | 25-34 | 32,83 | 30,76 | 0,94 |
| | 35-44 | 32,21 | 31,91 | 0,99 |
| | 45-54 | 32,96 | 29,18 | 0,89 |
| | 55-64 | 31,07 | 29,59 | 0,95 |
| | 65-74 | 30,69 | 30,63 | 1,00 |
| | 75 and higher | 29,70 | 22,95 | 0,77 |
| Job code | | | | |
| | Legislators, entrepreneurs, and senior management | 35,08 | 35,21 | 1,00 |
| | Intellectual, scientific, and highly specialized professions | 29,04 | 30,40 | 1,05 |
| | Technical professions | 31,39 | 30,77 | 0,98 |
| | Clerical support workers | 25,25 | 27,49 | 1,09 |
| | Skilled workers in commercial activities and services | 40,19 | 28,40 | 0,71 |
| | Craftsmen, skilled workers, and farmers | 31,81 | 31,67 | 1,00 |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | 27,53 | 31,16 | 1,13 |
| | Elementary occupations | 34,42 | 28,74 | 0,83 |
| | Armed forces | 33,93 | 32,45 | 0,96 |
| Domestic origin | | | | |
| | Italian | 31,64 | 30,22 | 0,96 |
| | Foreign | 36,97 | 29,35 | 0,79 |
| Level of education | | | | |
| | High school diploma | 31,52 | 29,62 | 0,94 |
| | Bachelor diploma or higher | 30,99 | 29,19 | 0,94 |
| | Elementary school diploma | 32,63 | 29,48 | 0,90 |
| | Middle school diploma | 33,50 | 31,66 | 0,95 |
| | No formal education | 58,30 | 39,49 | 0,68 |
| Mobile phone ownership | | | | |
| | Yes | 32,24 | 30,20 | 0,94 |
| | No | 31,37 | 27,53 | 0,88 |
| Number of children | | | | |
| | 0 | 33,00 | 31,56 | 0,96 |
| | 1 | 30,54 | 30,29 | 0,99 |
| | 2 | 32,13 | 28,13 | 0,88 |
| | 3 | 34,41 | 27,74 | 0,81 |
| | 4 | 32,18 | 22,71 | 0,71 |
| | 5 | 21,67 | 36,00 | 1,66 |
| | 6 | 170,00 | 60,00 | 0,35 |
| Number of children under 15 | | | | |
| | 0 | 32,72 | 31,09 | 0,95 |
| | 1 | 31,51 | 28,54 | 0,91 |
| | 2 | 30,16 | 27,96 | 0,93 |
| | 3 | 31,62 | 24,21 | 0,77 |
| | 4 | 23,64 | 19,50 | 0,83 |
| | 5 | 0,00 | 60,00 | |
| Source of income | | | | |
| | Employee (or Salaried worker) | 31,21 | 30,05 | 0,96 |
| | Self-employed | 36,34 | 30,73 | 0,85 |
| | Family support | 18,60 | 12,00 | 0,65 |
| | Capital income / Allowances / Rents / Securities | 25,50 | 13,48 | 0,53 |
| | Pension (or Retirement income) | 19,38 | 29,60 | 1,53 |
| Type of working contract | | | | |
| | Open-ended | 30,16 | 29,94 | 0,99 |
| | Fixed-term | 34,97 | 30,31 | 0,87 |
| Computer ownership | | | | |
| | Yes | 32,04 | 30,43 | 0,95 |
| | No | 33,48 | 28,79 | 0,86 |
| Internet access | | | | |
| | Yes | 31,97 | 29,88 | 0,93 |
| | No | 33,66 | 31,55 | 0,94 |
| Car ownership | | | | |
| | Yes | 31,76 | 29,98 | 0,94 |
| | No | 36,33 | 31,75 | 0,87 |
| Economic resources | | | | |
| | Absolutely insufficient | 34,03 | 30,16 | 0,89 |
| | Adequate | 31,15 | 29,60 | 0,95 |
| | Excellent | 32,01 | 27,83 | 0,87 |
| | Poor | 34,02 | 31,87 | 0,94 |

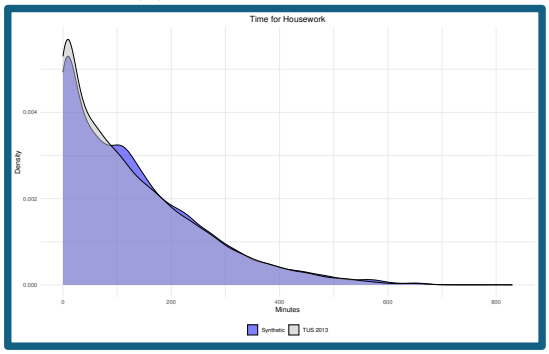
Table 2.44: Analysis of trends by covariate. Relationships between the mean commuting times for each covariate in the 2019 synthetic dataset and the 2013 TUS.



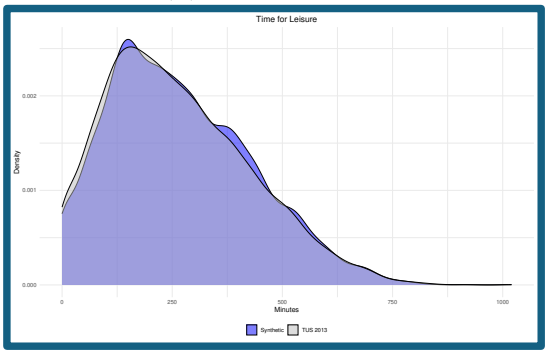

(a) Time for Education.



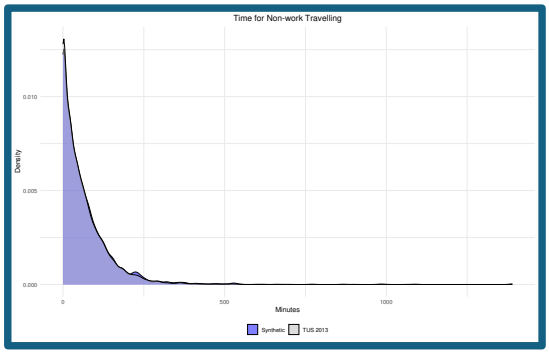

(b) Time for Care.



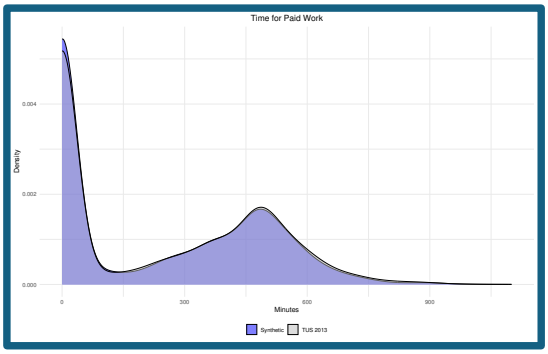

(c) Time for Housework.



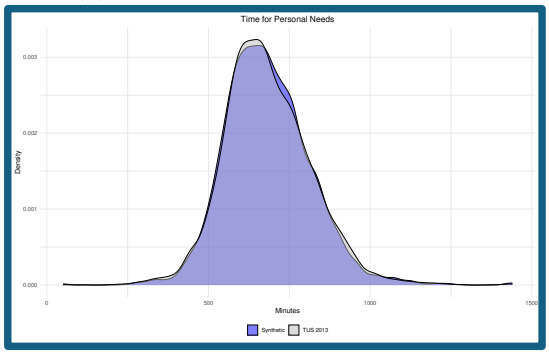

(d) Time for Leisure.



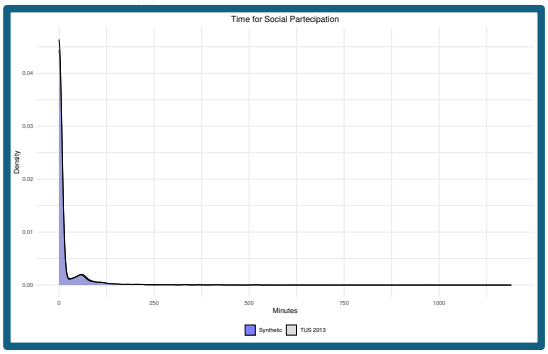

(e) Time for Non-work Travelling.




(f) Time for Paid Work.




(g) Time for Personal Needs.




(h) Time for Social Participation.

Figure 2.18: Robustness tests on other time categories. Kernel density plot of hours spent on other activities, comparing the 2013 TUS dataset (grey) with the 2019 synthetic dataset (blue).

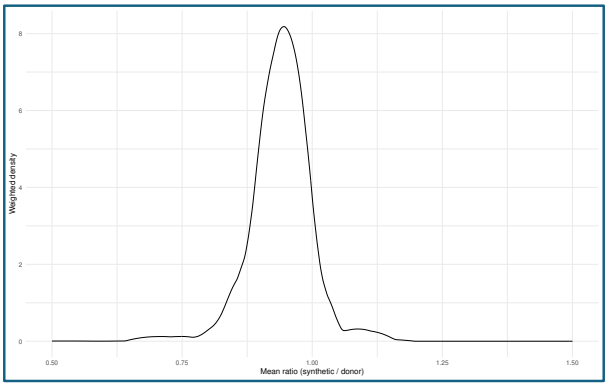



Figure 2.19: Trend analysis by covariates. Weighted kernel density of the ratios between the means in the 2019 synthetic dataset and the 2013 TUS dataset for the covariates used in the matching.

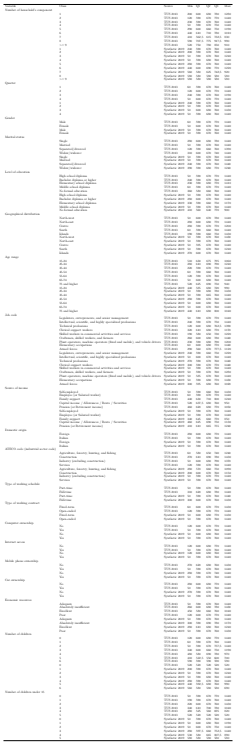


Table 2.47: Quartiles and extremes of the time spent on personal needs by class for each categorical variable, TUS 2013 vs Synthetic 2019.

| Variable | Class | Source | Min | Q1 | Q2 | Q3 | Max |
|---|---|---|---|---|---|---|---|
| Number of household's component | | | | | | | |
| | 1 | TUS 2013 | 0 | 0 | 0 | 50 | 410 |
| | 2 | TUS 2013 | 0 | 0 | 0 | 50 | 410 |
| | 3 | TUS 2013 | 0 | 0 | 0 | 50 | 410 |
| | 4 | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | 5 | TUS 2013 | 0 | 0 | 0 | 50 | 380 |
| | 6 | TUS 2013 | 0 | 0 | 0 | 50 | 410 |
| | 7 | TUS 2013 | 0 | 0 | 10 | 40 | 100 |
| | 8 | TUS 2013 | 0 | 0 | 15 | 45 | 170 |
| | >= 9 | TUS 2013 | 0 | 0 | 0 | 35 | 50 |
| | 1 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 2 | Synthetic 2019 | 0 | 0 | 0 | 50 | 400 |
| | 3 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 4 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 5 | Synthetic 2019 | 0 | 0 | 0 | 40 | 410 |
| | 6 | Synthetic 2019 | 0 | 0 | 0 | 40 | 270 |
| | 7 | Synthetic 2019 | 0 | 0 | 35 | 60 | 100 |
| | 8 | Synthetic 2019 | 60 | 60 | 60 | 60 | 60 |
| | >= 9 | Synthetic 2019 | 60 | 60 | 60 | 60 | 60 |
| Quarter | | | | | | | |
| | 1 | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | 2 | TUS 2013 | 0 | 0 | 0 | 50 | 470 |
| | 3 | TUS 2013 | 0 | 0 | 10 | 50 | 420 |
| | 4 | TUS 2013 | 0 | 0 | 0 | 50 | 410 |
| | 1 | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| | 2 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 3 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 4 | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| Gender | | | | | | | |
| | Female | TUS 2013 | 0 | 0 | 0 | 50 | 410 |
| | Male | TUS 2013 | 0 | 0 | 10 | 50 | 510 |
| | Female | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Male | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| Marital status | | | | | | | |
| | Single | TUS 2013 | 0 | 0 | 0 | 50 | 330 |
| | Married | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | Separated/divorced | TUS 2013 | 0 | 0 | 0 | 50 | 410 |
| | Widow/widower | TUS 2013 | 0 | 0 | 0 | 40 | 270 |
| | Single | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Married | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Separated/divorced | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| | Widow/widower | Synthetic 2019 | 0 | 0 | 0 | 40 | 380 |
| Level of education | | | | | | | |
| | High school diploma | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | Bachelor diploma or higher | TUS 2013 | 0 | 0 | 0 | 50 | 470 |
| | Elementary school diploma | TUS 2013 | 0 | 0 | 10 | 50 | 230 |
| | Middle school diploma | TUS 2013 | 0 | 0 | 20 | 50 | 410 |
| | No formal education | TUS 2013 | 0 | 0 | 50 | 100 | 220 |
| | High school diploma | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Bachelor diploma or higher | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Elementary school diploma | Synthetic 2019 | 0 | 0 | 10 | 50 | 210 |
| | Middle school diploma | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| | No formal education | Synthetic 2019 | 0 | 0 | 20 | 60 | 270 |
| Geographical distribution | | | | | | | |
| | North-west | TUS 2013 | 0 | 0 | 0 | 50 | 410 |
| | North-east | TUS 2013 | 0 | 0 | 0 | 40 | 340 |
| | Centre | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | South | TUS 2013 | 0 | 0 | 20 | 60 | 470 |
| | Islands | TUS 2013 | 0 | 0 | 20 | 50 | 370 |
| | North-west | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | North-east | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| | Centre | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| | South | Synthetic 2019 | 0 | 0 | 20 | 50 | 420 |
| | Islands | Synthetic 2019 | 0 | 0 | 10 | 50 | 420 |
| Age range | | | | | | | |
| | 15-24 | TUS 2013 | 0 | 0 | 0 | 52,5 | 120 |
| | 25-34 | TUS 2013 | 0 | 0 | 20 | 50 | 280 |
| | 35-44 | TUS 2013 | 0 | 0 | 0 | 50 | 350 |
| | 45-54 | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | 55-64 | TUS 2013 | 0 | 0 | 0 | 50 | 420 |
| | 65-74 | TUS 2013 | 0 | 0 | 0 | 50 | 340 |
| | 75 and higher | TUS 2013 | 0 | 0 | 0 | 40 | 200 |
| | 15-24 | Synthetic 2019 | 0 | 0 | 0 | 47,5 | 180 |
| | 25-34 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 35-44 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 45-54 | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| | 55-64 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 65-74 | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| | 75 and higher | Synthetic 2019 | 0 | 0 | 0 | 20 | 380 |
| Job code | | | | | | | |
| | Legislators, entrepreneurs, and senior management | TUS 2013 | 0 | 0 | 20 | 50 | 510 |
| | Intellectual, scientific, and highly specialized professions | TUS 2013 | 0 | 0 | 0 | 40 | 470 |
| | Technical professions | TUS 2013 | 0 | 0 | 0 | 50 | 420 |
| | Clerical support workers | TUS 2013 | 0 | 0 | 0 | 40 | 310 |
| | Skilled workers in commercial activities and services | TUS 2013 | 0 | 0 | 30 | 60 | 410 |
| | Craftsmen, skilled workers, and farmers | TUS 2013 | 0 | 0 | 0 | 50 | 340 |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | TUS 2013 | 0 | 0 | 0 | 40 | 380 |
| | Elementary occupations | TUS 2013 | 0 | 0 | 20 | 50 | 370 |
| | Armed forces | TUS 2013 | 0 | 0 | 10 | 50 | 310 |
| | Legislators, entrepreneurs, and senior management | Synthetic 2019 | 0 | 0 | 0 | 60 | 380 |
| | Intellectual, scientific, and highly specialized professions | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Technical professions | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Clerical support workers | Synthetic 2019 | 0 | 0 | 0 | 40 | 280 |
| | Skilled workers in commercial activities and services | Synthetic 2019 | 0 | 0 | 0 | 47,5 | 410 |
| | Craftsmen, skilled workers, and farmers | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | Synthetic 2019 | 0 | 0 | 0 | 50 | 400 |
| | Elementary occupations | Synthetic 2019 | 0 | 0 | 0 | 40 | 410 |
| | Armed forces | Synthetic 2019 | 0 | 0 | 0 | 60 | 340 |
| Source of income | | | | | | | |
| | Employee (or Salaried worker) | TUS 2013 | 0 | 0 | 20 | 50 | 510 |
| | Self-employed | TUS 2013 | 0 | 0 | 0 | 50 | 470 |
| | Family support | TUS 2013 | 0 | 0 | 0 | 20 | 170 |
| | Capital income / Allowances / Rents / Securities | TUS 2013 | 0 | 0 | 0 | 30 | 330 |
| | Pension (or Retirement income) | TUS 2013 | 0 | 0 | 0 | 30 | 160 |
| | Employee (or Salaried worker) | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Self-employed | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Family support | Synthetic 2019 | 0 | 0 | 0 | 20 | 50 |
| | Capital income / Allowances / Rents / Securities | Synthetic 2019 | 0 | 0 | 0 | 20 | 80 |
| | Pension (or Retirement income) | Synthetic 2019 | 0 | 0 | 20 | 50 | 180 |
| Domestic origin | | | | | | | |
| | Italian | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | Foreign | TUS 2013 | 0 | 0 | 0 | 60 | 370 |
| | Italian | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Foreign | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| ATECO code (industrial sector code) | | | | | | | |
| | Agriculture, forestry, hunting, and fishing | TUS 2013 | 0 | 0 | 30 | 50 | 250 |
| | Construction | TUS 2013 | 0 | 0 | 0 | 50 | 380 |
| | Industry (excluding construction) | TUS 2013 | 0 | 0 | 0 | 40 | 340 |
| | Services | TUS 2013 | 0 | 0 | 10 | 50 | 510 |
| | Agriculture, forestry, hunting, and fishing | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| | Construction | Synthetic 2019 | 0 | 0 | 0 | 50 | 410 |
| | Industry (excluding construction) | Synthetic 2019 | 0 | 0 | 0 | 50 | 400 |
| | Services | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| Type of working schedule | | | | | | | |
| | Part-time | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | Full-time | TUS 2013 | 0 | 0 | 0 | 40 | 300 |
| | Part-time | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Full-time | Synthetic 2019 | 0 | 0 | 0 | 40 | 420 |
| Type of working contract | | | | | | | |
| | Open-ended | TUS 2013 | 0 | 0 | 0 | 50 | 470 |
| | Fixed-term | TUS 2013 | 0 | 0 | 20 | 50 | 370 |
| | Open-ended | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Fixed-term | Synthetic 2019 | 0 | 0 | 0 | 50 | 290 |
| Computer ownership | | | | | | | |
| | Yes | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | No | TUS 2013 | 0 | 0 | 10 | 50 | 370 |
| | Yes | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | No | Synthetic 2019 | 0 | 0 | 0 | 40 | 410 |
| Internet access | | | | | | | |
| | Yes | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | No | TUS 2013 | 0 | 0 | 10 | 50 | 380 |
| | Yes | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | No | Synthetic 2019 | 0 | 0 | 0 | 50 | 380 |
| Mobile phone ownership | | | | | | | |
| | Yes | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | No | TUS 2013 | 0 | 0 | 0 | 50 | 190 |
| | Yes | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | No | Synthetic 2019 | 0 | 0 | 0 | 47,5 | 410 |
| Car ownership | | | | | | | |
| | Yes | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | No | TUS 2013 | 0 | 0 | 0 | 50 | 410 |
| | Yes | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | No | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| Economic resources | | | | | | | |
| | Adequate | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | Absolutely insufficient | TUS 2013 | 0 | 0 | 0 | 50 | 330 |
| | Excellent | TUS 2013 | 0 | 0 | 0 | 50 | 230 |
| | Poor | TUS 2013 | 0 | 0 | 10 | 50 | 420 |
| | Adequate | Synthetic 2019 | 0 | 0 | 0 | 50 | 330 |
| | Absolutely insufficient | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | Excellent | Synthetic 2019 | 0 | 0 | 0 | 40 | 380 |
| | Poor | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| Number of children | | | | | | | |
| | 0 | TUS 2013 | 0 | 0 | 0 | 50 | 410 |
| | 1 | TUS 2013 | 0 | 0 | 0 | 50 | 350 |
| | 2 | TUS 2013 | 0 | 0 | 0 | 50 | 510 |
| | 3 | TUS 2013 | 0 | 0 | 10 | 50 | 410 |
| | 4 | TUS 2013 | 0 | 0 | 0 | 45 | 350 |
| | 5 | TUS 2013 | 0 | 0 | 15 | 37,5 | 60 |
| | 6 | TUS 2013 | 170 | 170 | 170 | 170 | 170 |
| | 0 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 1 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 2 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 3 | Synthetic 2019 | 0 | 0 | 0 | 40 | 410 |
| | 4 | Synthetic 2019 | 0 | 0 | 0 | 40 | 270 |
| | 5 | Synthetic 2019 | 0 | 0 | 60 | 60 | 60 |
| | 6 | Synthetic 2019 | 60 | 60 | 60 | 60 | 60 |
| Number of children under 15 | | | | | | | |
| | 0 | TUS 2013 | 0 | 0 | 0 | 50 | 420 |
| | 1 | TUS 2013 | 0 | 0 | 20 | 50 | 510 |
| | 2 | TUS 2013 | 0 | 0 | 0 | 50 | 470 |
| | 3 | TUS 2013 | 0 | 0 | 0 | 45 | 410 |
| | 4 | TUS 2013 | 0 | 0 | 30 | 40 | 60 |
| | 5 | TUS 2013 | 0 | 0 | 0 | 0 | 0 |
| | 0 | Synthetic 2019 | 0 | 0 | 0 | 50 | 420 |
| | 1 | Synthetic 2019 | 0 | 0 | 0 | 40 | 420 |
| | 2 | Synthetic 2019 | 0 | 0 | 0 | 50 | 340 |
| | 3 | Synthetic 2019 | 0 | 0 | 0 | 40 | 150 |
| | 4 | Synthetic 2019 | 0 | 0 | 0 | 35 | 90 |
| | 5 | Synthetic 2019 | 60 | 60 | 60 | 60 | 60 |

Table 2.45: Quartiles and extremes of commuting time by class for each categorical variable, TUS 2013 vs Synthetic 2019.

| Variable | Class | Source | Min | Q1 | Q2 | Q3 | Max |
|---|---|---|---|---|---|---|---|
| Number of household's component | | | | | | | |
| | 1 | TUS 2013 | 0 | 150 | 250 | 370 | 920 |
| | 2 | TUS 2013 | 0 | 140 | 250 | 380 | 770 |
| | 3 | TUS 2013 | 0 | 130 | 230 | 360 | 900 |
| | 4 | TUS 2013 | 0 | 130 | 230 | 370 | 840 |
| | 5 | TUS 2013 | 0 | 140 | 230 | 370 | 790 |
| | 6 | TUS 2013 | 0 | 170 | 270 | 400 | 720 |
| | 7 | TUS 2013 | 0 | 140 | 245 | 387,5 | 1020 |
| | 8 | TUS 2013 | 60 | 82,5 | 140 | 362,5 | 540 |
| | >= 9 | TUS 2013 | 30 | 180 | 310 | 405 | 520 |
| | 1 | Synthetic 2019 | 0 | 140 | 240 | 370 | 810 |
| | 2 | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| | 3 | Synthetic 2019 | 0 | 150 | 250 | 390 | 790 |
| | 4 | Synthetic 2019 | 0 | 147,5 | 250 | 390 | 1020 |
| | 5 | Synthetic 2019 | 0 | 150 | 250 | 360 | 750 |
| | 6 | Synthetic 2019 | 0 | 150 | 240 | 380 | 920 |
| | 7 | Synthetic 2019 | 0 | 27,5 | 135 | 300 | 450 |
| | 8 | Synthetic 2019 | 0 | 0 | 0 | 0 | 0 |
| | >= 9 | Synthetic 2019 | 0 | 0 | 0 | 0 | 0 |
| Quarter | | | | | | | |
| | 1 | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | 2 | TUS 2013 | 0 | 140 | 240 | 370 | 820 |
| | 3 | TUS 2013 | 0 | 130 | 240 | 370 | 920 |
| | 4 | TUS 2013 | 0 | 140 | 245 | 380 | 850 |
| | 1 | Synthetic 2019 | 0 | 140 | 240 | 380 | 1020 |
| | 2 | Synthetic 2019 | 0 | 140 | 250 | 380 | 1020 |
| | 3 | Synthetic 2019 | 0 | 150 | 250 | 380 | 830 |
| | 4 | Synthetic 2019 | 0 | 150 | 250 | 380 | 920 |
| Gender | | | | | | | |
| | Male | TUS 2013 | 0 | 150 | 260 | 390 | 1020 |
| | Female | TUS 2013 | 0 | 115 | 200 | 310 | 790 |
| | Male | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| | Female | Synthetic 2019 | 0 | 140 | 250 | 380 | 1020 |
| Marital status | | | | | | | |
| | Single | TUS 2013 | 0 | 140 | 240 | 370 | 920 |
| | Married | TUS 2013 | 0 | 140 | 250 | 380 | 1020 |
| | Separated/divorced | TUS 2013 | 0 | 120 | 220 | 340 | 790 |
| | Widow/widower | TUS 2013 | 0 | 150 | 240 | 360 | 700 |
| | Single | Synthetic 2019 | 0 | 140 | 240 | 370 | 850 |
| | Married | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| | Separated/divorced | Synthetic 2019 | 0 | 150 | 250 | 370 | 1020 |
| | Widow/widower | Synthetic 2019 | 0 | 140 | 240 | 390 | 740 |
| Level of education | | | | | | | |
| | High school diploma | TUS 2013 | 0 | 140 | 240 | 370 | 830 |
| | Bachelor diploma or higher | TUS 2013 | 0 | 150 | 260 | 380 | 920 |
| | Elementary school diploma | TUS 2013 | 0 | 140 | 250 | 390 | 1020 |
| | Middle school diploma | TUS 2013 | 0 | 130 | 230 | 370 | 900 |
| | No formal education | TUS 2013 | 0 | 70 | 190 | 350 | 700 |
| | High school diploma | Synthetic 2019 | 0 | 150 | 250 | 387,5 | 1020 |
| | Bachelor diploma or higher | Synthetic 2019 | 0 | 140 | 250 | 380 | 790 |
| | Elementary school diploma | Synthetic 2019 | 0 | 135 | 220 | 345 | 750 |
| | Middle school diploma | Synthetic 2019 | 0 | 140 | 240 | 370 | 1020 |
| | No formal education | Synthetic 2019 | 0 | 150 | 300 | 395 | 650 |
| Geographical distribution | | | | | | | |
| | North-west | TUS 2013 | 0 | 140 | 240 | 360 | 900 |
| | North-east | TUS 2013 | 0 | 140 | 240 | 380 | 920 |
| | Centre | TUS 2013 | 0 | 140 | 240 | 370 | 820 |
| | South | TUS 2013 | 0 | 140 | 240 | 370 | 850 |
| | Islands | TUS 2013 | 0 | 140 | 240 | 380 | 1020 |
| | North-west | Synthetic 2019 | 0 | 140 | 250 | 380 | 850 |
| | North-east | Synthetic 2019 | 0 | 150 | 250 | 370 | 1020 |
| | Centre | Synthetic 2019 | 0 | 150 | 250 | 390 | 830 |
| | South | Synthetic 2019 | 0 | 140 | 250 | 380 | 920 |
| | Islands | Synthetic 2019 | 0 | 140 | 255 | 390 | 1020 |
| Age range | | | | | | | |
| | 15-24 | TUS 2013 | 0 | 117,5 | 260 | 370 | 610 |
| | 25-34 | TUS 2013 | 0 | 130 | 220 | 350 | 770 |
| | 35-44 | TUS 2013 | 0 | 120 | 210 | 340 | 920 |
| | 45-54 | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | 55-64 | TUS 2013 | 0 | 160 | 270 | 400 | 850 |
| | 65-74 | TUS 2013 | 0 | 170 | 290 | 422,5 | 790 |
| | 75 and higher | TUS 2013 | 30 | 185 | 320 | 470 | 700 |
| | 15-24 | Synthetic 2019 | 0 | 140 | 255 | 325 | 540 |
| | 25-34 | Synthetic 2019 | 0 | 140 | 240 | 380 | 750 |
| | 35-44 | Synthetic 2019 | 0 | 140 | 240 | 370 | 1020 |
| | 45-54 | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| | 55-64 | Synthetic 2019 | 0 | 150 | 260 | 390 | 810 |
| | 65-74 | Synthetic 2019 | 0 | 140 | 250 | 370 | 770 |
| | 75 and higher | Synthetic 2019 | 0 | 140 | 220 | 400 | 690 |
| Job code | | | | | | | |
| | Legislators, entrepreneurs, and senior management | TUS 2013 | 0 | 140 | 250 | 360 | 850 |
| | Intellectual, scientific, and highly specialized professions | TUS 2013 | 0 | 150 | 260 | 390 | 920 |
| | Technical professions | TUS 2013 | 0 | 150 | 250 | 380 | 900 |
| | Clerical support workers | TUS 2013 | 0 | 150 | 260 | 390 | 790 |
| | Skilled workers in commercial activities and services | TUS 2013 | 0 | 160 | 190 | 310 | 630 |
| | Craftsmen, skilled workers, and farmers | TUS 2013 | 0 | 150 | 250 | 380 | 1020 |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | TUS 2013 | 0 | 150 | 260 | 390 | 780 |
| | Elementary occupations | TUS 2013 | 0 | 130 | 230 | 350 | 840 |
| | Armed forces | TUS 2013 | 0 | 140 | 250 | 380 | 700 |
| | Legislators, entrepreneurs, and senior management | Synthetic 2019 | 0 | 140 | 230 | 390 | 740 |
| | Intellectual, scientific, and highly specialized professions | Synthetic 2019 | 0 | 140 | 250 | 380 | 790 |
| | Technical professions | Synthetic 2019 | 0 | 150 | 250 | 387,5 | 1020 |
| | Clerical support workers | Synthetic 2019 | 0 | 150 | 260 | 390 | 790 |
| | Skilled workers in commercial activities and services | Synthetic 2019 | 0 | 150 | 250 | 370 | 850 |
| | Craftsmen, skilled workers, and farmers | Synthetic 2019 | 0 | 140 | 240 | 370 | 920 |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | Synthetic 2019 | 0 | 140 | 250 | 390 | 750 |
| | Elementary occupations | Synthetic 2019 | 0 | 140 | 250 | 380 | 1020 |
| | Armed forces | Synthetic 2019 | 0 | 160 | 240 | 380 | 810 |
| Source of income | | | | | | | |
| | Self-employed | TUS 2013 | 0 | 120 | 220 | 360 | 820 |
| | Employee (or Salaried worker) | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | Family support | TUS 2013 | 10 | 180 | 240 | 360 | 790 |
| | Capital income / Allowances / Rents / Securities | TUS 2013 | 0 | 197,5 | 345 | 430 | 760 |
| | Pension (or Retirement income) | TUS 2013 | 0 | 230 | 340 | 480 | 790 |
| | Self-employed | Synthetic 2019 | 0 | 140 | 240 | 380 | 850 |
| | Employee (or Salaried worker) | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| | Family support | Synthetic 2019 | 20 | 175 | 320 | 500 | 650 |
| | Capital income / Allowances / Rents / Securities | Synthetic 2019 | 0 | 210 | 260 | 330 | 490 |
| | Pension (or Retirement income) | Synthetic 2019 | 0 | 112,5 | 200 | 350 | 620 |
| Domestic origin | | | | | | | |
| | Foreign | TUS 2013 | 0 | 120 | 230 | 350 | 750 |
| | Italian | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | Foreign | Synthetic 2019 | 0 | 150 | 260 | 390 | 1020 |
| | Italian | Synthetic 2019 | 0 | 140 | 250 | 380 | 1020 |
| ATECO code (industrial sector code) | | | | | | | |
| | Agriculture, forestry, hunting, and fishing | TUS 2013 | 0 | 140 | 220 | 360 | 820 |
| | Construction | TUS 2013 | 0 | 150 | 270 | 410 | 760 |
| | Industry (excluding construction) | TUS 2013 | 0 | 150 | 260 | 390 | 900 |
| | Services | TUS 2013 | 0 | 130 | 230 | 360 | 1020 |
| | Agriculture, forestry, hunting, and fishing | Synthetic 2019 | 0 | 140 | 240 | 370 | 710 |
| | Construction | Synthetic 2019 | 0 | 140 | 250 | 380 | 800 |
| | Industry (excluding construction) | Synthetic 2019 | 0 | 140 | 240 | 370 | 920 |
| | Services | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| Type of working schedule | | | | | | | |
| | Part-time | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | Full-time | TUS 2013 | 0 | 140 | 240 | 360 | 810 |
| | Part-time | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| | Full-time | Synthetic 2019 | 0 | 147,5 | 250 | 390 | 780 |
| Type of working contract | | | | | | | |
| | Fixed-term | TUS 2013 | 0 | 140 | 240 | 370 | 820 |
| | Open-ended | TUS 2013 | 0 | 140 | 250 | 370 | 1020 |
| | Fixed-term | Synthetic 2019 | 0 | 140 | 250 | 380 | 760 |
| | Open-ended | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| Computer ownership | | | | | | | |
| | No | TUS 2013 | 0 | 130 | 240 | 370 | 800 |
| | Yes | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | No | Synthetic 2019 | 0 | 140 | 230 | 360 | 750 |
| | Yes | Synthetic 2019 | 0 | 150 | 250 | 390 | 1020 |
| Internet access | | | | | | | |
| | No | TUS 2013 | 0 | 130 | 240 | 370 | 800 |
| | Yes | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | No | Synthetic 2019 | 0 | 140 | 240 | 370 | 750 |
| | Yes | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| Mobile phone ownership | | | | | | | |
| | No | TUS 2013 | 0 | 150 | 270 | 380 | 700 |
| | Yes | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | No | Synthetic 2019 | 0 | 120 | 230 | 367,5 | 710 |
| | Yes | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| Car ownership | | | | | | | |
| | No | TUS 2013 | 0 | 130 | 240 | 360 | 720 |
| | Yes | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | No | Synthetic 2019 | 0 | 140 | 250 | 382,5 | 790 |
| | Yes | Synthetic 2019 | 0 | 140 | 250 | 380 | 1020 |
| Economic resources | | | | | | | |
| | Adequate | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | Absolutely insufficient | TUS 2013 | 0 | 130 | 240 | 380 | 830 |
| | Excellent | TUS 2013 | 0 | 130 | 240 | 360 | 790 |
| | Poor | TUS 2013 | 0 | 130 | 230 | 370 | 830 |
| | Adequate | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| | Absolutely insufficient | Synthetic 2019 | 0 | 140 | 220 | 360 | 1020 |
| | Excellent | Synthetic 2019 | 0 | 140 | 240 | 370 | 750 |
| | Poor | Synthetic 2019 | 0 | 140 | 240 | 370 | 920 |
| Number of children | | | | | | | |
| | 0 | TUS 2013 | 0 | 140 | 250 | 370 | 920 |
| | 1 | TUS 2013 | 0 | 130 | 230 | 360 | 900 |
| | 2 | TUS 2013 | 0 | 140 | 240 | 380 | 840 |
| | 3 | TUS 2013 | 0 | 140 | 220 | 360 | 1020 |
| | 4 | TUS 2013 | 0 | 130 | 270 | 355 | 610 |
| | 5 | TUS 2013 | 120 | 140 | 195 | 295 | 430 |
| | 6 | TUS 2013 | 60 | 60 | 60 | 60 | 60 |
| | 0 | Synthetic 2019 | 0 | 140 | 240 | 370 | 1020 |
| | 1 | Synthetic 2019 | 0 | 140 | 250 | 390 | 790 |
| | 2 | Synthetic 2019 | 0 | 150 | 250 | 390 | 1020 |
| | 3 | Synthetic 2019 | 0 | 140 | 250 | 360 | 750 |
| | 4 | Synthetic 2019 | 0 | 152,5 | 265 | 387,5 | 920 |
| | 5 | Synthetic 2019 | 0 | 0 | 0 | 280 | 530 |
| | 6 | Synthetic 2019 | 0 | 0 | 0 | 0 | 0 |
| Number of children under 15 | | | | | | | |
| | 0 | TUS 2013 | 0 | 150 | 250 | 380 | 920 |
| | 1 | TUS 2013 | 0 | 120 | 210 | 340 | 1020 |
| | 2 | TUS 2013 | 0 | 120 | 210 | 350 | 830 |
| | 3 | TUS 2013 | 0 | 140 | 210 | 345 | 640 |
| | 4 | TUS 2013 | 30 | 135 | 240 | 305 | 410 |
| | 5 | TUS 2013 | 370 | 370 | 370 | 370 | 370 |
| | 0 | Synthetic 2019 | 0 | 150 | 250 | 380 | 1020 |
| | 1 | Synthetic 2019 | 0 | 140 | 250 | 380 | 790 |
| | 2 | Synthetic 2019 | 0 | 150 | 250 | 380 | 920 |
| | 3 | Synthetic 2019 | 0 | 150 | 250 | 352,5 | 710 |
| | 4 | Synthetic 2019 | 0 | 157,5 | 205 | 357,5 | 700 |
| | 5 | Synthetic 2019 | 0 | 0 | 0 | 0 | 0 |

Table 2.46: Quartiles and extremes of leisure time by class for each categorical variable, TUS 2013 vs Synthetic 2019.

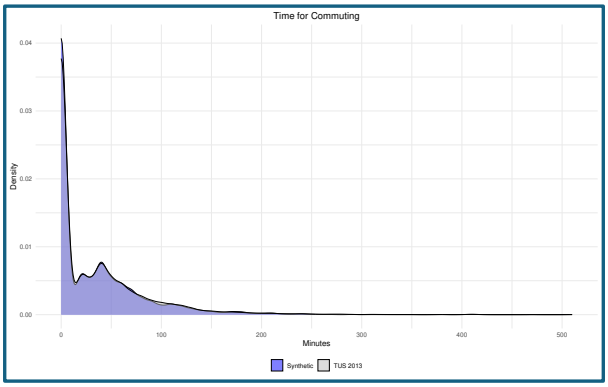
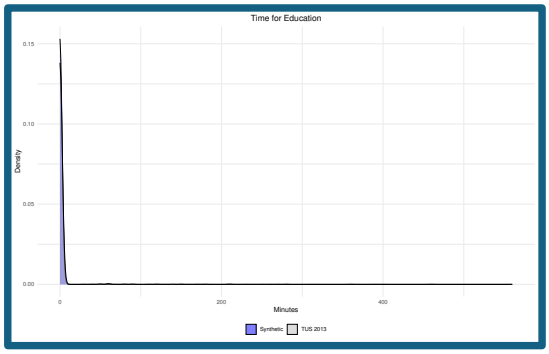


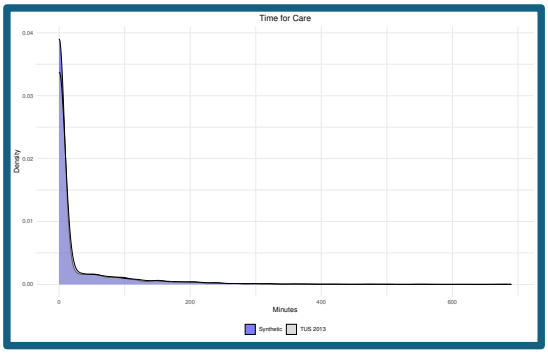

Figure 2.20: Kernel density plot of hours spent on commuting time, comparing the 2013 TUS dataset (grey) and the 2020 synthetic dataset (blue).

| Variable | Class | Mean (Donor Survey) | Mean (Synthetic Survey) | Ratio |
|---|---|---|---|---|
| Number of household's component | | | | |
| | 1 | 32,55 | 29,91 | 0,92 |
| | 2 | 32,25 | 29,84 | 0,93 |
| | 3 | 32,22 | 31,42 | 0,98 |
| | 4 | 32,11 | 30,24 | 0,94 |
| | 5 | 31,87 | 34,04 | 1,07 |
| | 6 | 32,81 | 26,73 | 0,81 |
| | 7 | 21,25 | 20,00 | 0,94 |
| | 8 | 41,67 | 0,00 | 0,00 |
| | >= 9 | 17,14 | 0,00 | 0,00 |
| Quarter | | | | |
| | 1 | 32,53 | 29,65 | 0,91 |
| | 2 | 31,95 | 29,85 | 0,93 |
| | 3 | 33,66 | 30,97 | 0,92 |
| | 4 | 30,79 | 31,03 | 1,01 |
| Geographical distribution | | | | |
| | North-west | 32,05 | 29,73 | 0,93 |
| | North-east | 27,10 | 30,13 | 1,11 |
| | Centre | 32,91 | 30,68 | 0,93 |
| | South | 36,28 | 31,99 | 0,88 |
| | Islands | 33,72 | 29,21 | 0,87 |
| Gender | | | | |
| | Male | 33,35 | 31,02 | 0,93 |
| | Female | 29,22 | 29,19 | 1,00 |
| Marital status | | | | |
| | Single | 31,58 | 28,90 | 0,92 |
| | Married | 32,69 | 31,30 | 0,96 |
| | Separated/divorced | 32,50 | 30,16 | 0,93 |
| | Widow/widower | 27,15 | 31,32 | 1,15 |
| Age range | | | | |
| | 15-24 | 30,00 | 29,10 | 0,97 |
| | 25-34 | 32,83 | 30,47 | 0,93 |
| | 35-44 | 32,21 | 31,49 | 0,98 |
| | 45-54 | 32,96 | 31,19 | 0,95 |
| | 55-64 | 31,07 | 28,87 | 0,93 |
| | 65-74 | 30,69 | 27,55 | 0,90 |
| | 75 and higher | 29,70 | 36,67 | 1,23 |
| Job code | | | | |
| | Legislators, entrepreneurs, and senior management | 35,08 | 34,87 | 0,99 |
| | Intellectual, scientific, and highly specialized professions | 29,04 | 27,30 | 0,94 |
| | Technical professions | 31,39 | 31,18 | 0,99 |
| | Clerical support workers | 25,25 | 29,77 | 1,18 |
| | Skilled workers in commercial activities and services | 40,19 | 32,09 | 0,80 |
| | Craftsmen, skilled workers, and farmers | 31,81 | 30,43 | 0,96 |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | 27,53 | 33,36 | 1,21 |
| | Elementary occupations | 34,42 | 29,23 | 0,85 |
| | Armed forces | 33,93 | 22,80 | 0,67 |
| Domestic origin | | | | |
| | Italian | 31,64 | 30,29 | 0,96 |
| | Foreign | 36,97 | 32,37 | 0,88 |
| Number of children | | | | |
| | 0 | 33,00 | 30,09 | 0,91 |
| | 1 | 30,54 | 31,26 | 1,02 |
| | 2 | 32,13 | 30,10 | 0,94 |
| | 3 | 34,41 | 32,12 | 0,93 |
| | 4 | 32,18 | 26,62 | 0,83 |
| | 5 | 21,67 | 19,09 | 0,88 |
| | 6 | 170,00 | 0,00 | 0,00 |
| Number of children under 15 | | | | |
| | 0 | 32,72 | 30,17 | 0,92 |
| | 1 | 31,51 | 31,34 | 0,99 |
| | 2 | 30,16 | 31,06 | 1,03 |
| | 3 | 31,62 | 28,84 | 0,91 |
| | 4 | 23,64 | 18,24 | 0,77 |
| | 5 | 0,00 | 0,00 | |
| Source of income | | | | |
| | Employee (or Salaried worker) | 31,21 | 29,98 | 0,96 |
| | Self-employed | 36,34 | 32,00 | 0,88 |
| | Family support | 19,38 | 30,89 | 1,59 |
| | Capital income / Allowances / Rents / Securities | 25,50 | 30,92 | 1,21 |
| | Pension (or Retirement income) | 18,60 | 10,71 | 0,58 |
| Type of working contract | | | | |
| | Open-ended | 30,16 | 30,00 | 0,99 |
| | Fixed-term | 34,97 | 30,29 | 0,87 |
| Computer ownership | | | | |
| | Yes | 32,04 | 30,74 | 0,96 |
| | No | 33,48 | 28,80 | 0,86 |
| Internet access | | | | |
| | Yes | 31,97 | 30,36 | 0,95 |
| | No | 33,66 | 31,15 | 0,93 |
| Car ownership | | | | |
| | Yes | 31,76 | 30,65 | 0,96 |
| | No | 36,33 | 28,37 | 0,78 |
| Economic resources | | | | |
| | Adequate | 31,15 | 29,92 | 0,96 |
| | Absolutely insufficient | 34,03 | 32,28 | 0,95 |
| | Excellent | 32,01 | 31,67 | 0,99 |
| | Poor | 34,02 | 31,78 | 0,93 |

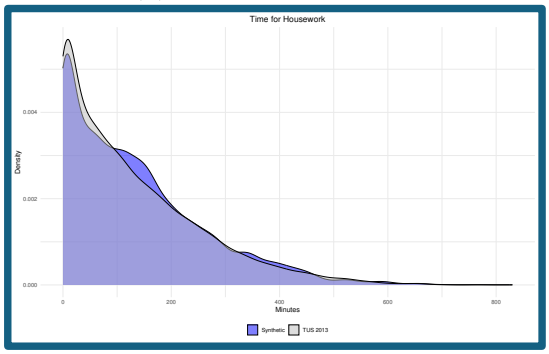
Table 2.48: Analysis of trends by covariate. Ratios of mean commuting times for each covariate between the 2020 synthetic dataset and TUS 2013.



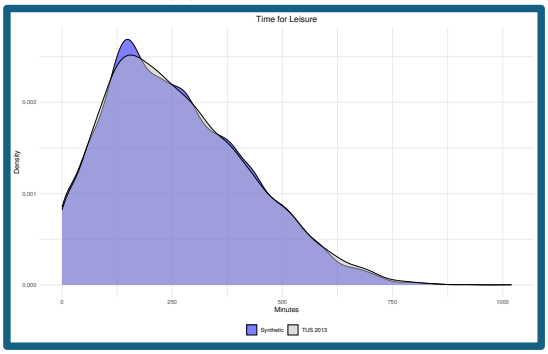

(a) Time for Education.



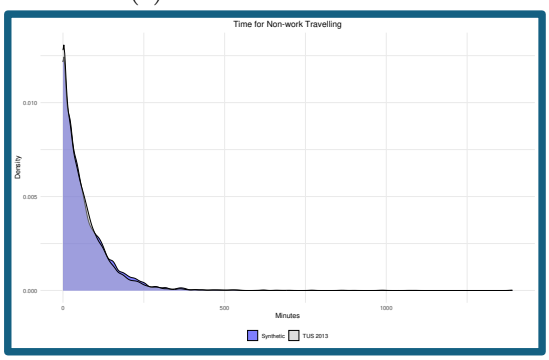

(b) Time for Care.



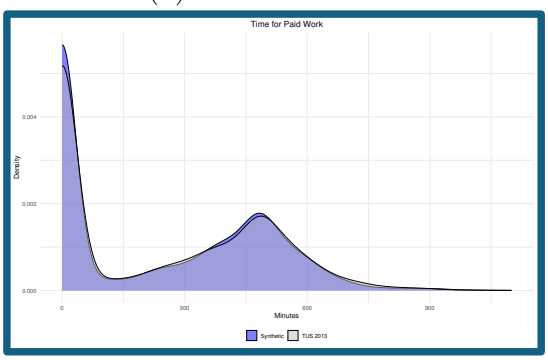

(c) Time for Housework.



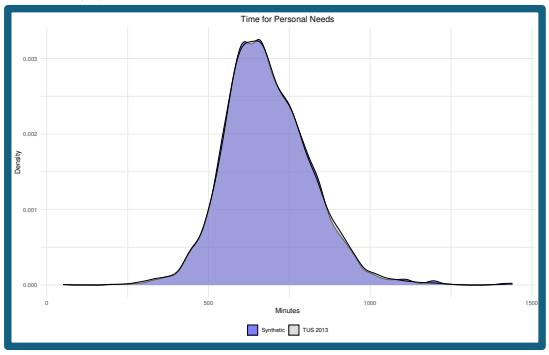

(d) Time for Leisure.



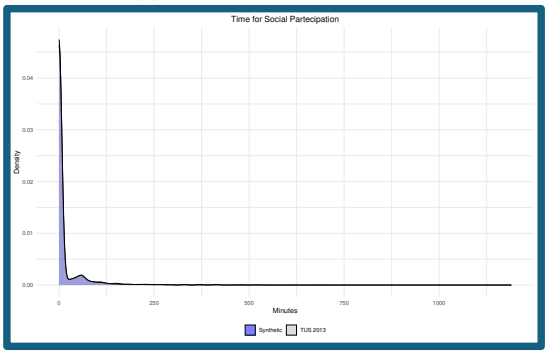

(e) Time for Non-work Travelling.




(f) Time for Paid Work.




(g) Time for Personal Needs.




(h) Time for Social Participation.

Figure 2.21: Robustness tests on other time categories. Kernel density plot of hours spent on other activities, comparing the 2013 TUS dataset (grey) with the 2020 synthetic dataset (blue).

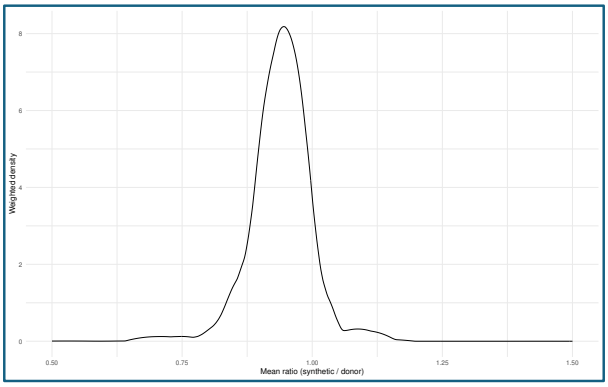



Figure 2.22: Trend analysis by covariates. Weighted kernel density of the ratios between the means in the 2019 synthetic dataset and the 2013 TUS dataset for the covariates used in the matching.

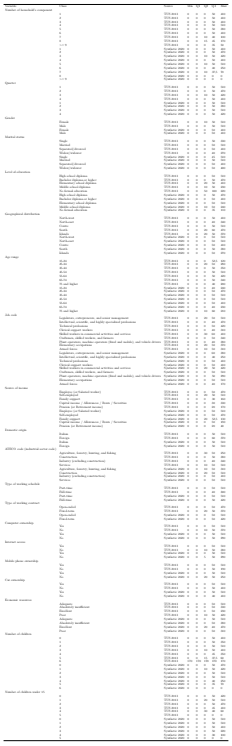


Table 2.49: Quartiles and extremes of commuting time by category for each categorical variable, TUS 2013 vs Synthetic 2020.

| Variable | Class | Source | Min | Q1 | Q2 | Q3 | Max |
|---|---|---|---|---|---|---|---|
| Number of household's component | | | | | | | |
| | 1 | TUS 2013 | 0 | 150 | 250 | 370 | 920 |
| | 2 | TUS 2013 | 0 | 140 | 250 | 380 | 770 |
| | 3 | TUS 2013 | 0 | 130 | 230 | 360 | 900 |
| | 4 | TUS 2013 | 0 | 130 | 230 | 370 | 840 |
| | 5 | TUS 2013 | 0 | 140 | 230 | 370 | 790 |
| | 6 | TUS 2013 | 0 | 170 | 270 | 400 | 720 |
| | 7 | TUS 2013 | 0 | 140 | 245 | 367.5 | 1020 |
| | 8 | TUS 2013 | 60 | 82.5 | 140 | 362.5 | 540 |
| | >= 9 | TUS 2013 | 30 | 180 | 310 | 405 | 520 |
| | 1 | Synthetic 2020 | 0 | 130 | 240 | 367.5 | 920 |
| | 2 | Synthetic 2020 | 0 | 140 | 250 | 380 | 800 |
| | 3 | Synthetic 2020 | 0 | 140 | 230 | 360 | 1020 |
| | 4 | Synthetic 2020 | 0 | 140 | 230 | 370 | 840 |
| | 5 | Synthetic 2020 | 0 | 150 | 240 | 370 | 720 |
| | 6 | Synthetic 2020 | 0 | 120 | 270 | 410 | 690 |
| | 7 | Synthetic 2020 | 0 | 95 | 175 | 297.5 | 490 |
| | 8 | Synthetic 2020 | 130 | 130 | 130 | 130 | 130 |
| | >= 9 | Synthetic 2020 | 130 | 130 | 130 | 130 | 130 |
| Quarter | | | | | | | |
| | 1 | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | 2 | TUS 2013 | 0 | 140 | 240 | 370 | 820 |
| | 3 | TUS 2013 | 0 | 130 | 240 | 370 | 920 |
| | 4 | TUS 2013 | 0 | 140 | 245 | 380 | 850 |
| | 1 | Synthetic 2020 | 0 | 140 | 240 | 370 | 850 |
| | 2 | Synthetic 2020 | 0 | 140 | 240 | 370 | 1020 |
| | 3 | Synthetic 2020 | 0 | 130 | 230 | 370 | 920 |
| | 4 | Synthetic 2020 | 0 | 140 | 240 | 370 | 830 |
| Gender | | | | | | | |
| | Male | TUS 2013 | 0 | 150 | 260 | 390 | 1020 |
| | Female | TUS 2013 | 0 | 115 | 200 | 310 | 790 |
| | Male | Synthetic 2020 | 0 | 140 | 240 | 370 | 1020 |
| | Female | Synthetic 2020 | 0 | 130 | 230 | 360 | 830 |
| Marital status | | | | | | | |
| | Single | TUS 2013 | 0 | 140 | 240 | 370 | 920 |
| | Married | TUS 2013 | 0 | 140 | 250 | 380 | 1020 |
| | Separated/divorced | TUS 2013 | 0 | 120 | 220 | 340 | 790 |
| | Widow/widower | TUS 2013 | 0 | 150 | 240 | 360 | 700 |
| | Single | Synthetic 2020 | 0 | 140 | 240 | 370 | 920 |
| | Married | Synthetic 2020 | 0 | 140 | 240 | 370 | 1020 |
| | Separated/divorced | Synthetic 2020 | 0 | 130 | 240 | 360 | 790 |
| | Widow/widower | Synthetic 2020 | 0 | 140 | 240 | 365 | 720 |
| Level of education | | | | | | | |
| | High school diploma | TUS 2013 | 0 | 140 | 240 | 370 | 830 |
| | Bachelor diploma or higher | TUS 2013 | 0 | 150 | 260 | 380 | 920 |
| | Elementary school diploma | TUS 2013 | 0 | 140 | 250 | 390 | 1020 |
| | Middle school diploma | TUS 2013 | 0 | 130 | 230 | 370 | 900 |
| | No formal education | TUS 2013 | 0 | 70 | 190 | 390 | 700 |
| | High school diploma | Synthetic 2020 | 0 | 140 | 240 | 370 | 850 |
| | Bachelor diploma or higher | Synthetic 2020 | 0 | 140 | 240 | 370 | 920 |
| | Elementary school diploma | Synthetic 2020 | 0 | 150 | 270 | 380 | 720 |
| | Middle school diploma | Synthetic 2020 | 0 | 140 | 230 | 360 | 1020 |
| | No formal education | Synthetic 2020 | 30 | 135 | 240 | 380 | 570 |
| Geographical distribution | | | | | | | |
| | North-west | TUS 2013 | 0 | 140 | 240 | 360 | 900 |
| | North-east | TUS 2013 | 0 | 140 | 240 | 380 | 920 |
| | Centre | TUS 2013 | 0 | 140 | 240 | 370 | 820 |
| | South | TUS 2013 | 0 | 140 | 240 | 370 | 850 |
| | Islands | TUS 2013 | 0 | 140 | 240 | 380 | 1020 |
| | North-west | Synthetic 2020 | 0 | 140 | 240 | 370 | 810 |
| | North-east | Synthetic 2020 | 0 | 130 | 240 | 370 | 1020 |
| | Centre | Synthetic 2020 | 0 | 130 | 230 | 360 | 850 |
| | South | Synthetic 2020 | 0 | 150 | 250 | 380 | 850 |
| | Islands | Synthetic 2020 | 0 | 140 | 230 | 380 | 800 |
| Age range | | | | | | | |
| | 15-24 | TUS 2013 | 0 | 117.5 | 260 | 370 | 610 |
| | 25-34 | TUS 2013 | 0 | 130 | 220 | 350 | 770 |
| | 35-44 | TUS 2013 | 0 | 120 | 210 | 340 | 920 |
| | 45-54 | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | 55-64 | TUS 2013 | 0 | 160 | 270 | 400 | 850 |
| | 65-74 | TUS 2013 | 0 | 170 | 290 | 422.5 | 790 |
| | 75 and higher | TUS 2013 | 30 | 185 | 320 | 470 | 700 |
| | 15-24 | Synthetic 2020 | 0 | 125 | 230 | 390 | 710 |
| | 25-34 | Synthetic 2020 | 0 | 140 | 240 | 360 | 850 |
| | 35-44 | Synthetic 2020 | 0 | 130 | 230 | 360 | 920 |
| | 45-54 | Synthetic 2020 | 0 | 140 | 230 | 360 | 840 |
| | 55-64 | Synthetic 2020 | 0 | 140 | 250 | 390 | 1020 |
| | 65-74 | Synthetic 2020 | 0 | 140 | 260 | 380 | 770 |
| | 75 and higher | Synthetic 2020 | 0 | 100 | 215 | 292.5 | 660 |
| Job code | | | | | | | |
| | Legislators, entrepreneurs, and senior management | TUS 2013 | 0 | 140 | 250 | 360 | 850 |
| | Intellectual, scientific, and highly specialized professions | TUS 2013 | 0 | 150 | 260 | 390 | 920 |
| | Technical professions | TUS 2013 | 0 | 150 | 250 | 380 | 900 |
| | Clerical support workers | TUS 2013 | 0 | 150 | 260 | 390 | 790 |
| | Skilled workers in commercial activities and services | TUS 2013 | 0 | 100 | 190 | 310 | 830 |
| | Craftsmen, skilled workers, and farmers | TUS 2013 | 0 | 150 | 250 | 380 | 1020 |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | TUS 2013 | 0 | 150 | 260 | 390 | 780 |
| | Elementary occupations | TUS 2013 | 0 | 130 | 230 | 350 | 840 |
| | Armed forces | TUS 2013 | 0 | 140 | 250 | 380 | 700 |
| | Legislators, entrepreneurs, and senior management | Synthetic 2020 | 0 | 130 | 230 | 350 | 770 |
| | Intellectual, scientific, and highly specialized professions | Synthetic 2020 | 0 | 140 | 250 | 370 | 920 |
| | Technical professions | Synthetic 2020 | 0 | 140 | 240 | 380 | 850 |
| | Clerical support workers | Synthetic 2020 | 0 | 140 | 240 | 380 | 850 |
| | Skilled workers in commercial activities and services | Synthetic 2020 | 0 | 130 | 230 | 360 | 850 |
| | Craftsmen, skilled workers, and farmers | Synthetic 2020 | 0 | 140 | 230 | 370 | 1020 |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | Synthetic 2020 | 0 | 132.5 | 240 | 370 | 850 |
| | Elementary occupations | Synthetic 2020 | 0 | 140 | 230 | 360 | 840 |
| | Armed forces | Synthetic 2020 | 0 | 162.5 | 285 | 405 | 710 |
| Source of income | | | | | | | |
| | Self-employed | TUS 2013 | 0 | 120 | 220 | 360 | 820 |
| | Employee (or Salaried worker) | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | Family support | TUS 2013 | 10 | 180 | 240 | 360 | 790 |
| | Capital income / Allowances / Rents / Securities | TUS 2013 | 0 | 197.5 | 345 | 430 | 760 |
| | Pension (or Retirement income) | TUS 2013 | 0 | 230 | 340 | 480 | 790 |
| | Self-employed | Synthetic 2020 | 0 | 130 | 230 | 370 | 850 |
| | Employee (or Salaried worker) | Synthetic 2020 | 0 | 140 | 240 | 370 | 1020 |
| | Family support | Synthetic 2020 | 50 | 255 | 365 | 457.5 | 660 |
| | Capital income / Allowances / Rents / Securities | Synthetic 2020 | 0 | 170 | 290 | 450 | 690 |
| | Pension (or Retirement income) | Synthetic 2020 | 0 | 110 | 255 | 412.5 | 670 |
| Domestic origin | | | | | | | |
| | Foreign | TUS 2013 | 0 | 120 | 230 | 350 | 750 |
| | Italian | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | Foreign | Synthetic 2020 | 0 | 130 | 230 | 357.5 | 830 |
| | Italian | Synthetic 2020 | 0 | 140 | 240 | 370 | 1020 |
| ATECO code (industrial sector code) | | | | | | | |
| | Agriculture, forestry, hunting, and fishing | TUS 2013 | 0 | 140 | 220 | 360 | 820 |
| | Construction | TUS 2013 | 0 | 150 | 270 | 410 | 760 |
| | Industry (excluding construction) | TUS 2013 | 0 | 150 | 260 | 390 | 900 |
| | Services | TUS 2013 | 0 | 130 | 230 | 360 | 1020 |
| | Agriculture, forestry, hunting, and fishing | Synthetic 2020 | 0 | 140 | 240 | 370 | 740 |
| | Construction | Synthetic 2020 | 0 | 130 | 220 | 360 | 1020 |
| | Industry (excluding construction) | Synthetic 2020 | 0 | 140 | 240 | 370 | 850 |
| | Services | Synthetic 2020 | 0 | 140 | 240 | 370 | 920 |
| Type of working schedule | | Synthetic 2020 | 0 | 125 | 230 | 390 | 630 |
| | Part-time | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | Full-time | TUS 2013 | 0 | 140 | 240 | 360 | 810 |
| | Part-time | Synthetic 2020 | 0 | 140 | 240 | 370 | 1020 |
| | Full-time | Synthetic 2020 | 0 | 130 | 230 | 347.5 | 830 |
| Type of working contract | | | | | | | |
| | Fixed-term | TUS 2013 | 0 | 140 | 240 | 370 | 820 |
| | Open-ended | TUS 2013 | 0 | 140 | 250 | 370 | 1020 |
| | Fixed-term | Synthetic 2020 | 0 | 130 | 230 | 360 | 1020 |
| | Open-ended | Synthetic 2020 | 0 | 140 | 240 | 370 | 920 |
| Computer ownership | | | | | | | |
| | No | TUS 2013 | 0 | 130 | 240 | 370 | 800 |
| | Yes | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | No | Synthetic 2020 | 0 | 140 | 240 | 360 | 850 |
| | Yes | Synthetic 2020 | 0 | 140 | 240 | 370 | 1020 |
| Internet access | | | | | | | |
| | No | TUS 2013 | 0 | 130 | 240 | 370 | 800 |
| | Yes | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | No | Synthetic 2020 | 0 | 150 | 240 | 370 | 850 |
| | Yes | Synthetic 2020 | 0 | 140 | 240 | 370 | 1020 |
| Mobile phone ownership | | | | | | | |
| | No | TUS 2013 | 0 | 150 | 270 | 380 | 700 |
| | Yes | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | No | Synthetic 2020 | 0 | 140 | 230 | 360 | 920 |
| | Yes | Synthetic 2020 | 0 | 140 | 240 | 370 | 1020 |
| Car ownership | | | | | | | |
| | No | TUS 2013 | 0 | 130 | 240 | 360 | 720 |
| | Yes | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | No | Synthetic 2020 | 0 | 140 | 240 | 360 | 790 |
| | Yes | Synthetic 2020 | 0 | 140 | 240 | 370 | 1020 |
| Economic resources | | | | | | | |
| | Adequate | TUS 2013 | 0 | 140 | 240 | 370 | 1020 |
| | Absolutely insufficient | TUS 2013 | 0 | 130 | 240 | 380 | 830 |
| | Excellent | TUS 2013 | 0 | 130 | 240 | 360 | 790 |
| | Poor | TUS 2013 | 0 | 130 | 230 | 370 | 830 |
| | Adequate | Synthetic 2020 | 0 | 140 | 240 | 370 | 920 |
| | Absolutely insufficient | Synthetic 2020 | 0 | 132.5 | 240 | 347.5 | 690 |
| | Excellent | Synthetic 2020 | 0 | 130 | 240 | 340 | 700 |
| | Poor | Synthetic 2020 | 0 | 140 | 230 | 360 | 1020 |
| Number of children | | | | | | | |
| | 0 | TUS 2013 | 0 | 140 | 250 | 370 | 920 |
| | 1 | TUS 2013 | 0 | 130 | 230 | 360 | 900 |
| | 2 | TUS 2013 | 0 | 140 | 240 | 380 | 840 |
| | 3 | TUS 2013 | 0 | 140 | 220 | 360 | 1020 |
| | 4 | TUS 2013 | 0 | 130 | 270 | 355 | 610 |
| | 5 | TUS 2013 | 120 | 140 | 195 | 295 | 430 |
| | 6 | TUS 2013 | 60 | 60 | 60 | 60 | 60 |
| | 0 | Synthetic 2020 | 0 | 140 | 250 | 370 | 920 |
| | 1 | Synthetic 2020 | 0 | 140 | 230 | 360 | 1020 |
| | 2 | Synthetic 2020 | 0 | 140 | 230 | 370 | 840 |
| | 3 | Synthetic 2020 | 0 | 150 | 250 | 380 | 710 |
| | 4 | Synthetic 2020 | 0 | 120 | 265 | 410 | 640 |
| | 5 | Synthetic 2020 | 0 | 115 | 130 | 220 | 360 |
| | 6 | Synthetic 2020 | 130 | 130 | 130 | 130 | 130 |
| Number of children under 15 | | | | | | | |
| | 0 | TUS 2013 | 0 | 150 | 250 | 380 | 920 |
| | 1 | TUS 2013 | 0 | 120 | 210 | 340 | 1020 |
| | 2 | TUS 2013 | 0 | 120 | 210 | 350 | 830 |
| | 3 | TUS 2013 | 0 | 140 | 210 | 345 | 640 |
| | 4 | TUS 2013 | 30 | 135 | 240 | 305 | 410 |
| | 5 | TUS 2013 | 370 | 370 | 370 | 370 | 370 |
| | 0 | Synthetic 2020 | 0 | 140 | 250 | 370 | 1020 |
| | 1 | Synthetic 2020 | 0 | 135 | 230 | 350 | 850 |
| | 2 | Synthetic 2020 | 0 | 130 | 220 | 360 | 800 |
| | 3 | Synthetic 2020 | 0 | 150 | 245 | 390 | 700 |
| | 4 | Synthetic 2020 | 0 | 140 | 320 | 370 | 560 |
| | 5 | Synthetic 2020 | 130 | 130 | 130 | 130 | 130 |

Table 2.50: Quartiles and extremes of leisure time by category for each categorical variable, TUS 2013 vs Synthetic 2020.

| Variable | Class | Source | Min | Q1 | Q2 | Q3 | Max |
|---|---|---|---|---|---|---|---|
| Number of household's component | | | | | | | |
| | 1 | TUS 2013 | 200 | 600 | 680 | 780 | 1280 |
| | 2 | TUS 2013 | 120 | 590 | 670 | 770 | 1440 |
| | 3 | TUS 2013 | 230 | 590 | 670 | 760 | 1440 |
| | 4 | TUS 2013 | 50 | 590 | 670 | 750 | 1440 |
| | 5 | TUS 2013 | 290 | 600 | 660 | 750 | 1190 |
| | 6 | TUS 2013 | 440 | 610 | 710 | 780 | 1010 |
| | 7 | TUS 2013 | 410 | 562.5 | 615 | 732.5 | 830 |
| | 8 | TUS 2013 | 500 | 707.5 | 775 | 917.5 | 990 |
| | >= 9 | TUS 2013 | 520 | 750 | 780 | 850 | 910 |
| | 1 | Synthetic 2020 | 200 | 600 | 680 | 770 | 1440 |
| | 2 | Synthetic 2020 | 50 | 590 | 660 | 760 | 1440 |
| | 3 | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | 4 | Synthetic 2020 | 200 | 590 | 670 | 760 | 1440 |
| | 5 | Synthetic 2020 | 320 | 610 | 670 | 770 | 1440 |
| | 6 | Synthetic 2020 | 290 | 610 | 690 | 780 | 1120 |
| | 7 | Synthetic 2020 | 530 | 612.5 | 660 | 752.5 | 980 |
| | 8 | Synthetic 2020 | 600 | 600 | 600 | 600 | 600 |
| | >= 9 | Synthetic 2020 | 600 | 600 | 600 | 600 | 600 |
| Quarter | | | | | | | |
| | 1 | TUS 2013 | 60 | 590 | 670 | 760 | 1440 |
| | 2 | TUS 2013 | 120 | 600 | 670 | 770 | 1440 |
| | 3 | TUS 2013 | 240 | 590 | 670 | 760 | 1190 |
| | 4 | TUS 2013 | 50 | 600 | 670 | 770 | 1440 |
| | 1 | Synthetic 2020 | 50 | 600 | 670 | 770 | 1410 |
| | 2 | Synthetic 2020 | 320 | 590 | 670 | 770 | 1440 |
| | 3 | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | 4 | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| Gender | | | | | | | |
| | Male | TUS 2013 | 60 | 590 | 670 | 770 | 1440 |
| | Female | TUS 2013 | 50 | 600 | 670 | 760 | 1440 |
| | Male | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | Female | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| Marital status | | | | | | | |
| | Single | TUS 2013 | 280 | 600 | 680 | 780 | 1440 |
| | Married | TUS 2013 | 50 | 590 | 670 | 760 | 1440 |
| | Separated/divorced | TUS 2013 | 120 | 590 | 660 | 760 | 1390 |
| | Widow/widower | TUS 2013 | 310 | 600 | 670 | 740 | 1440 |
| | Single | Synthetic 2020 | 50 | 590 | 670 | 770 | 1440 |
| | Married | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | Separated/divorced | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | Widow/widower | Synthetic 2020 | 380 | 590 | 680 | 780 | 1410 |
| Level of education | | | | | | | |
| | High school diploma | TUS 2013 | 50 | 590 | 670 | 770 | 1440 |
| | Bachelor diploma or higher | TUS 2013 | 240 | 590 | 670 | 760 | 1440 |
| | Elementary school diploma | TUS 2013 | 230 | 590 | 680 | 770 | 1410 |
| | Middle school diploma | TUS 2013 | 60 | 590 | 670 | 770 | 1440 |
| | No formal education | TUS 2013 | 360 | 580 | 660 | 760 | 1440 |
| | High school diploma | Synthetic 2020 | 50 | 600 | 670 | 760 | 1440 |
| | Bachelor diploma or higher | Synthetic 2020 | 200 | 590 | 670 | 770 | 1390 |
| | Elementary school diploma | Synthetic 2020 | 330 | 590 | 660 | 755 | 1410 |
| | Middle school diploma | Synthetic 2020 | 50 | 600 | 670 | 770 | 1440 |
| | No formal education | Synthetic 2020 | 330 | 595 | 660 | 735 | 980 |
| Geographical distribution | | | | | | | |
| | North-west | TUS 2013 | 50 | 600 | 670 | 780 | 1440 |
| | North-east | TUS 2013 | 280 | 600 | 680 | 770 | 1440 |
| | Centre | TUS 2013 | 280 | 590 | 670 | 770 | 1280 |
| | South | TUS 2013 | 60 | 590 | 660 | 760 | 1440 |
| | Islands | TUS 2013 | 190 | 590 | 660 | 750 | 1430 |
| | North-west | Synthetic 2020 | 200 | 590 | 670 | 770 | 1440 |
| | North-east | Synthetic 2020 | 50 | 600 | 670 | 760 | 1440 |
| | Centre | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | South | Synthetic 2020 | 200 | 590 | 670 | 760 | 1430 |
| | Islands | Synthetic 2020 | 50 | 590 | 670 | 750 | 1440 |
| Age range | | | | | | | |
| | 15-24 | TUS 2013 | 510 | 630 | 675 | 795 | 1060 |
| | 25-34 | TUS 2013 | 280 | 610 | 690 | 790 | 1240 |
| | 35-44 | TUS 2013 | 220 | 590 | 670 | 770 | 1440 |
| | 45-54 | TUS 2013 | 60 | 590 | 660 | 760 | 1440 |
| | 55-64 | TUS 2013 | 120 | 590 | 670 | 760 | 1440 |
| | 65-74 | TUS 2013 | 50 | 600 | 680 | 760 | 1440 |
| | 75 and higher | TUS 2013 | 520 | 625 | 690 | 750 | 940 |
| | 15-24 | Synthetic 2020 | 280 | 595 | 670 | 770 | 1260 |
| | 25-34 | Synthetic 2020 | 50 | 590 | 680 | 780 | 1440 |
| | 35-44 | Synthetic 2020 | 200 | 600 | 670 | 760 | 1440 |
| | 45-54 | Synthetic 2020 | 50 | 600 | 670 | 760 | 1440 |
| | 55-64 | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | 65-74 | Synthetic 2020 | 330 | 590 | 660 | 750 | 1200 |
| | 75 and higher | Synthetic 2020 | 460 | 580 | 650 | 762.5 | 1200 |
| Job code | | | | | | | |
| | Legislators, entrepreneurs, and senior management | TUS 2013 | 50 | 590 | 670 | 770 | 1440 |
| | Intellectual, scientific, and highly specialized professions | TUS 2013 | 240 | 590 | 670 | 750 | 1440 |
| | Technical professions | TUS 2013 | 120 | 600 | 680 | 762.5 | 1390 |
| | Clerical support workers | TUS 2013 | 320 | 610 | 680 | 770 | 1170 |
| | Skilled workers in commercial activities and services | TUS 2013 | 190 | 580 | 650 | 730 | 1220 |
| | Craftsmen, skilled workers, and farmers | TUS 2013 | 260 | 600 | 680 | 780 | 1440 |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | TUS 2013 | 230 | 590 | 680 | 790 | 1260 |
| | Elementary occupations | TUS 2013 | 60 | 600 | 680 | 770 | 1440 |
| | Armed forces | TUS 2013 | 290 | 560 | 670 | 777.5 | 1120 |
| | Legislators, entrepreneurs, and senior management | Synthetic 2020 | 320 | 610 | 680 | 770 | 1440 |
| | Intellectual, scientific, and highly specialized professions | Synthetic 2020 | 200 | 590 | 670 | 770 | 1260 |
| | Technical professions | Synthetic 2020 | 270 | 590 | 660 | 760 | 1440 |
| | Clerical support workers | Synthetic 2020 | 50 | 600 | 670 | 770 | 1440 |
| | Skilled workers in commercial activities and services | Synthetic 2020 | 50 | 590 | 670 | 760 | 1430 |
| | Craftsmen, skilled workers, and farmers | Synthetic 2020 | 50 | 600 | 680 | 780 | 1370 |
| | Plant operators, machine operators (fixed and mobile), and vehicle drivers | Synthetic 2020 | 50 | 590 | 670 | 760 | 1260 |
| | Elementary occupations | Synthetic 2020 | 200 | 600 | 670 | 760 | 1440 |
| | Armed forces | Synthetic 2020 | 280 | 600 | 665 | 727.5 | 930 |
| Source of income | | | | | | | |
| | Self-employed | TUS 2013 | 50 | 590 | 660 | 760 | 1430 |
| | Employee (or Salaried worker) | TUS 2013 | 60 | 590 | 670 | 770 | 1440 |
| | Family support | TUS 2013 | 440 | 630 | 710 | 800 | 1240 |
| | Capital income / Allowances / Rents / Securities | TUS 2013 | 520 | 637.5 | 680 | 760 | 950 |
| | Pension (or Retirement income) | TUS 2013 | 460 | 620 | 680 | 770 | 1050 |
| | Self-employed | Synthetic 2020 | 50 | 600 | 670 | 770 | 1440 |
| | Employee (or Salaried worker) | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | Family support | Synthetic 2020 | 320 | 632.5 | 670 | 777.5 | 890 |
| | Capital income / Allowances / Rents / Securities | Synthetic 2020 | 320 | 590 | 660 | 740 | 1410 |
| | Pension (or Retirement income) | Synthetic 2020 | 460 | 600 | 670 | 750 | 1080 |
| Domestic origin | | | | | | | |
| | Foreign | TUS 2013 | 280 | 600 | 680 | 770 | 1440 |
| | Italian | TUS 2013 | 50 | 590 | 670 | 760 | 1440 |
| | Foreign | Synthetic 2020 | 320 | 600 | 670 | 770 | 1440 |
| | Italian | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| ATECO code (industrial sector code) | | | | | | | |
| | Agriculture, forestry, hunting, and fishing | TUS 2013 | 60 | 580 | 650 | 740 | 1240 |
| | Construction | TUS 2013 | 270 | 610 | 690 | 780 | 1430 |
| | Industry (excluding construction) | TUS 2013 | 50 | 600 | 680 | 790 | 1270 |
| | Services | TUS 2013 | 120 | 590 | 670 | 760 | 1440 |
| | Agriculture, forestry, hunting, and fishing | Synthetic 2020 | 330 | 600 | 660 | 770 | 1260 |
| | Construction | Synthetic 2020 | 200 | 600 | 670 | 760 | 1440 |
| | Industry (excluding construction) | Synthetic 2020 | 200 | 590 | 670 | 760 | 1280 |
| | Services | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| Type of working schedule | | | | | | | |
| | Part-time | TUS 2013 | 50 | 590 | 670 | 760 | 1440 |
| | Full-time | TUS 2013 | 310 | 620 | 680 | 780 | 1440 |
| | Part-time | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | Full-time | Synthetic 2020 | 320 | 600 | 670 | 760 | 1430 |
| Type of working contract | | | | | | | |
| | Fixed-term | TUS 2013 | 60 | 600 | 670 | 770 | 1430 |
| | Open-ended | TUS 2013 | 120 | 590 | 670 | 770 | 1440 |
| | Fixed-term | Synthetic 2020 | 200 | 600 | 670 | 780 | 1440 |
| | Open-ended | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| Computer ownership | | | | | | | |
| | No | TUS 2013 | 120 | 600 | 670 | 770 | 1440 |
| | Yes | TUS 2013 | 50 | 590 | 670 | 760 | 1440 |
| | No | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | Yes | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| Internet access | | | | | | | |
| | No | TUS 2013 | 120 | 600 | 680 | 770 | 1440 |
| | Yes | TUS 2013 | 50 | 590 | 670 | 760 | 1440 |
| | No | Synthetic 2020 | 50 | 590 | 670 | 760 | 1410 |
| | Yes | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| Mobile phone ownership | | | | | | | |
| | No | TUS 2013 | 270 | 620 | 680 | 760 | 1430 |
| | Yes | TUS 2013 | 50 | 590 | 670 | 760 | 1440 |
| | No | Synthetic 2020 | 270 | 575 | 670 | 760 | 1410 |
| | Yes | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| Car ownership | | | | | | | |
| | No | TUS 2013 | 280 | 600 | 680 | 770 | 1440 |
| | Yes | TUS 2013 | 50 | 590 | 670 | 760 | 1440 |
| | No | Synthetic 2020 | 200 | 600 | 670 | 770 | 1440 |
| | Yes | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| Economic resources | | | | | | | |
| | Adequate | TUS 2013 | 50 | 590 | 670 | 760 | 1440 |
| | Absolutely insufficient | TUS 2013 | 260 | 600 | 680 | 780 | 1430 |
| | Excellent | TUS 2013 | 450 | 580 | 660 | 760 | 1040 |
| | Poor | TUS 2013 | 120 | 600 | 670 | 770 | 1440 |
| | Adequate | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | Absolutely insufficient | Synthetic 2020 | 200 | 600 | 690 | 770 | 1440 |
| | Excellent | Synthetic 2020 | 50 | 580 | 670 | 750 | 1210 |
| | Poor | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| Number of children | | | | | | | |
| | 0 | TUS 2013 | 120 | 600 | 680 | 770 | 1440 |
| | 1 | TUS 2013 | 60 | 590 | 670 | 760 | 1440 |
| | 2 | TUS 2013 | 50 | 590 | 670 | 757.5 | 1440 |
| | 3 | TUS 2013 | 340 | 600 | 660 | 750 | 1190 |
| | 4 | TUS 2013 | 480 | 580 | 690 | 780 | 970 |
| | 5 | TUS 2013 | 410 | 522.5 | 550 | 600 | 700 |
| | 6 | TUS 2013 | 590 | 590 | 590 | 590 | 590 |
| | 0 | Synthetic 2020 | 50 | 590 | 670 | 770 | 1440 |
| | 1 | Synthetic 2020 | 50 | 590 | 670 | 760 | 1430 |
| | 2 | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | 3 | Synthetic 2020 | 350 | 600 | 670 | 770 | 1440 |
| | 4 | Synthetic 2020 | 380 | 610 | 680 | 787.5 | 1120 |
| | 5 | Synthetic 2020 | 560 | 605 | 640 | 695 | 860 |
| | 6 | Synthetic 2020 | 600 | 600 | 600 | 600 | 600 |
| Number of children under 15 | | | | | | | |
| | 0 | TUS 2013 | 50 | 590 | 670 | 770 | 1440 |
| | 1 | TUS 2013 | 190 | 590 | 670 | 760 | 1440 |
| | 2 | TUS 2013 | 220 | 600 | 670 | 760 | 1430 |
| | 3 | TUS 2013 | 340 | 610 | 700 | 780 | 1040 |
| | 4 | TUS 2013 | 480 | 525 | 560 | 695 | 820 |
| | 5 | TUS 2013 | 520 | 520 | 520 | 520 | 520 |
| | 0 | Synthetic 2020 | 50 | 590 | 670 | 770 | 1440 |
| | 1 | Synthetic 2020 | 200 | 600 | 670 | 760 | 1430 |
| | 2 | Synthetic 2020 | 50 | 590 | 670 | 760 | 1440 |
| | 3 | Synthetic 2020 | 350 | 610 | 675 | 770 | 1060 |
| | 4 | Synthetic 2020 | 560 | 620 | 700 | 790 | 1120 |
| | 5 | Synthetic 2020 | 600 | 600 | 600 | 600 | 600 |

Table 2.51: Quartiles and extremes of the time spent on personal needs by class for each categorical variable, TUS 2013 vs Synthetic 2020.

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# CHAPTER 3

## Towards a Fully Electric Vehicle Production by 2035: Economic Implications for Italy's Automotive Sector Through an Input-Output Approach


### Abstract

The current economic model places a heavy burden on ecosystems and relies on finite natural resources, making a radical transformation of energy and production systems necessary. In Europe, decarbonization efforts span several sectors, with transport—especially the automotive industry—playing a central role. In this context, the Fit for 55 package sets increasingly stringent 2030 targets and requires zero tailpipe emissions for all new cars and vans placed on the market by 2035. This study assesses the economic and employment effects of full electrification of the automotive sector on the Italian economy, in the context of European policy measures. Using the FIGARO supply and use tables (Eurostat), national accounts from ISTAT, product-level trade flows from the BACI database, and sectoral data from ACEA and related sources, we construct counterfactual and policy scenarios and apply a cross-country input-output model to examine the effects of technological change and shifts in demand. The simulations compare a baseline scenario with partial offshoring of component supply, a scenario that passively adopts the Chinese electric vehicle production model at the European level, an application of this model to projected 2035 demand, and two variants with further reductions in demand. Electrification significantly reshapes manufacturing, driving growth in electronics and vehicle assembly sectors and reducing demand for traditional inputs from the metal-mechanical and rubber/plastics sectors, as well as from some service industries. The transition also reduces Italy's share in the supply chain, strengthening the role of hubs in Central and Northern Europe and Eastern Europe, as well as specialized Asian economies, particularly in batteries and semiconductors. This suggests a real risk of erosion of the national value chain if domestic capacity is not developed, especially in battery and cell production. Compared with the business-as-usual baseline, offshoring alone results in a moderate loss (€270 million in value added and 3,400 jobs, or 2%). Passive adoption of the Chinese production model at the European level leads to much larger losses (€3.4 billion and 44,000 jobs, or 23%). The most severe impact arises from combining this production model with the projected and estimated reduction in demand by 2035 (€6.2 billion and 82,000 jobs, or 40%), while scenarios with further demand erosion increase the losses to €6.5–6.7 billion and 86,000–89,000 jobs (42%–44%). These results suggest that, without targeted industrial and demand-side policies—such as localizing critical production stages, providing purchase incentives, and supporting small and medium-sized

enterprises—electrification could substantially erode the national value chain and generate significant job losses.

**Keywords**: Automotive Electrification, Energy Transition, Input-Output Analysis, Fit for 55, Italian EV Market, Electrified Vehicles, Green New Deal, Supply Chain, Industrial Policies.

**This essay, in the form of scientific paper, was published in the *International Journal of Automotive Technology and Management*.**

## 3.1 Introduction

The current economic model, still largely shaped by the industrial paradigm that emerged in nineteenth-century Europe, now exhibits clear signs of unsustainability, both in environmental terms and in relation to the limited availability of its underlying natural resources. The climate crisis, reflected in rising average temperatures, ecosystem disruption, biodiversity loss, and adverse effects on human health, is a direct consequence of an energy system based on fossil fuels. When burned, these fuels release carbon dioxide and other greenhouse gases that drive global warming. Moreover, fossil resources are finite, and their geographically concentrated distribution contributes to geopolitical tensions. Since energy production and use are major sources of emissions, and since approximately 75% of total EU greenhouse-gas emissions come from energy-related sectors, decarbonising energy systems is essential to mitigate climate change.

Energy transition is therefore imperative to address global warming, climate change, and their broader socio-environmental consequences. The term refers to the shift from an energy system predominantly based on non-renewable fossil fuels—such as oil, coal, and natural gas—towards an energy mix based on renewable sources, such as wind, solar photovoltaic, and geothermal energy.

A broader definition of energy transition includes not only the substitution of energy sources, but also the widespread adoption of energy-efficiency measures across the main consumption sectors, namely industry, services, and residential buildings. Other key components of this process include energy storage capacity, the adaptation and modernisation of distribution networks, and the integration of technological and digital solutions that support flexible and balanced demand-supply management.

Energy transition should therefore be understood primarily as a technological transition, since it occurs through the introduction and diffusion of technologies aimed at reducing emissions in production processes, energy generation and distribution, and use-phase activities.

The energy and automotive sectors are among the most emblematic in terms of the effects of this transition. The automotive sector, in particular, is the focus of this research.

In the following sections, the introduction will explore several key areas, delving into each element necessary to contextualize and clarify the dynamics of the automotive sector's electrification. It aims to provide the reader with a clear and comprehensive overview of all the factors—both strengths and challenges—that make up the puzzle of this significant and, in some ways, revolutionary technological shift. First, we will present the 'rules of the game' for manufacturers—that is, the regulations and standards introduced to address emissions in the sector, which define the framework within which European manufacturers must build their industrial strategies. Next, we will examine the current state of the automotive sector and its future prospects, both globally and in Europe. We will then delve into the concept of electrification and the technological innovation behind it, including from an engineering perspective. Next, we will focus on its environmental and social impacts. We conclude with the objectives and contribution of my research.

### 3.1.1 European Regulations for the Energy Transition

The European Commission has adopted the European Green Deal as the regulatory and policy framework guiding the transition towards a sustainable, competitive, low-emission growth model, with climate neutrality by 2050 as its central objective (EU, 2024). This target implies that, by that date, the European Union must achieve net zero greenhouse-gas emissions, offsetting any residual emissions through removals (e.g. forests and soils) and/or carbon-capture and storage technologies.

As an intermediate and binding milestone, the EU has set a target of at least a 55 per cent reduction in emissions by 2030 relative to 1990 levels. Pursuing climate neutrality therefore requires systemic transformations across strategic sectors — energy, transport, industry, buildings and agriculture — and coherent policies that promote technological innovation, economic competitiveness and social cohesion.

The measures foreseen by the Green Deal also include support for public and private investment in green technologies, assistance for territories and workers most exposed to transition risks, and the protection of natural capital through interventions on biodiversity, the circular economy and energy efficiency. From this perspective, climate neutrality functions as a development paradigm that integrates economic growth, social equity and environmental sustainability.

The Fit-for-55 legislative package constitutes a coordinated set of proposals and reforms designed to secure the binding objective of climate neutrality by 2050, with a dual aim: to ensure a fair and socially equitable transition and, at the same time, to preserve and strengthen European industry's innovation and competitiveness while maintaining a level playing field with non-EU operators (EU, 2025).

At the operational level, the package reorganises and strengthens the main instruments for emissions reduction. The reform of the EU Emissions Trading System[1] (EU ETS) seeks

[1]Among the amendments introduced are the extension of the scope to maritime transport; an accelerated reduction in the total number of allowances in circulation; the gradual phase-out of free allowances for certain industrial sectors; the integration of the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) into the EU ETS; and the strengthening of related financial mechanisms, such as the Modernisation Fund and the Innovation Fund.

to increase the ambition of emissions cuts in energy-intensive sectors and power generation. At the same time, a new and separate trading system is introduced for buildings, road transport and fuels not yet covered by the main scheme, with the aim of ensuring coherent emissions management across sectors.

To mitigate the social and distributional impacts of the transition, the package also establishes the Social Climate Fund[2], intended to support the most vulnerable groups — households, micro-enterprises and transport users — through temporary direct income support and investments aimed at adaptation.

Another structural pillar of the package is the Carbon Border Adjustment Mechanism (CBAM), designed to prevent the relocation of emissions outside the EU and to preserve the effectiveness of EU climate policies in the face of imports of high-carbon goods. Operating in parallel with the EU ETS, CBAM is intended to gradually replace certain existing protection measures, including free allowances. The legislative proposal and related rules were approved in 2022–2023, with subsequent simplification measures advanced by the Commission in 2025.

Within the measures aimed at reducing transport emissions, the Fit for 55 package introduces progressively stricter targets for 2030 and mandates, from 2035, net-zero emissions for all new vehicles placed on the market (equivalent to a 100 per cent reduction relative to the reference baseline). This provision represents a cornerstone for the automotive sector and underpins the shift towards electrification of the vehicle fleet (Eufitfor55, 2025). Specifically, the regulation establishes four temporal milestones: during 2021–2024 average limits of 95 g $CO_2$/km for passenger cars and 147 g $CO_2$/km for light commercial vehicles; for 2025–2029 a 15 per cent reduction relative to the 2021 reference target; for 2030–2034 a 55 per cent reduction relative to the 2021 target; and, finally, for 2035 a target of 0 g $CO_2$/km for new vehicles. The latter objective is the focus of this research.

[2]The Fund has an indicative ceiling of resources amounting to tens of billions of euros, funded by specific revenue streams.

### 3.1.2 Global and Regional Outlook for the Automotive Industry

The European automotive industry remains a strategic and highly interconnected economic sector. Its value chain encompasses not only manufacturing but also sales, after-sales services and infrastructure provision, generating an extensive network of economic linkages (Association et al., 2025). In the EU, the sector supports millions of jobs when direct and indirect employment are combined: direct production accounts for approximately 2.5 million jobs, while total employment exceeds 13 million once supply-chain activities such as services, transport, sales and maintenance are included. This dual feature—high production intensity and a wide-ranging value chain—helps explain why commercial, regulatory or technological shocks generate broad and multi-level effects across regional economies (Association et al., 2025).

The sector is also facing a 'perfect storm' of intensifying international competition, trade tensions and rising costs, all of which constrain the Union's capacity to retain and attract manufacturing activity (Association et al., 2025). Production data confirm these concerns. In 2024, global vehicle production fell to 75.5 million units ($-0.5\%$), with marked declines in Europe ($-4.6\%$), North America ($-3.2\%$) and Japan; the EU recorded a contraction of $-6.2\%$ relative to the previous year (Association et al., 2024). EU production has thus remained below pre-pandemic levels, declining by roughly 750,000 vehicles year-on-year (Association et al., 2025).

At the global level, production remains dominated by China, whose share increased by 5.2 percentage points to 35.4% of the global market, while Europe's share continued to erode (Association et al., 2024). Within the EU, production amounted to 11.4 million vehicles ($-6.2\%$), with particularly sharp contractions in Italy ($-43.4\%$), Belgium ($-31.2\%$) and France ($-12.4\%$). Germany limited the decline ($-0.4\%$), while Spain recorded a modest increase ($+0.7\%$), consolidating second place. Central and Eastern Europe displayed heterogeneous dynamics: the Czech Republic held up ($+3.5\%$), whereas Slovakia ($-7.6\%$) and Romania ($-6.5\%$) experienced declines.

The 2015–2024 series displays clear cyclical patterns, including the post-COVID

recovery, peaks driven by stock replenishment and a recent slowdown linked to stagnant demand, competitiveness problems and the relocation of production capacity to lower-cost locations. Commercial-vehicle output also contracted significantly, signalling pressure on demand for investment goods and on suppliers (Association et al., 2024, 2025). These developments suggest that the sector's crisis did not arise solely from the production paradigm associated with electrification; many difficulties had structural roots predating the EV transition. Historical data nonetheless indicate some employment resilience during 2019–2023: although certain segments—especially direct production—fluctuated because of supply disruptions and demand variation, overall employment remained relatively stable thanks to the weight of the broader supply chain, including sales, repairs and logistics (Association et al., 2025).

Turning to registrations, global volume reached 74.6 million units in 2024 (+2.5% relative to 2023), but regional trends were highly divergent (Association et al., 2024). Wider Europe grew by 3.9% to 16.1 million units, while the EU rose modestly by 0.8% to about 10.6 million; the United Kingdom showed resilience (+2.6%), whereas the EFTA region contracted (−4.6%). In North America, demand held up (+3.8%, with the United States at +3.1% and 12.7 million units); South America rose above 3 million registrations (+6.5%); and in Asia, China remained the hub with 22.9 million registrations (+2.6%), accounting for about 31% of the global total. Russia and Ukraine recorded strong rebounds (+46.4% and +12.6%, respectively). Within the EU, Spain grew (+7.1%), whereas France (−3.2%), Germany (−1.0%) and Italy (−0.5%) declined. Overall, 2024 remained materially below pre-pandemic volumes, at approximately 18.4% below 2019 levels (Association et al., 2024).

Regarding EU external trade, 2024 marked a reversal: both export and import volumes and values declined relative to 2023, partially reducing the sector's trade surplus, which nevertheless remained positive and sizeable, at around €90–94 billion. The geography of trade places the United Kingdom and the United States among the principal destination markets for EU products, while China emerges as the main source of electric-vehicle

imports. Turkey is playing an increasing role both as a source of imports and as a destination market, indicating a regional reorganisation of value chains. Analysis of the 2020–2024 series suggests that the 2024 decline reflects both cyclical factors, namely a global slowdown in demand, and structural factors[3] such as the relocation of production capacity to more competitive areas (Association et al., 2024, 2025).

With respect to the electric-vehicle market, 2024 represents a transitional phase. Global EV sales continued to grow, but at a slower pace than in previous years[4], with pronounced regional differences. Volumes remained robust in China, India and France, while Germany, Italy[5], Japan and the United States showed signs of slowdown linked to political uncertainty, weaker incentives and production constraints (McKerracher, 2024). After years of rapid growth in battery electric vehicle (BEV) demand in the EU, the BEV share of new registrations fell in 2024 to around 13.6% for passenger cars. Model availability does not automatically translate into penetration, which remains sensitive to national incentives, total cost of ownership, charging infrastructure and consumer preferences (McKerracher, 2024; Association et al., 2025).

The transition is highly heterogeneous by segment: penetration in light commercial vehicles remains low, with vans at around 6% and BEV trucks at approximately 2–3%, whereas electric buses show significant progress where public procurement and fleet-

[3]This raises the question of trade policy and the importance of preserving preferential access and stable trading conditions with key partners.

[4]The evidence from recent years points to an electrification transition that has accelerated on both the demand and the industrial-supply sides. On the expenditure side, 2022 marked a significant step change: global spending on electric cars rose by 50% versus 2021, reaching roughly USD 425 billion, with the bulk of funding coming from consumers at the point of purchase and a diminishing role for direct public support. The public share of total spending fell from over 20% in 2017 to just under 10% in 2022, and the average per-vehicle incentive roughly halved from about USD 9,000 to USD 4,000 as the market matured and volumes expanded. This pattern is not merely an accounting detail: it indicates that manufacturers are beginning to finance the transition from revenues generated by electric-vehicle sales themselves—particularly in the more profitable segments such as SUVs and large cars—thereby gradually reducing reliance on ICE sales to fund R&D and new EV platforms (Outlook et al., 2023).

[5]In 2023 Italy ranked among the main European plug-in markets, but with figures markedly lower than those of the continental leaders: in the European ranking by plug-in electric vehicles (PEVs) sales in 2023, Italy recorded approximately 66,000 PEVs sold, trailing the top seven markets (Germany, the United Kingdom, France, the Netherlands, Sweden, Norway and Belgium). This position indicates a rapidly growing market that has not yet reached the scale of countries with much higher penetration rates. Considering the vehicle stock, Italy's plug-in fleet has expanded from a few tens of thousands in the mid-2010s to about 490,000 plug-in hybrid electric vehicles (PHEVs) by the end of 2023—a strong acceleration in recent years, but still leaving scope for catch-up relative to more advanced countries (Hoffmann and Dev, 2024).

financing schemes support demand. China already appears to be in a 'take-off' phase, driven by robust domestic demand and the competitiveness of local manufacturers, which are increasingly expanding into foreign markets (McKerracher, 2024).

Projections point to rapid growth in EV shares: Bloomberg forecasts (McKerracher, 2024) anticipate an increase from 18% in 2023 to 33% in 2027, with annual sales exceeding 30 million units; geographic penetration is expected to vary markedly, at approximately 60% in China, 41% in Europe and 29% in the United States. Long-run scenarios point to even larger shares—for example, 45% in 2030 and 73% in 2040—although global vehicle stock penetration would remain below 50% by those dates. The economic opportunity is substantial, with trillions of dollars of potential value by 2050, and is fuelling competition to control supply chains, particularly for batteries and critical raw materials. Annual demand for lithium-ion cells is projected to rise sharply[6], requiring significant investment, even though announced production capacity raises risks of overcapacity and price compression, especially in China (McKerracher, 2024).

Impacts on the energy system and emissions are already visible: by 2024 there were tens of millions of electric vehicles in circulation, and the average emissions of new cars in the EU had declined to around 108 g $CO_2$/km. Estimates suggest that EV uptake will reduce oil demand by nearly 4 million barrels per day by 2027 relative to a no-EV scenario and will increase electricity demand substantially, with EV-related needs reaching thousands of TWh across scenarios. Despite significant improvements in the environmental intensity of production—emissions, water use and volatile organic compounds (VOCs) have fallen by more than half since 2005—slow fleet turnover and the volatility of BEV sales have slowed the reduction in on-road emissions. In sum, supply-side gains in efficiency and costs are substantial, while demand-side factors such as fleet renewal, incentives and infrastructure determine the actual pace of transport decarbonisation (McKerracher, 2024; Association et al., 2025).

[6]This dynamic promotes mass adoption but simultaneously creates pressures on producers and on Western governments, which are seeking to localise production.

### 3.1.3 The Concept of Electrification and Structural Change

Returning to the measures envisaged in the Fit for 55 package, it is clear that reductions in $CO_2$ emissions in the transport sector will depend heavily on the electrification of road transport[7]. *Electrification* refers to the shift in the energy source powering vehicles—today still predominantly derived from fossil fuels—towards electricity-based propulsion, through the diffusion of BEVs, PHEVs, conventional hybrids (HEVs) and, more broadly, electrified solutions applied to cars, vans, buses and heavy goods vehicles (IEA, 2025; Hawkins et al., 2013; Jaramillo et al., 2022; Gül et al., 2024; Olabi et al., 2021).

The transition from internal-combustion-engine vehicles (ICEVs) to fully electric vehicles entails a distinct production structure and, more broadly, a new industrial paradigm. In simplified terms, this paradigm can be reduced to two main component groups: the powertrain and power electronics (BostonConsoultingGroup, 2020). On the powertrain side, the principal ICEV components—the combustion engine and auxiliary systems such as the alternator, starter motor and complex fuel and exhaust systems—are replaced in BEVs by a battery pack and one or more electric motors. The battery pack itself consists of modules containing cells, a Battery Management System (BMS) that monitors status and performance, thermal management systems, interconnections and a protective enclosure. Moreover, the multi-speed transmission typical of ICEVs is generally replaced in BEVs by a single-ratio transmission, owing to the torque characteristics of electric motors.

Replacing the internal combustion engine with an electric motor reduces certain assembly complexities associated with ICEVs—fewer pipes, seals and delicate mechanical components—thereby increasing opportunities for automation in electric motor production. At the same time, BEV manufacturing introduces new processes and skill requirements: wiring assembly, winding and impregnation of electrical components, sealing, and advanced quality-control procedures for electrical systems and battery packs all require targeted investments in technology and training. These changes are particularly relevant for an

[7]Electrification also encompasses charging infrastructure, grid integration and policies designed to stimulate both the supply and the demand for electric mobility.

industry that has optimised combustion-engine production processes for more than a century (BostonConsoultingGroup, 2020).

Power electronics—including DC/DC converters, DC/AC inverters and associated controllers—are essential in BEVs and hybrids and rely on skills and components that are absent from pure ICEVs. Although ICE powertrains typically contain a larger number of discrete parts (an ICE powertrain may include over 1,000 components versus a few hundred for a BEV powertrain, excluding individual battery cells), the content-per-vehicle (CPV) of a BEV is nevertheless around 30% higher than that of an ICEV, mainly because of the high cost of batteries (BostonConsoultingGroup, 2020; Gaddi and Garbellini, 2021).

Another critical distinction concerns the battery cell supply chain. While many manufacturers assemble battery packs in-house from modules, cells are frequently supplied by specialist external producers, with production highly concentrated in Asia and substantial reliance on firms originating in the consumer-electronics sector. This makes the battery supply chain particularly sensitive to logistics and inventory constraints, since module and cell inventories are difficult to maintain because of safety risks and degradation over time; as a result, highly reliable just-in-time processes are needed to ensure production continuity (BostonConsoultingGroup, 2020).

Production technologies also differ substantially. Components for combustion engines often require complex casting and machining processes for blocks, cylinders, camshafts and connecting rods, whereas parts for electric motors can be manufactured through less complex and more modular processes—for example, the production of rotors, stators, magnets and bearings. This implies a different supplier base and a different set of machine tools. The shift to BEVs therefore affects not only vehicle manufacturers and direct suppliers, but also producers of machinery and automation systems suited to the new composition of electric motors (BostonConsoultingGroup, 2020).

Differences also emerge in other vehicle functions. Weight reduction is a cross-industry objective in response to increasingly stringent fuel-efficiency requirements, but it is especially important for BEV manufacturers: battery packs are heavy and materially

affect range, which pushes firms towards lightweighting and structural optimisation strategies (BostonConsoultingGroup, 2020).

A comparison of content-per-vehicle (CPV) reveals pronounced divergences between ICEVs and BEVs. Using an ICEV as a 100% benchmark, the ICE powertrain (engine, transmission and auxiliary components) represents approximately 31% of CPV. In BEVs, these elements are replaced by cells, modules and battery packs: the battery system alone accounts for roughly one-third of a BEV's CPV, with raw materials potentially representing up to 60% of battery cost. To this share must be added about 6 percentage points attributable to power electronics and a further c. 4 percentage points for specific items such as high-voltage wiring. Taken together, a BEV's CPV currently amounts to approximately 130% of an ICEV's. This gap, however, is expected to narrow in the coming years as battery costs decline due to economies of scale, factory automation and process improvements (BostonConsoultingGroup, 2020).

Some analyses challenge the widespread assumption that BEV production requires substantially less labour than ICEV production (BostonConsoultingGroup, 2020): assembly-phase labour inputs are broadly comparable. Although ICE-specific subsystems—such as fuel lines and exhaust systems—are eliminated, BEVs introduce distinct but equally demanding operations, for example the manufacture and installation of high-voltage converters and inverters, motor-charger units, connections for battery cooling circuits (BEVs typically employ three thermal circuits versus two in ICEVs) and, in certain models, additional front-compartment panelling. Several BEV assembly stages also impose more stringent quality-control requirements—for instance, to avoid foreign bodies within battery packs that could cause overheating or fires—thereby increasing operational complexity. Factory infrastructure likewise evolves: demand for exhaust-gas ventilation in test areas diminishes, while equipment for handling and managing modules and battery packs (specialised lifters, reinforced conveyors, etc.) becomes more prevalent, often making the reconversion of existing plants to BEV lines both complex and costly (BostonConsoultingGroup, 2020).

Understanding production differentials between ICEVs and BEVs is essential because they clarify shifts in value added along the value chain. Manufacturing value added captures the costs of transforming raw materials into a finished vehicle and, importantly, the direct and indirect labour hours per vehicle. A study comparing a midsize (segment D) reference vehicle estimated the total labour hours required by OEMs and first-tier suppliers to produce an ICEV versus a BEV, allocating the 'labour value' between direct labour (assemblers, machine operators) and indirect labour (quality control, maintenance) (BostonConsoultingGroup, 2020).

Aggregating the items above, current labour requirements[8] for BEVs are overall only marginally lower—on the order of c. 1%—than those for ICEVs. This comparison concerns pure ICEVs versus pure BEVs; hybrid vehicles, which combine a thermal engine and an electric motor, typically exhibit higher manufacturing value added than either pure ICEVs or pure BEVs, and therefore require more labour hours per vehicle (BostonConsoultingGroup, 2020).

Some studies report that total value added per vehicle is currently broadly comparable between BEVs and ICEVs, yet this apparent parity conceals a substantial reconfiguration of its composition and distribution along the value chain. As BEVs proliferate, an increasing share of labour value tends to shift away from OEMs towards first-tier suppli-

[8]The main differences in manufacturing value added may be summarised as follows. (a) Component manufacturing. Because electric motors involve fewer parts and less casting and machining, the share of hours devoted to component manufacture is lower for BEVs: roughly 47% of hours per vehicle for BEVs versus 54% for ICEVs. It should be noted, however, that some BEV operations—most notably wiring harness production—remain highly manual and time-intensive: wiring alone can require about 10 hours of manual labour compared with approximately 3 hours needed to assemble a combustion engine. (b) Motor/transmission assembly and installation. Building and fitting an electric motor requires relatively few hours: around 2% of a BEV's total hours (assuming a single motor), compared with about 7% for an ICEV. Single-ratio transmissions in BEVs also reduce transmission-assembly labour by more than 50% relative to the multi-speed gearboxes typical of ICEVs. (c) Battery production. Cell, module and pack assembly is intrinsic to BEVs and has no ICEV equivalent; although cell plants are highly automated, there is a substantial share of indirect labour for machine operation, process control and quality inspection: cell production contributes roughly +8 percentage points to hours per vehicle for a BEV relative to an ICEV baseline. (d) Stamping, body assembly and painting. These stages are largely independent of powertrain type and the hours required per vehicle are broadly equivalent for BEVs and ICEVs. (e) Final vehicle assembly. The installation of charging units (on-board chargers), high-voltage wiring and battery-pack placement involves additional work that partly offsets the ICEV processes that are eliminated (fuel tanks, shift-selector linkages, certain engine wiring). In some cases, BEV assembly hours are estimated to increase by up to c. 8% compared with ICEV baseline levels, all else equal in terms of automation (BostonConsoultingGroup, 2020).

ers—most notably battery-cell manufacturers when automakers source cells externally. This has important competitive implications for Western OEMs, since dominant cell producers remain largely Asian, although some Western firms are scaling up capacity (BostonConsoultingGroup, 2020). In practice, many carmakers currently procure cells from specialised suppliers, while assembling modules and battery packs and sometimes electric motors in-house; battery packs, being highly model-specific, are generally assembled close to vehicle plants for reasons of safety, transport cost and specialised handling (BostonConsoultingGroup, 2020).

Power electronics are frequently sourced from suppliers that capture value added through innovations such as silicon-carbide semiconductors and integrated cooling solutions; similarly, there is not yet a uniform industry practice regarding BEV transmissions, with some manufacturers producing them internally and others outsourcing them (BostonConsoultingGroup, 2020).

One study, drawing on the foregoing analysis of labour intensity, estimates that the current distribution of labour is already somewhat biased in favour of suppliers: approximately 53% of total hours are carried out by suppliers versus 47% by the OEM. Over the long term, under a full transition to BEVs, overall labour demand from vehicle manufacturers is likely to decline; however, during the transition phase, the expanded role of hybrid vehicles in many manufacturers' portfolios may temporarily raise labour-hour requirements in the medium term (BostonConsoultingGroup, 2020).

### 3.1.4 The Challenges of Electrification in the Automotive Sector

Electrification is not limited to the introduction of new vehicles; rather, it constitutes a systemic transformation that requires the simultaneous and coordinated evolution of the energy sector, industry, electricity networks, technical standards, public policy, and individual and collective behaviours (Boulanger et al., 2011). This process is constrained by several multidimensional challenges that hinder its full realisation:

- With respect to prices, electric vehicles currently have a higher upfront costs than

ICEVs, although they entail substantially lower operating costs in terms of fuel and maintenance. To shorten the payback period needed to recover this initial premium, many governments have introduced sizeable financial incentives. The main factor behind the price differential is battery cost, although this is falling rapidly (Boulanger et al., 2011). In comparing BEVs and ICEVs, one should also account for the so-called 'hidden costs' of fossil fuels—supply risks, geopolitical instability and price volatility—which reduce the short-term advantage of conventional vehicles.

- Batteries are a central and rapidly evolving component of the transition to electric mobility. Battery demand has grown explosively—doubling in 2021—driven by rising EV registrations (IEA, 2022). Global production capacity is highly concentrated geographically: China accounts for approximately three quarters of global capacity (over 70%), reflecting a multi-year strategy of vertical integration across the entire value chain, from refining to cell and pack assembly (IEA, 2022). Innovation in cell chemistry also creates new trade-offs. Lithium-iron-phosphate (LFP) cells are gaining market share because they do not require critical metals such as nickel, manganese or cobalt, thereby reducing supply risks. At the same time, alternative solutions such as sodium-ion (Na-ion) batteries are emerging; these use cheaper, lithium-free materials and are estimated to cost about 30% less than LFP, albeit with lower energy density, which limits their suitability for long-range vehicles and some stationary storage applications (IEA, 2022; Outlook et al., 2023). This asymmetry in the geographical location of production exposes Europe to industrial dependence: if production capacity and innovation remain concentrated outside the EU, much of the value added and technological progress will accrue abroad, compressing margins for European manufacturers and suppliers and contributing to a progressive loss of know-how in thermal mechanics without adequate reabsorption into emerging electric segments. Moreover, strong concentration at the OEM level—with a few producers accounting for more than half of global EV output—risks excluding small and medium-sized European firms from first-tier supply unless interoperable platforms and open standards are promoted to facilitate integration into the value

chain (IEA, 2022).

- The geographical concentration of rare-earth production and processing is another strategic risk for the electrification transition. Although these elements are not 'rare' in a geological sense, their economic concentration and governance structures limit effective market availability: production is dominated by China, which applies export constraints, while growing demand from electric motors and the wind sector continues to exert upward pressure on the market. Elements such as neodymium, dysprosium, terbium and europium are therefore critical in the short term, whereas the reorientation of supply chains requires long time horizons (Boulanger et al., 2011). In recent years, a substantial share of demand for lithium, cobalt and nickel has been absorbed by battery production for electric vehicles, with a highly uneven upstream distribution of mining and refining capacity. This concentration exposes the entire supply chain to price volatility, environmental and social constraints associated with opening new mines, and the long lead times required to develop new extraction and refining capacity. The use of lanthanum in NiMH batteries was one reason many manufacturers moved towards lithium. At the same time, lithium appears relatively more reassuring in terms of reserves and potential capacity, including alternative extraction pathways and recycling, at least through the middle of the century, although it remains exposed to geopolitical risks and temporary bottlenecks (Outlook et al., 2023; Boulanger et al., 2011). To mitigate these risks, policies aimed at diversifying sources, supporting technologies less dependent on critical elements (such as LFP chemistries and other alternatives), and systematically developing recycling and material recovery are essential for reducing net exposure to mineral markets. At the policy and industrial level, the European Union has responded with regulatory tools and binding targets under the Critical Raw Materials Act, which sets 2030 objectives of approximately 10% extraction, 40% processing and 15% recycling of strategic materials within Europe, with a clear focus on source diversification and on the environmental and social sustainability of mining activities, in coherence with climate objectives (Fit for 55) and with economic and industrial

security needs. At the same time, the strong profitability of the critical-metals extraction sector and investor interest—with significant outperformance by involved companies—are intensifying competition for resources: the aggregate value of critical minerals for clean technologies in 2021 is estimated at around USD 75 billion and, in a Net Zero scenario, could rise substantially by 2050, increasing pressure on prices, production capacity and supply-chain governance (Outlook et al., 2023).

- Range anxiety remains another obstacle to electric vehicle adoption. This issue is being addressed pragmatically. Daily travel data show that most trips fall within the range currently available; nevertheless, subjective perception often matters more than statistical evidence, and this misperception generates reluctance to purchase vehicles (Boulanger et al., 2011). Mitigation strategies have therefore developed along three main lines: 1) the diffusion of charging infrastructure, particularly slow or overnight charging, to normalise an 'invisible' charging routine; 2) technologies and services such as battery swapping, which can take only a few minutes and is especially suitable for taxis and fleet operations with centralised depots, although it requires physical standardisation of battery packs; 3) fast charging, which acts as a 'safety net' but involves important trade-offs in terms of battery cost, weight and longevity when used frequently.

- Charging infrastructure is a crucial part of the transition and faces predominantly practical obstacles (Boulanger et al., 2011). Installing a domestic or condominium charging point requires authorisation procedures, time and non-negligible costs, although these are lower when buildings are already equipped for such infrastructure. On the public side, numerous programmes have financed thousands of charging points, but the business model remains fragile: since most charging takes place at home, it is not always clear who should bear the costs or what return investors can expect. Cities and utilities are nonetheless investing in new charging stations, often integrated with renewable sources, but public awareness remains limited and many existing facilities are underutilised. In Europe, charging infrastructure is one of the

main bottlenecks to electric mobility (Association et al., 2025; Outlook et al., 2023; Hoffmann and Dev, 2024). There are almost 882,000 public charging points in the EU (2024), yet their distribution is highly concentrated in a few countries: France, Germany and the Netherlands together account for nearly 60% of the total. This creates, on the one hand, more favourable BEV-per-point ratios and a better user experience in those countries; on the other hand, territorial heterogeneity across the EU leaves some areas with infrastructural scarcity that hinders adoption. Further indicators show that in more than half of Member States there is less than one public charging point per 1,000 inhabitants and that, on average, there are about five BEVs per charging point—a ratio that is worse in many countries. Finally, slightly more than half of Member States provide specific incentives for charging-infrastructure construction, a policy gap relative to purchase incentives; this suggests the need to shift some policy attention from demand support towards targeted measures promoting both public and private infrastructure (Hoffmann and Dev, 2024).

- The electricity network is the other side of the infrastructure coin and represents both a constraint and an opportunity. At the global level, generation capacity is broadly adequate; however, local bottlenecks may arise if a large number of users charge simultaneously—for example, when returning home in the evening—thus affecting transformer capacity and distribution networks. Modelling simulations indicate that, by shifting charging to night-time hours, the impact on the network becomes negligible (Boulanger et al., 2011).

- Investment and innovation constitute a competitive strength for Europe[9] (Association et al., 2025). European manufacturers have allocated substantial resources to research and development—around €84–85 billion in 2023—a figure that represents

[9]Of 5,114 patenting firms in the Y02T category (2014–2021), 126 are Italian (2.46%). The principal innovators at the global level are the United States and Japan, while within Europe Germany leads the ranking. In Italy the main patenting actors are Magneti Marelli and various Fiat–Stellantis subsidiaries, followed by firms such as Lamborghini, Leonardo and several academic centres; however, most Italian patents still concern mitigation technologies for combustion engines (control systems, pistons and fuels), with a more limited presence of patents related to batteries and electrical distribution. Over time, a gradual shift towards greater technological heterogeneity and an increase in co-occurrences associated with electrification can be observed, although ICE-related innovations remain prevalent in the early years (Nelli, 2024).

a significant share of total industrial R&D in the EU and that increased by several billion relative to the previous year. These investments are concentrated mainly in electrification, batteries, software and driver-assistance/automation systems, positioning the European industry as a leading technological actor. The 'race for the value chain' has translated into policies and industrial plans aimed at retaining an increasing share of production and technological content domestically (Outlook et al., 2023). In this context, the European Commission's March 2023 proposal for the Net Zero Industry Act seeks to satisfy 40% of domestic demand for net-zero technologies through European production capacity by 2030; for the battery sector, the objective is that nearly 90% of EU demand be covered by European producers and that at least 550 GWh/year of manufacturing capacity be available, in line with the European Battery Alliance's targets. However, the volume of investment, while necessary, is not sufficient on its own to ensure the localisation of productive benefits: the conversion of R&D into domestic employment and production requires reliable supply chains (for example, for batteries), economies of scale and contextual conditions favourable to high-technology manufacturing. Finally, many common industrial solutions are left to private capital and national markets; the absence of a common instrument capable of aligning policies and capacities across European countries risks worsening the existing centre–periphery duality within the automotive value chain, with important socio-economic implications (Nelli, 2024).

In summary, the European automotive industry is subject to a dual pressure: on the one hand, a techno-economic strain stemming from the transition to electric vehicles and from the rise in electronic complexity; on the other hand, a geopolitical and supply-chain pressure linked to strategic dependence on external suppliers, in particular for semiconductors and batteries (Brown et al., 2021). With regard precisely to this second element, the electric and digital revolution in the automotive sector does not depend solely on cheaper batteries or on isolated technological advances, but decisively on control of critical raw materials and of the entire battery value chain (Jetin, 2020). The rising demand for metals such as cobalt, nickel, lithium and graphite may generate scarcity and strong price

volatility, jeopardising the scalability of mass-market electric-vehicle production unless technological changes, industrial policies, or procurement strategies are implemented. In this context China emerges as a dominant actor owing to an integrated strategy that combines domestic incentives, foreign investments and commercial agreements, enabling it to control key stages of extraction, refining and cell and pack production, and thus making it an almost unavoidable partner for many global manufacturers (Schwabe (2020); Jetin (2020); IEA (2022)). Europe and the United States, despite possessing significant technological capabilities, display vulnerabilities in resource access and in integrated production capacity, which is often fragmented or belated compared with competing initiatives. Consequently, control over batteries — understood not only as technological mastery but as stewardship of the entire value chain and of raw materials — will largely determine competitive advantages and the share of value in the sector's electrification process. For this reason, future strategies by governments and firms should prioritise coordinated industrial and diplomatic policies aimed at securing stable access to resources and developing competitive production capacities; otherwise, structural dependence on the currently dominant players—particularly China—will remain a significant risk (Jetin, 2020).

### 3.1.5 The Environmental Impacts of Electrification in the Automotive Industry

From an environmental perspective, the potential benefits of electrifying the automotive sector provide the main justification for efforts to advance this transition. Some analyses show that PHEVs reduce greenhouse-gas emissions relative to ICEVs across all scenarios considered, and that this advantage persists even when the electricity mix is heavily coal-dependent, increasing further as grids become less carbon-intensive (Boulanger et al., 2011).

Over the full life cycle, BEVs are in most cases less emission-intensive than ICEVs, with hybrids occupying an intermediate position. The BEV advantage, however, depends

on several factors (Inc, 2022). In particular, the production phase—especially battery manufacturing—entails higher upfront emissions than ICEV production, but these are offset by substantially lower emissions during use. The break-even point between BEVs and ICEVs varies with the carbon intensity of the electricity grid: in regions supplied by low-carbon sources, it is reached after roughly 30,000 km, whereas in areas dependent on coal or gas it may exceed 123,000 km.

Other relevant factors include climate and driving style, both of which significantly affect energy consumption and battery degradation relative to ICEVs. Under adverse conditions, battery replacement may become necessary, thereby increasing total emissions. Nevertheless, BEVs offer a clear advantage in terms of local pollution, since they produce no tailpipe emissions and can improve urban air quality, although some pollution may be 'displaced' to electricity-producing regions.

Circular-economy practices—such as materials recycling and battery repurposing for stationary storage—can further reduce the environmental impact of BEVs. However, these value chains are still under development, and their effectiveness will depend on large-scale industrial adoption and optimisation.

Finally, the environmental and social criticalities associated with the expansion of extractive activities should not be underestimated: lithium, nickel and other raw-material extraction in new areas affects water resources, biodiversity and local communities. Supply-chain sustainability is therefore central to limiting reputational and regulatory risks for OEMs and investors. Standards, due diligence practices and policies that promote responsible sourcing are needed, together with low-impact extraction technologies and enhanced recycling, as strategies to reduce pressure on virgin-material demand (Outlook et al., 2023).

### 3.1.6 The Employment Impacts of Electrification in the Automotive Sector

From the standpoint of employment effects, the literature generally finds that decarbonisation tends to generate a positive net employment balance, particularly in emerging markets (International Renewable Energy Agency (IRENA) and International Labour Organization (ILO), 2022; Dierdorff et al., 2009). However, the energy transition in the automotive sector appears to constitute an exception, with studies suggesting a neutral or slightly negative net impact on employment. More specifically, the transport sector—and the automotive industry in particular, which accounts for approximately 20% of $CO_2$ emissions—is expected to undergo profound restructuring. The progressive replacement of ICEVs with electric solutions or alternative-fuel technologies (biofuels, e-fuels), together with the European objective of phasing out fossil-fuel vehicles by 2035, creates tangible risks of job losses, especially in assembly and component manufacturing. This risk is linked to the fact that electric motors, currently the dominant electrified propulsion technology, contain significantly fewer components than internal combustion engines. Workers displaced by electrification may be reallocated within the sector—for example, to the production of intermediate goods or to EV assembly—or may be forced to transition to other sectors. These dynamics have been analysed in several contributions (Brown et al., 2021; Amelang, 2021; Pirie et al., 2022; Lüthje et al., 2023; Galgóczi, 2018).

A systematic analysis of the impact of e-mobility on employment considers multiple sectors, aggregates and macro-occupational groups, covering approximately 5.65 million employees in Europe (Kuhlmann et al., 2021). The study identifies five key trends shaping employment dynamics. First, European vehicle production is not expected to return to pre-COVID levels: after a partial recovery by 2025, output is projected to stabilise at around 17.1 million vehicles per year until 2030 (approximately $-0.4\%$ annually), while sales are expected to decline to about 16.3 million units ($-0.7\%$ annually) and the vehicle fleet to grow slowly (around $+0.7\%$ annually, reaching approximately 343 million vehicles by 2030). Second, technological change—particularly in autonomy, connectivity and

digitalisation—is expected to increase the software share of vehicle value (around 11% annually), raising demand for software and platform engineers. Third, a shift towards mid- and premium-segment vehicles is likely to increase content-per-vehicle by around 1% per year. Fourth, productivity gains are expected through digitalisation and automation, especially in battery production. Finally, production is projected to shift from ICE to electrified drivetrains, with ICE vehicles declining from approximately 80% of production in 2020 to well below 5% by 2030, and a projected 2030 mix of around 59% BEV, 11% PHEV and 25% HEV (Kuhlmann et al., 2021).

Table 3.1 provides a structured overview of the expected evolution of different supplier categories within the electric-vehicle ecosystem. The table is organised as follows: (i) supplier or component type; (ii) expected impact of the transition; (iii) impact intensity (low, medium, high, very high), capturing the speed and depth of market change; (iv) the underlying technical or economic rationale; (v) recommended actions, including adaptation or value-capture strategies (such as capability reconfiguration, development of new product lines, strategic partnerships or exit from declining markets); and (vi) urgency of intervention, graded from low to high, to guide the prioritisation of policy and strategic responses.

According to estimates, total employment in the European automotive sector would remain substantially stable: from 5.65 million in 2019 to roughly 5.62 million in 2030, with a modest net loss of $\approx 35,000$ jobs (less than 1%), albeit with scenarios ranging from $-88,000$ to $+17,000$ depending on production and sales volumes. The net balance derives from opposing forces: a decline in production and sales, gains linked to technological innovation and an increased share of mid/premium cars, and cuts owing to productivity improvements; there is also a net negative effect of the transition to EVs due to job reductions in OEMs and ICE suppliers that are not fully offset by positions in batteries, charging and related services. additional temporary labour demand is also expected by 2030, particularly for battery plants, charging infrastructure and renewable capacity. Overall, therefore, the employment balance remains almost unchanged, but the transition

| Component | Impact | Intensity | Why | Recommended action | Urgency |
|---|---|---|---|---|---|
| Exhaust manifolds / mufflers | Disadvantaged | High | EVs have no combustion engines: demand collapses | Redirect capacity toward non-powertrain products, metal recycling | High |
| Fuel supply systems (pumps, pipes, tanks) | Disadvantaged | High | Fuel-specific components become obsolete | Convert fluid-dynamics know-how to BTMS or technical liquid piping | High |
| Complex transmissions (gearboxes) | Disadvantaged | High → Medium | Many EVs use simple reduction gears; demand for complex gearboxes falls | Pivot to e-axles or heavy-duty vehicle components | Medium |
| Turbochargers | Disadvantaged | High | Not required in electric powertrains | Repurpose turbomachinery expertise to electric pumps or BTMS | High |
| Alternators / starters / mechanical oil pumps | Disadvantaged | High | Functions replaced by on-board electronics | Offer electrical alternatives, sensors or modular units | High |
| Catalytic converters & particulate filters | Disadvantaged | Very high | Not applicable to zero-tailpipe-emission vehicles | Enter precious-material recovery and recycling services | High |
| ICE engine management systems (ECU combustion) | Disadvantaged | Medium → High | Functionality shifts to BMS/inverters/unified control units | Retrain competencies toward power electronics and software | High |
| Oil filters / traditional lubrication | Disadvantaged | Medium | Fewer lubricated parts; reduced demand | Provide aftermarket offers and solutions for electric gear reducers | Medium |
| Engine components (crankshafts, pistons, valves) | Disadvantaged | Very high | Not present in EVs | Reconversion toward battery pack structures or non-powertrain components | High |
| Radiators / traditional engine cooling systems | Disadvantaged → Adaptable | Medium | BTMS needs remain but configurations change | Redesign for liquid BTMS or passive alternatives | Medium |
| Engine-related HVAC | Disadvantaged | Medium | HVAC architecture changes in EVs (heat pumps, etc.) | Evolve toward heat pumps and integrated thermal management | Medium |
| Precision mechanical component suppliers (ICE gears) | Disadvantaged / Adaptable | Medium | Engine volumes decline, but manufacturing capacity transferable | Reposition toward e-axles, battery-pack supports, structural parts | Medium |
| Windshields, body shell, exterior body elements | Favoured / Neutral | Low → Medium | Body demand persists; opportunities for smart glass | Develop HUD windshields, sensor/antenna integration | Low |
| Cell manufacturers and pack assemblers | Strongly favoured | Very high | Batteries are the core EV value; explosive demand | Scale production, secure raw materials and quality | High |
| BMS suppliers (Battery Management Systems) | Strongly favoured | Very high | BMS essential for safety and performance | Invest in software, diagnostics, cybersecurity and second-life solutions | High |
| Power electronics (inverters, DC-DC, on-board chargers) | Strongly favoured | Very high | Key components for EV efficiency and performance | Develop SiC / GaN tech, integrate thermal packaging | High |
| Electric motor / e-axle manufacturers | Strongly favoured | Very high | Electric motor and e-axles are central to EVs | Invest in motor design, magnets, rare-earth alternatives | High |
| HV wiring and high-voltage connectors | Strongly favoured | High | Certified HV cabling and special connectors required | Certify safety, produce HV cables and insulation solutions | High |
| Power semiconductors (SiC, GaN) | Strongly favoured | Very high | Growing demand for efficient inverters | Forge agreements with wafer producers, power module packaging | High |
| Battery thermal management systems (BTMS) | Strongly favoured | High | BTMS critical for battery life and performance | Specialise in liquid BTMS, heat pipes and thermal materials | High |
| Charging solutions / infrastructure (EVSE) | Strongly favoured | Very high | Large growth needed in public and private charging stations | Offer installation, smart charging and V2G readiness | High |
| Sensors, radar, lidar and ADAS | Favoured | High | Increased electronics and ADAS raise sensor demand | Expand sensor suites and SW/firmware integration | High |
| Software and telematics (fleet, energy mgmt) | Strongly favoured | Very high | Software becomes a key value driver (BMS, OTA, fleet SaaS) | Invest in cloud, cybersecurity and SaaS services | High |
| Lightweight materials and battery-integration structures | Favoured | High | Lightweighting and structural integration add value | Offer structural battery packs and composite materials | High |
| Battery recycling and second-life | Strongly favoured | Very high | Growing stock of used batteries; regulatory obligations | Develop treatment plants, diagnostics and reconditioning | High |
| Traditional aftermarket (brakes, tyres) | Neutral → Moderately favoured | Low → Medium | Brakes and tyres remain needed; regenerative braking changes wear | Offer EV-optimised products and specialised maintenance services | Low |
| ICE-specific after-sales services | Disadvantaged → Transforming | Medium | Less ICE maintenance reduces traditional service volumes | Create battery/BMS services, remote diagnostics and retrofit offers | Medium |

Table 3.1: Impact matrix of the EV transition on automotive suppliers. Sources: PwC (2019) and author's elaborations.

entails a marked territorial and sectoral reallocation: traditional clusters—especially OEMs and suppliers tied to combustion engines—would register significant losses (approximately $-20\%$ and $-42\%$ respectively), whereas substantial increases are expected in energy infrastructure (+543%), energy production (+128%), non-ICE suppliers (+10%) and the recycling sector (+8%). Maintenance, repair and service activities appear substantially stable. The transformation will require extensive training and reskilling programmes[10]: it is estimated that approximately 2.4 million workers in the European automotive sector will need to undertake training pathways by 2030. From a geographic perspective, impacts are unevenly distributed: Germany is the only large European country projected to experience net employment growth, whereas other countries—such as Spain—are expected to contract and countries like Poland display stability. Social, cultural and administrative barriers to transnational labour mobility, however, may limit the capacity to rebalance employment imbalances across Europe. Employment management will therefore be a strategic component of the transition (BostonConsoultingGroup, 2020): firms will need careful workforce planning to assess which resources can be upskilled to remain in the same role or be redeployed internally, and to define adaptation policies where reductions are unavoidable. Possible measures include continuous training plans, internal transfers, incentives for voluntary departure, allowances and early-retirement packages, as well as policies supporting geographic mobility and reintegration.

### 3.1.7 Purpose and Contribution of this Research

This study offers an original contribution to the literature by adopting an input–output (IO) approach to assess the effects of the European electrification policy for the automotive sector embedded in the Fit for 55 package, relative to a 'business-as-usual' scenario. Specifically, the analysis focuses on the economic effects of electrifying product C29 (from

[10]Their breakdown by type of intervention is as follows: approximately 1.6 million will retain their original occupational and corporate profiles but will require on-the-job updates; 610,000 will move to similar roles (e.g., from ICE component assembly to electric motor assembly), requiring retraining and sometimes geographic relocation; about $225,000$ will need substantial reskilling, shifting to new sectors (e.g., cell production for batteries), often necessitating relocation. The remaining roughly 3.2 million positions would remain essentially unchanged and without significant training needs.

the IO tables) on the Italian economy, with particular attention to impacts on value added and employment.

To build the analysis, we integrated multiple data sources: the FIGARO inter-country Supply and Use Input–Output Tables (Eurostat), national accounts data provided by the National Institute of Statistics (ISTAT), bilateral product-level trade flows from the International Trade Database at the Product-Level (BACI), and additional sectoral information (ACEA and related sources). From these inputs we defined and constructed counterfactual and policy scenarios and applied a quantitative model based on IO matrices to isolate and quantify the effects of technological transition and demand shifts.

The principal research questions addressed in this work are the following. (a) What is the economic impact of the offshoring of part of the component production for the Italian automotive product within the current production context? In other words, what shock would the production system experience if final producers of the automotive product no longer demanded part of the components and intermediate goods supplied by Italian suppliers; (b) What are the economic effects resulting from the full implementation of the measures envisaged by the Fit for 55 package — that is, from widespread electrification of the European automotive sector — and is such a policy sustainable relative to the status quo in the Italian context? (c) What role will future vehicle demand by 2035 play: to what extent do demand variations or differing market penetration capacities alter the economic effects of the productive transition?

These questions are exploratory in nature and aim to inform policy choices intended to mitigate risks of erosion of the national value chain.

Our analyses clearly show that electrification of the automotive product is not a mere technological switch but a profound sectoral and geographic reallocation: the electric production recipe shifts demand toward sectors with a high electronic component and vehicle-module content (batteries, inverters, power electronics), while concurrently reducing demand for traditional metalworking supplies, rubber–plastic goods and certain services; simultaneously, the share of national sourcing declines in favour of central–northern and

eastern European hubs and specialised Asian economies, with a consequent risk of erosion of the domestic value chain. Demand dynamics play a further pivotal role. There are serious risks for firm profitability and, consequently, a necessity to reduce costs through labour downsizing. This may occur for two main reasons. The first relates to demographic trends, changes in consumer preferences and the evolving concept of mobility in the new millennium, increasingly oriented toward minimising travel and providing services on demand, which could reduce car demand. The second reason is that, even assuming an increase in automotive demand through 2035, such demand could be captured by non-domestic and extra-European producers because of an inability of domestic firms to penetrate those markets. The challenge for European companies will be to adopt pricing strategies that make electric vehicles competitive. Here a pre-existing critical issue is already evident: the price differential between electric vehicles produced in Europe and those from China currently favours the latter.

These results call for reflection: the transition to electric vehicles can create significant opportunities, but if it proceeds without coordinated industrial strategies and demand-side policies it risks translating into a substantial loss of productive capacity and employment within traditional supply chains — a challenge that requires policy decisions aimed at preserving scale, competences and high value-added stages.

The chapter is structured as follows. Section 3.2 reviews the relevant literature. Section 3.3 describes the data used. Section 3.4 and its subsections outline the methodology, assumptions, and scenario definitions. Section 3.5 presents the results, while Section 3.6 discusses and concludes the findings. Finally, Section 3.7 closes the chapter by outlining the study's limitations.

## 3.2 Literature Review

There are several approaches to assessing the macroeconomic effects of a policy, which can be broadly distinguished by their demand- or supply-side focus (Hartwig et al., 2017). Among the principal methodologies, cost–benefit analysis compares costs and benefits but typically does not account for long-run effects or intersectoral interactions. Computable General Equilibrium (CGE) models, which simulate the entire economy, are another common instrument, though they have limitations in representing long-term dynamics. Macroeconometric models, grounded in historical data and Keynesian reasoning, principally emphasise demand and encounter difficulties in incorporating supply-side constraints. Input–output (IO) models are frequently used to analyse sectoral impacts, and these methods are often combined to provide a more comprehensive assessment of policy effects. An additional tool is the Social Accounting Matrix (Pirmana et al., 2023), an extension of the IO framework that links incomes distributed to workers—disaggregated by skill level—with final consumption, thereby enabling the evaluation of distributional impacts of policies.

The IO system is a well-established method for analysing intersectoral linkages and final demand. Under specified assumptions, the model is a useful instrument to examine how changes in final demand propagate through production across sectors (Allan et al. (2007); Zhang et al. (2025); Leontief (1986); Miller and Blair (2009)). Technology within a Leontief IO model is described by technical and primary-input coefficients (Faber et al. (2007); Wiebe (2016); Wilting et al. (2008); Wimmer et al. (2023)). These technical coefficients express the inputs required from other sectors to produce one unit of output in the receiving sector. In most empirical studies, technical coefficients are derived from IO tables compiled from statistical surveys; however, they reflect production costs more than the physical input requirements of production. Because IO tables are essentially static and descriptive, numerous macroeconomic studies have replaced pure IO models with more advanced tools that incorporate price adjustments, microeconomic behaviours and temporal lags, thereby better accommodating long-run industrial development scenarios and regulatory changes

(Leurent and Windisch (2015); Pirmana et al. (2023)). Nevertheless, IO analysis remains widely used for preliminary estimates of macroeconomic impacts of sectoral policies (for example, the multiplier effects of tourism expenditure on a regional economy; Frechtling and Horváth (1999)) or of catastrophic events such as earthquakes or Hurricane Katrina (Kim et al. (2002); Hallegatte (2008)). For an overview of the methodological principles, see Wiedmann et al. (2007).

Technological change is typically modelled within IO frameworks by altering input coefficients, which indicate the combination of intermediate goods and labour required to produce one unit of output. To represent such technological shifts, researchers sometimes create a new sector with a revised production recipe—derived from the original but endowed with forward-looking characteristics—while preserving coherence with the row and column totals and balances of the reference IO matrices, thus ensuring a high degree of homogeneity (Wydra, 2011).

Within IO modelling, two principal methodological strategies can be identified for projecting future technological development and quantifying changes in direct input coefficients (Faber et al. (2007); Wilting et al. (2008); Wimmer et al. (2023)). The first is trend analysis, which extrapolates past coefficient trajectories into the future. This technique rests on the assumption that new technologies follow an S-curve with progressive saturation rather than a linear path. Trend extrapolation is mathematically simple and data-parsimonious, but it has a major limitation: it cannot adequately project disruptive technological innovations because future technological pathways need not mirror past trends.

The second approach constructs future coefficients on the basis of expert judgement (Faber et al., 2007). This method is particularly useful when technological change is driven by regulatory factors—such as standards, environmental regulations, taxes or subsidies—that shape technology adoption (Rose, 1984). In such cases, coefficients vary not only per unit of product but also with the capital stock, requiring the modelling of investment dynamics and depreciation schedules. Expert elicitation can be used to

specify future technical, primary-input and emission coefficients grounded in projections of future technology characteristics and trajectories. Although data are often scarce and the process labour-intensive, this approach yields a more realistic representation of future production than simple trend extrapolation, enabling the evaluation of emerging, innovative technologies alongside established ones.

To our knowledge, IO analysis has been applied only partially—and not decisively—to assess the economic effects of substituting conventional vehicles (CVs) with EV. To date, this substitution has been examined along several research strands (Leurent and Windisch, 2015). One strand concerns demand-side studies in which the individual decision to own and use an EV or a CV is modelled as a discrete motoring choice based on a utility function (Massiani, 2012), the Total Cost of Ownership or a Process-Based Cost Model (Windisch (2011); Cotterman et al. (2024)). Another strand focuses on cost–benefit assessments of policies supporting electric mobility in specific countries. Additional work employs macroeconomic scenario models (Herrmann et al. (2020); Wingender et al. (2024); Ulrich and Lehr (2020)), expert interviews and elicitation (Grosso et al. (2021); Calabrese et al. (2025); Bozzola et al. (2024); Jetin (2023); Heim et al. (2025); Klier and Rubenstein (2024)), life-cycle assessment (Hacker et al. (2009); Rinawati et al. (2025)) and econometric analyses (Novaresio, 2024).

Very few studies, however, analyse the impacts of the productive paradigm shift from internal combustion engines to electric drivetrains using an IO approach. Some works concentrate on economic impacts (Mase (2020); Mönnig et al. (2019); Pirmana et al. (2023); Kolpakov and Galinger (2020); Shibusawa and Miyata (2016); Suehiro et al. (2020); Tamba et al. (2022); Cresti et al. (2025b); Bravo et al. (2024); Chen et al. (2023); Zhang et al. (2025)), while others address environmental impacts (Bravo et al. (2024); Guo et al. (2022); Nakamoto et al. (2023); Rinawati et al. (2025); Wiebe et al. (2018); Chen et al. (2023); Gregori et al. (2015); Wilting et al. (2008); Zhang et al. (2025)).

The literature on the economic effects of automotive electrification—especially for Europe and Italy—is limited. Few studies provide comprehensive estimates of impacts on

output, value added, employment and supply-chain exposure; the main contributions are summarised succinctly. Bravo et al. (2024) employ an multi-regional IO model (Exiobase) for Spain and find a small short-run output increase (2030) from isolated technological substitution but, under very high EV penetration, a near $-1\%$ global contraction by 2050; traditional automotive output may fall up to $-8.23\%$ while electric components rise marginally ($+1.01\%$), and medium-skill employment in Spain could decline up to $-8.31\%$ by 2050. Leurent and Windisch (2015) use a national IO model with fiscal transfers for France and conclude that purchase subsidies are more defensible on energy-security or industrial-policy grounds than on pure fiscal efficiency; imported EVs that displace domestic production produce the worst fiscal outcome. Mönnig et al. (2019) apply an integrated macro–IO approach for Germany and report an initial growth impulse from investment in industry, charging infrastructure and grids, but medium-to-long-run net losses if imports of cars and battery cells increase; in a moderate scenario (23% EV by 2035) they project roughly $-114k$ net jobs and a GDP loss of $\approx$ 20bn euros ($\approx 0.6\%$). Kolpakov and Galinger (2020) analyse Russia and highlight structural unpreparedness, arguing for coordinated institutional, industrial and technological policies including import-substitution and domestic green-industry development. Tamba et al. (2022) introduce a BEV sector in an IO model for the EU27+UK and show that higher electrification reduces the GDP cost of climate policy (impact between $-0.54\%$ and $-0.24\%$ versus a weak-action baseline); employment gains are possible provided European supply chains and industrial policy are preserved.

For Italy, IO-based evidence is nearly absent; Cresti et al. (2025b) is a notable exception and finds that inaction is costly—without targeted policies the Italian automotive sector faces substantial losses in production, employment and competitiveness. Overall, existing work points to heterogeneous short-run benefits but non-trivial medium-to-long-run risks, with outcomes critically dependent on domestic production capacity, supply-chain retention and complementary industrial and fiscal policies.

Accordingly, our contribution is both necessary and timely: it seeks to fill this empirical

gap and to lay the groundwork for further studies and policy-oriented analyses.

## 3.3 Data

The tables employed are contained in the FIGARO 2024 release[11], which provides annual Supply, Use and inter-country Input–Output tables for the European Union and covers the period 2010–2022. The Supply and Use Tables (SUTs) are matrices that describe detailed production processes and transactions, classifying industries according to NACE Rev. 2 and products according to CPA version 2.1 (see Tables 3.14-3.15 in the Appendix 3.A.1). The tables cover a wide set of economies, including EU Member States and several non-European countries such as the United States, China, the United Kingdom, Japan and other industrialised and developing nations (see Tables 3.16-3.17 in the Appendix 3.A.1).

SUTs provide information on the structure of production costs, the value added generated, and the flows of goods and services within the national economy and between the national economy and the rest of the world. The Supply Table details the origin of goods and services by supplier type, distinguishing domestic production from imports. The Use Table reports the use of goods and services across four principal categories: intermediate consumption, final consumption, gross capital formation and exports. Besides flows of goods and services, the SUTs present the composition of gross value added, including items such as compensation of employees, other taxes less subsidies on production, net mixed income, net operating surplus and consumption of fixed capital.

The tables are linked by three main identities: i) an industry's output equals the sum of its intermediate consumption plus value added (and adjustments); ii) total supply of a product (domestic production + imports) must equal total use of that product (intermediate + final uses); and iii) value added computed from the production side (output − intermediate consumption) must equal value added computed from the income side.

To estimate employment effects in Italy, we used 2022 macrodata[12] from the Italian

[11]They can be found here: `https://ec.europa.eu/eurostat/web/esa-supply-use-input-tables/`
[12]They can be found here: `https://esploradati.istat.it/`

National Institute of Statistics (ISTAT), National Accounts section, which adopt the same sectoral disaggregation level as the FIGARO tables. Table 3.18 in the Appendix 3.A.1 reports employment by branch of economic activity. These data were used to compute employment coefficients, defined as the ratio between the number of employees and a sector's gross output. These coefficients express each sector's labour intensity by indicating how many workers are employed per unit of sectoral production: a higher value denotes labour-intensive activities, whereas a lower value signals greater reliance on capital or technology relative to labour.

To derive the shares of sales of internal-combustion and electric vehicles produced by European countries and demanded by domestic and foreign consumers, we employed the product-level International Trade Database[13] (BACI). BACI provides annual bilateral trade flows at product level identified by the Harmonized System (HS), the standard nomenclature used in international trade statistics. We used the 2024 release (reference period 2022). Each BACI flow is defined by exporter–importer–product–year and includes both value and quantity. This dataset was used to split automotive demand into two product categories: internal-combustion vehicles and electric vehicles (including PHEVs and pure BEVs).

Finally, data on new vehicle registrations in Europe were obtained from ACEA's Pocket Guide[14].

[13] `https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37`
[14] You can find Pocket Guides here: `https://www.acea.auto/nav/?content=publications`

## 3.4 Methodology

### 3.4.1 Input-output Accounting and Counterfactual Analysis

A specific formalization for our framework is defined as follows (the complete derivation of the equations presented below can be found in the Appendix 3.A.3). Starting from the definition, and within an input–output framework, a value chain can be defined as the combination of two components (Miller and Blair, 2009):

- a demand shock that affects a specific need or function;
- the set of production processes that respond to that shock.

We define $Fd_{z,i}$ as the demand-shock vector of dimensions $(MxN)x1$ where M×N is the number of rows which, in an interregional SUT context, equals the number of regions multiplied by the number of products; in this case the regions are in fact the countries reported in the tables. In the subscript, $z$ and $i$ indicate, respectively, the producer — i.e., the country/geographical area where the product or basket of products are produced — and the demander, i.e., the geographical area that generates the final demand shock.

In our context, having employed SUTs, a value chain for a sector s, $X^s_{z,i}$, can be defined as follows:

$$DFd^s_{z,i} + DBDFd^s_{z,i} + (DB)^2DFd^s_{z,i} + (DB)^3DFd^s_{z,i} + \ldots + (DB)(DB)^{n-1}DFd^s_{z,i} = X^s_{z,i} \tag{3.1}$$

By factoring out $DFd_{z,i}$ in the left-hand side, we obtain:

$$(I + DB + (DB)^2 + (DB)^3 \ + \ldots + (DB)(DB)^{n-1})DFd^s_{z,i} \tag{3.2}$$

$$= \sum_{n=0}^{\infty}(DB)^n DFd^s_{z,i} \tag{3.3}$$

As n $\rightarrow +\infty$, the power series given by the Neumann expansion converges to:

$$(I - DB)^{-1} \ DFd^{s}_{z,i} = X^{s}_{z,i} \tag{3.4}$$

Where $X^{s}_{z,i}$ is the total level of sectoral output and $(I - DB)^{-1}$ denotes the Leontief inverse.

$D = V\hat{q}^{-1}$ is the so-called market-shares matrix, where $\hat{q}^{-1}$ denotes the diagonal matrix whose main diagonal contains the total commodity outputs and whose off-diagonal entries are zero. Each element of D represents the share of the total output of commodity $j$ that is produced by sector $i$.

$B = U\hat{x}^{-1}$ is the technical coefficients matrix, where $\hat{x}^{-1}$ is the diagonal matrix whose main diagonal contains total industry outputs and zeros elsewhere. Each column of B contains coefficients that represent the value of each commodity input per unit of output in value terms produced by the industry corresponding to that column.

Equation (3.4) provides the response to changes in final demand $DFd^{s}_{z,i}$, transforming those changes into the sectoral output levels $X^{s}_{z,i}$ required to satisfy that demand, while accounting for intersectoral linkages and market shares. If $DFd^{s}_{z,i}$ is altered, the resulting $X^{s}_{z,i}$ will change linearly, according to the inverse of the intersectoral system $(I - DB)^{-1}$ and the market-shares matrix D.

Each term of the series in (3.1) defines a so-called activation round. For example, the first round, $DFd^{s}_{z,i}$, represents the direct effect or activation due to the final-demand shock $Fd^{s}_{z,i}$—that is, the final demand is allocated across sectors according to the market shares encoded in matrix D. The second round, $(DB)DFd^{s}_{z,i}$, indicates that sectors begin to require intermediate inputs according to the technical-coefficients matrix B; in other words, it captures the demand for intermediate inputs from direct suppliers. The third round, $(DB)^2DFd^{s}_{z,i}$, represents the demand induced in suppliers' suppliers by the initial demand shock: suppliers themselves require inputs from their own suppliers, thereby propagating the effect throughout the production chain, and so on.

The equation (3.4) can be expressed in terms of sector/region value added as:

$$V^s_{z,i} = \hat{v}(I - DB)^{-1} DFd^s_{z,i} \tag{3.5}$$

Where $\hat{v}$ is a diagonal matrix whose main diagonal contains the value-added coefficients. In terms of sector/region employment as:

$$E^s_{z,i} = \hat{\varepsilon}(I - DB)^{-1} DFd^s_{z,i} \tag{3.6}$$

Where $\hat{\varepsilon}$ is a diagonal matrix whose main diagonal contains the employment coefficients, indicating the number of jobs per unit of output.

In this specific case, we undertake a counterfactual analysis to determine the impact of a shift to entirely electric vehicle production driven by European green policies. The scenario considered is that, from 2035 onward, new vehicles placed on the EU market must have zero tailpipe $CO_2$ emissions. We aim to assess this scenario through two distinct but sequential steps that together provide the overall estimate of sectoral production levels in the Italian economy and the corresponding employment.

The first stage consists of simulating a change in the production recipe for vehicles toward electric propulsion: we assume that, from the present onward, the production recipe for vehicles becomes fully electric. In particular, because the the tables available to us refer to 2022, we assume that, starting in 2022, firms in the automotive sector adopt the new production recipe corresponding to fully electric vehicle production. We implement this modification to the production paradigm according to a 'what-if' logic, i.e., by applying a mixture of prospective technologies to the matrices under consideration.

Although IO models normally represent sectoral technology as a fixed physical mix of inputs — and therefore do not embed a production function that permits continuous factor substitution — this does not imply that they are intrinsically unsuitable for long-run or ex-ante analysis (Faber et al., 2007). The crucial distinction is between ex-post production,

which describes output with the technology already installed and offers limited scope for input substitution, and ex-ante production, which represents choice among alternative technologies that may be installed over the long run. To study long-run scenarios it is therefore sufficient to represent explicitly the variety of available technologies by updating the model's technical coefficients.

The second stage simulates the regulatory condition anticipated by European standards, namely that from 2035 only electric vehicles will be demanded; consequently we also modify the vehicle demand structure for 2035. Because we focus on the economic and social impact of this production shift on the Italian economy and the automotive sector, we have set to zero all elements of the final-demand vector except for the Italian automotive sector in order to isolate the effect. The final-demand vector, f, is therefore defined as:

$$f = (0, 0, \ldots, f_{ita,automotive}, 0, .., 0)' \tag{3.7}$$

Where $f_{ita,automotive}$ denotes the monetary amount of global demand for the final product of the Italian automotive sector. The system described above corresponds to the 'open' Leontief model, in which all components of final demand are treated as exogenous and are therefore determined entirely outside the system.

Specifically, we aim to estimate the following impacts. Starting from the relationship whereby the overall effect is given by:

$$\Delta x = (x_1 - x_0) \tag{3.8}$$

where $x_0$ is defined as:

$$x_0 = [(I - DB)^{-1} D] f_{2022} \tag{3.9}$$

- Impact of the change in the production recipe

$$x_1 = [(I - DB^*)^{-1}D]f_{2022} \tag{3.10}$$

Where $B^*$ is the modified Use matrix reflecting the new electric production recipe, and $f_{2022}$ denotes the 2022 final demand vector, which takes a positive value only for the Italian automotive sector. The difference, $\Delta x$, captures the isolated impact of the new production recipe, assuming an unchanged level of final demand. In practice, it shows how the transition to a different production structure (for instance, increased use of electronic components and batteries) alters the distribution of sectoral outputs under the same level of final demand in the automotive sector. This allows for an assessment of the extent to which total production depends on the underlying technological structure.

- Combined impact of the production recipe and the new demand

$$x_1 = [(I - DB^*)^{-1}D]f_{2035} \tag{3.11}$$

Where $B^*$ is the modified Use matrix reflecting the new electric production recipe, $f_{2035}$ denotes the final demand vector for 2035, while $f_{2022}$ represents the 2022 final demand vector used as the baseline for comparison. Remind that f takes a positive value only for the Italian automotive sector. The difference, $\Delta x$, captures the combined impact of the new production recipe and the change in demand within the Italian automotive sector by 2035. This calculation allows for the assessment not only of the effect of technological change but also of the dynamics of future demand.

The following two sections describe the criteria used to modify the production recipes and the final demand.

### 3.4.2 Modelling Structural Change

This analysis aims to examine the impact of electrification in the automotive sector, i.e., the transition from ICEV production to the production of electric vehicles. This shift principally implies a change in the production recipe — namely, the combination of intermediate goods used as inputs in the manufacture of the final product.

We posit a modification of the production recipe required to produce electric vehicles by intervening on the Use matrix while keeping the Make matrix unchanged. In other words, we assume that the sectoral composition of the supply of goods and services remains stable notwithstanding the policy under consideration. This assumption implies, for example, that the increased demand for certain intermediate inputs — in particular electronic products and semiconductors — generated by the automotive sector's altered production recipe can be reasonably absorbed by the sectors that are currently specialized in their production. Put differently, we do not anticipate a change in the identity of producers, nor the emergence of new sectors producing those goods.

As noted above, technological variation within an IO framework can be modelled by changing the direct input coefficients. Shibusawa and Miyata (2016) treats the emergence of next-generation vehicles as a variation in production technology within the automotive industry. The introduction of a new technology into the automotive production process is interpreted as a modification of the industry's input structure; in an IO framework, this change is represented by a transformation of the input-coefficients matrix. The same holds in Bravo et al. (2024) where they progressively adjust technical coefficients over time: the input vectors for branches related to propulsion (vehicle production, components, maintenance, etc.) are updated to reflect an increasing share of electric components and a corresponding reduction in traditional combustion components. Guo et al. (2022), by contrast, disaggregate the IO automotive sector into two distinct sectors — electric vehicles and internal combustion vehicles — to introduce the production of new or specific products such as EVs; coefficients for the new sector are derived from detailed cost sheets, market research, life-cycle inventories, and so forth. Leurent and

Windisch (2015) follow a similar procedure: to model electric production technology they construct a detailed sectoral representation that splits an aggregated automotive sector into a specific 'EV Construction' column and defines its production requirements over time. Operationally, the EV product is decomposed into components (body, battery, charging station), monetary values are assigned to each component, and the input structure is renormalized based on a vehicle reference price net of VAT. Gregori et al. (2015) employs the results of Leurent and Windisch (2015) to build the vector of direct input coefficients for EV production.

Comparable approaches appear in Tamba et al. (2022) and Zhang et al. (2025). Pirmana et al. (2023) construct, in addition to a purely electric automotive sector, a separate sector for electric battery production. In Mase (2020), technical coefficients for electric vehicles are calculated from the reconstructed 2016 SNA-IO table disaggregated into subsectors using the RAS method: first, the input structure per vehicle type (ICE, HV, PHEV, BEV) is determined by estimating the number and types of parts from real models and converting quantities into monetary values using unit prices of components. In Suehiro et al. (2020), they introduce new subsectors dedicated to EVs and decompose automobile production into four propulsion types (internal combustion engine, HEV, PHEV, and BEV), assessed for passenger cars and motorcycles. Input technical coefficients for each EV type are estimated as the ratio of raw materials and other inputs to production value, using benchmark data from other studies. A similar methodology is used by Chen et al. (2023).

Our approach shares the basic concept advanced by Shibusawa and Miyata (2016) and Bravo et al. (2024). However, our objective is to construct a production recipe that reflects only electric vehicle production. To this end we adopt a different strategy that relies exclusively on IO table data. We take China as a benchmark because its production system is often regarded as an advanced and sophisticated model for EV manufacturing, owing to substantial investments in research and development over recent decades.

We assume that the Chinese production recipe can serve as a global reference for EV

manufacturing. Consequently, we posit that major European vehicle-producing countries — Italy, Germany, Spain and France — will adopt the same production model used by China. Although ambitious, this assumption reflects China's leading technological position in the electric vehicle sector.

Nevertheless, in the 2022 Use matrix the Chinese automotive production recipe (column C29 for China) comprises a mix of ICE, hybrid and electric vehicles. Therefore, it is necessary to isolate the Chinese production recipe that corresponds specifically to electric vehicle production in terms of inputs. To simplify the analysis, we assume the existence of two distinct recipes that we wish to disentangle from the single Chinese technological recipe provided by the tables: one representing internal combustion vehicles and the other representing electric vehicles.

The technical coefficients were determined by weighting the column values according to the production shares of internal-combustion and electric vehicles in the total. The formula applied is:

$$\begin{aligned} d_{\textit{chinese automotive, 2022}} = {} & w^{EV}_{2022}\; d^{EV}_{\textit{chinese automotive, 2022}} \\ & + w^{ICE}_{2022}\; d^{ICE}_{\textit{chinese automotive, 2022}} \end{aligned} \tag{3.12}$$

where $d_{\textit{chinese automotive, 2022}}$ is the vector of the technical coefficients of each commodity needed to assemble the Chinese automotive product by 2022. $w^{EV}_{2022} + w^{ICE}_{2022} = 1$ are the weights of the production quotas for electric and internal combustion engine cars in 2022. $w^{EV}_{2022} = \frac{Q^{EV}_{2022}}{Q^{EV}_{2022}+Q^{ICE}_{2022}}$ is defined as the ratio of electric car production to total production in 2022, while $w^{ICE}_{2022} = \frac{Q^{ICE}_{2022}}{Q^{EV}_{2022}+Q^{ICE}_{2022}}$ is defined as the ratio between the production of internal combustion engine cars and total production in 2022. Table 3.20 shows the share of electric-vehicle production in the Chinese automotive sector from 2013 to 2022. $d^{EV}_{\textit{chinese automotive, 2022}}$ and $d^{ICE}_{\textit{chinese automotive, 2022}}$ are the vectors of the technical coefficients for electric cars and internal combustion engines in 2022, respectively. From these relationships, it is possible to derive:

$$d^{EV}_{\textit{chinese automotive, 2022}} = \frac{d_{\textit{chinese automotive, 2022}} - w^{ICE}_{2022}\, d^{ICE}_{\textit{chinese automotive, 2022}}}{{w_{2022}}^{EV}} \tag{3.13}$$

In order to determine $d^{EV}_{\textit{chinese automotive, 2022}}$, it is necessary to compute values of the vector $d^{ICE}_{\textit{chinese automotive, 2022}}$.

To determine the latter, we used historical technical-coefficient data for the Chinese automotive sector derived from the Use matrices for 2012, which effectively represent a production recipe that is almost entirely ICE-based (Table 3.21 in the Appendix 3.A.1 reports the direct technical coefficients for the input requirements of product C29 — China, year 2012). This conjecture rests on the fact that the share of electric-vehicle production in China in 2012 was negligible (below 0.08% of total vehicles produced), so the 2012 Use-based recipe can be treated as representative of a fully conventional, ICE-based technology.

As noted above, we assume that the Chinese electric-vehicle production recipe for the automotive sector is adopted, as of 2022, by the four main European vehicle producers: Italy, France, Germany and Spain.

The complete and technical derivation is presented in the Appendix 3.A.4.

### 3.4.3 Modelling Vehicle Demand

The objective is to estimate the impact of European policies on the electrification of the automotive sector, under the assumption that the European Commission's target of fully electric vehicle production will be achieved by 2035. In this paragraph we explain how we constructed the reference final-demand vector and the vector projected for 2035.

Since SUTs report the total monetary value of demand without distinguishing product types or product mixes, it is first necessary to separate total automotive-sector demand into demand for ICEVs and demand for EVs. As shown in Section 3.4.2, since the final-demand vector for 2035 contains positive values only for Italy while all other countries are set to zero, our attention focuses on estimating the 2035 values for European countries, including Italy.

For a given producing country, the automotive sector's total demand (C29) can be decomposed into demand originating from EU countries and demand originating from non-EU countries; these flows can be derived directly from the tables. For simplicity, we assume that the product mix underlying that demand comprises both ICEVs and EVs.

The principal unknown is how to quantify demand for each vehicle type. To address this issue, we employed data from the BACI database using the same reference year as the FIGARO tables. This dataset provides values of trade flows for numerous products and goods, both imports and exports. Our analysis focused on export values (including domestic sales), and we used specific product codes in the database to identify the electric-vehicle categories of interest.

Following standard practice in automotive statistics, we treat both hybrid vehicles and fully electric vehicles as electric vehicles (see Table 3.19 in the Appendix 3.A.1). Under this convention, we aggregated the data at the EU and non-EU levels and computed the respective sales shares over total vehicle production for each European producer, distinguishing between sales that satisfy domestic demand and those that satisfy foreign demand.

For each European country, this procedure yielded four shares that represent the distribution of ICE and electric-vehicle sales, separated by domestic and foreign demand (see Table 3.24 in the Appendix 3.A.1).

Based on these shares and the total monetary values of final demand derived from the table, we calculated the four reference values for 2022 corresponding to the final demand for internal-combustion and electric vehicles produced in sector C29 by European producers: $f_{european,\ ICE,\ 2022}$, $f_{extra\text{-}european,\ ICE,\ 2022}$, $f_{european,\ electric,\ 2022}$ and $f_{extra\text{-}european,\ electric,\ 2022}$. We now compute each of these components for the year 2035.

- $\mathbf{f_{european,\ ICE,\ 2035}}$

  In line with the Green Deal directives, we assume that by 2035 there will be no demand for ICEvs in Europe; therefore, $f_{\text{european, ICE, 2035}} = 0$.

- $\mathbf{f_{european,\ electric,\ 2035}}$

  Similarly, we assume that the entire vehicle fleet demanded in 2035 will consist of electric vehicles. Accordingly, it is necessary to estimate the value of demand in 2035 under the assumption of full electrification. The simplest approach is to project the value of new vehicle registrations for 2035, which corresponds to European vehicle demand. The formula employed for this projection is $\text{Registrations}_{2035} = \text{Registrations}_{2022} \times \left(1+g\right)^{2035-2022}$, where the growth rate (g) is calculated as $g = \left(\frac{\text{Registrations}_{2022}}{\text{Registrations}_{2012}}\right)^{\frac{1}{2022-2012}} - 1$. The average annual growth rate, computed on registration data for the period 2012–2022, is 1.1%. It was derived using ACEA Pocket Guide series (see Table 3.25 in the Appendix 3.A.1). To obtain a monetary value for that demand, we multiplied the projected number of vehicles by an estimate of the average price per electric vehicle, derived from estimates of the price differential between internal-combustion vehicles and electric vehicles[15]. We assumed an average

[15]Knowing the number of vehicles registered in Europe in 2022 and the monetary value of EU demand reported in the FIGARO tables, it was possible to calculate an average selling price for the sector. Specifically, we summed the values in row (C29) corresponding to the EU demand and divided that aggregate by the number of registrations in 2022, thus obtaining the average price in 2022. Assuming this average price is representative of internal-combustion vehicles, we estimated the price of electric vehicles using information from various sources. Electric-vehicle prices may range from 10% to 50% above those of conventional vehicles; to derive a plausible estimate we adopted the upper bound of this differential,

price of approximately 42,000 euro.

Once EU-demand for electric vehicles projected to 2035 was established, it was necessary to determine the portion that would be met by European production and the portion supplied by the rest of the world. As a starting assumption, we used the market shares implied by the 2022 electric-vehicle demand vector and assumed these shares remain unchanged through 2035. This procedure yields the vector $f_{european,\ electric,\ 2035}$ with values for each producing country.

- $\mathbf{f}_{\text{extra-european, ICE, 2035}}$

  If the ban on the production of internal-combustion vehicles is extended to exports directed to non-EU countries, it will not be possible to export such vehicles outside the continent. Therefore, $f_{\text{extra-european, ICE, 2035}} = 0$.

- $\mathbf{f}_{\text{extra-european, electric, 2035}}$

  To calculate this vector, the simplest method consists of projecting the values of $f_{\text{extra-european, electric, 2022}}$ by applying a growth rate, while keeping the vector disaggregated and preserving existing market shares. To this end, the following CAGR formula was applied: Extra-EU demand vector for EU-produced EVs in 2035 = Extra-EU demand vector for EU-produced EVs in $2022 \times (1+g_{\text{demand}})^{2035-2022}$. The demand growth rate was set at 6.95%, consistent with the most recent estimates for medium-term global growth in electric-vehicle registrations.

yielding a realistic value for the price of electric vehicles.

### 3.4.4 Definition of Scenarios

In this exercise, we define five scenarios:

1 **Impact of offshoring component demand in the Italian automotive sector**.

The first scenario does not concern either the electric production recipe or the Fit for 55 green policy. This baseline scenario examines the impact of relocating the demand for automotive components away from domestic suppliers in Italy. It assumes that the Italian automotive sector completely ceases to source electric equipment, combustion engines and components from domestic suppliers, so that the entire demand for these products in Italy is eliminated and shifts entirely to foreign suppliers. Technically, this means zeroing the coefficients in the Italian automotive column of the Use matrix for products C27 and C29, which correspond to the aforementioned intermediate goods.

2 **Electric transition in the European automotive: redefinition of the production recipe in 2022**.

The second scenario concerns the first part of the impact of the industrial measures that firms must adopt (equation 3.9-3.10, section 3.4.1). We assume that the production recipe described by the technical coefficients of column C29 in the Use table for the main European car-producing countries (Italy, France, Spain and Germany) in 2022 does not yet represent a consolidated electric-vehicle production, since electrification is not yet predominant. Instead, we assume that China already possessed, in that same year, the most advanced technology for electric-vehicle production and therefore serves as the benchmark for future European production. For this reason, we replaced the C29 columns of Italy, France, Spain and Germany with the Chinese electric-vehicle production recipe.

3 **Impact of the Fit for 55 package on the Italian automotive sector**.

We assume the joint occurrence of the change in the automotive production recipe and variations in demand by 2035 (equation 3.9-3.11, section 3.4.1). The C29 columns

for Italy, Germany, France and Spain are replaced with the electric production recipe, and final demand in 2035 is calculated using the vector derived from assumptions on vehicle registrations.

4 **Fit for 55 and a 20% reduction in demand for Italian automotive products by 2035**.

This scenario is the same as Scenario 3, but we assume a lower capacity of supply penetration for European automotive producers. We estimate that by 2035 a portion of demand shifts toward vehicles produced outside Europe, resulting in a 20% reduction in demand for Italian automotive products. Technically, we reduce by 20% the monetary value of final demand in the vector $\mathbf{f}_{2035}$.

5 **Fit for 55 and contraction of registrations by 2035**.

This scenario is also based on Scenario 3, but we assume that the growth rate of vehicle registrations in the EU by 2035 is reduced by one third relative to the rate adopted in the previous scenarios.

## 3.5 Results

After constructing the electric-vehicle production recipe for the Italian product C29, it is possible to compare it with the original recipe derived from the 2022 Use table. Table 3.2 reports, by column, the production recipes for Italian automotive output: on the one hand, the actual production recipe adopted in 2022—required to produce a mix of heterogeneous products—and, on the other hand, the counterfactual production recipe associated with a fully non-ICE (electric) technology, presented for sectors aggregated at the 1-digit level. Table 3.3 provides a more detailed view, reporting the technical coefficients for inputs originating from the manufacturing sector at the 2-digit level.

The third column in both tables shows the difference between the two recipes, expressed in hundredths of input per unit of C29 output (electric-vehicle production recipe minus mixed vehicle production recipe). A positive value indicates that the adoption of the electric production recipe increases the use of inputs from a given sector per unit of output, and vice versa.

This difference captures what can be defined as a technology-driven substitution effect (Cresti et al., 2025b; Garcia et al., 2020; Connell Garcia et al., 2024; Goulder, 2004; Wingender et al., 2024), namely the change in the structure of the input–output (IO) technical coefficients matrix—that is, the different combination of inputs required to produce one unit of output. In turn, this technological substitution effect is driven by policy-induced changes (Rose, 1984).

| Commodity | 2022 Production recipe mix | 2022 electric-vehicle production recipe | Diff. |
|---|---|---|---|
| Agricultural, forestry and fishing products | 0,00 | 0,00 | 0,00 |
| Mining and quarrying products | 0,04 | 0,08 | 0,04 |
| Manufactured products | 54,23 | 68,86 | 14,63 |
| Electricity, gas, steam and air conditioning | 0,81 | 1,13 | 0,31 |
| Water supply; sewerage; waste treatment and decontamination services | 1,07 | 0,03 | -1,04 |
| Construction and civil engineering works | 0,26 | 0,12 | -0,14 |
| Wholesale and retail trade; repair of motor vehicles and motorcycles | 7,73 | 6,84 | -0,89 |
| Transport and storage | 3,68 | 1,83 | -1,85 |
| Accommodation and food service activities | 0,68 | 0,00 | -0,68 |
| Information and communication | 1,24 | 0,61 | -0,63 |
| Financial and insurance activities | 0,94 | 0,14 | -0,80 |
| Real estate activities | 0,46 | 0,21 | -0,25 |
| Professional, scientific and technical services | 7,73 | 1,30 | -6,43 |
| Administrative and support services | 1,26 | 1,05 | -0,21 |
| Public services and other services | 0,30 | 0,42 | 0,12 |

Table 3.2: Direct technical coefficients of the production mix and electric-vehicle production recipe for the Italian automotive sector in 2022. The coefficients are in hundredths and are aggregated to 1 digit.

The electric production recipe constructed for product C29 shows, at an aggregate level and as expected, a reallocation of input values relative to the heterogeneous production recipe[16]. This reallocation is, however, highly uneven. The manufacturing aggregate increases by +14.63 hundredths (from 54.23 to 68.86), accounting for the bulk of the overall deviation, while many other components decline. In particular, the direct increase in electricity input is modest, as are the small increases observed in sectors such as extractive activities. By contrast, the largest reductions occur in services linked to logistics and traditional production: Transport and storage services (−1.85), Water supply, sewerage, waste management and remediation activities (−1.04), and Wholesale and retail trade and repair of motor vehicles (−0.89), alongside significant declines in professional, scientific and technical services that were more prominent in the mixed recipe.

A more disaggregated view of manufacturing reveals that this compositional shift underlies the +14.63 hundredths increase. The change is driven primarily by the Manufacture of motor vehicles, trailers and semi-trailers, which rises from 12.22 to 41.61, contributing alone +29.39 hundredths. This indicates that, in the electric-vehicle production recipe, a substantial share of the productive content of C29 is reallocated within the motor-vehicle manufacturing sector itself. This likely reflects the structure of the new recipe—partly 'sourced' from China—in which several components and activities (such as EV-specific modules and assemblies) are produced in-house, thereby increasing the weight of the C29 sector as both a producer of intermediate inputs and of the final good.

At the same time, the electric-vehicle production recipe exhibits notable increases in electrical and electronic components: Manufacture of electrical equipment (+3.32) and Manufacture of computers and electronic and optical products (+1.20). This pattern indicates a shift in manufacturing demand away from the traditional mechanical–metal paradigm towards electrical systems, electronics and vehicle-specific modules. These increases are offset by marked declines in traditional supply chains, including Manufacture of fabricated metal products, except machinery (−4.96), Manufacture of basic metals

[16]What is reported is the electric production recipe constructed for this analysis and should be interpreted as the outcome of the assumptions and adjustments introduced.

(−4.71), and Manufacture of rubber and plastic products (−3.18).

Changes in the technical coefficients reflect both technological differences and the reconfiguration of the input structure. Increases indicate a higher input requirement per unit of C29 output: in the case of manufacturing—and especially motor-vehicle production—this is consistent with the incorporation of batteries, electric motors, inverters, power electronics and other high-technology components. The rise in electricity reflects both direct use in production processes and the growing importance of integrated electrical systems. Conversely, decreases are largely associated with the reduced relevance of inputs typical of combustion-engine technology. Declines in basic metals, fabricated metal products and rubber and plastics are consistent with the lower importance of combustion engines, cooling systems and other conventional components. Reductions in transport services, retail and repair may reflect changes in supply-chain organisation, lower maintenance requirements, or different logistics structures associated with EV production. Finally, some of the larger declines in tertiary sectors may also be attributable to accounting reclassifications or to the internalisation of activities previously outsourced, now captured within the 'manufacture of motor vehicles' category in the simulated recipe.

| Commodity | 2022 Production recipe mix | 2022 Electrical production recipe | Diff. |
|---|---|---|---|
| Food, beverages and tobacco products | 0,00 | 0,01 | 0,01 |
| Textiles, wearing apparel, leather and related products | 0,93 | 0,85 | -0,08 |
| Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials | 0,26 | 0,33 | 0,07 |
| Paper and paper products | 0,44 | 0,19 | -0,24 |
| Printing and recording services | 0,13 | 0,09 | -0,04 |
| Coke and refined petroleum products | 0,13 | 0,00 | -0,13 |
| Chemicals and chemical products | 1,82 | 0,00 | -1,82 |
| Basic pharmaceutical products and pharmaceutical preparations | 0,00 | 0,01 | 0,01 |
| Rubber and plastic products | 5,70 | 2,52 | -3,18 |
| Other non-metallic mineral products | 1,90 | 0,18 | -1,71 |
| Basic metals | 5,13 | 0,42 | -4,71 |
| Fabricated metal products, except machinery and equipment | 13,39 | 8,43 | -4,96 |
| Computer, electronic and optical products | 1,93 | 3,14 | 1,20 |
| Electrical equipment | 3,19 | 6,51 | 3,32 |
| Machinery and equipment n.e.c. | 5,54 | 3,72 | -1,82 |
| Motor vehicles, trailers and semi-trailers | 12,22 | 41,61 | 29,39 |
| Other transport equipment | 0,52 | 0,04 | -0,48 |
| Furniture and other manufactured goods | 0,73 | 0,74 | 0,01 |
| Repair and installation services of machinery and equipment | 0,28 | 0,08 | -0,20 |

Table 3.3: Direct technical coefficients of the production mix and electric-vehicle production recipe for the Italian automotive sector in 2022, broken down by manufacturing sector. The coefficients are in hundredths and aggregated to 2 digits.

Another important dimension concerns how the geography and relative weight of input suppliers for the production of Italian product C29 change under full electrification. This is referred to as the geographical relocation effect (Gül et al., 2024; Slowik et al., 2020; Jagani

et al., 2024; Bauer et al., 2018; Cresti et al., 2025b; Ulrich and Lehr, 2020; Heim et al., 2025), i.e. the spatial reallocation of the supply chain. It concerns the origin of inputs rather than their technical composition. Some key goods (e.g., batteries, rare-earths and microchips) are not produced domestically but imported from third countries, introducing a geographical displacement in sectoral interdependencies.

Figure 3.1 presents this analysis by identifying the main input suppliers to the Italian automotive sector. With total inputs normalised to 100, each value represents the share of inputs sourced from a given country. The most pronounced change is the sharp reduction in Italy's share, which declines from 52.34% in the 2022 mixed recipe to 31.40% in the electric-vehicle production recipe (a decrease of −20.94 percentage points). This contraction is accompanied by substantial increases for Germany (from 9.18% to 16.14%), Spain (from 2.98% to 6.21%) and France (from 4.01% to 5.39%). Significant increases are also observed in Central and Eastern Europe: Poland (+1.76 pp), the Czech Republic (+1.48 pp), Romania (+1.01 pp), Turkey (+1.48 pp) and Slovakia (+0.70 pp). Smaller increases include China (+0.84 pp), Japan (+0.53 pp) and South Korea (+0.66 pp), while the 'Rest of the world' category declines slightly (from 4.96% to 4.71%) and Sweden remains broadly unchanged.

These patterns reflect the reconfiguration of the supply chain induced by the transition to electric vehicles. The decline in Italy's share likely reflects the fact that many inputs critical to electrification—particularly batteries, storage systems, semiconductors and power electronics—are supplied by globally dispersed value chains with a strong foreign concentration. In addition, part of the value previously attributed to domestic suppliers in the mixed recipe may be reclassified under 'manufacture of motor vehicles' or shifted to specialised foreign suppliers in the reconstruction. The increase in Germany's share is consistent with its strengthened role in supplying advanced automotive components and EV platforms. Similarly, the rising shares of countries such as Poland, the Czech Republic, Romania and Slovakia reflect the importance of European production hubs, where component manufacturers are located close to assembly plants (Klier and Rubenstein,

2024; Pavlínek, 2018). The growing presence of China, South Korea and Japan aligns with the concentration of battery, cell and semiconductor value chains in Asia (Cresti et al., 2025a), while increases in Spain and France likely reflect both domestic production capacity and recent relocations or expansions in electronics and vehicle assembly.

Overall, the electric production recipe points to a marked reduction in reliance on domestic Italian sourcing, in favour of suppliers located in Central and Eastern Europe and in specialised Asian economies. This shift is driven both by the demand for high-technology inputs (batteries, electronics and EV-specific modules) and by the accounting reclassifications embedded in the construction of the counterfactual scenario.

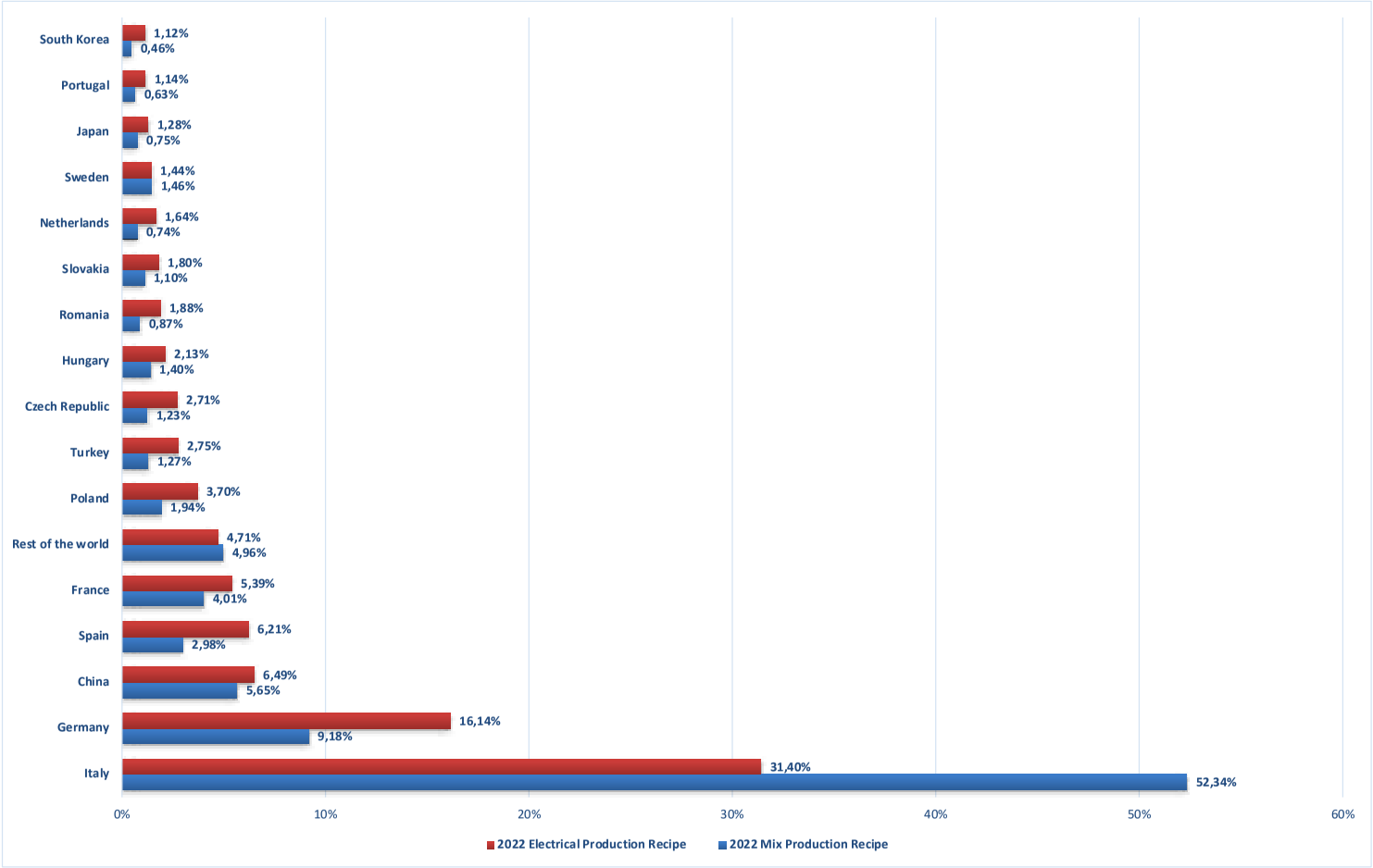



Figure 3.1: Comparison of the weight of the main suppliers of inputs for the Italian automotive sector between the adoption of the automotive mix recipe and the fully electric one. The list only includes the most important suppliers in terms of weight.

We now present the main results that emerged from the analysis conducted on the scenarios outlined in Section 3.4.4. The objective of the research is to estimate and isolate the potential impact of environmental policies aimed at the transition from the production of internal combustion engine vehicles to entirely electric production, in the context of the Italian economy. The analysis is divided into two distinct phases. The first phase assumes that, starting in 2022 – the reference year of the latest FIGARO table available – the main European car manufacturers (Italy, Germany, France and Spain) would completely convert their production to electric vehicles. This scenario is implemented through a revision of the production structure of sector C29 within the Use matrix for the above-mentioned countries, constructing a configuration that reflects a production system exclusively oriented towards electric vehicles (scenario 2). The impact of this transformation is assessed by comparing the results with a reference scenario in which production continues according to the pre-existing model, without changes. In order to isolate the direct and indirect effects on production and employment relating exclusively to the Italian economy, the final demand vector is kept positive only for the current value of global demand for vehicles produced by the Italian sector. Before presenting this scenario, we tested a more basic scenario in which we assume that the fundamental inputs for the manufacture of electric automotive products are no longer supplied by Italian suppliers but by those from the rest of the world (scenario 1).

The second phase expands the analysis by introducing a time dimension that considers the impact of estimated final demand for 2035, the year in which the ban on the production of internal combustion engine vehicles will come into force. In this scenario, consumer purchasing choices are fully influenced by the legislation, and the final demand vector reflects demand exclusively oriented towards electric vehicles. The impact of the transition is then quantified by comparing the situation forecast for 2035 with that of 2022. The results are presented in the paragraphs at an aggregate level for the 1-digit NACE sectors, while the manufacturing sector is analysed in disaggregated form.

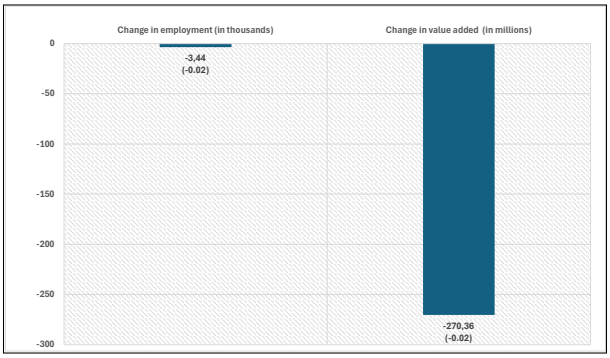



Figure 3.2: Results Scenario 1. The changes in employment levels and value added obtained in the scenario outlined above are shown in comparison with the 'business as usual' scenario. The changes in decimal points are shown in brackets.

Figure 3.2 shows the results for scenario 1. The results show that the relocation of demand for Italian automotive components - achieved by setting the coefficients in the automotive column of the Use matrix for products C27 and C29 to zero - results in a relatively modest overall loss compared to the 'business as usual' scenario, but concentrated in a few key sectors. At the aggregate level, the shock results in a reduction in value added of €270 million and a loss of $3,400$ jobs; this overall percentage reduction is approximately $-2\%$, but the distribution by sector reveals where the effect is most intense. Manufacturing absorbs most of the fall in value added (€$-169.99$ million) and job losses (approximately $-2$ thousand employees), a sign that the cancellation of domestic purchases by the automotive industry mainly affects industrial suppliers (Table 3.4). Within manufacturing (Table 3.5), the most significant decline in absolute terms is in the manufacture of electrical equipment (€$-72.66$ million; approximately $-0.83$ thousand employees), followed by the manufacture of motor vehicles, trailers and semi-trailers (€$-31.20$ million; $-0.41$ thousand), the manufacture of metal products excluding machinery (€$-20.25$ million; $-0.30$ thousand) and the manufacture of rubber and plastic products (€$-5.08$ million; $-0.06$ thousand). Tertiary sectors directly linked to the supply chain also show significant losses: wholesale and retail trade and repair services suffer €$-21.10$ million and approximately $-0.32$ thousand employees, professional services €$-19.02$ million and $-0.30$ thousand, transport and storage services €$-14.15$ million and $-0.16$ thousand. Many other sectors recorded smaller negative changes in value and

employment (agriculture, energy, paper, chemicals, etc.), with percentages relative to the 'business as usual' scenario mostly fluctuating around $-0.01/-0.02$; this indicates that the shock is limited on a macro scale but with effects concentrated in absolute terms on a few sectors. The underlying logic is simple and technical: zeroing the Use coefficients means removing from the system the domestic demand that was previously directed to domestic suppliers; the knock-on effect spreads through input-output multipliers and hits hardest those sectors that previously supplied the automotive industry the most (hence the strong impact on electrical equipment, metalworking supplies and specific components).

| Sector and service | Change in value added | Change in employment | Change compared to the 'business as usual scenario' |
|---|---|---|---|
| Agricultural, forestry and fishing products | -1,19 | -0,03 | -0.02 |
| Mining and quarrying products | -0,8 | 0 | -0.01 |
| Manufactured products | -169,99 | -2 | -0.02 |
| Electricity, gas, steam and air conditioning | -8,11 | -0,01 | -0.02 |
| Water supply; sewerage; waste treatment and decontamination services | -2,72 | -0,03 | -0.02 |
| Construction and civil engineering works | -3,58 | -0,06 | -0.01 |
| Wholesale and retail trade; repair of motor vehicles and motorcycles | -21,1 | -0,32 | -0.01 |
| Transport and storage | -14,15 | -0,16 | -0.02 |
| Accommodation and food service activities | -2,69 | -0,08 | -0.02 |
| Information and communication | -5,72 | -0,06 | -0.02 |
| Financial and insurance activities | -8,21 | -0,07 | -0.02 |
| Real estate activities | -8,18 | -0,01 | -0.02 |
| Professional, scientific and technical services | -19,02 | -0,3 | -0.01 |
| Administrative and support services | -8,52 | -0,22 | -0.02 |
| Public services and other services | -5,78 | -0,11 | -0.02 |
| Total | -270,36 | -3.44 | -0.02 |

Table 3.4: Scenario 1 results aggregated to 1 digit. The first two columns show the changes in employment and value added, expressed respectively in thousands of jobs and millions of euros, obtained in the scenario outlined compared to 'business as usual', while the third column shows changes in decimal points.

| Sector and service | Change in value added | Change in employment | Change compared to the 'business as usual' scenario |
|---|---|---|---|
| Food, beverages and tobacco products | -0,57 | -0,01 | -0.02 |
| Textiles, wearing apparel, leather and related products | -0,85 | -0,02 | -0.01 |
| Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials | -0,58 | -0,01 | -0.02 |
| Paper and paper products | -0,97 | -0,01 | -0.02 |
| Printing and recording services | -0,77 | -0,01 | -0.01 |
| Coke and refined petroleum products | -0,11 | 0 | -0.02 |
| Chemicals and chemical products | -1,75 | -0,01 | -0.02 |
| Basic pharmaceutical products and pharmaceutical preparations | -0,21 | 0 | -0.01 |
| Rubber and plastic products | -5,08 | -0,06 | -0.02 |
| Other non-metallic mineral products | -2,43 | -0,03 | -0.02 |
| Basic metals | -4,25 | -0,04 | -0.02 |
| Fabricated metal products, except machinery and equipment | -20,25 | -0,3 | -0.01 |
| Computer, electronic and optical products | -5,77 | -0,06 | -0.09 |
| Electrical equipment | -72,66 | -0,83 | -0.28 |
| Machinery and equipment n.e.c. | -9,21 | -0,1 | -0.02 |
| Motor vehicles, trailers and semi-trailers | -31,2 | -0,41 | -0.01 |
| Other transport equipment | -0,73 | -0,01 | -0.01 |
| Furniture and other manufactured goods | -1,05 | -0,02 | -0.01 |
| Repair and installation services of machinery and equipment | -2,12 | -0,04 | -0.03 |
| Total | -169,99 | -2 | -0.02 |

Table 3.5: Scenario 1 results broken down for the double-digit manufacturing sector. The first two columns show the changes in employment and value added, expressed respectively in thousands of jobs and millions of euros, obtained in the scenario outlined compared to the 'business as usual' scenario, while the third column shows changes in decimal points.

Scenario 2 involves the adoption of a fully electric production formula for C29 products in Italy, France, Spain and Germany, based on the Chinese production paradigm, assuming that China possesses the most advanced technologies for the production of electric vehicles and could therefore serve as a benchmark for future European production. Overall,

the shock introduced by the adoption of the Chinese recipe for C29 products in Italy, France, Spain and Germany translates into a very significant loss: $-44,000$ jobs and €$-3.4$ billion in value added compared to the 'business as usual' scenario, an aggregate reduction of $-23\%$ (Figure 3.3). At the sectoral level, the effects are massive and relatively concentrated (Table 3.6). The manufacturing sector records the largest decline in absolute terms (€$-931.01$ million) and contributes decisively to the contraction in employment ($-11.76$ thousand): this loss is distributed across many intermediate production activities, with particularly marked declines in the manufacture of metal products (€$-384.22$ million; $-5.70$ thousand), the manufacture of rubber and plastic products (€$-129.16$ million; $-1.59$ thousand) and the manufacture of other non-metallic mineral products (€$-107.45$ million; $-1.37$ thousand). Service sectors closely linked to the supply chain—wholesale and retail trade and repair (€$-286.17$ million), transport and storage (€$-272.61$ million), professional, scientific and technical services (€$-916.71$ million) - also suffers significant losses in both value added and employment, while areas such as construction, water management and public services showed significant declines in absolute terms ($-153.13$, $-111.07$ and €$-112.36$ million respectively), indicating a transmission of the shock from industry to the tertiary sector. However, a composite picture emerges from the disaggregated results for manufacturing (Table 3.7): many sub-activities are losing ground, but some are recording increases. In particular, the manufacture of electrical equipment shows a net increase of €$+67.67$ million (with a positive employment balance of $+0.77$ thousand) and the manufacture of motor vehicles also shows an increase of €$+85.24$ million ($+1.12$ thousand). This coexistence of large sectoral losses and localised gains can be explained by the nature of the Chinese recipe we have imposed: on the one hand, the benchmark recipe may imply greater centralisation or specialisation in specific stages of the value chain (final assembly, electrical modules, certain electrical equipment) and greater demand and requirement for inputs that were not previously necessary, resulting in increases for those sectors; on the other hand, the same recipe may lead to a sharp reduction in domestic input content in favour of imports or foreign supply chains for many intermediate components or inputs that are no longer necessary, causing the large

losses observed in metalworking, chemical, rubber/plastic supplies and numerous support services. In mechanical terms, replacing national Use coefficients with a 'Chinese'-type matrix reduces direct demand for many local suppliers and alters the composition of the inputs required: this generates both internal redistribution effects within manufacturing (some sectors gain) and a sharp net loss of overall demand for industry and related sectors.

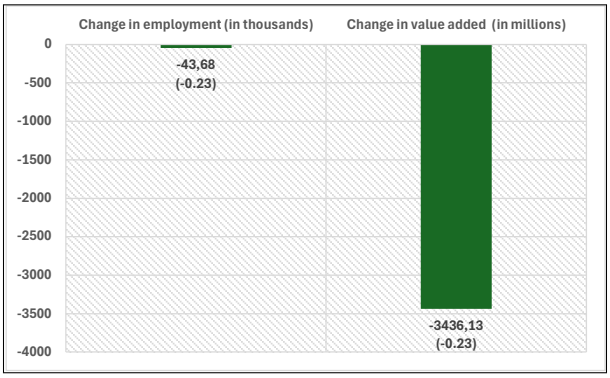



Figure 3.3: Results Scenario 2. The changes in employment levels and value added, obtained in the scenario outlined above are shown in comparison with the 'business as usual' scenario. The changes in decimal points are shown in brackets.

| Sector and service | Change in value added | Change in employment | Change compared to the 'business as usual scenario' |
|---|---|---|---|
| Agricultural, forestry and fishing products | -24,6 | -0,57 | -0,37 |
| Mining and quarrying products | -39,47 | -0,11 | -0,68 |
| Manufactured products | -931,01 | -11,76 | -0,08 |
| Electricity, gas, steam and air conditioning | -48,28 | -0,08 | -0,13 |
| Water supply; sewerage; waste treatment and decontamination services | -111,07 | -1,4 | -0,65 |
| Construction and civil engineering works | -153,13 | -2,67 | -0,63 |
| Wholesale and retail trade; repair of motor vehicles and motorcycles | -286,17 | -2,73 | -0,17 |
| Transport and storage | -272,61 | -3,09 | -0,37 |
| Accommodation and food service activities | -47,27 | -1,33 | -0,37 |
| Information and communication | -163,02 | -1,51 | -0,45 |
| Financial and insurance activities | -201,2 | -1,5 | -0,46 |
| Real estate activities | -162,4 | -0,13 | -0,35 |
| Professional, scientific and technical services | -916,71 | -13,87 | -0,63 |
| Administrative and support services | -97,19 | -2,14 | -0,29 |
| Public services and other services | -112,36 | -1,8 | -0,32 |
| Total | -3436,13 | -43,68 | -0.23 |

Table 3.6: Scenario 2 results aggregated to 1 digit. The first two columns show the changes in employment and value added, expressed respectively in thousands of jobs and millions of euros, obtained in the scenario outlined compared to 'business as usual', while the third column shows changes in decimal points.

| Sector and service | Change in value added | Change in employment | Change compared to the 'business as usual' scenario |
|---|---|---|---|
| Food, beverages and tobacco products | -14,48 | -0,21 | -0,44 |
| Textiles, wearing apparel, leather and related products | -14,51 | -0,27 | -0,17 |
| Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials | -5,15 | -0,09 | -0,14 |
| Paper and paper products | -18,53 | -0,2 | -0,41 |
| Printing and recording services | -14,64 | -0,25 | -0,25 |
| Coke and refined petroleum products | -2,31 | -0,02 | -0,39 |
| Chemicals and chemical products | -45,56 | -0,37 | -0,51 |
| Basic pharmaceutical products and pharmaceutical preparations | -9,77 | -0,06 | -0,6 |
| Rubber and plastic products | -129,16 | -1,59 | -0,4 |
| Other non-metallic mineral products | -107,45 | -1,37 | -0,71 |
| Basic metals | -94,29 | -0,99 | -0,48 |
| Fabricated metal products, except machinery and equipment | -384,22 | -5,7 | -0,24 |
| Computer, electronic and optical products | -6,07 | -0,06 | -0,09 |
| Electrical equipment | 67,67 | 0,77 | 0,26 |
| Machinery and equipment n.e.c. | -39,5 | -0,44 | -0,07 |
| Motor vehicles, trailers and semi-trailers | 85,24 | 1,12 | 0,02 |
| Other transport equipment | -30,69 | -0,38 | -0,45 |
| Furniture and other manufactured goods | -14,69 | -0,24 | -0,18 |
| Repair and installation services of machinery and equipment | -22,52 | -0,41 | -0,36 |
| Total | -931,01 | -11,76 | -0,08 |

Table 3.7: Scenario 2 results broken down for the double-digit manufacturing sector. The first two columns show the changes in employment and value added, expressed respectively in thousands of jobs and millions of euros, obtained in the scenario outlined compared to the 'business as usual' scenario, while the third column shows changes in decimal points.

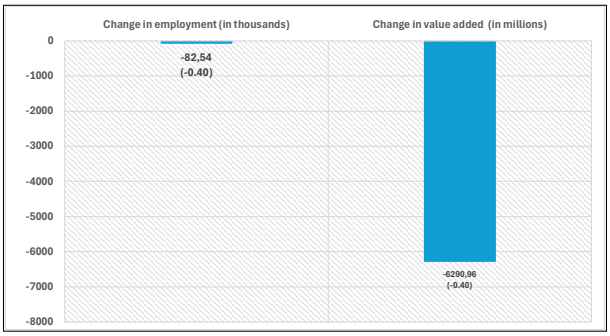



Figure 3.4: Results Scenario 3. The changes in employment levels and value added obtained in the scenario outlined above are shown in comparison with the 'business as usual' scenario. The changes in decimal points are shown in brackets.

In Scenario 3, we estimate the impact of the Fit for 55 package on the Italian automotive sector. In our exercise we integrate the change in the production recipe with demand projections up to 2035: for Italy, Germany, France and Spain the C29 columns were replaced with the electric production recipe we constructed, and final demand for 2035 was reconstructed by applying the assumed vehicle registrations vector. The adoption of the Fit for 55 package results in a much more severe impact than in the previous scenarios: we estimate $-82$ thousand jobs and a contraction of €$-6.2$ billion in value added, equivalent to approximately $-40\%$ of the 'business as usual' scenario (Figure 3.4). The reduction is widespread across both industrial sectors and services linked to the automotive supply chain, showing how the combination of an electric production recipe and lower demand projections for 2035 generates a double-dampening effect.

At the sectoral level (Table 3.8), manufacturing is by far the hardest hit sector, with a

fall of roughly €−2.8 billion and −36 thousand jobs. Within manufacturing (Table 3.9), losses concentrate primarily in motor vehicle manufacture (€−1.08 billion; −14.2 thousand jobs) and in the manufacture of fabricated metal products (€−686 million; −10.2 thousand jobs). Other substantial reductions are observed in the manufacture of rubber and plastic products (€−176 million), basic metals (€−119 million) and machinery (€−160 million), reflecting the erosion of the traditional combustion-engine supply chain. Unlike in Scenario 2, here no manufacturing subsectors record net gains: even the manufacture of electrical equipment, which previously benefited from the transition, shows a small decline (€−11.9 million). This outcome stems from the fact that, in addition to replacing the production recipe, the lower final demand projected for 2035 drags down those sectors that, in theory, would have benefited from the diffusion of electric vehicles.

Losses are not limited to manufacturing. Numerous services connected to the automotive sector suffer heavy contractions: wholesale and repair (€−584 million; −8 thousand jobs), transport and storage (€−383 million; −4.4 thousand jobs), and professional and technical services (−1.04 billion; −15.8 thousand jobs). These declines arise both from the smaller overall production volume and from the different maintenance and logistics profile associated with electric vehicles. Sectors such as construction, water management and energy also register reductions, albeit smaller, indicating a broad weakening of the induced (indirect) economy.

Compared with the earlier scenarios, the combination of an electric-vehicle production recipe and lower demand projection for 2035 amplifies losses and reduces opportunities for sectoral offsetting: the traditional industrial supply chain loses weight without emerging sectors related to electric mobility being able to fully compensate.

| Sector and service | Change in value added | Change in employment | Change compared to the 'business as usual scenario' |
|---|---|---|---|
| Agricultural, forestry and fishing products | -34,66 | -0,81 | -0,52 |
| Mining and quarrying products | -43,9 | -0,13 | -0,76 |
| Manufactured products | -2856,83 | -36,23 | -0,3 |
| Electricity, gas, steam and air conditioning | -124,59 | -0,2 | -0,34 |
| Water supply; sewerage; waste treatment and decontamination services | -125,64 | -1,58 | -0,74 |
| Construction and civil engineering works | -175,21 | -3,05 | -0,72 |
| Wholesale and retail trade; repair of motor vehicles and motorcycles | -584,11 | -7,97 | -0,37 |
| Transport and storage | -383,38 | -4,4 | -0,53 |
| Accommodation and food service activities | -66,67 | -1,87 | -0,52 |
| Information and communication | -211,7 | -2,05 | -0,58 |
| Financial and insurance activities | -258,68 | -1,97 | -0,59 |
| Real estate activities | -235,6 | -0,19 | -0,51 |
| Professional, scientific and technical services | -1039,58 | -15,8 | -0,72 |
| Administrative and support services | -186,55 | -4,47 | -0,46 |
| Public services and other services | -163,09 | -2,74 | -0,49 |
| Total | -6290,96 | -82,54 | -0.41 |

Table 3.8: Scenario 3 results aggregated to 1 digit. The first two columns show the changes in employment and value added, expressed respectively in thousands of jobs and millions of euros, obtained in the scenario outlined compared to 'business as usual', while the third column shows changes in decimal points.

| Sector and service | Change in value added | Change in employment | Change compared to the 'business as usual' scenario |
|---|---|---|---|
| Food, beverages and tobacco products | -18,9 | -0,27 | -0,58 |
| Textiles, wearing apparel, leather and related products | -32,12 | -0,6 | -0,37 |
| Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials | -13,08 | -0,23 | -0,35 |
| Paper and paper products | -24,9 | -0,27 | -0,56 |
| Printing and recording services | -25,34 | -0,44 | -0,43 |
| Coke and refined petroleum products | -3,21 | -0,02 | -0,53 |
| Chemicals and chemical products | -56,31 | -0,45 | -0,63 |
| Basic pharmaceutical products and pharmaceutical preparations | -11,32 | -0,07 | -0,7 |
| Rubber and plastic products | -176,01 | -2,17 | -0,55 |
| Other non-metallic mineral products | -117,87 | -1,5 | -0,78 |
| Basic metals | -119,13 | -1,25 | -0,61 |
| Fabricated metal products, except machinery and equipment | -686,18 | -10,18 | -0,42 |
| Computer, electronic and optical products | -20,77 | -0,2 | -0,31 |
| Electrical equipment | -11,9 | -0,14 | -0,05 |
| Machinery and equipment n.e.c. | -159,62 | -1,77 | -0,3 |
| Motor vehicles, trailers and semi-trailers | -1078,15 | -14,16 | -0,23 |
| Other transport equipment | -39,95 | -0,49 | -0,58 |
| Furniture and other manufactured goods | -30,77 | -0,51 | -0,38 |
| Repair and installation services of machinery and equipment | -32,09 | -0,59 | -0,52 |
| Total | -2856,83 | -36,23 | -0,3 |

Table 3.9: Scenario 3 results broken down for the double-digit manufacturing sector. The first two columns show the changes in employment and value added, expressed respectively in thousands of jobs and millions of euros, obtained in the scenario outlined compared to the 'business as usual' scenario, while the third column shows changes in decimal points.

Scenario 4 estimates the impact of the Fit for 55 package under a 20% reduction in demand for Italian automotive products by 2035. In this scenario we assume a more limited penetration capacity for European automotive producers: by 2035 a share of demand is projected to be satisfied by vehicles produced outside Europe, resulting in a 20% contraction of the Italian automotive sector. Scenario 4 shows a further deterioration relative to Scenario 3: aggregate estimates indicate −86 thousand jobs and €-6.5 billion in value added (-43%) compared with the 'business as usual' scenario (Figure 3.5). The hardest-hit sector remains manufacturing (Table 3.10), with an estimated loss of about €−3.1 billion and −39 thousand jobs. Within manufacturing (Table 3.11), the central role of motor-vehicle manufacture is confirmed (€−1.08 billion; −14.2 thousand jobs), representing roughly one third of the total decline. Losses also deepen in the manufacture of fabricated metal products (€−790 million; −11.7 thousand), rubber and plastic products (€−194 million) and basic metals (€−127 million). Compared with the previous scenario,

the fall in demand projected for 2035 drags into negative territory even sectors that had been relatively more resilient, such as electrical equipment (€−38 million; −0.4 thousand jobs), underscoring how a quantitative market contraction weighs on segments that might otherwise benefit from the transition.

The decline in automotive production transmits strongly to related services: wholesale and repair (€−603 million; −8.2 thousand jobs), transport and storage (€−396 million; −4.6 thousand), professional and technical services (€−1.06 billion; −16 thousand) and administrative and support services (€−197 million; −4.7 thousand). Losses are widespread and confirm that the Italian automotive supply chain, already penalised by the technological transition, suffers an additional blow from the erosion of demand in favour of foreign producers. The percentage changes show that contractions are distributed relatively uniformly across sectors (in the range −0.2% to −0.8%), but the aggregation of many negative effects in sectors with high labour intensity and high value added produces a large macroeconomic impact. Unlike Scenario 3, here the reduction in specific demand for Italian C29 products translates into a larger, less-compensated net loss, indicating not merely a change in production composition but a genuine quantitative downsizing of the industrial base.

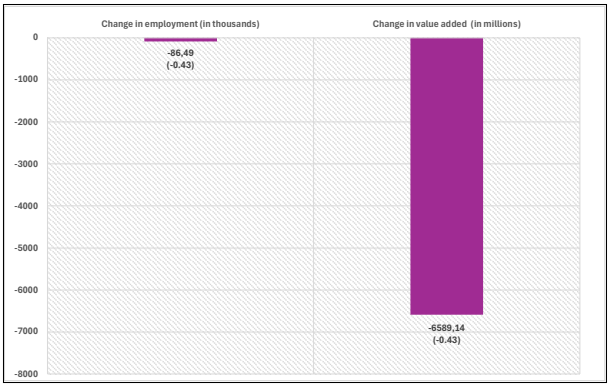



Figure 3.5: Results Scenario 4. The changes in employment levels and value added obtained in the scenario outlined above are shown in comparison with the 'business as usual' scenario. The changes in decimal points are shown in brackets.

| Sector and service | Change in value added | Change in employment | Change compared to the 'business as usual' scenario |
|---|---|---|---|
| Agricultural, forestry and fishing products | -36,14 | -0,84 | -0,55 |
| Mining and quarrying products | -44,85 | -0,13 | -0,78 |
| Manufactured products | -3057,63 | -38,81 | -0,32 |
| Electricity, gas, steam and air conditioning | -134,62 | -0,22 | -0,37 |
| Water supply; sewerage; waste treatment and decontamination services | -128,5 | -1,62 | -0,75 |
| Construction and civil engineering works | -178,37 | -3,11 | -0,73 |
| Wholesale and retail trade; repair of motor vehicles and motorcycles | -602,65 | -8,23 | -0,38 |
| Transport and storage | -396,2 | -4,55 | -0,54 |
| Accommodation and food service activities | -69,32 | -1,94 | -0,54 |
| Information and communication | -217,71 | -2,11 | -0,6 |
| Financial and insurance activities | -267,67 | -2,04 | -0,61 |
| Real estate activities | -245,31 | -0,19 | -0,53 |
| Professional, scientific and technical services | -1055,2 | -16,05 | -0,73 |
| Administrative and support services | -196,74 | -4,74 | -0,48 |
| Public services and other services | -168,82 | -2,84 | -0,51 |
| Total | -6589,14 | -86,49 | -0,43 |

Table 3.10: Scenario 4 results aggregated to 1 digit. The first two columns show the changes in employment and value added, expressed respectively in thousands of jobs and millions of euros, obtained in the scenario outlined compared to 'business as usual', while the third column shows changes in decimal points.

Scenario 5 illustrates the impact of the Fit for 55 package coupled with a contraction in vehicle registrations by 2035. This represents a more severe version of Scenario 3: holding the technological transformation constant, we assume a substantially lower growth rate of European registrations (one-third lower than the initial assumptions). The outcome is a deterioration of the macroeconomic effects: −89 thousand jobs and €−6.7 billion in value added, equivalent to a reduction of approximately −44% relative to the 'business as usual' scenario (Figure 3.6). The principal blow again falls on manufacturing (€−3.2 billion; −40 thousand jobs), led by motor-vehicle manufacture (€−1.26 billion; −16.6 thousand jobs), which alone accounts for a large share of the total value-added loss (Table 3.12). Alongside automotive, the most affected sectors remain the manufacture of fabricated metal products €−735 million; 10.9 thousand), rubber and plastic products (€−184 million; −2.3 thousand) and basic metals (€−123 million; −1.3 thousand) (Table 3.13). Compared with the previous scenarios, even sectors that might temporarily benefit from the transition (such as electrical equipment) turn negative (€−25 million), indicating that lower overall demand erodes any compensatory margin.

Effects propagate strongly to services connected with the supply chain: wholesale and repair (€−632 million; −8.8 thousand jobs), transport and logistics (€−401 million; −4.6 thousand), professional and technical services (€−1.06 billion; −16.1 thousand), and administrative support services (€−201 million; −4.9 thousand). It is evident that the contraction in the automotive market affects not only direct production but also a wide range of upstream and downstream activities, amplifying employment losses. In percentage

terms, losses remain relatively uniformly distributed across sectors, but the depth of the fall in a key sector such as automotive pushes the entire economy into a scenario of structural contraction. Compared with Scenario 4, the results are similar in magnitude but differ importantly in their driver: here the shock stems less from substitution of Italian production and more from a lower overall demand in Europe. This makes the shock less selective but more pervasive, producing widespread impacts and reducing the prospects for competitive recovery by domestic producers.

The Appendix 3.A.2 provides a further detailed analysis of the results using activation rounds (Tables 3.27-3.35).

| Sector and service | Change in value added | Change in Employment | Change compared to the 'business as usual' scenario |
|---|---|---|---|
| Food, beverages and tobacco products | -19,54 | -0,28 | -0,6 |
| Textiles, wearing apparel, leather and related products | -32,99 | -0,61 | -0,38 |
| Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials | -13,85 | -0,25 | -0,37 |
| Paper and paper products | -25,93 | -0,28 | -0,58 |
| Printing and recording services | -26,01 | -0,45 | -0,44 |
| Coke and refined petroleum products | -3,35 | -0,02 | -0,56 |
| Chemicals and chemical products | -59,15 | -0,48 | -0,66 |
| Basic pharmaceutical products and pharmaceutical preparations | -11,56 | -0,07 | -0,72 |
| Rubber and plastic products | -193,76 | -2,39 | -0,6 |
| Other non-metallic mineral products | -119,93 | -1,53 | -0,8 |
| Basic metals | -127,25 | -1,34 | -0,65 |
| Fabricated metal products, except machinery and equipment | -789,89 | -11,72 | -0,48 |
| Computer, electronic and optical products | -25,59 | -0,25 | -0,38 |
| Electrical equipment | -37,96 | -0,43 | -0,15 |
| Machinery and equipment n.e.c. | -170,85 | -1,89 | -0,32 |
| Motor vehicles, trailers and semi-trailers | -1080,58 | -14,19 | -0,23 |
| Other transport equipment | -40,9 | -0,5 | -0,59 |
| Furniture and other manufactured goods | -33,09 | -0,55 | -0,41 |
| Repair and installation services of machinery and equipment | -34,86 | -0,64 | -0,56 |
| Total | -3057,63 | -38,81 | -0,32 |

Table 3.11: Scenario 4 results broken down for the double-digit manufacturing sector. The first two columns show the changes in employment and value added, expressed respectively in thousands of jobs and millions of euros, obtained in the scenario outlined compared to the 'business as usual' scenario, while the third column shows changes in decimal points.

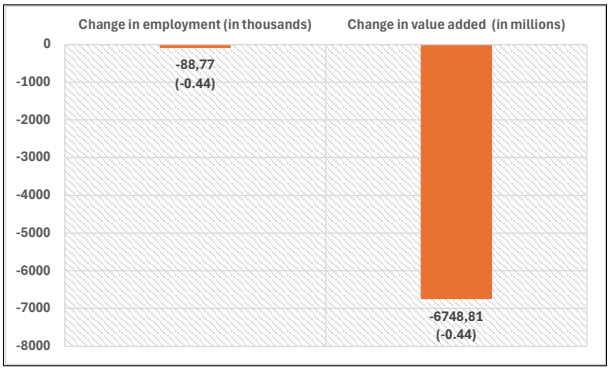



Figure 3.6: Results Scenario 5. The changes in employment levels and value added obtained in the scenario outlined above are shown in comparison with the 'business as usual' scenario. The changes in decimal points are shown in brackets.

| Sector and service | Change in value added | Change in employment | Change compared to the 'business as usual scenario' |
|---|---|---|---|
| Agricultural, forestry and fishing products | -36,27 | -0,84 | -0,55 |
| Mining and quarrying products | -44,61 | -0,13 | -0,77 |
| Manufactured products | -3165,68 | -40,15 | -0,34 |
| Electricity, gas, steam and air conditioning | -136,83 | -0,22 | -0,38 |
| Water supply; sewerage; waste treatment and decontamination services | -127,98 | -1,61 | -0,75 |
| Construction and civil engineering works | -178,75 | -3,11 | -0,73 |
| Wholesale and retail trade; repair of motor vehicles and motorcycles | -631,9 | -8,81 | -0,4 |
| Transport and storage | -401,15 | -4,61 | -0,55 |
| Accommodation and food service activities | -69,78 | -1,96 | -0,55 |
| Information and communication | -219,5 | -2,13 | -0,6 |
| Financial and insurance activities | -267,9 | -2,04 | -0,61 |
| Real estate activities | -247,34 | -0,19 | -0,53 |
| Professional, scientific and technical services | -1059,28 | -16,11 | -0,74 |
| Administrative and support services | -200,88 | -4,85 | -0,49 |
| Public services and other services | -171,22 | -2,89 | -0,51 |
| Total | -6748,81 | -88,77 | -0.44 |

Table 3.12: Scenario 5 results aggregated to 1 digit. The first two columns show the changes in employment and value added, expressed respectively in thousands of jobs and millions of euros, obtained in the scenario outlined compared to 'business as usual', while the third column shows the changes in decimal points.

| Sector and service | Change in value added | Change in employment | Change compared to the 'business as usual' scenario |
|---|---|---|---|
| Food, beverages and tobacco products | -19,61 | -0,28 | -0,6 |
| Textiles, wearing apparel, leather and related products | -34,94 | -0,65 | -0,4 |
| Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials | -14,35 | -0,26 | -0,38 |
| Paper and paper products | -25,92 | -0,28 | -0,58 |
| Printing and recording services | -27,05 | -0,47 | -0,46 |
| Coke and refined petroleum products | -3,35 | -0,02 | -0,56 |
| Chemicals and chemical products | -58,03 | -0,47 | -0,65 |
| Basic pharmaceutical products and pharmaceutical preparations | -11,56 | -0,07 | -0,72 |
| Rubber and plastic products | -183,52 | -2,26 | -0,57 |
| Other non-metallic mineral products | -119,54 | -1,52 | -0,79 |
| Basic metals | -123,12 | -1,29 | -0,63 |
| Fabricated metal products, except machinery and equipment | -734,6 | -10,9 | -0,45 |
| Computer, electronic and optical products | -23,12 | -0,23 | -0,35 |
| Electrical equipment | -24,66 | -0,28 | -0,09 |
| Machinery and equipment n.e.c. | -178,89 | -1,98 | -0,33 |
| Motor vehicles, trailers and semi-trailers | -1264,73 | -16,61 | -0,27 |
| Other transport equipment | -41,44 | -0,51 | -0,6 |
| Furniture and other manufactured goods | -33,35 | -0,55 | -0,41 |
| Repair and installation services of machinery and equipment | -33,63 | -0,61 | -0,54 |
| Total | -3165,68 | -40,15 | -0,34 |

Table 3.13: Scenario 5 results broken down for the double-digit manufacturing sector. The first two columns show the changes in employment and value added, expressed respectively in thousands of jobs and millions of euros, obtained in the scenario outlined compared to the 'business as usual' scenario, while the third column shows changes in decimal points.

## 3.6 Discussion and Conclusions

This study adopts an inter-country input–output approach to assess the economic effects of vehicle electrification (product C29 in the IO tables employed) on the Italian economy, with particular focus on impacts on value added and employment. For the analysis we integrated the FIGARO Supply and Use Input–Output Tables (Eurostat) with ISTAT national accounts, product-level trade flows from the BACI database and sectoral sources (ACEA and related datasets). From these series we defined counterfactual and policy scenarios and applied a quantitative model based on input–output matrices to isolate the effects of technological transition and demand variation. The empirical assessment rests on the construction of the following scenarios: (1) Delocalisation, a baseline case in which Italian demand for part of automotive componentry is entirely relocated abroad (Use matrix coefficients for C27 and C29 set to zero); (2) 2022 Chinese benchmark: the C29 columns for Italy, France, Spain and Germany are replaced by the Chinese production 'recipe' for electric vehicles; (3) Fit for 55 + 2035 demand: the electric-vehicle production recipe is applied to C29 columns and final demand for 2035 is recalculated according to the assumed vehicle-registration vector; (4) Fit for 55 + market-share loss: as in (3) but with a 20% reduction in Italian demand by 2035 (greater penetration by non-EU producers); (5) Fit for 55 + contraction in registrations: as in (3) but with the EU registration growth rate to 2035 reduced by one third.

Two findings emerge immediately from the construction of the Italian electric production recipe, which we derived from the vector of direct input coefficients for the Chinese C29 sector and from a set of technological assumptions and adjustments. First, the electric production recipe for product C29 produces a marked reallocation within manufacturing: there is a strong shift toward electronic-content industries and vehicle modules (an increase in the 'Manufacture of motor vehicles' item and in electrical/electronic equipment) accompanied by a reduction in demand for traditional metal-mechanical supplies, rubber/plastics and certain tertiary services (Mase (2020); Mönnig et al. (2019); Pirmana et al. (2023); Kolpakov and Galinger (2020); Shibusawa and Miyata (2016);

Tamba et al. (2022); Cresti et al. (2025b); Bravo et al. (2024); Chen et al. (2023); Zhang et al. (2025); Suehiro et al. (2020)). This pattern is consistent with the technological nature of electrification: batteries, electric motors, inverters and power electronics require a different set of inputs than internal-combustion engines. Moreover, the increased weight of intermediate-goods activities and production processes within C29 can be interpreted as a rise in the share of production of new electric-vehicle parts and their assembly, as noted by Klier and Rubenstein (2024), who find that OEMs' role in assembly has not changed: most vehicles sold in Europe—whether ICE or BEV—continue to be assembled by European manufacturers, driven by agglomeration economies and scale.

Second, the geography of suppliers changes substantially, producing a geographical-relocation effect (Gül et al. (2024); Slowik et al. (2020); Jagani et al. (2024); Bauer et al. (2018); Cresti et al. (2025a); Ulrich and Lehr (2020); Heim et al. (2025)). In our case the Italian share declines sharply under the electric-vehicle production recipe, in favour of Central, Northern and Eastern European hubs and specialised Asian economies (notably for batteries and semiconductors). This pattern signals a concrete risk of erosion of the domestic value chain. The observed change in supplier geography aligns with Klier and Rubenstein (2024): in the transition from ICE to BEV, core activities that remain domestically concentrated tend to be those with high value and high skill intensity—final BEV assembly, battery-pack assembly (close to vehicle assembly), design and R&D, power electronics (inverters, BMS, software), strategic functions and capital-intensive activities—whereas high-volume, relatively standardised production typically shifts to integrated peripheries (Pavlínek, 2018): large-scale cell manufacturing (gigafactories), mass-production of generic low-value components (stamping, standard mechanical parts, non-strategic modules, mass wiring) and, in some cases, recycling and end-of-life facilities.

Figures 3.7 and 3.8 report the impacts of the different scenarios on value added and employment relative to the 'business-as-usual' scenario. Under Scenario 1, we observe that setting domestic coefficients (C27 and C29) to zero and assuming that essential inputs are supplied from the rest of the world produces a limited aggregate loss in percentage

terms ($\approx -2\%$) but one concentrated in a few supply chains (electrical equipment, metal-mechanical components). Mechanically, this outcome follows from the cancellation of direct demand for national suppliers and from the action of IO multipliers, which disproportionately affect the sectors that previously supplied the automotive industry. The scenario therefore shows that geographical displacement can produce significant distributive impacts even when the macro loss is contained.

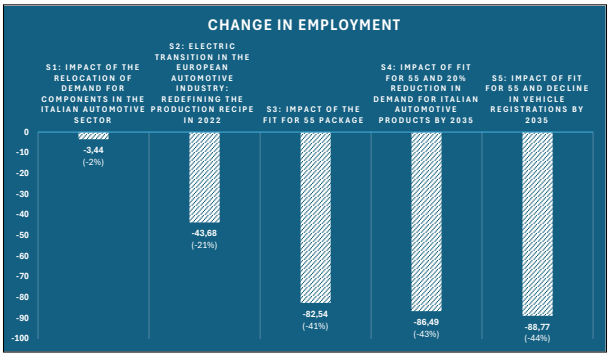



Figure 3.7: Change in employment levels in the different scenarios compared (in thousands of units).

Scenario 2 - the adoption of the Chinese technological recipe at European scale[17] - leads to a large contraction (23 %; €−3.4 billion; −44k jobs). The production-paradigm shift alters input demand according to the new combination required to produce the reconfigured automotive product, generating widespread losses in traditional manufacturing. Some subsectors (electrical equipment, motor-vehicle manufacture) can expand, but these gains do not offset net losses. The fact that the transition may yield sectoral gains for, for example, electrical equipment, is also noted by Bauer et al. (2018); Cotterman et al. (2024), who suggest potential employment increases in the powertrain if battery production is local. Similarly, Mönnig et al. (2019) anticipate net employment losses and a GDP decline in the absence of domestic capacity to produce vehicles and cells; Grosso et al. (2021) report comparable findings. Conversely, studies focused on Eastern economies such as Indonesia — which exploit a localized, export-oriented EV supply chain — document large output and employment gains concentrated in the EV value chain (Pirmana et al., 2023).

[17]This scenario may be interpreted as one in which automotive firms in the four European countries adopt a passive benchmarking of the Chinese production recipe. If that production model is accepted as given - i.e., implemented without accompanying industrial adaptation strategies - it exposes national economies to a significant risk of deindustrialisation.

Other contributions report slightly positive or neutral effects on GDP and employment (Chen et al. (2023); Tamba et al. (2022); Wingender et al. (2024)) converge with our evidence of geographical displacement: a limited aggregate EU impact but substantial losses for countries and expertise hubs in central Europe, a result very similar to our observations on relocation and distributive effects.

Scenario 3 implements the Fit for 55 $CO_2$-abatement measure. This requires analysing both the new production paradigm and the change in final demand for product C29 to 2035; the policy in question is binding. Integrating the electric-vehicle production recipe with 2035 demand projections produces a very severe combined effect (40%; €−6.2 billion; 82k jobs). The demand contraction also drains potential benefits for emerging sectors: the smaller market scale cancels sectoral gains that, under constant-demand scenarios, might have mitigated losses. Cresti et al. (2025b) obtain results of the same sign and magnitude, forecasting extremely large direct employment losses and a real risk of deindustrialisation. If our demand assumptions prove correct, applying stringent regulation without accompanying demand-support and industrial policies risks producing dramatic social and economic impacts. Were domestic demand to fall as projected, the cost to the Italian productive system would be high and difficult to sustain.

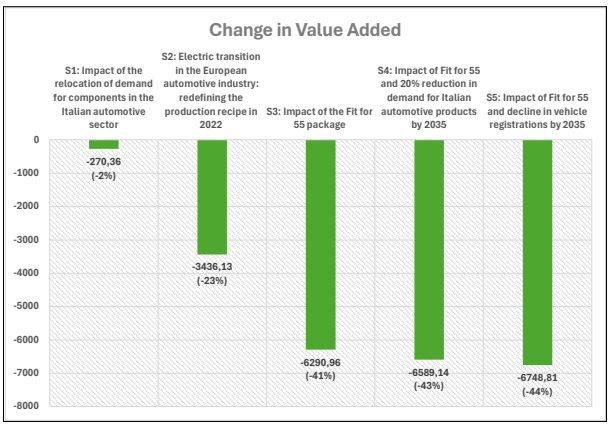



Figure 3.8: Change in value added in the different scenarios compared (in millions of euros).

Our estimates confirm a recurring thesis: the transition to electric mobility aggravates the difficulties of an Italian automotive sector already weakened by falling sales, semiconductor shortages and pandemic effects (Nelli, 2024). The absence of an effective

institutional strategy and the progressive loss of centrality of Stellantis make the transition slow and risk relegating Italy to a peripheral role. Stellantis has reduced production in Italy, shifted toward premium models and offshored parts of manufacturing, while Italian research centres have lost relative importance to foreign counterparts. Major vulnerabilities include eastward delocalisation, the sale of strategic firms (e.g., Magneti Marelli) to foreign groups, and a lack of investments and industrial policies capable of steering sectoral transformation.

Scenario 4 — the combination of the electric-vehicle production recipe and loss of demand to non-national producers — amplifies losses relative to Scenario 3 (−43%; €6.5 billion; 86k jobs). Here the challenge is not only technological but competitive: market-share erosion. Finally, Scenario 5 assumes a contraction in vehicle registrations and outlines a harsher version of Scenario 3: lower overall demand exacerbates contractionary effects (−44%; €−6.7 billion; 89k jobs) and produces losses even in sectors that could otherwise benefit. The reduction in scale undermines sectoral compensation mechanisms.

In light of these results, policy intervention is required on both the supply and demand sides to avoid structural decline. On the supply side, securing supply chains and domestic value is essential. A primary concern is access to raw materials and rare-earth elements: the EU depends on imports for many critical inputs used in electric-vehicle production and cannot rapidly and substantially reduce that dependence through immediate increases in domestic extraction and refining — not least because local populations often resist resource-intensive extraction (due to its water use and perceived environmental risks) (Heim et al., 2025). Consequently, the EU will rely on raw-material diplomacy to maintain access to resource-rich countries and will increasingly participate in alliances and geopolitical networks, entailing a politicisation of commercial practices. At the same time, the EU must pursue an autonomous strategy to secure critical raw materials, reducing dependence on free-trade agreements and strengthening its strategic autonomy.

The potential reallocation of employment losses associated with the simplification of componentry in an electric-vehicle-dominated production regime depends critically

on OEM decisions—specifically whether to produce or import batteries and where to locate battery plants. In Italy battery production is virtually absent, implying that job losses in component suppliers and in the automotive sector more broadly are likely to be substantial. Global battery manufacturing is today highly concentrated in China, Japan and South Korea, which possess technological advantages and privileged access to critical raw materials. In particular, China dominates the refining of cobalt, lithium and graphite and a large share of cathode, anode and cell production (Schwabe (2020); Jetin (2020); IEA (2022); Nelli (2024)). It is therefore essential to promote national and European capabilities in batteries, cells and power electronics[18], to attract investment for productive repositioning (modules, assembly) and to encourage selective vertical integration (Bravo et al. (2024); Bauer et al. (2018); Chen et al. (2023); Cresti et al. (2025b,a)). Policy measures should strengthen financial instruments for the modernization of small and medium-sized enterprises and provide substantial incentives for innovation and the digitalisation of production. On the demand side, temporary but meaningful purchase incentives, green-oriented public procurement and investment in fast home-charging infrastructure are required to support market development (Leurent and Windisch (2015); Chen et al. (2023); Cresti et al. (2025b)). Nonetheless, the decarbonisation of the automotive sector and the associated change in production paradigms will inevitably have significant labour-market consequences. For this reason, social-mitigation and productive-adaptation policies are indispensable: targeted relocation and retraining programmes for workers and firms within the traditional automotive supply chain should accompany industrial and demand-side measures.

## 3.7 Limitations

The study presents several limitations linked to the assumptions adopted. While these do not call into question the validity of the methodology or the data employed, it should

[18]One study shows that such supply-chain policies are more salient for large or very small Italian firms, for foreign-owned companies, and for firms actively engaged in the electric transition, whereas they attract less interest among medium-sized enterprises, firms located in Central Italy, and companies with a strong export orientation (Di Sisto and Calabrese, 2025).

be emphasised that modifications to those assumptions could affect the magnitude of the estimated effects, even if they are unlikely to change the direction of the impacts identified. The results remain meaningful insofar as actual sector dynamics and future scenarios approximate the hypotheses used here. The principal limitations are described below.

The decision to keep the Make matrix invariant is a common assumption in input–output studies but is frequently criticised for its rigidity. A substantial change in input demand—as that induced by the transition to electric vehicles—can alter production structures and suppliers' market shares. This issue is particularly salient for strategic inputs such as batteries and rare-earth materials, whose production is highly concentrated in a few countries. The invariance assumption does not account for potential bottlenecks or for possible restructurings of global value chains that may materialise in response to new industrial policies.

In the steps used to compute the electric production recipes for European producers, we relied on normalised vectors that exclude components such as value added and balancing adjustments. This procedure implicitly assumes that changes in the composition of inputs do not affect the generation of value added, an assumption that may not hold for electric-vehicle production, which requires different technologies and skills compared with internal-combustion vehicles.

Relatedly, the hypothesis that value added remains constant during the transition from internal-combustion to electric vehicles is a simplifying assumption open to criticism. EV production may exhibit a different value-added mix, particularly with respect to labour intensity and industrial profit margins.

The assumption that European countries would adopt a Chinese production recipe can be motivated by China's technological leadership in the EV sector, but it remains a strong simplification. Supply chains and technological choices differ substantially across regions because of institutional, regulatory and industrial-policy heterogeneity. Transferring the Chinese-type vector of direct coefficients directly to European contexts implies importing those structural characteristics wholesale, which may not reflect local realities. Likewise,

the average electric-vehicle price used in the analysis was constructed from figures reported in various studies and reports and is therefore subject to uncertainty.

Estimates of the growth rate of EV demand are also based on assumptions drawn from previous studies and may not fully capture future market dynamics. These projections are exposed to uncertainty from economic, political and technological drivers—such as the evolution of environmental regulation, advances in battery production, and changes in consumer behaviour.

Finally, market shares of electric-vehicle sales for European producers were held constant at 2022 levels when constructing the components of final demand for 2035. This simplifying assumption neglects potential market-share shifts over time and may therefore bias the distributional and geographical implications of the scenarios.

# Appendix

## 3.A.1 Classification and additional data used

| Codification | Industries |
|---|---|
| A01 | Crop and animal production, hunting and related service activities |
| A02 | Forestry and logging |
| A03 | Fishing and aquaculture |
| B | Mining and quarrying |
| C10T12 | Manufacture of food products; beverages and tobacco products |
| C13T15 | Manufacture of textiles, wearing apparel, leather and related products |
| C16 | Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials |
| C17 | Manufacture of paper and paper products |
| C18 | Printing and reproduction of recorded media |
| C19 | Manufacture of coke and refined petroleum products |
| C20 | Manufacture of chemicals and chemical products |
| C21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations |
| C22 | Manufacture of rubber and plastic products |
| C23 | Manufacture of other non-metallic mineral products |
| C24 | Manufacture of basic metals |
| C25 | Manufacture of fabricated metal products, except machinery and equipment |
| C26 | Manufacture of computer, electronic and optical products |
| C27 | Manufacture of electrical equipment |
| C28 | Manufacture of machinery and equipment n.e.c. |
| C29 | Manufacture of motor vehicles, trailers and semi-trailers |
| C30 | Manufacture of other transport equipment |
| C31_32 | Manufacture of furniture; other manufacturing |
| C33 | Repair and installation of machinery and equipment |
| D35 | Electricity, gas, steam and air conditioning supply |
| E36 | Water collection, treatment and supply |
| E37T39 | Sewerage, waste management, remediation activities |
| F | Construction |
| G45 | Wholesale and retail trade and repair of motor vehicles and motorcycles |
| G46 | Wholesale trade, except of motor vehicles and motorcycles |
| G47 | Retail trade, except of motor vehicles and motorcycles |
| H49 | Land transport and transport via pipelines |
| H50 | Water transport |
| H51 | Air transport |
| H52 | Warehousing and support activities for transportation |
| H53 | Postal and courier activities |
| I | Accommodation and food service activities |
| J58 | Publishing activities |
| J59_60 | Motion picture, video, television programme production; programming and broadcasting activities |
| J61 | Telecommunications |
| J62_63 | Computer programming, consultancy, and information service activities |
| K64 | Financial service activities, except insurance and pension funding |
| K65 | Insurance, reinsurance and pension funding, except compulsory social security |
| K66 | Activities auxiliary to financial services and insurance activities |
| L | Real estate activities |
| M69_70 | Legal and accounting activities; activities of head offices; management consultancy activities |
| M71 | Architectural and engineering activities; technical testing and analysis |
| M72 | Scientific research and development |
| M73 | Advertising and market research |
| M74_75 | Other professional, scientific and technical activities; veterinary activities |
| N77 | Rental and leasing activities |
| N78 | Employment activities |
| N79 | Travel agency, tour operator and other reservation service and related activities |
| N80T82 | Security and investigation, service and landscape, office administrative and support activities |
| O84 | Public administration and defence; compulsory social security |
| P85 | Education |
| Q86 | Human health activities |
| Q87_88 | Residential care activities and social work activities without accommodation |
| R90T92 | Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities; gambling and betting activities |
| R93 | Sports activities and amusement and recreation activities |
| S94 | Activities of membership organisations |
| S95 | Repair of computers and personal and household goods |
| S96 | Other personal service activities |
| T | Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use |
| U | Activities of extraterritorial organisations and bodies |

Table 3.14: Classification of industrial sectors in the FIGARO IO tables.

| Codification | Products of industries |
|---|---|
| A01 | Products of agriculture, hunting and related services |
| A02 | Products of forestry, logging and related services |
| A03 | Fish and other fishing products; aquaculture products; support services to fishing |
| B | Mining and quarrying |
| C10T12 | Food, beverages and tobacco products |
| C13T15 | Textiles, wearing apparel, leather and related products |
| C16 | Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials |
| C17 | Paper and paper products |
| C18 | Printing and recording services |
| C19 | Coke and refined petroleum products |
| C20 | Chemicals and chemical products |
| C21 | Basic pharmaceutical products and pharmaceutical preparations |
| C22 | Rubber and plastic products |
| C23 | Other non-metallic mineral products |
| C24 | Basic metals |
| C25 | Fabricated metal products, except machinery and equipment |
| C26 | Computer, electronic and optical products |
| C27 | Electrical equipment |
| C28 | Machinery and equipment n.e.c. |
| C29 | Motor vehicles, trailers and semi-trailers |
| C30 | Other transport equipment |
| C31_32 | Furniture and other manufactured goods |
| C33 | Repair and installation services of machinery and equipment |
| D35 | Electricity, gas, steam and air conditioning |
| E36 | Natural water; water treatment and supply services |
| E37T39 | Sewerage services; sewage sludge; waste collection, treatment and disposal services; materials recovery services; remediation services and other waste management services |
| F | Constructions and construction works |
| G45 | Wholesale and retail trade and repair services of motor vehicles and motorcycles |
| G46 | Wholesale trade services, except of motor vehicles and motorcycles |
| G47 | Retail trade services, except of motor vehicles and motorcycles |
| H49 | Land transport services and transport services via pipelines |
| H50 | Water transport services |
| H51 | Air transport services |
| H52 | Warehousing and support services for transportation |
| H53 | Postal and courier services |
| I | Accommodation and food services |
| J58 | Publishing services |
| J59_60 | Motion picture, video and television programme production services, sound recording and music publishing; programming and broadcasting services |
| J61 | Telecommunications services |
| J62_63 | Computer programming, consultancy and related services; Information services |
| K64 | Financial services, except insurance and pension funding |
| K65 | Insurance, reinsurance and pension funding services, except compulsory social security |
| K66 | Services auxiliary to financial services and insurance services |
| L | Real estate services |
| M69_70 | Legal and accounting services; services of head offices; management consultancy services |
| M71 | Architectural and engineering services; technical testing and analysis services |
| M72 | Scientific research and development services |
| M73 | Advertising and market research services |
| M74_75 | Other professional, scientific and technical services and veterinary services |
| N77 | Rental and leasing services |
| N78 | Employment services |
| N79 | Travel agency, tour operator and other reservation services and related services |
| N80T82 | Security and investigation services; services to buildings and landscape; office administrative, office support and other business support services |
| O84 | Public administration and defence services; compulsory social security services |
| P85 | Education services |
| Q86 | Human health services |
| Q87_88 | Residential care services; social work services without accommodation |
| R90T92 | Creative, arts, entertainment, library, archive, museum, other cultural services; gambling and betting services |
| R93 | Sporting services and amusement and recreation services |
| S94 | Services furnished by membership organisations |
| S95 | Repair services of computers and personal and household goods |
| S96 | Other personal services |
| T | Services of households as employers; undifferentiated goods and services produced by households for own use |
| U | Services provided by extraterritorial organisations and bodies |

Table 3.15: Classification of products in the FIGARO IO tables.

| FIGARO IO Countries (EU-27) | |
|---|---|
| **Codification** | **Countries** |
| BE | Belgium |
| BG | Bulgaria |
| CZ | Czech Republic |
| DK | Denmark |
| DE | Germany |
| EE | Estonia |
| IE | Ireland |
| EL | Greece |
| ES | Spain |
| FR | France |
| HR | Croatia |
| IT | Italy |
| CY | Cyprus |
| LV | Latvia |
| LT | Lithuania |
| LU | Luxembourg |
| HU | Hungary |
| MT | Malta |
| NL | Netherlands |
| AT | Austria |
| PL | Poland |
| PT | Portugal |
| RO | Romania |
| SI | Slovenia |
| SK | Slovakia |
| FI | Finland |
| SE | Sweden |

Table 3.16: Geographical areas for European Countries (EU-27).

| FIGARO IO Countries (non-EU) | |
|---|---|
| **Codification** | **Countries** |
| AR | Argentina |
| AU | Australia |
| BR | Brazil |
| CA | Canada |
| CH | Switzerland |
| CN | China |
| ID | Indonesia |
| IN | India |
| JP | Japan |
| KR | South Korea |
| MX | Mexico |
| NO | Norway |
| RU | Russia |
| SA | Saudi Arabia |
| TR | Turkey |
| UK | United Kingdom |
| US | United States |
| ZA | South Africa |
| FIGW1 | Rest of the world |

Table 3.17: Extra-Ue geographical areas.

| Nace 2 Classification | Economic activity according to ATECO 2007 | Number of employed persons (in thousands) |
|---|---|---|
| A01 | Crop and animal production, hunting and related service activities | 886,3 |
| A02 | Forestry and logging | 31,7 |
| A03 | Fishing and aquaculture | 25,5 |
| B | Mining and quarrying | 18,9 |
| C10T12 | Manufacture of food products; beverages and tobacco products | 474 |
| C13T15 | Manufacture of textiles, wearing apparel, leather and related products | 464,7 |
| C16 | Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials | 98,3 |
| C17 | Manufacture of paper and paper products | 75,3 |
| C18 | Printing and reproduction of recorded media | 74,2 |
| C19 | Manufacture of coke and refined petroleum products | 14,1 |
| C20 | Manufacture of chemicals and chemical products | 113,6 |
| C21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations | 63,3 |
| C22 | Manufacture of rubber and plastic products | 189,9 |
| C23 | Manufacture of other non-metallic mineral products | 153,1 |
| C24 | Manufacture of basic metals | 120,8 |
| C25 | Manufacture of fabricated metal products, except machinery and equipment | 596 |
| C26 | Manufacture of computer, electronic and optical products | 104,8 |
| C27 | Manufacture of electrical equipment | 152,7 |
| C28 | Manufacture of machinery and equipment n.e.c. | 482,2 |
| C29 | Manufacture of motor vehicles, trailers and semi-trailers | 163,3 |
| C30 | Manufacture of other transport equipment | 98,9 |
| C31_32 | Manufacture of furniture; other manufacturing | 266,8 |
| C33 | Repair and installation of machinery and equipment | 164,7 |
| D35 | Electricity, gas, steam and air conditioning supply | 79,4 |
| E36 | Water collection, treatment and supply | 47,2 |
| E37T39 | Sewerage, waste management, remediation activities | 189,8 |
| F | Construction | 1732,5 |
| G45 | Wholesale and retail trade and repair of motor vehicles and motorcycles | 411,6 |
| G46 | Wholesale trade, except of motor vehicles and motorcycles | 1213 |
| G47 | Retail trade, except of motor vehicles and motorcycles | 2033,8 |
| H49 | Land transport and transport via pipelines | 609,1 |
| H50 | Water transport | 46,3 |
| H51 | Air transport | 11,2 |
| H52 | Warehousing and support activities for transportation | 424,8 |
| H53 | Postal and courier activities | 81,8 |
| I | Accommodation and food service activities | 1694,2 |
| J58 | Publishing activities | 36,7 |
| J59_60 | Motion picture, video, television programme production; programming and broadcasting activities | 57,3 |
| J61 | Telecommunications | 76,2 |
| J62_63 | Computer programming, consultancy, and information service activities | 483,9 |
| K64 | Financial service activities, except insurance and pension funding | 317,5 |
| K65 | Insurance, reinsurance and pension funding, except compulsory social security | 44,5 |
| K66 | Activities auxiliary to financial services and insurance activities | 261,4 |
| L | Real estate activities | 180,9 |
| M69_70 | Legal and accounting activities; activities of head offices; management consultancy activities | 882,6 |
| M71 | Architectural and engineering activities; technical testing and analysis | 370,5 |
| M72 | Scientific research and development | 128,9 |
| M73 | Advertising and market research | 90,8 |
| M74_75 | Other professional, scientific and technical activities; veterinary activities | 319,9 |
| N77 | Rental and leasing activities | 58,3 |
| N78 | Employment activities | 460 |
| N79 | Travel agency, tour operator and other reservation service and related activities | 48,4 |
| N80T82 | Security and investigation, service and landscape, office administrative and support activities | 1014,4 |
| O84 | Public administration and defence; compulsory social security | 1193 |
| P85 | Education | 1713,2 |
| Q86 | Human health activities | 1464,3 |
| Q87_88 | Residential care activities and social work activities without accommodation | 558,2 |
| R90T92 | Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities; gambling and betting activities | 186,5 |
| R93 | Sports activities and amusement and recreation activities | 178,3 |
| S94 | Activities of membership organisations | 145,8 |
| S95 | Repair of computers and personal and household goods | 48,3 |
| S96 | Other personal service activities | 546,4 |
| T | Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use | 1280,3 |
| U | Activities of extraterritorial organisations and bodies | 0 |

Table 3.18: Number of persons employed by economic sector in Italy. Reference year 2022. National accounts, Istat.

| Classification of internal combustion engine vehicles | Description | Classification of electric vehicles | Description |
|---|---|---|---|
| 870321 | Vehicles: with only spark-ignition internal combustion piston engine, cylinder capacity not over 1000cc | 870340 | Vehicles: with both spark-ignition internal combustion piston engine and electric motor for propulsion, incapable of being charged by plugging to external source of electric power |
| 870322 | Vehicles: with only spark-ignition internal combustion piston engine, cylinder capacity over 1000 but not over 1500cc | 870350 | Vehicles: with both compression-ignition internal combustion piston engine (diesel or semi-diesel) and electric motor for propulsion, incapable of being charged by plugging to external source of electric power |
| 870323 | Vehicles: with only spark-ignition internal combustion reciprocating piston engine, cylinder capacity over 1500 but not over 3000cc | 870360 | Vehicles: with both spark-ignition internal combustion piston engine and electric motor for propulsion, capable of being charged by plugging to external source of electric power |
| 870324 | Vehicles: with only spark-ignition internal combustion reciprocating piston engine, cylinder capacity over 3000cc | 870370 | Vehicles: with both compression-ignition internal combustion piston engine (diesel or semi-diesel) and electric motor for propulsion, capable of being charged by plugging to external source of electric power |
| 870331 | Vehicles: with only compression-ignition internal combustion piston engine (diesel or semi-diesel), cylinder capacity not over 1500cc | 870380 | Vehicles: with only electric motor for propulsion |
| 870332 | Vehicles: with only compression-ignition internal combustion piston engine (diesel or semi-diesel), cylinder capacity over 1500 but not over 2500cc | | |
| 870333 | Vehicles: with only compression-ignition internal combustion piston engine (diesel or semi-diesel), cylinder capacity over 2500cc | | |

Table 3.19: Categorisation of products sold by the automotive sector by type in accordance with BACI classes.

| Year | Electric vehicle production (thousands of units) | Total vehicle production (thousands of units) | Share of electric vehicle production |
|---|---|---|---|
| 2013 | 17.533 | 22.100.000 | 0,0008 |
| 2014 | 78.499 | 23.700.000 | 0,0033 |
| 2015 | 340.471 | 24.600.000 | 0,0138 |
| 2016 | 516.000 | 28.100.000 | 0,0184 |
| 2017 | 794.000 | 29.000.000 | 0,0274 |
| 2018 | 1.270.527 | 27.800.000 | 0,0457 |
| 2019 | 1.242.833 | 25.700.000 | 0,0484 |
| 2020 | 1.365.000 | 25.200.000 | 0,0542 |
| 2021 | 3.543.000 | 26.100.000 | 0,1357 |
| 2022 | 7.055.000 | 27.000.000 | 0,2613 |

Table 3.20: Data on electric vehicle production quotas for Chinese automotive manufacturing, reference years 2013–2022. Source: Statista and International Organisation of Motor Vehicle Manufacturers.

| Industries | China, C29 | Industries | China, C29 |
|---|---|---|---|
| A01 | 0,0005 | K65 | 0,0017 |
| A02 | 0,0002 | K66 | 0,0008 |
| A03 | 0 | L | 0,0043 |
| B | 0,0012 | M69_70 | 0,0055 |
| C10T12 | 0,0006 | M71 | 0,0039 |
| C13T15 | 0,0217 | M72 | 0,0039 |
| C16 | 0,0026 | M73 | 0,0033 |
| C17 | 0,0041 | M74_75 | 0,002 |
| C18 | 0,0016 | N77 | 0,0002 |
| C19 | 0,0054 | N78 | 0,0024 |
| C20 | 0,0267 | N79 | 0,0008 |
| C21 | 0,0002 | N80T82 | 0,002 |
| C22 | 0,0516 | O84 | 0,0004 |
| C23 | 0,0134 | P85 | 0 |
| C24 | 0,1204 | Q86 | 0,0022 |
| C25 | 0,0173 | Q87_88 | 0 |
| C26 | 0,0179 | R90T92 | 0,0001 |
| C27 | 0,0157 | R93 | 0 |
| C28 | 0,0349 | S94 | 0,0005 |
| C29 | 0,2739 | S95 | 0,002 |
| C30 | 0,0002 | S96 | 0,0008 |
| C31_32 | 0,0054 | T | 0 |
| C33 | 0,0006 | U | 0 |
| D35 | 0,0131 | | |
| E36 | 0,001 | | |
| E37T39 | 0,0011 | | |
| F | 0,0002 | | |
| G45 | 0,0321 | | |
| G46 | 0,0129 | | |
| G47 | 0,0055 | | |
| H49 | 0,0164 | | |
| H50 | 0,0085 | | |
| H51 | 0,0032 | | |
| H52 | 0,0035 | | |
| H53 | 0,0004 | | |
| I | 0,0045 | | |
| J58 | 0,0002 | | |
| J59_60 | 0,0001 | | |
| J61 | 0,0029 | | |
| J62_63 | 0,0017 | | |
| K64 | 0,0191 | | |

Table 3.21: Direct technical coefficients Use matrix for the Chinese automotive sector aggregated into 64 sectors, regardless of the country lending the intermediate good, reference period 2012.

| Products | Recipe for manufacturing internal combustion engine vehicles | Electric vehicle production recipe |
|---|---|---|
| A01 | 0,00 | 0,00 |
| A02 | 0,00 | 0,00 |
| A03 | 0,00 | 0,00 |
| B | 0,00 | 0,00 |
| C10T12 | 0,00 | 0,00 |
| C13T15 | 0,02 | 0,01 |
| C16 | 0,00 | 0,00 |
| C17 | 0,00 | 0,00 |
| C18 | 0,00 | 0,00 |
| C19 | 0,00 | 0,00 |
| C20 | 0,02 | 0,00 |
| C21 | 0,00 | 0,00 |
| C22 | 0,05 | 0,03 |
| C23 | 0,01 | 0,00 |
| C24 | 0,10 | 0,00 |
| C25 | 0,04 | 0,09 |
| C26 | 0,02 | 0,03 |
| C27 | 0,03 | 0,07 |
| C28 | 0,04 | 0,04 |
| C29 | 0,33 | 0,42 |
| C30 | 0,00 | 0,00 |
| C31_32 | 0,01 | 0,01 |
| C33 | 0,00 | 0,00 |
| D35 | 0,01 | 0,01 |
| E36 | 0,00 | 0,00 |
| E37T39 | 0,00 | 0,00 |
| F | 0,00 | 0,00 |
| G45 | 0,04 | 0,05 |
| G46 | 0,01 | 0,01 |
| G47 | 0,01 | 0,01 |
| H49 | 0,02 | 0,01 |
| H50 | 0,00 | 0,00 |
| H51 | 0,00 | 0,00 |
| H52 | 0,00 | 0,00 |
| H53 | 0,00 | 0,00 |
| I | 0,00 | 0,00 |
| J58 | 0,00 | 0,00 |
| J59_60 | 0,00 | 0,00 |
| J61 | 0,00 | 0,00 |
| J62_63 | 0,00 | 0,01 |
| K64 | 0,02 | 0,00 |
| K65 | 0,00 | 0,00 |
| K66 | 0,00 | 0,00 |
| L | 0,00 | 0,00 |
| M69_70 | 0,01 | 0,01 |
| M71 | 0,00 | 0,00 |
| M72 | 0,00 | 0,00 |
| M73 | 0,00 | 0,00 |
| M74_75 | 0,00 | 0,00 |
| N77 | 0,00 | 0,00 |
| N78 | 0,00 | 0,00 |
| N79 | 0,00 | 0,00 |
| N80T82 | 0,00 | 0,00 |
| O84 | 0,00 | 0,00 |
| P85 | 0,00 | 0,00 |
| Q86 | 0,00 | 0,00 |
| Q87_88 | 0,00 | 0,00 |
| R90T92 | 0,00 | 0,00 |
| R93 | 0,00 | 0,00 |
| S94 | 0,00 | 0,00 |
| S95 | 0,00 | 0,00 |
| S96 | 0,00 | 0,00 |
| T | 0,00 | 0,00 |
| U | 0,00 | 0,00 |

Table 3.22: Derivation of direct technical coefficients for production recipes for internal combustion and electric vehicles from the Use matrix for the Chinese automotive sector in 2022, considering adjustments and value-added components.

| Products | Recipe for manufacturing internal combustion engine vehicles | Electric vehicle production recipe |
|---|---|---|
| A01 | 0,00000 | 0,00000 |
| A02 | 0,00002 | 0,00000 |
| A03 | 0,00000 | 0,00000 |
| B | 0,00038 | 0,00080 |
| C10T12 | 0,00001 | 0,00008 |
| C13T15 | 0,00930 | 0,00853 |
| C16 | 0,00263 | 0,00330 |
| C17 | 0,00436 | 0,00193 |
| C18 | 0,00129 | 0,00088 |
| C19 | 0,00127 | 0,00000 |
| C20 | 0,01820 | 0,00000 |
| C21 | 0,00000 | 0,00008 |
| C22 | 0,05697 | 0,02518 |
| C23 | 0,01898 | 0,00185 |
| C24 | 0,05133 | 0,00418 |
| C25 | 0,13394 | 0,08430 |
| C26 | 0,01935 | 0,03137 |
| C27 | 0,03187 | 0,06507 |
| C28 | 0,05536 | 0,03716 |
| C29 | 0,12221 | 0,41609 |
| C30 | 0,00521 | 0,00040 |
| C31_32 | 0,00726 | 0,00740 |
| C33 | 0,00276 | 0,00080 |
| D35 | 0,00813 | 0,01126 |
| E36 | 0,00046 | 0,00008 |
| E37T39 | 0,01024 | 0,00024 |
| F | 0,00257 | 0,00121 |
| G45 | 0,03419 | 0,04786 |
| G46 | 0,03330 | 0,01215 |
| G47 | 0,00982 | 0,00837 |
| H49 | 0,02727 | 0,01432 |
| H50 | 0,00032 | 0,00000 |
| H51 | 0,00109 | 0,00000 |
| H52 | 0,00811 | 0,00282 |
| H53 | 0,00002 | 0,00121 |
| I | 0,00682 | 0,00000 |
| J58 | 0,00041 | 0,00024 |
| J59_60 | 0,00007 | 0,00008 |
| J61 | 0,00295 | 0,00000 |
| J62_63 | 0,00902 | 0,00579 |
| K64 | 0,00506 | 0,00056 |
| K65 | 0,00324 | 0,00064 |
| K66 | 0,00112 | 0,00024 |
| L | 0,00459 | 0,00209 |
| M69_70 | 0,01994 | 0,00563 |
| M71 | 0,04084 | 0,00000 |
| M72 | 0,02791 | 0,00450 |
| M73 | 0,00407 | 0,00282 |
| M74_75 | 0,00451 | 0,00008 |
| N77 | 0,00452 | 0,00370 |
| N78 | 0,00089 | 0,00467 |
| N79 | 0,00016 | 0,00064 |
| N80T82 | 0,00700 | 0,00145 |
| O84 | 0,00005 | 0,00000 |
| P85 | 0,00272 | 0,00072 |
| Q86 | 0,00001 | 0,00241 |
| Q87_88 | 0,00000 | 0,00000 |
| R90T92 | 0,00002 | 0,00000 |
| R93 | 0,00001 | 0,00008 |
| S94 | 0,00000 | 0,00000 |
| S95 | 0,00023 | 0,00097 |
| S96 | 0,00000 | 0,00000 |
| T | 0,00000 | 0,00000 |
| U | 0,00000 | 0,00000 |

Table 3.23: direct technical coefficients per production recipe for internal combustion and electric cars from the Use matrix for the Italian automotive sector in 2022 (The coefficients were calculated as the ratio between each cell value in the automotive column and the total production value (intermediate goods + adjustments and value added).

| Producer (Exporter) | Final Demand (Importer) | Type | Share |
|---|---|---|---|
| Austria | Extra-ue | BEV, PHEV, HEV | 0,11 |
| Austria | UE | BEV, PHEV, HEV | 0,23 |
| Austria | Extra-ue | ICEV | 0,89 |
| Austria | UE | ICEV | 0,77 |
| Belgium | Extra-ue | BEV, PHEV, HEV | 0,62 |
| Belgium | UE | BEV, PHEV, HEV | 0,60 |
| Belgium | Extra-ue | ICEV | 0,38 |
| Belgium | UE | ICEV | 0,40 |
| Bulgaria | Extra-ue | BEV, PHEV, HEV | 0,19 |
| Bulgaria | UE | BEV, PHEV, HEV | 0,53 |
| Bulgaria | Extra-ue | ICEV | 0,81 |
| Bulgaria | UE | ICEV | 0,47 |
| Croatia | Extra-ue | BEV, PHEV, HEV | 0,15 |
| Croatia | UE | BEV, PHEV, HEV | 0,09 |
| Croatia | Extra-ue | ICEV | 0,85 |
| Croatia | UE | ICEV | 0,91 |
| Cyprus | Extra-ue | BEV, PHEV, HEV | 0,35 |
| Cyprus | UE | BEV, PHEV, HEV | 0,18 |
| Cyprus | Extra-ue | ICEV | 0,65 |
| Cyprus | UE | ICEV | 0,82 |
| Czechia | Extra-ue | BEV, PHEV, HEV | 0,24 |
| Czechia | UE | BEV, PHEV, HEV | 0,31 |
| Czechia | Extra-ue | ICEV | 0,76 |
| Czechia | UE | ICEV | 0,69 |
| Denmark | Extra-ue | BEV, PHEV, HEV | 0,37 |
| Denmark | UE | BEV, PHEV, HEV | 0,18 |
| Denmark | Extra-ue | ICEV | 0,63 |
| Denmark | UE | ICEV | 0,82 |
| Estonia | Extra-ue | BEV, PHEV, HEV | 0,14 |
| Estonia | UE | BEV, PHEV, HEV | 0,20 |
| Estonia | Extra-ue | ICEV | 0,86 |
| Estonia | UE | ICEV | 0,80 |
| Finland | Extra-ue | BEV, PHEV, HEV | 0,09 |
| Finland | UE | BEV, PHEV, HEV | 0,20 |
| Finland | Extra-ue | ICEV | 0,91 |
| Finland | UE | ICEV | 0,80 |
| France | Extra-ue | BEV, PHEV, HEV | 0,33 |
| France | UE | BEV, PHEV, HEV | 0,34 |
| France | Extra-ue | ICEV | 0,67 |
| France | UE | ICEV | 0,66 |
| Germany | Extra-ue | BEV, PHEV, HEV | 0,38 |
| Germany | UE | BEV, PHEV, HEV | 0,45 |
| Germany | Extra-ue | ICEV | 0,62 |
| Germany | UE | ICEV | 0,55 |
| Greece | Extra-ue | BEV, PHEV, HEV | 0,29 |
| Greece | UE | BEV, PHEV, HEV | 0,07 |
| Greece | Extra-ue | ICEV | 0,71 |
| Greece | UE | ICEV | 0,93 |
| Hungary | Extra-ue | BEV, PHEV, HEV | 0,24 |
| Hungary | UE | BEV, PHEV, HEV | 0,34 |
| Hungary | Extra-ue | ICEV | 0,76 |
| Hungary | UE | ICEV | 0,66 |
| Ireland | Extra-ue | BEV, PHEV, HEV | 0,04 |
| Ireland | UE | BEV, PHEV, HEV | 0,09 |
| Ireland | Extra-ue | ICEV | 0,96 |
| Ireland | UE | ICEV | 0,91 |
| Italy | Extra-ue | BEV, PHEV, HEV | 0,11 |
| Italy | UE | BEV, PHEV, HEV | 0,24 |
| Italy | Extra-ue | ICEV | 0,89 |
| Italy | UE | ICEV | 0,76 |
| Latvia | Extra-ue | BEV, PHEV, HEV | 0,04 |
| Latvia | UE | BEV, PHEV, HEV | 0,11 |
| Latvia | Extra-ue | ICEV | 0,96 |
| Latvia | UE | ICEV | 0,89 |
| Lithuania | Extra-ue | BEV, PHEV, HEV | 0,12 |
| Lithuania | UE | BEV, PHEV, HEV | 0,11 |
| Lithuania | Extra-ue | ICEV | 0,88 |
| Lithuania | UE | ICEV | 0,89 |
| Luxembourg | Extra-ue | BEV, PHEV, HEV | 0,09 |
| Luxembourg | UE | BEV, PHEV, HEV | 0,10 |
| Luxembourg | Extra-ue | ICEV | 0,91 |
| Luxembourg | UE | ICEV | 0,90 |
| Malta | Extra-ue | BEV, PHEV, HEV | 0,26 |
| Malta | UE | BEV, PHEV, HEV | 0,01 |
| Malta | Extra-ue | ICEV | 0,74 |
| Malta | UE | ICEV | 0,99 |
| Netherlands | Extra-ue | BEV, PHEV, HEV | 0,14 |
| Netherlands | UE | BEV, PHEV, HEV | 0,50 |
| Netherlands | Extra-ue | ICEV | 0,86 |
| Netherlands | UE | ICEV | 0,50 |
| Poland | Extra-ue | BEV, PHEV, HEV | 0,14 |
| Poland | UE | BEV, PHEV, HEV | 0,36 |
| Poland | Extra-ue | ICEV | 0,86 |
| Poland | UE | ICEV | 0,64 |
| Portugal | Extra-ue | BEV, PHEV, HEV | 0,00 |
| Portugal | UE | BEV, PHEV, HEV | 0,00 |
| Portugal | Extra-ue | ICEV | 1,00 |
| Portugal | UE | ICEV | 1,00 |
| Romania | Extra-ue | BEV, PHEV, HEV | 0,13 |
| Romania | UE | BEV, PHEV, HEV | 0,11 |
| Romania | Extra-ue | ICEV | 0,87 |
| Romania | UE | ICEV | 0,89 |
| Slovakia | Extra-ue | BEV, PHEV, HEV | 0,39 |
| Slovakia | UE | BEV, PHEV, HEV | 0,38 |
| Slovakia | Extra-ue | ICEV | 0,61 |
| Slovakia | UE | ICEV | 0,62 |
| Slovenia | Extra-ue | BEV, PHEV, HEV | 0,33 |
| Slovenia | UE | BEV, PHEV, HEV | 0,47 |
| Slovenia | Extra-ue | ICEV | 0,67 |
| Slovenia | UE | ICEV | 0,53 |
| Spain | Extra-ue | BEV, PHEV, HEV | 0,17 |
| Spain | UE | BEV, PHEV, HEV | 0,29 |
| Spain | Extra-ue | ICEV | 0,83 |
| Spain | UE | ICEV | 0,71 |
| Sweden | Extra-ue | BEV, PHEV, HEV | 0,36 |
| Sweden | UE | BEV, PHEV, HEV | 0,46 |
| Sweden | Extra-ue | ICEV | 0,64 |
| Sweden | UE | ICEV | 0,54 |

Table 3.24: Car sales share for European manufacturers by type and market, derived and calculated from the BACI 2022 database.

| Year | New registration |
|---|---|
| 2022 | 15,365 |
| 2021 | 17,227 |
| 2020 | 17,15 |
| 2019 | 17,885 |
| 2018 | 17,643 |
| 2017 | 17,543 |
| 2016 | 16,968 |
| 2015 | 15,793 |
| 2014 | 14,401 |
| 2013 | 13,563 |
| 2012 | 13,749 |

Table 3.25: Number of vehicle registrations in Europe, expressed in thousands. Data from Acea Pocket Guide Automotive.

### 3.A.2 Activation Rounds

Following Equation 3.1, each component of the LHS represents the impact of the scenario on C29's direct suppliers, on suppliers of those suppliers, and so on, allowing a comparison with the 'business as usual' scenario to identify which supplying sectors are most affected in each round in terms of employment and value added. Focusing on the initial activation rounds 1–3, where the largest absorption of the shock occurs, several regular patterns emerge. The manufacturing core consistently constitutes the primary origin of damage: component and mechanical/electrical supply sectors—most notably fabricated metal products, basic metals, rubber and plastic products, and other non-metallic mineral products—rank among the most affected in the initial rounds, as they are the direct or indirect suppliers losing automotive demand. Intermediation and support services amplify this effect; wholesale trade, land transport and warehousing, construction, real estate and professional services (legal, accounting, head-office activities, engineering and R&D) repeatedly appear among the most impacted sectors in rounds 2–3, reflecting the classic multiplier transmission whereby demand losses in manufacturing inputs translate into reduced distributive activity, real-estate transactions and business services. In some scenarios—particularly Scenario 2—very localized positive effects are observed: immediate net gains emerge in electrical equipment, motor vehicles (due to reclassification or assembling) and vehicle sales/repair, mirroring the alternative recipe that reallocates productive content toward these sectors or turns them into integration hubs; however, such increases are often insufficient to offset aggregate losses. Finally, the intensity of impacts depends heavily on the demand component: scenarios that include a large reduction in demand (S3–S5) produce more widespread and deeper effects on labour-intensive and high value-added services, since a smaller market scale erodes potential gains for sectors that might otherwise benefit from the transition.

| Industry | Round 0 | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 | Round 6 | Round 7 | Round 8 | Round 9 | Round 10 | Total | Δ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A01 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.00) | -0.01 (-0.02) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,03 | (-0.02) |
| A02 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.00) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.02) |
| A03 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.02) |
| B | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.01) |
| C10T12 | 0.00 (0.00) | -0.00 (-0.00) | -0.00 (-0.01) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| C13T15 | 0.00 (0.00) | -0.00 (-0.00) | -0.01 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,02 | (-0.01) |
| C16 | 0.00 (0.00) | -0.00 (-0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| C17 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| C18 | 0.00 (0.00) | -0.00 (-0.01) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.01) |
| C19 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.01) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.02) |
| C20 | 0.00 (0.00) | -0.00 (-0.00) | -0.01 (-0.03) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| C21 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.01) |
| C22 | 0.00 (0.00) | -0.01 (-0.00) | -0.04 (-0.05) | -0.01 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0,06 | (-0.02) |
| C23 | 0.00 (0.00) | -0.00 (-0.00) | -0.02 (-0.04) | -0.01 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,03 | (-0.02) |
| C24 | 0.00 (0.00) | -0.00 (-0.00) | -0.03 (-0.04) | -0.01 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0,04 | (-0.02) |
| C25 | 0.00 (0.00) | -0.06 (-0.00) | -0.16 (-0.04) | -0.05 (-0.04) | -0.02 (-0.04) | -0.01 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0,3 | (-0.01) |
| C26 | 0.00 (0.00) | -0.04 (-0.15) | -0.01 (-0.06) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0,06 | (-0.09) |
| C27 | 0.00 (0.00) | -0.76 (-0.70) | -0.05 (-0.17) | -0.01 (-0.10) | -0.00 (-0.07) | -0.00 (-0.06) | -0.00 (-0.05) | -0.00 (-0.05) | -0.00 (-0.05) | -0.00 (-0.05) | -0.00 (-0.05) | -0,83 | (-0.28) |
| C28 | 0.00 (0.00) | -0.07 (-0.05) | -0.02 (-0.04) | -0.01 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.03) | -0.00 (-0.03) | -0,1 | (-0.02) |
| C29 | 0.00 (0.00) | -0.38 (-0.36) | -0.02 (-0.04) | -0.01 (-0.07) | -0.00 (-0.05) | -0.00 (-0.05) | -0.00 (-0.05) | -0.00 (-0.05) | -0.00 (-0.05) | -0.00 (-0.05) | -0.00 (-0.05) | -0,41 | (-0.01) |
| C30 | 0.00 (0.00) | -0.00 (-0.01) | -0.00 (-0.05) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.01) |
| C31_32 | 0.00 (0.00) | -0.00 (-0.00) | -0.01 (-0.03) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,02 | (-0.01) |
| C33 | 0.00 (0.00) | -0.02 (-0.03) | -0.01 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0,04 | (-0.03) |
| D35 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| E36 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.04) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.02) |
| E37T39 | 0.00 (0.00) | 0.00 (0.00) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,03 | (-0.02) |
| F | 0.00 (0.00) | -0.00 (-0.00) | -0.02 (-0.02) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,06 | (-0.01) |
| G45 | 0.00 (0.00) | -0.02 (-0.00) | -0.05 (-0.08) | -0.01 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0,09 | (-0.01) |
| G46 | 0.00 (0.00) | -0.00 (-0.00) | -0.09 (-0.04) | -0.03 (-0.04) | -0.02 (-0.04) | -0.01 (-0.04) | -0.00 (-0.04) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,15 | (-0.02) |
| G47 | 0.00 (0.00) | -0.00 (-0.00) | -0.04 (-0.05) | -0.01 (-0.04) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,07 | (-0.02) |
| H49 | 0.00 (0.00) | 0.00 (0.00) | -0.04 (-0.03) | -0.03 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,09 | (-0.02) |
| H50 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.02) |
| H51 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.02) |
| H52 | 0.00 (0.00) | 0.00 (0.00) | -0.02 (-0.02) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,06 | (-0.02) |
| H53 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.01) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| I | 0.00 (0.00) | 0.00 (0.00) | -0.02 (-0.02) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,08 | (-0.02) |
| J58 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.01) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.02) |
| J59_60 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.01) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.02) |
| J61 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| J62_63 | 0.00 (0.00) | 0.00 (0.00) | -0.02 (-0.02) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,05 | (-0.02) |
| K64 | 0.00 (0.00) | 0.00 (0.00) | -0.01 (-0.02) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,04 | (-0.02) |
| K65 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.02) |
| K66 | 0.00 (0.00) | 0.00 (0.00) | -0.01 (-0.02) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,03 | (-0.02) |
| L | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| M69_70 | 0.00 (0.00) | 0.00 (0.00) | -0.06 (-0.02) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,14 | (-0.02) |
| M71 | 0.00 (0.00) | 0.00 (0.00) | -0.05 (-0.05) | -0.02 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,08 | (-0.01) |
| M72 | 0.00 (0.00) | 0.00 (0.00) | -0.01 (-0.11) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0,01 | (-0.01) |
| M73 | 0.00 (0.00) | -0.00 (-0.00) | -0.01 (-0.02) | -0.00 (-0.04) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| M74_75 | 0.00 (0.00) | -0.00 (-0.00) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,05 | (-0.02) |
| N77 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| N78 | 0.00 (0.00) | 0.00 (0.00) | -0.04 (-0.02) | -0.03 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,08 | (-0.02) |
| N79 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.07) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.04) |
| N80T82 | 0.00 (0.00) | -0.00 (-0.00) | -0.04 (-0.02) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,12 | (-0.02) |
| O84 | 0.00 (0.00) | 0.00 (0.00) | -0.01 (-0.02) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,02 | (-0.02) |
| P85 | 0.00 (0.00) | 0.00 (0.00) | -0.01 (-0.02) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,02 | (-0.02) |
| Q86 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.02) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.01) |
| Q87_88 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| R90T92 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.01) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| R93 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.01) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| S94 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.01) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.02) |
| S95 | 0.00 (0.00) | -0.01 (-0.12) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,01 | (-0.05) |
| S96 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.00) | -0.00 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | 0 | (-0.02) |
| T | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (-0.00) |
| U | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | | (0.00) |
| Total | | | | | | | | | | | | -3,44 | (-0.02) |

Table 3.26: Change in the quantity of labour (in thousands of units) in Scenario 1 relative to the 'business as usual' scenario, by activation round. Each round corresponds to a term in the summation of Equation 3.1. Round zero denotes the variation in the final-demand vector for sector C29 only. The first round indicates the effect on suppliers closest to the automotive supply chain, the second round the effect on suppliers of those suppliers, and so forth. The last column reports the cumulative effect for each sector. Decimal points are shown in parentheses.

| Industry | Round 0 | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 | Round 6 | Round 7 | Round 8 | Round 9 | Round 10 | Total Δ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A01 | 0.00 (0.00) | 0.00 (0.00) | -0.10 (-0.00) | -0.36 (-0.02) | -0.28 (-0.03) | -0.17 (-0.03) | -0.09 (-0.03) | -0.05 (-0.03) | -0.03 (-0.03) | -0.03 (-0.03) | -0.03 (-0.03) | -1,1 | (-0.02) |
| A02 | 0.00 (0.00) | 0.00 (0.00) | -0.01 (-0.00) | -0.03 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,07 | (-0.02) |
| A03 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.00) | -0.01 (-0.02) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,02 | (-0.02) |
| B | 0.00 (0.00) | 0.00 (0.00) | -0.32 (-0.02) | -0.23 (-0.03) | -0.12 (-0.03) | -0.06 (-0.03) | -0.03 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,8 | (-0.01) |
| C10T12 | 0.00 (0.00) | -0.00 (-0.00) | -0.07 (-0.01) | -0.19 (-0.02) | -0.14 (-0.03) | -0.08 (-0.03) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,57 | (-0.02) |
| C13T15 | 0.00 (0.00) | -0.01 (-0.00) | -0.41 (-0.02) | -0.22 (-0.03) | -0.11 (-0.03) | -0.05 (-0.03) | -0.03 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,85 | (-0.01) |
| C16 | 0.00 (0.00) | -0.03 (-0.00) | -0.23 (-0.02) | -0.16 (-0.03) | -0.08 (-0.03) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,58 | (-0.02) |
| C17 | 0.00 (0.00) | 0.00 (0.00) | -0.44 (-0.03) | -0.25 (-0.03) | -0.14 (-0.03) | -0.07 (-0.03) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,97 | (-0.02) |
| C18 | 0.00 (0.00) | -0.11 (-0.01) | -0.21 (-0.02) | -0.20 (-0.03) | -0.12 (-0.03) | -0.06 (-0.03) | -0.03 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,77 | (-0.01) |
| C19 | 0.00 (0.00) | 0.00 (0.00) | -0.01 (-0.01) | -0.04 (-0.02) | -0.03 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,11 | (-0.02) |
| C20 | 0.00 (0.00) | -0.06 (-0.00) | -0.78 (-0.03) | -0.50 (-0.04) | -0.21 (-0.04) | -0.10 (-0.03) | -0.05 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -1,75 | (-0.02) |
| C21 | 0.00 (0.00) | 0.00 (0.00) | -0.11 (-0.03) | -0.05 (-0.03) | -0.03 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,21 | (-0.01) |
| C22 | 0.00 (0.00) | -0.43 (-0.00) | -3.17 (-0.05) | -0.90 (-0.04) | -0.33 (-0.04) | -0.14 (-0.04) | -0.06 (-0.04) | -0.03 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -5,08 | (-0.02) |
| C23 | 0.00 (0.00) | -0.20 (-0.00) | -1.34 (-0.04) | -0.49 (-0.04) | -0.21 (-0.04) | -0.09 (-0.04) | -0.05 (-0.04) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -2,43 | (-0.02) |
| C24 | 0.00 (0.00) | -0.15 (-0.00) | -2.44 (-0.04) | -1.01 (-0.04) | -0.38 (-0.04) | -0.15 (-0.04) | -0.06 (-0.04) | -0.03 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -4,25 | (-0.02) |
| C25 | 0.00 (0.00) | -4.12 (-0.00) | -10.76 (-0.04) | -3.36 (-0.04) | -1.19 (-0.04) | -0.45 (-0.04) | -0.19 (-0.04) | -0.09 (-0.04) | -0.04 (-0.04) | -0.04 (-0.04) | -0.04 (-0.04) | -20,25 | (-0.01) |
| C26 | 0.00 (0.00) | -4.51 (-0.15) | -0.81 (-0.06) | -0.25 (-0.04) | -0.10 (-0.04) | -0.05 (-0.04) | -0.02 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -5,77 | (-0.09) |
| C27 | 0.00 (0.00) | -66.95 (-0.70) | -4.31 (-0.17) | -0.92 (-0.10) | -0.27 (-0.07) | -0.11 (-0.06) | -0.05 (-0.05) | -0.02 (-0.05) | -0.01 (-0.05) | -0.01 (-0.05) | -0.01 (-0.05) | -72,66 | (-0.28) |
| C28 | 0.00 (0.00) | -5.90 (-0.05) | -1.88 (-0.04) | -0.82 (-0.04) | -0.33 (-0.04) | -0.14 (-0.04) | -0.07 (-0.04) | -0.03 (-0.04) | -0.02 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -9,21 | (-0.02) |
| C29 | 0.00 (0.00) | -29.20 (-0.36) | -1.24 (-0.04) | -0.51 (-0.07) | -0.14 (-0.05) | -0.06 (-0.05) | -0.03 (-0.05) | -0.01 (-0.05) | -0.01 (-0.05) | -0.01 (-0.05) | -0.01 (-0.05) | -31,2 | (-0.01) |
| C30 | 0.00 (0.00) | -0.23 (-0.01) | -0.32 (-0.05) | -0.10 (-0.04) | -0.04 (-0.04) | -0.02 (-0.04) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,73 | (-0.01) |
| C31_32 | 0.00 (0.00) | -0.17 (-0.00) | -0.47 (-0.03) | -0.22 (-0.04) | -0.10 (-0.04) | -0.04 (-0.04) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -1,05 | (-0.01) |
| C33 | 0.00 (0.00) | -1.04 (-0.03) | -0.65 (-0.04) | -0.23 (-0.04) | -0.10 (-0.04) | -0.05 (-0.04) | -0.02 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -2,12 | (-0.03) |
| D35 | 0.00 (0.00) | 0.00 (0.00) | -2.20 (-0.02) | -2.21 (-0.03) | -1.54 (-0.03) | -0.95 (-0.03) | -0.55 (-0.03) | -0.30 (-0.03) | -0.17 (-0.03) | -0.17 (-0.03) | -0.17 (-0.03) | -8,11 | (-0.02) |
| E36 | 0.00 (0.00) | 0.00 (0.00) | -0.23 (-0.03) | -0.15 (-0.03) | -0.07 (-0.03) | -0.04 (-0.03) | -0.02 (-0.04) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,53 | (-0.02) |
| E37T39 | 0.00 (0.00) | 0.00 (0.00) | -1.01 (-0.03) | -0.60 (-0.03) | -0.30 (-0.04) | -0.15 (-0.04) | -0.07 (-0.04) | -0.03 (-0.04) | -0.02 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -2,2 | (-0.02) |
| F | 0.00 (0.00) | -0.12 (-0.00) | -1.38 (-0.02) | -0.95 (-0.03) | -0.55 (-0.03) | -0.29 (-0.03) | -0.15 (-0.03) | -0.07 (-0.03) | -0.04 (-0.03) | -0.04 (-0.03) | -0.04 (-0.03) | -3,58 | (-0.01) |
| G45 | 0.00 (0.00) | -0.93 (-0.00) | -2.70 (-0.08) | -0.48 (-0.04) | -0.19 (-0.04) | -0.08 (-0.04) | -0.04 (-0.04) | -0.02 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -4,45 | (-0.01) |
| G46 | 0.00 (0.00) | -0.36 (-0.00) | -7.53 (-0.04) | -2.89 (-0.04) | -1.32 (-0.04) | -0.62 (-0.04) | -0.30 (-0.04) | -0.15 (-0.03) | -0.07 (-0.03) | -0.07 (-0.03) | -0.07 (-0.03) | -13,32 | (-0.02) |
| G47 | 0.00 (0.00) | -0.12 (-0.00) | -1.95 (-0.05) | -0.66 (-0.04) | -0.31 (-0.03) | -0.15 (-0.03) | -0.07 (-0.03) | -0.04 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -3,34 | (-0.02) |
| H49 | 0.00 (0.00) | 0.00 (0.00) | -3.05 (-0.03) | -2.16 (-0.03) | -1.18 (-0.03) | -0.61 (-0.03) | -0.31 (-0.03) | -0.16 (-0.03) | -0.08 (-0.03) | -0.08 (-0.03) | -0.08 (-0.03) | -7,64 | (-0.02) |
| H50 | 0.00 (0.00) | 0.00 (0.00) | -0.05 (-0.02) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,13 | (-0.02) |
| H51 | 0.00 (0.00) | 0.00 (0.00) | -0.03 (-0.02) | -0.03 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,09 | (-0.02) |
| H52 | 0.00 (0.00) | 0.00 (0.00) | -2.28 (-0.02) | -1.76 (-0.03) | -0.94 (-0.03) | -0.47 (-0.03) | -0.24 (-0.03) | -0.12 (-0.03) | -0.06 (-0.03) | -0.06 (-0.03) | -0.06 (-0.03) | -5,92 | (-0.02) |
| H53 | 0.00 (0.00) | 0.00 (0.00) | -0.06 (-0.01) | -0.13 (-0.03) | -0.09 (-0.03) | -0.05 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,38 | (-0.02) |
| I | 0.00 (0.00) | 0.00 (0.00) | -0.83 (-0.02) | -0.86 (-0.03) | -0.49 (-0.03) | -0.25 (-0.03) | -0.13 (-0.03) | -0.06 (-0.03) | -0.03 (-0.03) | -0.03 (-0.03) | -0.03 (-0.03) | -2,69 | (-0.02) |
| J58 | 0.00 (0.00) | 0.00 (0.00) | -0.02 (-0.01) | -0.06 (-0.02) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,16 | (-0.02) |
| J59_60 | 0.00 (0.00) | 0.00 (0.00) | -0.05 (-0.01) | -0.10 (-0.02) | -0.07 (-0.03) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,28 | (-0.02) |
| J61 | 0.00 (0.00) | 0.00 (0.00) | -0.63 (-0.02) | -0.50 (-0.03) | -0.27 (-0.03) | -0.13 (-0.03) | -0.06 (-0.03) | -0.03 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -1,65 | (-0.02) |
| J62_63 | 0.00 (0.00) | 0.00 (0.00) | -1.48 (-0.02) | -1.00 (-0.03) | -0.56 (-0.03) | -0.29 (-0.03) | -0.15 (-0.03) | -0.07 (-0.03) | -0.04 (-0.03) | -0.04 (-0.03) | -0.04 (-0.03) | -3,62 | (-0.02) |
| K64 | 0.00 (0.00) | 0.00 (0.00) | -2.22 (-0.02) | -1.68 (-0.03) | -0.92 (-0.03) | -0.46 (-0.03) | -0.23 (-0.03) | -0.11 (-0.03) | -0.06 (-0.03) | -0.06 (-0.03) | -0.06 (-0.03) | -5,74 | (-0.02) |
| K65 | 0.00 (0.00) | 0.00 (0.00) | -0.19 (-0.02) | -0.18 (-0.03) | -0.09 (-0.03) | -0.05 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,56 | (-0.02) |
| K66 | 0.00 (0.00) | 0.00 (0.00) | -0.63 (-0.02) | -0.61 (-0.03) | -0.34 (-0.03) | -0.17 (-0.03) | -0.08 (-0.03) | -0.04 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -1,91 | (-0.02) |
| L | 0.00 (0.00) | 0.00 (0.00) | -2.94 (-0.02) | -2.63 (-0.03) | -1.31 (-0.03) | -0.65 (-0.03) | -0.32 (-0.03) | -0.16 (-0.03) | -0.08 (-0.03) | -0.08 (-0.03) | -0.08 (-0.03) | -8,18 | (-0.02) |
| M69_70 | 0.00 (0.00) | 0.00 (0.00) | -3.86 (-0.02) | -2.67 (-0.03) | -1.41 (-0.03) | -0.71 (-0.03) | -0.35 (-0.03) | -0.17 (-0.03) | -0.09 (-0.03) | -0.09 (-0.03) | -0.09 (-0.03) | -9,36 | (-0.02) |
| M71 | 0.00 (0.00) | 0.00 (0.00) | -2.80 (-0.05) | -0.87 (-0.03) | -0.44 (-0.03) | -0.21 (-0.03) | -0.11 (-0.03) | -0.05 (-0.03) | -0.03 (-0.03) | -0.03 (-0.03) | -0.03 (-0.03) | -4,54 | (-0.01) |
| M72 | 0.00 (0.00) | 0.00 (0.00) | -1.74 (-0.11) | -0.23 (-0.04) | -0.09 (-0.04) | -0.04 (-0.04) | -0.02 (-0.04) | -0.01 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -2,14 | (-0.01) |
| M73 | 0.00 (0.00) | -0.02 (-0.00) | -0.32 (-0.02) | -0.25 (-0.04) | -0.11 (-0.03) | -0.05 (-0.03) | -0.03 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,8 | (-0.02) |
| M74_75 | 0.00 (0.00) | -0.01 (-0.00) | -0.96 (-0.03) | -0.59 (-0.03) | -0.31 (-0.03) | -0.16 (-0.03) | -0.08 (-0.03) | -0.04 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -2,18 | (-0.02) |
| N77 | 0.00 (0.00) | 0.00 (0.00) | -0.41 (-0.02) | -0.40 (-0.03) | -0.22 (-0.03) | -0.11 (-0.03) | -0.06 (-0.03) | -0.03 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -1,26 | (-0.02) |
| N78 | 0.00 (0.00) | 0.00 (0.00) | -1.23 (-0.02) | -0.83 (-0.04) | -0.37 (-0.04) | -0.17 (-0.04) | -0.08 (-0.04) | -0.04 (-0.04) | -0.02 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -2,76 | (-0.02) |
| N79 | 0.00 (0.00) | 0.00 (0.00) | -0.09 (-0.07) | -0.03 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,15 | (-0.04) |
| N80T82 | 0.00 (0.00) | -0.00 (-0.00) | -1.39 (-0.02) | -1.42 (-0.03) | -0.76 (-0.03) | -0.38 (-0.03) | -0.19 (-0.03) | -0.09 (-0.03) | -0.05 (-0.03) | -0.05 (-0.03) | -0.05 (-0.03) | -4,35 | (-0.02) |
| O84 | 0.00 (0.00) | 0.00 (0.00) | -0.87 (-0.02) | -0.66 (-0.03) | -0.37 (-0.03) | -0.19 (-0.03) | -0.09 (-0.03) | -0.05 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -0.02 (-0.03) | -2,27 | (-0.02) |
| P85 | 0.00 (0.00) | 0.00 (0.00) | -0.43 (-0.02) | -0.30 (-0.03) | -0.16 (-0.03) | -0.08 (-0.03) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -1,04 | (-0.02) |
| Q86 | 0.00 (0.00) | 0.00 (0.00) | -0.11 (-0.02) | -0.11 (-0.02) | -0.08 (-0.03) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,37 | (-0.01) |
| Q87_88 | 0.00 (0.00) | 0.00 (0.00) | -0.01 (-0.00) | -0.11 (-0.02) | -0.08 (-0.03) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,3 | (-0.02) |
| R90T92 | 0.00 (0.00) | 0.00 (0.00) | -0.11 (-0.01) | -0.15 (-0.02) | -0.11 (-0.03) | -0.06 (-0.03) | -0.03 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,51 | (-0.02) |
| R93 | 0.00 (0.00) | 0.00 (0.00) | -0.13 (-0.01) | -0.16 (-0.02) | -0.11 (-0.03) | -0.06 (-0.03) | -0.03 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0,52 | (-0.02) |
| S94 | 0.00 (0.00) | 0.00 (0.00) | -0.09 (-0.01) | -0.09 (-0.03) | -0.06 (-0.03) | -0.03 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,3 | (-0.02) |
| S95 | 0.00 (0.00) | -0.19 (-0.12) | -0.05 (-0.02) | -0.03 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,31 | (-0.05) |
| S96 | 0.00 (0.00) | 0.00 (0.00) | -0.01 (-0.00) | -0.06 (-0.02) | -0.04 (-0.03) | -0.02 (-0.03) | -0.01 (-0.03) | -0.01 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0.00 (-0.03) | -0,15 | (-0.02) |
| T | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| U | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| Total | | | | | | | | | | | | -270,36 | (-0.02) |

Table 3.27: Change in the value added (in millions of euros) in Scenario 1 relative to the 'business as usual' scenario, by activation round. Each round corresponds to a term in the summation of Equation 3.1. Round zero denotes the variation in the final-demand vector for sector C29 only. The first round indicates the effect on suppliers closest to the automotive supply chain, the second round the effect on suppliers of those suppliers, and so forth. The last column reports the cumulative effect for each sector. Decimal points are shown in parentheses.

| Industry | Round 0 | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 | Round 6 | Round 7 | Round 8 | Round 9 | Round 10 | Total Δ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A01 | 0.00 (0.00) | 0.00 (0.03) | -0.23 (-0.46) | -0.15 (-0.40) | -0.09 (-0.36) | -0.04 (-0.33) | -0.02 (-0.30) | -0.01 (-0.26) | -0.00 (-0.23) | -0.00 (-0.23) | -0.00 (-0.23) | -0,54 | (-0.37) |
| A02 | 0.00 (0.00) | -0.01 (-0.65) | -0.01 (-0.30) | -0.00 (-0.34) | -0.00 (-0.32) | -0.00 (-0.28) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.19) | -0.00 (-0.19) | -0.00 (-0.19) | -0,02 | (-0.36) |
| A03 | 0.00 (0.00) | 0.00 (0.00) | -0.00 (-0.50) | -0.00 (-0.41) | -0.00 (-0.37) | -0.00 (-0.34) | -0.00 (-0.30) | -0.00 (-0.26) | -0.00 (-0.23) | -0.00 (-0.23) | -0.00 (-0.23) | -0,01 | (-0.4) |
| B | 0.00 (0.00) | -0.07 (-0.86) | -0.03 (-0.64) | -0.01 (-0.47) | -0.00 (-0.37) | -0.00 (-0.31) | -0.00 (-0.27) | -0.00 (-0.23) | -0.00 (-0.20) | -0.00 (-0.20) | -0.00 (-0.20) | -0,11 | (-0.68) |
| C10T12 | 0.00 (0.00) | -0.05 (-0.64) | -0.07 (-0.49) | -0.05 (-0.41) | -0.03 (-0.37) | -0.01 (-0.33) | -0.01 (-0.29) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | -0,21 | (-0.44) |
| C13T15 | 0.00 (0.00) | -0.16 (-0.16) | -0.07 (-0.19) | -0.03 (-0.18) | -0.01 (-0.16) | -0.00 (-0.13) | -0.00 (-0.10) | -0.00 (-0.07) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.04) | -0,27 | (-0.17) |
| C16 | 0.00 (0.00) | 0.01 (0.05) | -0.05 (-0.29) | -0.03 (-0.31) | -0.01 (-0.30) | -0.01 (-0.27) | -0.00 (-0.24) | -0.00 (-0.21) | -0.00 (-0.18) | -0.00 (-0.18) | -0.00 (-0.18) | -0,09 | (-0.14) |
| C17 | 0.00 (0.00) | -0.07 (-0.46) | -0.07 (-0.45) | -0.03 (-0.38) | -0.02 (-0.33) | -0.01 (-0.29) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.19) | -0.00 (-0.19) | -0.00 (-0.19) | -0,2 | (-0.41) |
| C18 | 0.00 (0.00) | -0.07 (-0.26) | -0.09 (-0.45) | -0.05 (-0.40) | -0.02 (-0.36) | -0.01 (-0.33) | -0.00 (-0.29) | -0.00 (-0.26) | -0.00 (-0.24) | -0.00 (-0.24) | -0.00 (-0.24) | -0,25 | (-0.25) |
| C19 | 0.00 (0.00) | -0.00 (-0.42) | -0.01 (-0.48) | -0.00 (-0.39) | -0.00 (-0.33) | -0.00 (-0.29) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.19) | -0.00 (-0.19) | -0.00 (-0.19) | -0,02 | (-0.39) |
| C20 | 0.00 (0.00) | -0.21 (-0.74) | -0.11 (-0.43) | -0.03 (-0.32) | -0.01 (-0.23) | -0.00 (-0.18) | -0.00 (-0.14) | -0.00 (-0.10) | -0.00 (-0.08) | -0.00 (-0.08) | -0.00 (-0.08) | -0,37 | (-0.51) |
| C21 | 0.00 (0.00) | -0.04 (-0.78) | -0.01 (-0.44) | -0.00 (-0.35) | -0.00 (-0.27) | -0.00 (-0.21) | -0.00 (-0.16) | -0.00 (-0.12) | -0.00 (-0.09) | -0.00 (-0.09) | -0.00 (-0.09) | -0,06 | (-0.6) |
| C22 | 0.00 (0.00) | -1.26 (-0.50) | -0.23 (-0.32) | -0.06 (-0.26) | -0.02 (-0.22) | -0.01 (-0.19) | -0.00 (-0.17) | -0.00 (-0.15) | -0.00 (-0.13) | -0.00 (-0.13) | -0.00 (-0.13) | -1,59 | (-0.4) |
| C23 | 0.00 (0.00) | -1.02 (-0.84) | -0.23 (-0.58) | -0.07 (-0.44) | -0.02 (-0.35) | -0.01 (-0.29) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.19) | -0.00 (-0.19) | -0.00 (-0.19) | -1,37 | (-0.71) |
| C24 | 0.00 (0.00) | -0.68 (-0.68) | -0.23 (-0.39) | -0.06 (-0.26) | -0.01 (-0.15) | -0.00 (-0.06) | -0.00 (-0.01) | 0.00 (0.02) | 0.00 (0.04) | 0.00 (0.04) | 0.00 (0.04) | -0,99 | (-0.48) |
| C25 | 0.00 (0.00) | -4.37 (-0.32) | -0.97 (-0.27) | -0.25 (-0.22) | -0.07 (-0.17) | -0.02 (-0.14) | -0.01 (-0.12) | -0.00 (-0.10) | -0.00 (-0.09) | -0.00 (-0.09) | -0.00 (-0.09) | -5,7 | (-0.24) |
| C26 | 0.00 (0.00) | -0.01 (-0.04) | -0.03 (-0.22) | -0.01 (-0.17) | -0.00 (-0.18) | -0.00 (-0.18) | -0.00 (-0.17) | -0.00 (-0.16) | -0.00 (-0.14) | -0.00 (-0.14) | -0.00 (-0.14) | -0,06 | (-0.09) |
| C27 | 0.00 (0.00) | 0.70 (0.65) | 0.06 (0.19) | 0.01 (0.11) | 0.00 (0.05) | 0.00 (0.01) | -0.00 (-0.01) | -0.00 (-0.02) | -0.00 (-0.02) | -0.00 (-0.02) | -0.00 (-0.02) | 0,77 | (0.26) |
| C28 | 0.00 (0.00) | -0.33 (-0.24) | -0.08 (-0.14) | -0.02 (-0.09) | -0.01 (-0.06) | -0.00 (-0.04) | -0.00 (-0.04) | -0.00 (-0.03) | -0.00 (-0.02) | -0.00 (-0.02) | -0.00 (-0.02) | -0,44 | (-0.07) |
| C29 | 0.00 (0.00) | 0.85 (0.79) | 0.20 (0.51) | 0.05 (0.53) | 0.01 (0.41) | 0.00 (0.30) | 0.00 (0.22) | 0.00 (0.16) | 0.00 (0.13) | 0.00 (0.13) | 0.00 (0.13) | 1,12 | (0.02) |
| C30 | 0.00 (0.00) | -0.33 (-0.72) | -0.03 (-0.35) | -0.01 (-0.33) | -0.00 (-0.29) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.19) | -0.00 (-0.17) | -0.00 (-0.17) | -0.00 (-0.17) | -0,38 | (-0.45) |
| C31_32 | 0.00 (0.00) | -0.14 (-0.20) | -0.06 (-0.25) | -0.03 (-0.25) | -0.01 (-0.24) | -0.00 (-0.22) | -0.00 (-0.19) | -0.00 (-0.17) | -0.00 (-0.15) | -0.00 (-0.15) | -0.00 (-0.15) | -0,24 | (-0.18) |
| C33 | 0.00 (0.00) | -0.26 (-0.41) | -0.09 (-0.34) | -0.04 (-0.31) | -0.02 (-0.29) | -0.01 (-0.26) | -0.00 (-0.24) | -0.00 (-0.22) | -0.00 (-0.19) | -0.00 (-0.19) | -0.00 (-0.19) | -0,41 | (-0.36) |
| D35 | 0.00 (0.00) | 0.03 (0.28) | -0.03 (-0.19) | -0.03 (-0.25) | -0.02 (-0.27) | -0.01 (-0.27) | -0.01 (-0.26) | -0.00 (-0.25) | -0.00 (-0.24) | -0.00 (-0.24) | -0.00 (-0.24) | -0,08 | (-0.13) |
| E36 | 0.00 (0.00) | -0.10 (-0.81) | -0.04 (-0.51) | -0.02 (-0.41) | -0.01 (-0.34) | -0.00 (-0.30) | -0.00 (-0.26) | -0.00 (-0.23) | -0.00 (-0.21) | -0.00 (-0.21) | -0.00 (-0.21) | -0,17 | (-0.61) |
| E37T39 | 0.00 (0.00) | -0.79 (-0.87) | -0.27 (-0.55) | -0.10 (-0.42) | -0.04 (-0.35) | -0.02 (-0.29) | -0.01 (-0.25) | -0.00 (-0.22) | -0.00 (-0.20) | -0.00 (-0.20) | -0.00 (-0.20) | -1,23 | (-0.66) |
| F | 0.00 (0.00) | -1.51 (-0.79) | -0.65 (-0.58) | -0.28 (-0.47) | -0.12 (-0.40) | -0.05 (-0.35) | -0.02 (-0.31) | -0.01 (-0.28) | -0.00 (-0.25) | -0.00 (-0.25) | -0.00 (-0.25) | -2,67 | (-0.63) |
| G45 | 0.00 (0.00) | 2.28 (0.34) | 0.14 (0.20) | 0.01 (0.03) | -0.01 (-0.07) | -0.00 (-0.10) | -0.00 (-0.10) | -0.00 (-0.09) | -0.00 (-0.08) | -0.00 (-0.08) | -0.00 (-0.08) | 2,41 | (0.22) |
| G46 | 0.00 (0.00) | -2.92 (-0.55) | -0.76 (-0.38) | -0.32 (-0.34) | -0.13 (-0.30) | -0.05 (-0.26) | -0.02 (-0.23) | -0.01 (-0.20) | -0.00 (-0.18) | -0.00 (-0.18) | -0.00 (-0.18) | -4,21 | (-0.46) |
| G47 | 0.00 (0.00) | -0.47 (-0.17) | -0.25 (-0.27) | -0.12 (-0.28) | -0.05 (-0.26) | -0.02 (-0.23) | -0.01 (-0.20) | -0.00 (-0.17) | -0.00 (-0.14) | -0.00 (-0.14) | -0.00 (-0.14) | -0,93 | (-0.21) |
| H49 | 0.00 (0.00) | -0.71 (-0.42) | -0.52 (-0.37) | -0.28 (-0.35) | -0.13 (-0.33) | -0.06 (-0.30) | -0.03 (-0.27) | -0.01 (-0.25) | -0.01 (-0.22) | -0.01 (-0.22) | -0.01 (-0.22) | -1,75 | (-0.37) |
| H50 | 0.00 (0.00) | -0.04 (-0.71) | -0.02 (-0.40) | -0.01 (-0.35) | -0.00 (-0.31) | -0.00 (-0.27) | -0.00 (-0.23) | -0.00 (-0.20) | -0.00 (-0.17) | -0.00 (-0.17) | -0.00 (-0.17) | -0,08 | (-0.47) |
| H51 | 0.00 (0.00) | -0.01 (-0.63) | -0.01 (-0.44) | -0.00 (-0.38) | -0.00 (-0.34) | -0.00 (-0.31) | -0.00 (-0.28) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | -0,02 | (-0.45) |
| H52 | 0.00 (0.00) | -0.48 (-0.52) | -0.41 (-0.39) | -0.21 (-0.37) | -0.10 (-0.34) | -0.05 (-0.31) | -0.02 (-0.28) | -0.01 (-0.25) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | -1,28 | (-0.41) |
| H53 | 0.00 (0.00) | 0.21 (3.74) | -0.08 (-0.49) | -0.04 (-0.41) | -0.02 (-0.36) | -0.01 (-0.32) | -0.00 (-0.28) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | 0,05 | (0.12) |
| I | 0.00 (0.00) | -0.15 (-0.32) | -0.59 (-0.41) | -0.31 (-0.39) | -0.15 (-0.35) | -0.07 (-0.32) | -0.03 (-0.28) | -0.01 (-0.25) | -0.01 (-0.23) | -0.01 (-0.23) | -0.01 (-0.23) | -1,33 | (-0.37) |
| J58 | 0.00 (0.00) | -0.00 (-0.33) | -0.02 (-0.44) | -0.01 (-0.34) | -0.01 (-0.35) | -0.00 (-0.32) | -0.00 (-0.29) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | -0,05 | (-0.37) |
| J59_60 | 0.00 (0.00) | -0.01 (-0.20) | -0.03 (-0.39) | -0.02 (-0.36) | -0.01 (-0.36) | -0.00 (-0.33) | -0.00 (-0.30) | -0.00 (-0.26) | -0.00 (-0.23) | -0.00 (-0.23) | -0.00 (-0.23) | -0,06 | (-0.34) |
| J61 | 0.00 (0.00) | -0.16 (-0.84) | -0.07 (-0.54) | -0.03 (-0.43) | -0.01 (-0.36) | -0.01 (-0.32) | -0.00 (-0.28) | -0.00 (-0.24) | -0.00 (-0.21) | -0.00 (-0.21) | -0.00 (-0.21) | -0,29 | (-0.62) |
| J62_63 | 0.00 (0.00) | -0.49 (-0.39) | -0.32 (-0.40) | -0.17 (-0.37) | -0.08 (-0.35) | -0.04 (-0.32) | -0.02 (-0.29) | -0.01 (-0.26) | -0.00 (-0.23) | -0.00 (-0.23) | -0.00 (-0.23) | -1,12 | (-0.38) |
| K64 | 0.00 (0.00) | -0.47 (-0.71) | -0.25 (-0.40) | -0.13 (-0.37) | -0.06 (-0.34) | -0.03 (-0.31) | -0.01 (-0.28) | -0.01 (-0.25) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | -0,94 | (-0.48) |
| K65 | 0.00 (0.00) | -0.02 (-0.59) | -0.02 (-0.41) | -0.01 (-0.38) | -0.00 (-0.34) | -0.00 (-0.31) | -0.00 (-0.28) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | -0,04 | (-0.44) |
| K66 | 0.00 (0.00) | -0.04 (-0.28) | -0.25 (-0.44) | -0.12 (-0.37) | -0.06 (-0.34) | -0.03 (-0.31) | -0.01 (-0.28) | -0.00 (-0.25) | -0.00 (-0.21) | -0.00 (-0.21) | -0.00 (-0.21) | -0,52 | (-0.38) |
| L | 0.00 (0.00) | -0.04 (-0.40) | -0.04 (-0.33) | -0.02 (-0.35) | -0.01 (-0.33) | -0.00 (-0.31) | -0.00 (-0.28) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | -0,13 | (-0.35) |
| M69_70 | 0.00 (0.00) | -2.23 (-0.62) | -1.27 (-0.48) | -0.52 (-0.39) | -0.23 (-0.35) | -0.10 (-0.32) | -0.04 (-0.28) | -0.02 (-0.25) | -0.01 (-0.23) | -0.01 (-0.23) | -0.01 (-0.23) | -4,43 | (-0.5) |
| M71 | 0.00 (0.00) | -5.20 (-0.95) | -0.52 (-0.50) | -0.21 (-0.43) | -0.09 (-0.37) | -0.04 (-0.33) | -0.02 (-0.30) | -0.01 (-0.27) | -0.00 (-0.24) | -0.00 (-0.24) | -0.00 (-0.24) | -6,08 | (-0.82) |
| M72 | 0.00 (0.00) | -1.24 (-0.83) | -0.06 (-0.53) | -0.02 (-0.45) | -0.01 (-0.38) | -0.00 (-0.34) | -0.00 (-0.31) | -0.00 (-0.29) | -0.00 (-0.26) | -0.00 (-0.26) | -0.00 (-0.26) | -1,32 | (-0.79) |
| M73 | 0.00 (0.00) | -0.09 (-0.29) | -0.07 (-0.22) | -0.04 (-0.32) | -0.02 (-0.31) | -0.01 (-0.29) | -0.00 (-0.26) | -0.00 (-0.23) | -0.00 (-0.21) | -0.00 (-0.21) | -0.00 (-0.21) | -0,23 | (-0.27) |
| M74_75 | 0.00 (0.00) | -1.11 (-0.83) | -0.40 (-0.48) | -0.16 (-0.40) | -0.07 (-0.35) | -0.03 (-0.32) | -0.01 (-0.28) | -0.01 (-0.25) | -0.00 (-0.23) | -0.00 (-0.23) | -0.00 (-0.23) | -1,8 | (-0.6) |
| N77 | 0.00 (0.00) | -0.02 (-0.15) | -0.06 (-0.40) | -0.03 (-0.38) | -0.01 (-0.34) | -0.01 (-0.31) | -0.00 (-0.27) | -0.00 (-0.24) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | -0,13 | (-0.3) |
| N78 | 0.00 (0.00) | 2.24 (2.17) | -0.56 (-0.32) | -0.22 (-0.31) | -0.10 (-0.30) | -0.04 (-0.28) | -0.02 (-0.25) | -0.01 (-0.22) | -0.00 (-0.20) | -0.00 (-0.20) | -0.00 (-0.20) | 1,29 | (0.31) |
| N79 | 0.00 (0.00) | 0.01 (0.48) | -0.02 (-0.42) | -0.01 (-0.38) | -0.01 (-0.35) | -0.00 (-0.31) | -0.00 (-0.28) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | -0,04 | (-0.29) |
| N80T82 | 0.00 (0.00) | -1.11 (-0.59) | -1.21 (-0.47) | -0.53 (-0.40) | -0.23 (-0.35) | -0.10 (-0.31) | -0.04 (-0.28) | -0.02 (-0.25) | -0.01 (-0.22) | -0.01 (-0.22) | -0.01 (-0.22) | -3,25 | (-0.46) |
| O84 | 0.00 (0.00) | -0.43 (-0.79) | -0.21 (-0.50) | -0.09 (-0.41) | -0.04 (-0.35) | -0.02 (-0.31) | -0.01 (-0.27) | -0.00 (-0.24) | -0.00 (-0.21) | -0.00 (-0.21) | -0.00 (-0.21) | -0,81 | (-0.57) |
| P85 | 0.00 (0.00) | -0.25 (-0.55) | -0.15 (-0.33) | -0.08 (-0.37) | -0.04 (-0.34) | -0.02 (-0.31) | -0.01 (-0.28) | -0.00 (-0.25) | -0.00 (-0.23) | -0.00 (-0.23) | -0.00 (-0.23) | -0,55 | (-0.41) |
| Q86 | 0.00 (0.00) | 0.44 (2.49) | -0.00 (-0.03) | -0.02 (-0.29) | -0.01 (-0.32) | -0.01 (-0.30) | -0.00 (-0.28) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | 0,39 | (0.88) |
| Q87_88 | 0.00 (0.00) | 0.04 (2.90) | -0.08 (-0.37) | -0.06 (-0.33) | -0.03 (-0.35) | -0.02 (-0.34) | -0.01 (-0.31) | -0.00 (-0.28) | -0.00 (-0.25) | -0.00 (-0.25) | -0.00 (-0.25) | -0,17 | (-0.28) |
| R90T92 | 0.00 (0.00) | -0.00 (-0.14) | -0.05 (-0.40) | -0.04 (-0.40) | -0.02 (-0.37) | -0.01 (-0.34) | -0.00 (-0.31) | -0.00 (-0.28) | -0.00 (-0.25) | -0.00 (-0.25) | -0.00 (-0.25) | -0,14 | (-0.36) |
| R93 | 0.00 (0.00) | -0.00 (-0.04) | -0.09 (-0.39) | -0.06 (-0.40) | -0.03 (-0.37) | -0.01 (-0.33) | -0.01 (-0.30) | -0.00 (-0.27) | -0.00 (-0.24) | -0.00 (-0.24) | -0.00 (-0.24) | -0,21 | (-0.33) |
| S94 | 0.00 (0.00) | -0.04 (-0.46) | -0.07 (-0.43) | -0.04 (-0.40) | -0.02 (-0.36) | -0.01 (-0.33) | -0.00 (-0.29) | -0.00 (-0.26) | -0.00 (-0.23) | -0.00 (-0.23) | -0.00 (-0.23) | -0,18 | (-0.41) |
| S95 | 0.00 (0.00) | 0.01 (0.32) | -0.02 (-0.43) | -0.01 (-0.37) | -0.01 (-0.34) | -0.00 (-0.31) | -0.00 (-0.27) | -0.00 (-0.24) | -0.00 (-0.22) | -0.00 (-0.22) | -0.00 (-0.22) | -0,03 | (-0.2) |
| S96 | 0.00 (0.00) | -0.01 (-0.29) | -0.04 (-0.40) | -0.03 (-0.41) | -0.01 (-0.37) | -0.01 (-0.34) | -0.00 (-0.30) | -0.00 (-0.27) | -0.00 (-0.24) | -0.00 (-0.24) | -0.00 (-0.24) | -0,1 | (-0.38) |
| T | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| U | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | | (0.00) |
| Total | | | | | | | | | | | | -43,68 | (-0.23) |

Table 3.28: Change in the quantity of labour (in thousands of units) in Scenario 2 relative to the 'business as usual' scenario, by activation round. Each round corresponds to a term in the summation of Equation 3.1. Round zero denotes the variation in the final-demand vector for sector C29 only. The first round indicates the effect on suppliers closest to the automotive supply chain, the second round the effect on suppliers of those suppliers, and so forth. The last column reports the cumulative effect for each sector. Decimal points are shown in parentheses.

| Industry | Round 0 | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 | Round 6 | Round 7 | Round 8 | Round 9 | Round 10 | Total Δ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A01 | 0.00 (0.00) | 0.07 (0.03) | -9.54 (-0.46) | -6.24 (-0.40) | -3.57 (-0.36) | -1.79 (-0.33) | -0.85 (-0.30) | -0.39 (-0.26) | -0.18 (-0.23) | -0.18 (-0.23) | -0.18 (-0.23) | -22,64 | (-0.37) |
| A02 | 0.00 (0.00) | -0.43 (-0.65) | -0.56 (-0.30) | -0.36 (-0.34) | -0.16 (-0.32) | -0.07 (-0.28) | -0.03 (-0.25) | -0.01 (-0.22) | -0.01 (-0.19) | -0.01 (-0.19) | -0.01 (-0.19) | -1,64 | (-0.36) |
| A03 | 0.00 (0.00) | 0.00 (0.00) | -0.11 (-0.50) | -0.11 (-0.41) | -0.06 (-0.37) | -0.03 (-0.34) | -0.01 (-0.30) | -0.01 (-0.26) | -0.00 (-0.23) | -0.00 (-0.23) | -0.00 (-0.23) | -0,32 | (-0.4) |
| B | 0.00 (0.00) | -24.01 (-0.86) | -9.60 (-0.64) | -3.43 (-0.47) | -1.40 (-0.37) | -0.59 (-0.31) | -0.25 (-0.27) | -0.11 (-0.23) | -0.05 (-0.20) | -0.05 (-0.20) | -0.05 (-0.20) | -39,47 | (-0.68) |
| C10T12 | 0.00 (0.00) | -3.16 (-0.64) | -4.55 (-0.49) | -3.43 (-0.41) | -1.80 (-0.37) | -0.85 (-0.33) | -0.38 (-0.29) | -0.17 (-0.25) | -0.07 (-0.22) | -0.07 (-0.22) | -0.07 (-0.22) | -14,48 | (-0.44) |
| C13T15 | 0.00 (0.00) | -8.63 (-0.16) | -3.62 (-0.19) | -1.39 (-0.18) | -0.54 (-0.16) | -0.21 (-0.13) | -0.08 (-0.10) | -0.03 (-0.07) | -0.01 (-0.04) | -0.01 (-0.04) | -0.01 (-0.04) | -14,51 | (-0.17) |
| C16 | 0.00 (0.00) | 0.75 (0.05) | -3.07 (-0.29) | -1.60 (-0.31) | -0.71 (-0.30) | -0.30 (-0.27) | -0.13 (-0.24) | -0.06 (-0.21) | -0.02 (-0.18) | -0.02 (-0.18) | -0.02 (-0.18) | -5,15 | (-0.14) |
| C17 | 0.00 (0.00) | -6.65 (-0.46) | -6.36 (-0.45) | -3.08 (-0.38) | -1.38 (-0.33) | -0.60 (-0.29) | -0.26 (-0.25) | -0.11 (-0.22) | -0.05 (-0.19) | -0.05 (-0.19) | -0.05 (-0.19) | -18,53 | (-0.41) |
| C18 | 0.00 (0.00) | -3.89 (-0.26) | -5.44 (-0.45) | -2.88 (-0.40) | -1.35 (-0.36) | -0.61 (-0.33) | -0.27 (-0.29) | -0.12 (-0.26) | -0.05 (-0.24) | -0.05 (-0.24) | -0.05 (-0.24) | -14,64 | (-0.25) |
| C19 | 0.00 (0.00) | -0.18 (-0.42) | -0.90 (-0.48) | -0.64 (-0.39) | -0.32 (-0.33) | -0.15 (-0.29) | -0.07 (-0.25) | -0.03 (-0.22) | -0.01 (-0.19) | -0.01 (-0.19) | -0.01 (-0.19) | -2,31 | (-0.39) |
| C20 | 0.00 (0.00) | -25.88 (-0.74) | -13.39 (-0.43) | -4.15 (-0.32) | -1.37 (-0.23) | -0.49 (-0.18) | -0.18 (-0.14) | -0.07 (-0.10) | -0.03 (-0.08) | -0.03 (-0.08) | -0.03 (-0.08) | -45,56 | (-0.51) |
| C21 | 0.00 (0.00) | -7.26 (-0.78) | -1.60 (-0.44) | -0.56 (-0.35) | -0.21 (-0.27) | -0.08 (-0.21) | -0.03 (-0.16) | -0.01 (-0.12) | -0.00 (-0.09) | -0.00 (-0.09) | -0.00 (-0.09) | -9,77 | (-0.6) |
| C22 | 0.00 (0.00) | -102.35 (-0.50) | -18.60 (-0.32) | -5.23 (-0.26) | -1.78 (-0.22) | -0.69 (-0.19) | -0.29 (-0.17) | -0.12 (-0.15) | -0.05 (-0.13) | -0.05 (-0.13) | -0.05 (-0.13) | -129,16 | (-0.4) |
| C23 | 0.00 (0.00) | -80.46 (-0.84) | -18.13 (-0.58) | -5.56 (-0.44) | -1.96 (-0.35) | -0.77 (-0.29) | -0.32 (-0.25) | -0.14 (-0.22) | -0.06 (-0.19) | -0.06 (-0.19) | -0.06 (-0.19) | -107,45 | (-0.71) |
| C24 | 0.00 (0.00) | -64.40 (-0.68) | -22.19 (-0.39) | -6.09 (-0.26) | -1.40 (-0.15) | -0.25 (-0.06) | -0.01 (-0.01) | 0.02 (0.02) | 0.01 (0.04) | 0.01 (0.04) | 0.01 (0.04) | -94,29 | (-0.48) |
| C25 | 0.00 (0.00) | -294.53 (-0.32) | -65.21 (-0.27) | -17.03 (-0.22) | -4.85 (-0.17) | -1.58 (-0.14) | -0.59 (-0.12) | -0.24 (-0.10) | -0.11 (-0.09) | -0.11 (-0.09) | -0.11 (-0.09) | -384,22 | (-0.24) |
| C26 | 0.00 (0.00) | -1.26 (-0.04) | -2.88 (-0.22) | -0.99 (-0.17) | -0.50 (-0.18) | -0.24 (-0.18) | -0.11 (-0.17) | -0.05 (-0.16) | -0.02 (-0.14) | -0.02 (-0.14) | -0.02 (-0.14) | -6,07 | (-0.09) |
| C27 | 0.00 (0.00) | 61.60 (0.65) | 4.86 (0.19) | 1.03 (0.11) | 0.19 (0.05) | 0.02 (0.01) | -0.01 (-0.01) | -0.01 (-0.02) | -0.00 (-0.02) | -0.00 (-0.02) | -0.00 (-0.02) | 67,67 | (0.26) |
| C28 | 0.00 (0.00) | -29.44 (-0.24) | -7.44 (-0.14) | -1.84 (-0.09) | -0.51 (-0.06) | -0.17 (-0.04) | -0.06 (-0.04) | -0.03 (-0.03) | -0.01 (-0.02) | -0.01 (-0.02) | -0.01 (-0.02) | -39,5 | (-0.07) |
| C29 | 0.00 (0.00) | 64.72 (0.79) | 15.15 (0.51) | 3.73 (0.53) | 1.10 (0.41) | 0.35 (0.30) | 0.12 (0.22) | 0.04 (0.16) | 0.02 (0.13) | 0.02 (0.13) | 0.02 (0.13) | 85,24 | (0.02) |
| C30 | 0.00 (0.00) | -26.76 (-0.72) | -2.43 (-0.35) | -0.89 (-0.33) | -0.35 (-0.29) | -0.15 (-0.25) | -0.06 (-0.22) | -0.03 (-0.19) | -0.01 (-0.17) | -0.01 (-0.17) | -0.01 (-0.17) | -30,69 | (-0.45) |
| C31_32 | 0.00 (0.00) | -8.33 (-0.20) | -3.70 (-0.25) | -1.53 (-0.25) | -0.65 (-0.24) | -0.28 (-0.22) | -0.12 (-0.19) | -0.05 (-0.17) | -0.02 (-0.15) | -0.02 (-0.15) | -0.02 (-0.15) | -14,69 | (-0.18) |
| C33 | 0.00 (0.00) | -14.13 (-0.41) | -4.92 (-0.34) | -1.96 (-0.31) | -0.84 (-0.29) | -0.37 (-0.26) | -0.16 (-0.24) | -0.07 (-0.22) | -0.03 (-0.19) | -0.03 (-0.19) | -0.03 (-0.19) | -22,52 | (-0.36) |
| D35 | 0.00 (0.00) | 19.95 (0.28) | -18.74 (-0.19) | -19.54 (-0.25) | -13.25 (-0.27) | -7.79 (-0.27) | -4.28 (-0.26) | -2.26 (-0.25) | -1.17 (-0.24) | -1.17 (-0.24) | -1.17 (-0.24) | -48,28 | (-0.13) |
| E36 | 0.00 (0.00) | -12.49 (-0.81) | -4.47 (-0.51) | -1.83 (-0.41) | -0.74 (-0.34) | -0.31 (-0.30) | -0.13 (-0.26) | -0.06 (-0.23) | -0.03 (-0.21) | -0.03 (-0.21) | -0.03 (-0.21) | -20,09 | (-0.61) |
| E37T39 | 0.00 (0.00) | -58.64 (-0.87) | -19.62 (-0.55) | -7.60 (-0.42) | -2.99 (-0.35) | -1.22 (-0.29) | -0.51 (-0.25) | -0.22 (-0.22) | -0.10 (-0.20) | -0.10 (-0.20) | -0.10 (-0.20) | -90,99 | (-0.66) |
| F | 0.00 (0.00) | -86.52 (-0.79) | -37.55 (-0.58) | -16.32 (-0.47) | -7.10 (-0.40) | -3.12 (-0.35) | -1.38 (-0.31) | -0.62 (-0.28) | -0.28 (-0.25) | -0.28 (-0.25) | -0.28 (-0.25) | -153,13 | (-0.63) |
| G45 | 0.00 (0.00) | 111.87 (0.34) | 6.87 (0.20) | 0.36 (0.03) | -0.34 (-0.07) | -0.22 (-0.10) | -0.11 (-0.10) | -0.05 (-0.09) | -0.02 (-0.08) | -0.02 (-0.08) | -0.02 (-0.08) | 118,35 | (0.22) |
| G46 | 0.00 (0.00) | -250.98 (-0.55) | -65.25 (-0.38) | -27.12 (-0.34) | -11.08 (-0.30) | -4.62 (-0.26) | -1.97 (-0.23) | -0.85 (-0.20) | -0.38 (-0.18) | -0.38 (-0.18) | -0.38 (-0.18) | -362,54 | (-0.46) |
| G47 | 0.00 (0.00) | -21.39 (-0.17) | -11.28 (-0.27) | -5.26 (-0.28) | -2.32 (-0.26) | -1.00 (-0.23) | -0.43 (-0.20) | -0.18 (-0.17) | -0.08 (-0.14) | -0.08 (-0.14) | -0.08 (-0.14) | -41,98 | (-0.21) |
| H49 | 0.00 (0.00) | -60.05 (-0.42) | -43.87 (-0.37) | -23.66 (-0.35) | -11.48 (-0.33) | -5.35 (-0.30) | -2.46 (-0.27) | -1.13 (-0.25) | -0.52 (-0.22) | -0.52 (-0.22) | -0.52 (-0.22) | -148,98 | (-0.37) |
| H50 | 0.00 (0.00) | -1.64 (-0.71) | -0.87 (-0.40) | -0.41 (-0.35) | -0.18 (-0.31) | -0.08 (-0.27) | -0.03 (-0.23) | -0.01 (-0.20) | -0.01 (-0.17) | -0.01 (-0.17) | -0.01 (-0.17) | -3,25 | (-0.47) |
| H51 | 0.00 (0.00) | -0.71 (-0.63) | -0.68 (-0.44) | -0.33 (-0.38) | -0.16 (-0.34) | -0.07 (-0.31) | -0.03 (-0.28) | -0.01 (-0.25) | -0.01 (-0.22) | -0.01 (-0.22) | -0.01 (-0.22) | -2 | (-0.45) |
| H52 | 0.00 (0.00) | -45.58 (-0.52) | -38.24 (-0.39) | -20.01 (-0.37) | -9.39 (-0.34) | -4.24 (-0.31) | -1.89 (-0.28) | -0.85 (-0.25) | -0.38 (-0.22) | -0.38 (-0.22) | -0.38 (-0.22) | -120,89 | (-0.41) |
| H53 | 0.00 (0.00) | 10.32 (3.74) | -3.92 (-0.49) | -2.09 (-0.41) | -1.00 (-0.36) | -0.45 (-0.32) | -0.20 (-0.28) | -0.09 (-0.25) | -0.04 (-0.22) | -0.04 (-0.22) | -0.04 (-0.22) | 2,51 | (0.12) |
| I | 0.00 (0.00) | -5.47 (-0.32) | -21.13 (-0.41) | -11.10 (-0.39) | -5.27 (-0.35) | -2.38 (-0.32) | -1.06 (-0.28) | -0.47 (-0.25) | -0.21 (-0.23) | -0.21 (-0.23) | -0.21 (-0.23) | -47,27 | (-0.37) |
| J58 | 0.00 (0.00) | -0.38 (-0.33) | -1.64 (-0.44) | -0.87 (-0.34) | -0.41 (-0.35) | -0.18 (-0.32) | -0.08 (-0.29) | -0.03 (-0.25) | -0.02 (-0.22) | -0.02 (-0.22) | -0.02 (-0.22) | -3,63 | (-0.37) |
| J59_60 | 0.00 (0.00) | -0.63 (-0.20) | -2.42 (-0.39) | -1.52 (-0.36) | -0.77 (-0.36) | -0.35 (-0.33) | -0.16 (-0.30) | -0.07 (-0.26) | -0.03 (-0.23) | -0.03 (-0.23) | -0.03 (-0.23) | -5,96 | (-0.34) |
| J61 | 0.00 (0.00) | -37.63 (-0.84) | -17.45 (-0.54) | -7.17 (-0.43) | -2.93 (-0.36) | -1.22 (-0.32) | -0.51 (-0.28) | -0.22 (-0.24) | -0.10 (-0.21) | -0.10 (-0.21) | -0.10 (-0.21) | -67,31 | (-0.62) |
| J62_63 | 0.00 (0.00) | -37.45 (-0.39) | -24.95 (-0.40) | -12.80 (-0.37) | -6.00 (-0.35) | -2.72 (-0.32) | -1.22 (-0.29) | -0.54 (-0.26) | -0.24 (-0.23) | -0.24 (-0.23) | -0.24 (-0.23) | -86,13 | (-0.38) |
| K64 | 0.00 (0.00) | -76.42 (-0.71) | -40.44 (-0.40) | -20.82 (-0.37) | -9.51 (-0.34) | -4.22 (-0.31) | -1.86 (-0.28) | -0.82 (-0.25) | -0.37 (-0.22) | -0.37 (-0.22) | -0.37 (-0.22) | -154,75 | (-0.48) |
| K65 | 0.00 (0.00) | -5.28 (-0.59) | -4.88 (-0.41) | -2.21 (-0.38) | -0.98 (-0.34) | -0.43 (-0.31) | -0.19 (-0.28) | -0.08 (-0.25) | -0.04 (-0.22) | -0.04 (-0.22) | -0.04 (-0.22) | -14,12 | (-0.44) |
| K66 | 0.00 (0.00) | -2.58 (-0.28) | -15.81 (-0.44) | -7.58 (-0.37) | -3.54 (-0.34) | -1.57 (-0.31) | -0.69 (-0.28) | -0.30 (-0.25) | -0.13 (-0.21) | -0.13 (-0.21) | -0.13 (-0.21) | -32,33 | (-0.38) |
| L | 0.00 (0.00) | -53.35 (-0.40) | -57.02 (-0.33) | -28.51 (-0.35) | -13.01 (-0.33) | -5.82 (-0.31) | -2.59 (-0.28) | -1.15 (-0.25) | -0.52 (-0.22) | -0.52 (-0.22) | -0.52 (-0.22) | -162,4 | (-0.35) |
| M69_70 | 0.00 (0.00) | -145.39 (-0.62) | -83.07 (-0.48) | -34.13 (-0.39) | -14.92 (-0.35) | -6.56 (-0.32) | -2.89 (-0.28) | -1.29 (-0.25) | -0.58 (-0.23) | -0.58 (-0.23) | -0.58 (-0.23) | -289,3 | (-0.5) |
| M71 | 0.00 (0.00) | -281.73 (-0.95) | -28.21 (-0.50) | -11.50 (-0.43) | -4.66 (-0.37) | -2.03 (-0.33) | -0.89 (-0.30) | -0.40 (-0.27) | -0.18 (-0.24) | -0.18 (-0.24) | -0.18 (-0.24) | -329,75 | (-0.82) |
| M72 | 0.00 (0.00) | -188.59 (-0.83) | -8.45 (-0.53) | -2.58 (-0.45) | -0.87 (-0.38) | -0.36 (-0.34) | -0.16 (-0.31) | -0.07 (-0.29) | -0.03 (-0.26) | -0.03 (-0.26) | -0.03 (-0.26) | -201,14 | (-0.79) |
| M73 | 0.00 (0.00) | -5.13 (-0.29) | -3.83 (-0.22) | -2.16 (-0.32) | -1.01 (-0.31) | -0.45 (-0.29) | -0.20 (-0.26) | -0.09 (-0.23) | -0.04 (-0.21) | -0.04 (-0.21) | -0.04 (-0.21) | -12,94 | (-0.27) |
| M74_75 | 0.00 (0.00) | -51.50 (-0.83) | -18.50 (-0.48) | -7.63 (-0.40) | -3.31 (-0.35) | -1.46 (-0.32) | -0.65 (-0.28) | -0.29 (-0.25) | -0.13 (-0.23) | -0.13 (-0.23) | -0.13 (-0.23) | -83,58 | (-0.6) |
| N77 | 0.00 (0.00) | -4.23 (-0.15) | -10.37 (-0.40) | -5.11 (-0.38) | -2.32 (-0.34) | -1.03 (-0.31) | -0.46 (-0.27) | -0.20 (-0.24) | -0.09 (-0.22) | -0.09 (-0.22) | -0.09 (-0.22) | -23,89 | (-0.3) |
| N78 | 0.00 (0.00) | 72.83 (2.17) | -18.35 (-0.32) | -7.13 (-0.31) | -3.12 (-0.30) | -1.34 (-0.28) | -0.58 (-0.25) | -0.25 (-0.22) | -0.11 (-0.20) | -0.11 (-0.20) | -0.11 (-0.20) | 41,85 | (0.31) |
| N79 | 0.00 (0.00) | 0.16 (0.48) | -0.52 (-0.42) | -0.32 (-0.38) | -0.16 (-0.35) | -0.07 (-0.31) | -0.03 (-0.28) | -0.01 (-0.25) | -0.01 (-0.22) | -0.01 (-0.22) | -0.01 (-0.22) | -0,97 | (-0.29) |
| N80T82 | 0.00 (0.00) | -38.94 (-0.59) | -42.50 (-0.47) | -18.46 (-0.40) | -8.06 (-0.35) | -3.50 (-0.31) | -1.52 (-0.28) | -0.67 (-0.25) | -0.30 (-0.22) | -0.30 (-0.22) | -0.30 (-0.22) | -114,19 | (-0.46) |
| O84 | 0.00 (0.00) | -41.25 (-0.79) | -20.43 (-0.50) | -9.03 (-0.41) | -3.97 (-0.35) | -1.71 (-0.31) | -0.74 (-0.27) | -0.33 (-0.24) | -0.14 (-0.21) | -0.14 (-0.21) | -0.14 (-0.21) | -77,73 | (-0.57) |
| P85 | 0.00 (0.00) | -10.94 (-0.55) | -6.25 (-0.33) | -3.50 (-0.37) | -1.57 (-0.34) | -0.70 (-0.31) | -0.31 (-0.28) | -0.14 (-0.25) | -0.06 (-0.23) | -0.06 (-0.23) | -0.06 (-0.23) | -23,52 | (-0.41) |
| Q86 | 0.00 (0.00) | 26.08 (2.49) | -0.17 (-0.03) | -1.35 (-0.29) | -0.79 (-0.32) | -0.37 (-0.30) | -0.17 (-0.28) | -0.07 (-0.25) | -0.03 (-0.22) | -0.03 (-0.22) | -0.03 (-0.22) | 23,1 | (0.88) |
| Q87_88 | 0.00 (0.00) | 1.00 (2.90) | -2.14 (-0.37) | -1.79 (-0.33) | -0.96 (-0.35) | -0.45 (-0.34) | -0.20 (-0.31) | -0.09 (-0.28) | -0.04 (-0.25) | -0.04 (-0.25) | -0.04 (-0.25) | -4,71 | (-0.28) |
| R90T92 | 0.00 (0.00) | -0.29 (-0.14) | -3.42 (-0.40) | -2.60 (-0.40) | -1.43 (-0.37) | -0.69 (-0.34) | -0.31 (-0.31) | -0.14 (-0.28) | -0.06 (-0.25) | -0.06 (-0.25) | -0.06 (-0.25) | -9 | (-0.36) |
| R93 | 0.00 (0.00) | -0.16 (-0.04) | -3.72 (-0.39) | -2.70 (-0.40) | -1.39 (-0.37) | -0.65 (-0.33) | -0.29 (-0.30) | -0.13 (-0.27) | -0.06 (-0.24) | -0.06 (-0.24) | -0.06 (-0.24) | -9,14 | (-0.33) |
| S94 | 0.00 (0.00) | -1.46 (-0.46) | -2.54 (-0.43) | -1.41 (-0.40) | -0.69 (-0.36) | -0.31 (-0.33) | -0.14 (-0.29) | -0.06 (-0.26) | -0.03 (-0.23) | -0.03 (-0.23) | -0.03 (-0.23) | -6,67 | (-0.41) |
| S95 | 0.00 (0.00) | 0.50 (0.32) | -0.91 (-0.43) | -0.42 (-0.37) | -0.20 (-0.34) | -0.09 (-0.31) | -0.04 (-0.27) | -0.02 (-0.24) | -0.01 (-0.22) | -0.01 (-0.22) | -0.01 (-0.22) | -1,18 | (-0.2) |
| S96 | 0.00 (0.00) | -0.18 (-0.29) | -1.39 (-0.40) | -1.07 (-0.41) | -0.49 (-0.37) | -0.21 (-0.34) | -0.09 (-0.30) | -0.04 (-0.27) | -0.02 (-0.24) | -0.02 (-0.24) | -0.02 (-0.24) | -3,51 | (-0.38) |
| T | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (-1.57) |
| U | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| Total | | | | | | | | | | | | -3436,13 | (-0.23) |

Table 3.29: Change in the value added (in millions of euros) in Scenario 2 relative to the 'business as usual' scenario, by activation round. Each round corresponds to a term in the summation of Equation 3.1. Round zero denotes the variation in the final-demand vector for sector C29 only. The first round indicates the effect on suppliers closest to the automotive supply chain, the second round the effect on suppliers of those suppliers, and so forth. The last column reports the cumulative effect for each sector. Decimal points are shown in parentheses.

| Industry | Round 0 | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 | Round 6 | Round 7 | Round 8 | Round 9 | Round 10 | Total Δ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A01 | 0.00 (0.00) | -0.02 (-0.22) | -0.29 (-0.59) | -0.20 (-0.54) | -0.12 (-0.52) | -0.06 (-0.49) | -0.03 (-0.47) | -0.02 (-0.44) | -0.01 (-0.42) | -0.01 (-0.42) | -0.01 (-0.42) | -0,76 | (-0.52) |
| A02 | 0.00 (0.00) | -0.01 (-0.73) | -0.01 (-0.47) | -0.01 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.39) | -0.00 (-0.39) | -0.00 (-0.39) | -0,03 | (-0.51) |
| A03 | 0.00 (0.00) | -0.00 (-0.24) | -0.00 (-0.62) | -0.00 (-0.55) | -0.00 (-0.53) | -0.00 (-0.50) | -0.00 (-0.47) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,01 | (-0.55) |
| B | 0.00 (0.00) | -0.07 (-0.89) | -0.03 (-0.73) | -0.01 (-0.60) | -0.01 (-0.53) | -0.00 (-0.48) | -0.00 (-0.45) | -0.00 (-0.42) | -0.00 (-0.40) | -0.00 (-0.40) | -0.00 (-0.40) | -0,13 | (-0.76) |
| C10T12 | 0.00 (0.00) | -0.05 (-0.73) | -0.08 (-0.61) | -0.07 (-0.55) | -0.04 (-0.52) | -0.02 (-0.49) | -0.01 (-0.46) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,27 | (-0.58) |
| C13T15 | 0.00 (0.00) | -0.36 (-0.37) | -0.14 (-0.39) | -0.06 (-0.38) | -0.02 (-0.36) | -0.01 (-0.34) | -0.00 (-0.32) | -0.00 (-0.30) | -0.00 (-0.28) | -0.00 (-0.28) | -0.00 (-0.28) | -0,6 | (-0.37) |
| C16 | 0.00 (0.00) | -0.06 (-0.21) | -0.09 (-0.46) | -0.04 (-0.48) | -0.02 (-0.47) | -0.01 (-0.45) | -0.00 (-0.42) | -0.00 (-0.40) | -0.00 (-0.38) | -0.00 (-0.38) | -0.00 (-0.38) | -0,23 | (-0.35) |
| C17 | 0.00 (0.00) | -0.09 (-0.59) | -0.09 (-0.59) | -0.05 (-0.53) | -0.02 (-0.49) | -0.01 (-0.46) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.39) | -0.00 (-0.39) | -0.00 (-0.39) | -0,27 | (-0.56) |
| C18 | 0.00 (0.00) | -0.11 (-0.44) | -0.12 (-0.59) | -0.07 (-0.54) | -0.03 (-0.51) | -0.02 (-0.49) | -0.01 (-0.47) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,44 | (-0.43) |
| C19 | 0.00 (0.00) | -0.00 (-0.56) | -0.01 (-0.61) | -0.01 (-0.54) | -0.00 (-0.49) | -0.00 (-0.46) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.39) | -0.00 (-0.39) | -0.00 (-0.39) | -0,02 | (-0.53) |
| C20 | 0.00 (0.00) | -0.23 (-0.81) | -0.14 (-0.57) | -0.05 (-0.48) | -0.02 (-0.42) | -0.01 (-0.38) | -0.00 (-0.35) | -0.00 (-0.32) | -0.00 (-0.30) | -0.00 (-0.30) | -0.00 (-0.30) | -0,45 | (-0.63) |
| C21 | 0.00 (0.00) | -0.05 (-0.83) | -0.01 (-0.58) | -0.00 (-0.50) | -0.00 (-0.45) | -0.00 (-0.40) | -0.00 (-0.37) | -0.00 (-0.33) | -0.00 (-0.31) | -0.00 (-0.31) | -0.00 (-0.31) | -0,07 | (-0.7) |
| C22 | 0.00 (0.00) | -1.57 (-0.62) | -0.35 (-0.48) | -0.11 (-0.44) | -0.04 (-0.41) | -0.02 (-0.39) | -0.01 (-0.37) | -0.00 (-0.36) | -0.00 (-0.34) | -0.00 (-0.34) | -0.00 (-0.34) | -2,17 | (-0.55) |
| C23 | 0.00 (0.00) | -1.07 (-0.88) | -0.27 (-0.68) | -0.09 (-0.57) | -0.04 (-0.50) | -0.02 (-0.46) | -0.01 (-0.43) | -0.00 (-0.41) | -0.00 (-0.39) | -0.00 (-0.39) | -0.00 (-0.39) | -1,5 | (-0.78) |
| C24 | 0.00 (0.00) | -0.76 (-0.76) | -0.32 (-0.54) | -0.11 (-0.44) | -0.03 (-0.36) | -0.01 (-0.29) | -0.00 (-0.25) | -0.00 (-0.22) | -0.00 (-0.21) | -0.00 (-0.21) | -0.00 (-0.21) | -1,25 | (-0.61) |
| C25 | 0.00 (0.00) | -6.64 (-0.48) | -1.61 (-0.45) | -0.47 (-0.41) | -0.15 (-0.37) | -0.06 (-0.35) | -0.02 (-0.33) | -0.01 (-0.32) | -0.01 (-0.31) | -0.01 (-0.31) | -0.01 (-0.31) | -10,18 | (-0.42) |
| C26 | 0.00 (0.00) | -0.08 (-0.27) | -0.05 (-0.41) | -0.02 (-0.37) | -0.01 (-0.38) | -0.01 (-0.38) | -0.00 (-0.37) | -0.00 (-0.36) | -0.00 (-0.35) | -0.00 (-0.35) | -0.00 (-0.35) | -0,2 | (-0.31) |
| C27 | 0.00 (0.00) | 0.27 (0.25) | -0.03 (-0.10) | -0.02 (-0.16) | -0.01 (-0.21) | -0.01 (-0.24) | -0.00 (-0.25) | -0.00 (-0.26) | -0.00 (-0.26) | -0.00 (-0.26) | -0.00 (-0.26) | -0,14 | (-0.05) |
| C28 | 0.00 (0.00) | -0.57 (-0.42) | -0.21 (-0.35) | -0.07 (-0.31) | -0.03 (-0.29) | -0.01 (-0.28) | -0.01 (-0.27) | -0.00 (-0.26) | -0.00 (-0.26) | -0.00 (-0.26) | -0.00 (-0.26) | -1,77 | (-0.3) |
| C29 | -16.48 (-0.24) | 0.38 (0.36) | 0.06 (0.14) | 0.01 (0.16) | 0.00 (0.07) | -0.00 (-0.01) | -0.00 (-0.08) | -0.00 (-0.12) | -0.00 (-0.15) | -0.00 (-0.15) | -0.00 (-0.15) | -14,16 | (-0.23) |
| C30 | 0.00 (0.00) | -0.36 (-0.79) | -0.04 (-0.50) | -0.02 (-0.49) | -0.01 (-0.46) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.39) | -0.00 (-0.37) | -0.00 (-0.37) | -0.00 (-0.37) | -0,49 | (-0.58) |
| C31_32 | 0.00 (0.00) | -0.27 (-0.40) | -0.11 (-0.43) | -0.04 (-0.43) | -0.02 (-0.42) | -0.01 (-0.41) | -0.00 (-0.39) | -0.00 (-0.37) | -0.00 (-0.35) | -0.00 (-0.35) | -0.00 (-0.35) | -0,51 | (-0.38) |
| C33 | 0.00 (0.00) | -0.35 (-0.55) | -0.13 (-0.50) | -0.05 (-0.48) | -0.02 (-0.46) | -0.01 (-0.44) | -0.01 (-0.42) | -0.00 (-0.41) | -0.00 (-0.39) | -0.00 (-0.39) | -0.00 (-0.39) | -0,59 | (-0.52) |
| D35 | 0.00 (0.00) | -0.00 (-0.03) | -0.06 (-0.38) | -0.05 (-0.43) | -0.04 (-0.45) | -0.02 (-0.44) | -0.01 (-0.44) | -0.01 (-0.43) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,2 | (-0.34) |
| E36 | 0.00 (0.00) | -0.11 (-0.86) | -0.05 (-0.63) | -0.02 (-0.55) | -0.01 (-0.50) | -0.00 (-0.47) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.40) | -0.00 (-0.40) | -0.00 (-0.40) | -0,19 | (-0.7) |
| E37T39 | 0.00 (0.00) | -0.82 (-0.90) | -0.32 (-0.66) | -0.14 (-0.56) | -0.06 (-0.50) | -0.03 (-0.46) | -0.01 (-0.44) | -0.01 (-0.41) | -0.00 (-0.39) | -0.00 (-0.39) | -0.00 (-0.39) | -1,39 | (-0.74) |
| F | 0.00 (0.00) | -1.60 (-0.84) | -0.77 (-0.68) | -0.36 (-0.60) | -0.17 (-0.55) | -0.08 (-0.51) | -0.04 (-0.48) | -0.02 (-0.46) | -0.01 (-0.43) | -0.01 (-0.43) | -0.01 (-0.43) | -3,05 | (-0.72) |
| G45 | 0.00 (0.00) | 0.11 (0.02) | -0.07 (-0.09) | -0.05 (-0.22) | -0.03 (-0.30) | -0.01 (-0.32) | -0.01 (-0.32) | -0.00 (-0.31) | -0.00 (-0.30) | -0.00 (-0.30) | -0.00 (-0.30) | -0,8 | (-0.07) |
| G46 | 0.00 (0.00) | -3.50 (-0.66) | -1.06 (-0.53) | -0.46 (-0.50) | -0.20 (-0.47) | -0.09 (-0.44) | -0.04 (-0.42) | -0.02 (-0.40) | -0.01 (-0.38) | -0.01 (-0.38) | -0.01 (-0.38) | -5,39 | (-0.59) |
| G47 | 0.00 (0.00) | -1.02 (-0.37) | -0.41 (-0.44) | -0.19 (-0.46) | -0.09 (-0.44) | -0.04 (-0.42) | -0.02 (-0.39) | -0.01 (-0.37) | -0.00 (-0.35) | -0.00 (-0.35) | -0.00 (-0.35) | -1,78 | (-0.4) |
| H49 | 0.00 (0.00) | -0.94 (-0.56) | -0.73 (-0.52) | -0.40 (-0.51) | -0.20 (-0.49) | -0.10 (-0.47) | -0.05 (-0.45) | -0.02 (-0.43) | -0.01 (-0.41) | -0.01 (-0.41) | -0.01 (-0.41) | -2,47 | (-0.52) |
| H50 | 0.00 (0.00) | -0.04 (-0.78) | -0.03 (-0.55) | -0.01 (-0.51) | -0.01 (-0.48) | -0.00 (-0.45) | -0.00 (-0.42) | -0.00 (-0.39) | -0.00 (-0.37) | -0.00 (-0.37) | -0.00 (-0.37) | -0,1 | (-0.6) |
| H51 | 0.00 (0.00) | -0.01 (-0.72) | -0.01 (-0.57) | -0.01 (-0.53) | -0.00 (-0.50) | -0.00 (-0.48) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,03 | (-0.58) |
| H52 | 0.00 (0.00) | -0.59 (-0.64) | -0.56 (-0.54) | -0.30 (-0.52) | -0.15 (-0.50) | -0.07 (-0.48) | -0.03 (-0.45) | -0.02 (-0.43) | -0.01 (-0.41) | -0.01 (-0.41) | -0.01 (-0.41) | -1,73 | (-0.55) |
| H53 | 0.00 (0.00) | 0.14 (2.59) | -0.10 (-0.62) | -0.06 (-0.55) | -0.03 (-0.52) | -0.01 (-0.49) | -0.01 (-0.46) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,07 | (-0.15) |
| I | 0.00 (0.00) | -0.23 (-0.48) | -0.80 (-0.55) | -0.43 (-0.53) | -0.21 (-0.51) | -0.10 (-0.48) | -0.05 (-0.46) | -0.02 (-0.44) | -0.01 (-0.42) | -0.01 (-0.42) | -0.01 (-0.42) | -1,87 | (-0.52) |
| J58 | 0.00 (0.00) | -0.01 (-0.49) | -0.03 (-0.58) | -0.02 (-0.50) | -0.01 (-0.51) | -0.00 (-0.49) | -0.00 (-0.46) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,07 | (-0.52) |
| J59_60 | 0.00 (0.00) | -0.01 (-0.40) | -0.04 (-0.54) | -0.02 (-0.52) | -0.01 (-0.51) | -0.01 (-0.49) | -0.00 (-0.47) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,09 | (-0.5) |
| J61 | 0.00 (0.00) | -0.17 (-0.88) | -0.09 (-0.65) | -0.04 (-0.57) | -0.02 (-0.52) | -0.01 (-0.48) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.40) | -0.00 (-0.40) | -0.00 (-0.40) | -0,33 | (-0.71) |
| J62_63 | 0.00 (0.00) | -0.67 (-0.54) | -0.44 (-0.54) | -0.23 (-0.52) | -0.11 (-0.50) | -0.05 (-0.48) | -0.03 (-0.46) | -0.01 (-0.44) | -0.01 (-0.42) | -0.01 (-0.42) | -0.01 (-0.42) | -1,56 | (-0.53) |
| K64 | 0.00 (0.00) | -0.51 (-0.78) | -0.34 (-0.54) | -0.18 (-0.52) | -0.09 (-0.50) | -0.04 (-0.48) | -0.02 (-0.46) | -0.01 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -1,19 | (-0.61) |
| K65 | 0.00 (0.00) | -0.02 (-0.69) | -0.02 (-0.55) | -0.01 (-0.53) | -0.00 (-0.50) | -0.00 (-0.48) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,06 | (-0.57) |
| K66 | 0.00 (0.00) | -0.07 (-0.46) | -0.33 (-0.58) | -0.17 (-0.52) | -0.08 (-0.50) | -0.04 (-0.48) | -0.02 (-0.45) | -0.01 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,72 | (-0.53) |
| L | 0.00 (0.00) | -0.06 (-0.54) | -0.07 (-0.49) | -0.03 (-0.51) | -0.02 (-0.49) | -0.01 (-0.47) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,19 | (-0.51) |
| M69_70 | 0.00 (0.00) | -2.56 (-0.71) | -1.60 (-0.61) | -0.72 (-0.54) | -0.33 (-0.51) | -0.15 (-0.48) | -0.07 (-0.46) | -0.03 (-0.44) | -0.02 (-0.42) | -0.02 (-0.42) | -0.02 (-0.42) | -5,5 | (-0.62) |
| M71 | 0.00 (0.00) | -5.26 (-0.96) | -0.65 (-0.62) | -0.28 (-0.56) | -0.12 (-0.52) | -0.06 (-0.49) | -0.03 (-0.47) | -0.01 (-0.44) | -0.01 (-0.42) | -0.01 (-0.42) | -0.01 (-0.42) | -6,42 | (-0.86) |
| M72 | 0.00 (0.00) | -1.30 (-0.87) | -0.07 (-0.65) | -0.02 (-0.58) | -0.01 (-0.53) | -0.00 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -1,41 | (-0.84) |
| M73 | 0.00 (0.00) | -0.15 (-0.46) | -0.13 (-0.41) | -0.06 (-0.48) | -0.03 (-0.48) | -0.01 (-0.46) | -0.01 (-0.44) | -0.00 (-0.42) | -0.00 (-0.40) | -0.00 (-0.40) | -0.00 (-0.40) | -0,39 | (-0.44) |
| M74_75 | 0.00 (0.00) | -1.16 (-0.87) | -0.50 (-0.61) | -0.22 (-0.54) | -0.10 (-0.51) | -0.05 (-0.48) | -0.02 (-0.46) | -0.01 (-0.44) | -0.01 (-0.41) | -0.01 (-0.41) | -0.01 (-0.41) | -2,09 | (-0.7) |
| N77 | 0.00 (0.00) | -0.05 (-0.36) | -0.08 (-0.55) | -0.04 (-0.53) | -0.02 (-0.50) | -0.01 (-0.48) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,2 | (-0.47) |
| N78 | 0.00 (0.00) | 1.45 (1.40) | -0.85 (-0.49) | -0.34 (-0.48) | -0.15 (-0.47) | -0.07 (-0.45) | -0.03 (-0.43) | -0.01 (-0.41) | -0.01 (-0.39) | -0.01 (-0.39) | -0.01 (-0.39) | -0,02 | (0) |
| N79 | 0.00 (0.00) | 0.00 (0.12) | -0.03 (-0.56) | -0.02 (-0.53) | -0.01 (-0.51) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,07 | (-0.46) |
| N80T82 | 0.00 (0.00) | -1.30 (-0.69) | -1.54 (-0.60) | -0.72 (-0.54) | -0.33 (-0.51) | -0.15 (-0.48) | -0.07 (-0.45) | -0.03 (-0.43) | -0.02 (-0.41) | -0.02 (-0.41) | -0.02 (-0.41) | -4,18 | (-0.59) |
| O84 | 0.00 (0.00) | -0.46 (-0.84) | -0.26 (-0.62) | -0.13 (-0.56) | -0.06 (-0.51) | -0.03 (-0.48) | -0.01 (-0.45) | -0.01 (-0.42) | -0.00 (-0.40) | -0.00 (-0.40) | -0.00 (-0.40) | -0,96 | (-0.67) |
| P85 | 0.00 (0.00) | -0.30 (-0.66) | -0.22 (-0.49) | -0.12 (-0.52) | -0.05 (-0.50) | -0.03 (-0.48) | -0.01 (-0.46) | -0.01 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,74 | (-0.55) |
| Q86 | 0.00 (0.00) | 0.29 (1.65) | -0.03 (-0.26) | -0.04 (-0.46) | -0.02 (-0.48) | -0.01 (-0.47) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | 0,19 | (0.42) |
| Q87_88 | 0.00 (0.00) | 0.02 (1.96) | -0.11 (-0.52) | -0.09 (-0.49) | -0.05 (-0.51) | -0.02 (-0.50) | -0.01 (-0.48) | -0.01 (-0.45) | -0.00 (-0.43) | -0.00 (-0.43) | -0.00 (-0.43) | -0,27 | (-0.45) |
| R90T92 | 0.00 (0.00) | -0.01 (-0.34) | -0.07 (-0.54) | -0.06 (-0.55) | -0.03 (-0.52) | -0.02 (-0.50) | -0.01 (-0.48) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.43) | -0.00 (-0.43) | -0,2 | (-0.51) |
| R93 | 0.00 (0.00) | -0.02 (-0.27) | -0.12 (-0.54) | -0.09 (-0.55) | -0.05 (-0.52) | -0.02 (-0.50) | -0.01 (-0.47) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,32 | (-0.49) |
| S94 | 0.00 (0.00) | -0.05 (-0.59) | -0.09 (-0.57) | -0.05 (-0.55) | -0.03 (-0.52) | -0.01 (-0.49) | -0.01 (-0.46) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,24 | (-0.55) |
| S95 | 0.00 (0.00) | 0.00 (0.00) | -0.03 (-0.57) | -0.02 (-0.52) | -0.01 (-0.50) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,06 | (-0.39) |
| S96 | 0.00 (0.00) | -0.01 (-0.47) | -0.05 (-0.54) | -0.04 (-0.55) | -0.02 (-0.52) | -0.01 (-0.50) | -0.00 (-0.47) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,14 | (-0.53) |
| T | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| U | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | | (0.00) |
| Total | | | | | | | | | | | | -82,54 | (-0.41) |

Table 3.30: Change in the quantity of labour (in thousands of units) in Scenario 3 relative to the 'business as usual' scenario, by activation round. Each round corresponds to a term in the summation of Equation 3.1. Round zero denotes the variation in the final-demand vector for sector C29 only. The first round indicates the effect on suppliers closest to the automotive supply chain, the second round the effect on suppliers of those suppliers, and so forth. The last column reports the cumulative effect for each sector. Decimal points are shown in parentheses.

| Industry | Round 0 | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 | Round 6 | Round 7 | Round 8 | Round 9 | Round 10 | Total Δ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A01 | 0.00 (0.00) | -0.66 (-0.22) | -12.28 (-0.59) | -8.55 (-0.54) | -5.10 (-0.52) | -2.68 (-0.49) | -1.34 (-0.47) | -0.65 (-0.44) | -0.31 (-0.42) | -0.31 (-0.42) | -0.31 (-0.42) | -31,88 | (-0.52) |
| A02 | 0.00 (0.00) | -0.49 (-0.73) | -0.87 (-0.47) | -0.53 (-0.50) | -0.25 (-0.48) | -0.11 (-0.46) | -0.05 (-0.43) | -0.02 (-0.41) | -0.01 (-0.39) | -0.01 (-0.39) | -0.01 (-0.39) | -2,35 | (-0.51) |
| A03 | 0.00 (0.00) | -0.00 (-0.24) | -0.13 (-0.62) | -0.15 (-0.55) | -0.08 (-0.53) | -0.04 (-0.50) | -0.02 (-0.47) | -0.01 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,43 | (-0.55) |
| B | 0.00 (0.00) | -24.97 (-0.89) | -10.89 (-0.73) | -4.37 (-0.60) | -1.96 (-0.53) | -0.90 (-0.48) | -0.42 (-0.45) | -0.20 (-0.42) | -0.10 (-0.40) | -0.10 (-0.40) | -0.10 (-0.40) | -43,9 | (-0.76) |
| C10T12 | 0.00 (0.00) | -3.59 (-0.73) | -5.69 (-0.61) | -4.62 (-0.55) | -2.55 (-0.52) | -1.28 (-0.49) | -0.61 (-0.46) | -0.29 (-0.43) | -0.14 (-0.41) | -0.14 (-0.41) | -0.14 (-0.41) | -18,9 | (-0.58) |
| C13T15 | 0.00 (0.00) | -19.38 (-0.37) | -7.39 (-0.39) | -2.96 (-0.38) | -1.24 (-0.36) | -0.55 (-0.34) | -0.25 (-0.32) | -0.12 (-0.30) | -0.05 (-0.28) | -0.05 (-0.28) | -0.05 (-0.28) | -32,12 | (-0.37) |
| C16 | 0.00 (0.00) | -3.22 (-0.21) | -4.88 (-0.46) | -2.44 (-0.48) | -1.11 (-0.47) | -0.50 (-0.45) | -0.23 (-0.42) | -0.11 (-0.40) | -0.05 (-0.38) | -0.05 (-0.38) | -0.05 (-0.38) | -13,08 | (-0.35) |
| C17 | 0.00 (0.00) | -8.52 (-0.59) | -8.20 (-0.59) | -4.30 (-0.53) | -2.06 (-0.49) | -0.96 (-0.46) | -0.45 (-0.43) | -0.21 (-0.41) | -0.10 (-0.39) | -0.10 (-0.39) | -0.10 (-0.39) | -24,9 | (-0.56) |
| C18 | 0.00 (0.00) | -6.55 (-0.44) | -7.03 (-0.59) | -3.94 (-0.54) | -1.93 (-0.51) | -0.91 (-0.49) | -0.42 (-0.47) | -0.20 (-0.44) | -0.09 (-0.42) | -0.09 (-0.42) | -0.09 (-0.42) | -25,34 | (-0.43) |
| C19 | 0.00 (0.00) | -0.24 (-0.56) | -1.14 (-0.61) | -0.88 (-0.54) | -0.48 (-0.49) | -0.24 (-0.46) | -0.12 (-0.43) | -0.06 (-0.41) | -0.03 (-0.39) | -0.03 (-0.39) | -0.03 (-0.39) | -3,21 | (-0.53) |
| C20 | 0.00 (0.00) | -28.03 (-0.81) | -17.61 (-0.57) | -6.31 (-0.48) | -2.45 (-0.42) | -1.03 (-0.38) | -0.46 (-0.35) | -0.21 (-0.32) | -0.10 (-0.30) | -0.10 (-0.30) | -0.10 (-0.30) | -56,31 | (-0.63) |
| C21 | 0.00 (0.00) | -7.77 (-0.83) | -2.09 (-0.58) | -0.81 (-0.50) | -0.35 (-0.45) | -0.16 (-0.40) | -0.07 (-0.37) | -0.03 (-0.33) | -0.02 (-0.31) | -0.02 (-0.31) | -0.02 (-0.31) | -11,32 | (-0.7) |
| C22 | 0.00 (0.00) | -127.49 (-0.62) | -28.22 (-0.48) | -8.91 (-0.44) | -3.34 (-0.41) | -1.41 (-0.39) | -0.64 (-0.37) | -0.30 (-0.36) | -0.14 (-0.34) | -0.14 (-0.34) | -0.14 (-0.34) | -176,01 | (-0.55) |
| C23 | 0.00 (0.00) | -84.07 (-0.88) | -21.33 (-0.68) | -7.31 (-0.57) | -2.86 (-0.50) | -1.23 (-0.46) | -0.56 (-0.43) | -0.26 (-0.41) | -0.13 (-0.39) | -0.13 (-0.39) | -0.13 (-0.39) | -117,87 | (-0.78) |
| C24 | 0.00 (0.00) | -71.85 (-0.76) | -30.69 (-0.54) | -10.20 (-0.44) | -3.28 (-0.36) | -1.11 (-0.29) | -0.42 (-0.25) | -0.17 (-0.22) | -0.08 (-0.21) | -0.08 (-0.21) | -0.08 (-0.21) | -119,13 | (-0.61) |
| C25 | 0.00 (0.00) | -447.57 (-0.48) | -108.40 (-0.45) | -31.71 (-0.41) | -10.41 (-0.37) | -3.92 (-0.35) | -1.65 (-0.33) | -0.75 (-0.32) | -0.36 (-0.31) | -0.36 (-0.31) | -0.36 (-0.31) | -686,18 | (-0.42) |
| C26 | 0.00 (0.00) | -8.28 (-0.27) | -5.36 (-0.41) | -2.11 (-0.37) | -1.03 (-0.38) | -0.51 (-0.38) | -0.25 (-0.37) | -0.12 (-0.36) | -0.06 (-0.35) | -0.06 (-0.35) | -0.06 (-0.35) | -20,77 | (-0.31) |
| C27 | 0.00 (0.00) | 23.64 (0.25) | -2.44 (-0.10) | -1.52 (-0.16) | -0.85 (-0.21) | -0.45 (-0.24) | -0.23 (-0.25) | -0.12 (-0.26) | -0.06 (-0.26) | -0.06 (-0.26) | -0.06 (-0.26) | -11,9 | (-0.05) |
| C28 | 0.00 (0.00) | -51.93 (-0.42) | -18.57 (-0.35) | -6.38 (-0.31) | -2.47 (-0.29) | -1.06 (-0.28) | -0.49 (-0.27) | -0.24 (-0.26) | -0.12 (-0.26) | -0.12 (-0.26) | -0.12 (-0.26) | -159,62 | (-0.3) |
| C29 | -1254.36 (-0.24) | 29.17 (0.36) | 4.27 (0.14) | 1.13 (0.16) | 0.19 (0.07) | -0.02 (-0.01) | -0.04 (-0.08) | -0.03 (-0.12) | -0.02 (-0.15) | -0.02 (-0.15) | -0.02 (-0.15) | -1078,15 | (-0.23) |
| C30 | 0.00 (0.00) | -29.28 (-0.79) | -3.55 (-0.50) | -1.34 (-0.49) | -0.56 (-0.46) | -0.25 (-0.43) | -0.12 (-0.41) | -0.06 (-0.39) | -0.03 (-0.37) | -0.03 (-0.37) | -0.03 (-0.37) | -39,95 | (-0.58) |
| C31_32 | 0.00 (0.00) | -16.25 (-0.40) | -6.42 (-0.43) | -2.64 (-0.43) | -1.15 (-0.42) | -0.51 (-0.41) | -0.24 (-0.39) | -0.11 (-0.37) | -0.05 (-0.35) | -0.05 (-0.35) | -0.05 (-0.35) | -30,77 | (-0.38) |
| C33 | 0.00 (0.00) | -19.14 (-0.55) | -7.27 (-0.50) | -3.01 (-0.48) | -1.34 (-0.46) | -0.62 (-0.44) | -0.29 (-0.42) | -0.14 (-0.41) | -0.07 (-0.39) | -0.07 (-0.39) | -0.07 (-0.39) | -32,09 | (-0.52) |
| D35 | 0.00 (0.00) | -2.09 (-0.03) | -38.41 (-0.38) | -33.50 (-0.43) | -22.05 (-0.45) | -13.00 (-0.44) | -7.26 (-0.44) | -3.93 (-0.43) | -2.09 (-0.42) | -2.09 (-0.42) | -2.09 (-0.42) | -124,59 | (-0.34) |
| E36 | 0.00 (0.00) | -13.19 (-0.86) | -5.53 (-0.63) | -2.47 (-0.55) | -1.09 (-0.50) | -0.49 (-0.47) | -0.22 (-0.44) | -0.11 (-0.42) | -0.05 (-0.40) | -0.05 (-0.40) | -0.05 (-0.40) | -23,2 | (-0.7) |
| E37T39 | 0.00 (0.00) | -60.86 (-0.90) | -23.51 (-0.66) | -10.12 (-0.56) | -4.36 (-0.50) | -1.93 (-0.46) | -0.88 (-0.44) | -0.41 (-0.41) | -0.20 (-0.39) | -0.20 (-0.39) | -0.20 (-0.39) | -102,45 | (-0.74) |
| F | 0.00 (0.00) | -92.00 (-0.84) | -44.18 (-0.68) | -20.82 (-0.60) | -9.67 (-0.55) | -4.50 (-0.51) | -2.11 (-0.48) | -0.99 (-0.46) | -0.47 (-0.43) | -0.47 (-0.43) | -0.47 (-0.43) | -175,21 | (-0.72) |
| G45 | 0.00 (0.00) | 5.51 (0.02) | -3.29 (-0.09) | -2.50 (-0.22) | -1.41 (-0.30) | -0.70 (-0.32) | -0.34 (-0.32) | -0.17 (-0.31) | -0.08 (-0.30) | -0.08 (-0.30) | -0.08 (-0.30) | -39,15 | (-0.07) |
| G46 | 0.00 (0.00) | -301.08 (-0.66) | -91.51 (-0.53) | -39.69 (-0.50) | -17.32 (-0.47) | -7.76 (-0.44) | -3.56 (-0.42) | -1.67 (-0.40) | -0.80 (-0.38) | -0.80 (-0.38) | -0.80 (-0.38) | -464,17 | (-0.59) |
| G47 | 0.00 (0.00) | -46.24 (-0.37) | -18.78 (-0.44) | -8.49 (-0.46) | -3.89 (-0.44) | -1.79 (-0.42) | -0.84 (-0.39) | -0.40 (-0.37) | -0.19 (-0.35) | -0.19 (-0.35) | -0.19 (-0.35) | -80,79 | (-0.4) |
| H49 | 0.00 (0.00) | -80.33 (-0.56) | -62.11 (-0.52) | -34.25 (-0.51) | -17.20 (-0.49) | -8.38 (-0.47) | -4.06 (-0.45) | -1.97 (-0.43) | -0.97 (-0.41) | -0.97 (-0.41) | -0.97 (-0.41) | -210,23 | (-0.52) |
| H50 | 0.00 (0.00) | -1.81 (-0.78) | -1.19 (-0.55) | -0.59 (-0.51) | -0.28 (-0.48) | -0.13 (-0.45) | -0.06 (-0.42) | -0.03 (-0.39) | -0.01 (-0.37) | -0.01 (-0.37) | -0.01 (-0.37) | -4,13 | (-0.6) |
| H51 | 0.00 (0.00) | -0.81 (-0.72) | -0.90 (-0.57) | -0.46 (-0.53) | -0.23 (-0.50) | -0.11 (-0.48) | -0.05 (-0.45) | -0.02 (-0.43) | -0.01 (-0.41) | -0.01 (-0.41) | -0.01 (-0.41) | -2,6 | (-0.58) |
| H52 | 0.00 (0.00) | -55.77 (-0.64) | -52.77 (-0.54) | -28.27 (-0.52) | -13.81 (-0.50) | -6.56 (-0.48) | -3.10 (-0.45) | -1.47 (-0.43) | -0.71 (-0.41) | -0.71 (-0.41) | -0.71 (-0.41) | -163,14 | (-0.55) |
| H53 | 0.00 (0.00) | 7.15 (2.59) | -4.89 (-0.62) | -2.84 (-0.55) | -1.43 (-0.52) | -0.68 (-0.49) | -0.32 (-0.46) | -0.15 (-0.43) | -0.07 (-0.41) | -0.07 (-0.41) | -0.07 (-0.41) | -3,29 | (-0.15) |
| I | 0.00 (0.00) | -8.30 (-0.48) | -28.45 (-0.55) | -15.39 (-0.53) | -7.64 (-0.51) | -3.62 (-0.48) | -1.71 (-0.46) | -0.81 (-0.44) | -0.39 (-0.42) | -0.39 (-0.42) | -0.39 (-0.42) | -66,67 | (-0.52) |
| J58 | 0.00 (0.00) | -0.57 (-0.49) | -2.15 (-0.58) | -1.28 (-0.50) | -0.59 (-0.51) | -0.27 (-0.49) | -0.13 (-0.46) | -0.06 (-0.43) | -0.03 (-0.41) | -0.03 (-0.41) | -0.03 (-0.41) | -5,11 | (-0.52) |
| J59_60 | 0.00 (0.00) | -1.23 (-0.40) | -3.32 (-0.54) | -2.17 (-0.52) | -1.11 (-0.51) | -0.53 (-0.49) | -0.25 (-0.47) | -0.11 (-0.44) | -0.05 (-0.42) | -0.05 (-0.42) | -0.05 (-0.42) | -8,81 | (-0.5) |
| J61 | 0.00 (0.00) | -39.43 (-0.88) | -21.00 (-0.65) | -9.46 (-0.57) | -4.17 (-0.52) | -1.85 (-0.48) | -0.84 (-0.45) | -0.38 (-0.43) | -0.18 (-0.40) | -0.18 (-0.40) | -0.18 (-0.40) | -77,48 | (-0.71) |
| J62_63 | 0.00 (0.00) | -51.49 (-0.54) | -34.09 (-0.54) | -18.07 (-0.52) | -8.75 (-0.50) | -4.15 (-0.48) | -1.96 (-0.46) | -0.93 (-0.44) | -0.44 (-0.42) | -0.44 (-0.42) | -0.44 (-0.42) | -120,3 | (-0.53) |
| K64 | 0.00 (0.00) | -84.06 (-0.78) | -55.25 (-0.54) | -29.43 (-0.52) | -13.95 (-0.50) | -6.48 (-0.48) | -3.02 (-0.46) | -1.42 (-0.43) | -0.67 (-0.41) | -0.67 (-0.41) | -0.67 (-0.41) | -194,92 | (-0.61) |
| K65 | 0.00 (0.00) | -6.17 (-0.69) | -6.57 (-0.55) | -3.10 (-0.53) | -1.43 (-0.50) | -0.66 (-0.48) | -0.30 (-0.45) | -0.14 (-0.43) | -0.07 (-0.41) | -0.07 (-0.41) | -0.07 (-0.41) | -18,51 | (-0.57) |
| K66 | 0.00 (0.00) | -4.17 (-0.46) | -20.61 (-0.58) | -10.72 (-0.52) | -5.18 (-0.50) | -2.42 (-0.48) | -1.13 (-0.45) | -0.53 (-0.43) | -0.25 (-0.41) | -0.25 (-0.41) | -0.25 (-0.41) | -45,25 | (-0.53) |
| L | 0.00 (0.00) | -73.03 (-0.54) | -84.96 (-0.49) | -41.17 (-0.51) | -19.34 (-0.49) | -9.02 (-0.47) | -4.22 (-0.45) | -1.99 (-0.43) | -0.95 (-0.41) | -0.95 (-0.41) | -0.95 (-0.41) | -235,6 | (-0.51) |
| M69_70 | 0.00 (0.00) | -167.23 (-0.71) | -104.58 (-0.61) | -46.90 (-0.54) | -21.62 (-0.51) | -10.00 (-0.48) | -4.66 (-0.46) | -2.20 (-0.44) | -1.05 (-0.42) | -1.05 (-0.42) | -1.05 (-0.42) | -359,24 | (-0.62) |
| M71 | 0.00 (0.00) | -285.18 (-0.96) | -34.96 (-0.62) | -15.26 (-0.56) | -6.62 (-0.52) | -3.03 (-0.49) | -1.41 (-0.47) | -0.67 (-0.44) | -0.32 (-0.42) | -0.32 (-0.42) | -0.32 (-0.42) | -347,75 | (-0.86) |
| M72 | 0.00 (0.00) | -198.24 (-0.87) | -10.26 (-0.65) | -3.36 (-0.58) | -1.21 (-0.53) | -0.52 (-0.50) | -0.24 (-0.48) | -0.11 (-0.46) | -0.05 (-0.44) | -0.05 (-0.44) | -0.05 (-0.44) | -214,04 | (-0.84) |
| M73 | 0.00 (0.00) | -8.18 (-0.46) | -7.17 (-0.41) | -3.30 (-0.48) | -1.55 (-0.48) | -0.72 (-0.46) | -0.34 (-0.44) | -0.16 (-0.42) | -0.07 (-0.40) | -0.07 (-0.40) | -0.07 (-0.40) | -21,55 | (-0.44) |
| M74_75 | 0.00 (0.00) | -53.97 (-0.87) | -23.29 (-0.61) | -10.45 (-0.54) | -4.80 (-0.51) | -2.23 (-0.48) | -1.04 (-0.46) | -0.49 (-0.44) | -0.24 (-0.41) | -0.24 (-0.41) | -0.24 (-0.41) | -97 | (-0.7) |
| N77 | 0.00 (0.00) | -9.91 (-0.36) | -14.12 (-0.55) | -7.15 (-0.53) | -3.40 (-0.50) | -1.59 (-0.48) | -0.75 (-0.45) | -0.35 (-0.43) | -0.17 (-0.41) | -0.17 (-0.41) | -0.17 (-0.41) | -37,6 | (-0.47) |
| N78 | 0.00 (0.00) | 47.06 (1.40) | -27.63 (-0.49) | -10.94 (-0.48) | -4.89 (-0.47) | -2.20 (-0.45) | -1.01 (-0.43) | -0.47 (-0.41) | -0.22 (-0.39) | -0.22 (-0.39) | -0.22 (-0.39) | -0,52 | (0) |
| N79 | 0.00 (0.00) | 0.04 (0.12) | -0.69 (-0.56) | -0.45 (-0.53) | -0.23 (-0.51) | -0.11 (-0.48) | -0.05 (-0.46) | -0.02 (-0.43) | -0.01 (-0.41) | -0.01 (-0.41) | -0.01 (-0.41) | -1,54 | (-0.46) |
| N80T82 | 0.00 (0.00) | -45.61 (-0.69) | -54.21 (-0.60) | -25.29 (-0.54) | -11.69 (-0.51) | -5.37 (-0.48) | -2.48 (-0.45) | -1.16 (-0.43) | -0.55 (-0.41) | -0.55 (-0.41) | -0.55 (-0.41) | -146,89 | (-0.59) |
| O84 | 0.00 (0.00) | -43.89 (-0.84) | -25.31 (-0.62) | -12.13 (-0.56) | -5.72 (-0.51) | -2.64 (-0.48) | -1.22 (-0.45) | -0.57 (-0.42) | -0.27 (-0.40) | -0.27 (-0.40) | -0.27 (-0.40) | -92,02 | (-0.67) |
| P85 | 0.00 (0.00) | -13.07 (-0.66) | -9.30 (-0.49) | -4.97 (-0.52) | -2.31 (-0.50) | -1.08 (-0.48) | -0.50 (-0.46) | -0.24 (-0.43) | -0.11 (-0.41) | -0.11 (-0.41) | -0.11 (-0.41) | -31,68 | (-0.55) |
| Q86 | 0.00 (0.00) | 17.22 (1.65) | -1.65 (-0.26) | -2.16 (-0.46) | -1.19 (-0.48) | -0.58 (-0.47) | -0.27 (-0.45) | -0.13 (-0.43) | -0.06 (-0.41) | -0.06 (-0.41) | -0.06 (-0.41) | 11,13 | (0.42) |
| Q87_88 | 0.00 (0.00) | 0.68 (1.96) | -3.03 (-0.52) | -2.66 (-0.49) | -1.39 (-0.51) | -0.67 (-0.50) | -0.32 (-0.48) | -0.15 (-0.45) | -0.07 (-0.43) | -0.07 (-0.43) | -0.07 (-0.43) | -7,68 | (-0.45) |
| R90T92 | 0.00 (0.00) | -0.74 (-0.34) | -4.68 (-0.54) | -3.55 (-0.55) | -2.01 (-0.52) | -1.01 (-0.50) | -0.49 (-0.48) | -0.23 (-0.45) | -0.11 (-0.43) | -0.11 (-0.43) | -0.11 (-0.43) | -12,91 | (-0.51) |
| R93 | 0.00 (0.00) | -1.05 (-0.27) | -5.12 (-0.54) | -3.68 (-0.55) | -1.97 (-0.52) | -0.96 (-0.50) | -0.45 (-0.47) | -0.21 (-0.44) | -0.10 (-0.42) | -0.10 (-0.42) | -0.10 (-0.42) | -13,65 | (-0.49) |
| S94 | 0.00 (0.00) | -1.88 (-0.59) | -3.35 (-0.57) | -1.92 (-0.55) | -0.98 (-0.52) | -0.47 (-0.49) | -0.23 (-0.46) | -0.11 (-0.44) | -0.05 (-0.42) | -0.05 (-0.42) | -0.05 (-0.42) | -9,04 | (-0.55) |
| S95 | 0.00 (0.00) | 0.00 (0.00) | -1.20 (-0.57) | -0.59 (-0.52) | -0.29 (-0.50) | -0.14 (-0.47) | -0.06 (-0.45) | -0.03 (-0.43) | -0.01 (-0.41) | -0.01 (-0.41) | -0.01 (-0.41) | -2,34 | (-0.39) |
| S96 | 0.00 (0.00) | -0.28 (-0.47) | -1.90 (-0.54) | -1.45 (-0.55) | -0.69 (-0.52) | -0.32 (-0.50) | -0.15 (-0.47) | -0.07 (-0.44) | -0.03 (-0.42) | -0.03 (-0.42) | -0.03 (-0.42) | -4,9 | (-0.53) |
| T | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| U | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| Total | | | | | | | | | | | | -6290,96 | (-0.41) |

Table 3.31: Change in the value added (in millions of euros) in Scenario 3 relative to the 'business as usual' scenario, by activation round. Each round corresponds to a term in the summation of Equation 3.1. Round zero denotes the variation in the final-demand vector for sector C29 only. The first round indicates the effect on suppliers closest to the automotive supply chain, the second round the effect on suppliers of those suppliers, and so forth. The last column reports the cumulative effect for each sector. Decimal points are shown in parentheses.

| Industry | Round 0 | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 | Round 6 | Round 7 | Round 8 | Round 9 | Round 10 | Total Δ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A01 | 0.00 (0.00) | -0.02 (-0.22) | -0.30 (-0.60) | -0.21 (-0.57) | -0.13 (-0.55) | -0.07 (-0.53) | -0.03 (-0.50) | -0.02 (-0.48) | -0.01 (-0.46) | -0.01 (-0.46) | -0.01 (-0.46) | -0,8 | (-0.55) |
| A02 | 0.00 (0.00) | -0.01 (-0.73) | -0.01 (-0.49) | -0.01 (-0.53) | -0.00 (-0.52) | -0.00 (-0.50) | -0.00 (-0.48) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.43) | -0.00 (-0.43) | -0,03 | (-0.54) |
| A03 | 0.00 (0.00) | -0.00 (-0.24) | -0.00 (-0.63) | -0.00 (-0.57) | -0.00 (-0.55) | -0.00 (-0.53) | -0.00 (-0.51) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,01 | (-0.57) |
| B | 0.00 (0.00) | -0.07 (-0.90) | -0.03 (-0.75) | -0.01 (-0.63) | -0.01 (-0.56) | -0.00 (-0.52) | -0.00 (-0.49) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,13 | (-0.78) |
| C10T12 | 0.00 (0.00) | -0.05 (-0.73) | -0.08 (-0.62) | -0.07 (-0.58) | -0.04 (-0.55) | -0.02 (-0.53) | -0.01 (-0.50) | -0.00 (-0.48) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,28 | (-0.6) |
| C13T15 | 0.00 (0.00) | -0.36 (-0.37) | -0.14 (-0.40) | -0.06 (-0.40) | -0.03 (-0.40) | -0.01 (-0.38) | -0.01 (-0.36) | -0.00 (-0.34) | -0.00 (-0.32) | -0.00 (-0.32) | -0.00 (-0.32) | -0,61 | (-0.38) |
| C16 | 0.00 (0.00) | -0.06 (-0.21) | -0.09 (-0.49) | -0.05 (-0.52) | -0.02 (-0.51) | -0.01 (-0.49) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.43) | -0.00 (-0.43) | -0,25 | (-0.37) |
| C17 | 0.00 (0.00) | -0.09 (-0.60) | -0.09 (-0.61) | -0.05 (-0.56) | -0.02 (-0.53) | -0.01 (-0.50) | -0.01 (-0.48) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.43) | -0.00 (-0.43) | -0,28 | (-0.58) |
| C18 | 0.00 (0.00) | -0.11 (-0.44) | -0.12 (-0.60) | -0.07 (-0.57) | -0.04 (-0.55) | -0.02 (-0.53) | -0.01 (-0.51) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,45 | (-0.44) |
| C19 | 0.00 (0.00) | -0.00 (-0.56) | -0.01 (-0.62) | -0.01 (-0.57) | -0.00 (-0.53) | -0.00 (-0.50) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.43) | -0.00 (-0.43) | -0,02 | (-0.56) |
| C20 | 0.00 (0.00) | -0.23 (-0.82) | -0.15 (-0.61) | -0.06 (-0.53) | -0.02 (-0.47) | -0.01 (-0.43) | -0.00 (-0.40) | -0.00 (-0.37) | -0.00 (-0.35) | -0.00 (-0.35) | -0.00 (-0.35) | -0,48 | (-0.66) |
| C21 | 0.00 (0.00) | -0.05 (-0.83) | -0.01 (-0.61) | -0.01 (-0.54) | -0.00 (-0.49) | -0.00 (-0.45) | -0.00 (-0.41) | -0.00 (-0.38) | -0.00 (-0.36) | -0.00 (-0.36) | -0.00 (-0.36) | -0,07 | (-0.72) |
| C22 | 0.00 (0.00) | -1.72 (-0.68) | -0.39 (-0.55) | -0.12 (-0.49) | -0.05 (-0.46) | -0.02 (-0.44) | -0.01 (-0.42) | -0.00 (-0.41) | -0.00 (-0.40) | -0.00 (-0.40) | -0.00 (-0.40) | -2,39 | (-0.6) |
| C23 | 0.00 (0.00) | -1.07 (-0.88) | -0.28 (-0.71) | -0.10 (-0.61) | -0.04 (-0.55) | -0.02 (-0.50) | -0.01 (-0.48) | -0.00 (-0.45) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -1,53 | (-0.8) |
| C24 | 0.00 (0.00) | -0.78 (-0.78) | -0.36 (-0.60) | -0.12 (-0.51) | -0.04 (-0.43) | -0.01 (-0.36) | -0.01 (-0.32) | -0.00 (-0.29) | -0.00 (-0.28) | -0.00 (-0.28) | -0.00 (-0.28) | -1,34 | (-0.65) |
| C25 | 0.00 (0.00) | -7.76 (-0.56) | -1.90 (-0.53) | -0.56 (-0.48) | -0.18 (-0.44) | -0.07 (-0.41) | -0.03 (-0.40) | -0.01 (-0.38) | -0.01 (-0.37) | -0.01 (-0.37) | -0.01 (-0.37) | -11,72 | (-0.48) |
| C26 | 0.00 (0.00) | -0.11 (-0.39) | -0.06 (-0.47) | -0.02 (-0.43) | -0.01 (-0.43) | -0.01 (-0.43) | -0.00 (-0.42) | -0.00 (-0.41) | -0.00 (-0.40) | -0.00 (-0.40) | -0.00 (-0.40) | -0,25 | (-0.38) |
| C27 | 0.00 (0.00) | 0.03 (0.02) | -0.06 (-0.22) | -0.03 (-0.26) | -0.01 (-0.29) | -0.01 (-0.31) | -0.00 (-0.32) | -0.00 (-0.33) | -0.00 (-0.33) | -0.00 (-0.33) | -0.00 (-0.33) | -0,43 | (-0.15) |
| C28 | 0.00 (0.00) | -0.65 (-0.48) | -0.23 (-0.40) | -0.08 (-0.36) | -0.03 (-0.34) | -0.01 (-0.33) | -0.01 (-0.32) | -0.00 (-0.32) | -0.00 (-0.31) | -0.00 (-0.31) | -0.00 (-0.31) | -1,89 | (-0.32) |
| C29 | -16.48 (-0.24) | 0.37 (0.34) | 0.05 (0.12) | 0.01 (0.12) | 0.00 (0.02) | -0.00 (-0.07) | -0.00 (-0.13) | -0.00 (-0.18) | -0.00 (-0.21) | -0.00 (-0.21) | -0.00 (-0.21) | -14,19 | (-0.23) |
| C30 | 0.00 (0.00) | -0.37 (-0.80) | -0.05 (-0.54) | -0.02 (-0.53) | -0.01 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.43) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,5 | (-0.59) |
| C31_32 | 0.00 (0.00) | -0.29 (-0.43) | -0.12 (-0.47) | -0.05 (-0.48) | -0.02 (-0.47) | -0.01 (-0.45) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.40) | -0.00 (-0.40) | -0.00 (-0.40) | -0,55 | (-0.41) |
| C33 | 0.00 (0.00) | -0.38 (-0.60) | -0.14 (-0.54) | -0.06 (-0.52) | -0.03 (-0.50) | -0.01 (-0.49) | -0.01 (-0.47) | -0.00 (-0.45) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,64 | (-0.56) |
| D35 | 0.00 (0.00) | -0.00 (-0.03) | -0.07 (-0.41) | -0.06 (-0.47) | -0.04 (-0.48) | -0.02 (-0.48) | -0.01 (-0.48) | -0.01 (-0.47) | -0.00 (-0.47) | -0.00 (-0.47) | -0.00 (-0.47) | -0,22 | (-0.37) |
| E36 | 0.00 (0.00) | -0.11 (-0.86) | -0.05 (-0.66) | -0.02 (-0.59) | -0.01 (-0.54) | -0.00 (-0.51) | -0.00 (-0.49) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,2 | (-0.72) |
| E37T39 | 0.00 (0.00) | -0.82 (-0.90) | -0.33 (-0.68) | -0.15 (-0.60) | -0.06 (-0.55) | -0.03 (-0.51) | -0.01 (-0.48) | -0.01 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -1,42 | (-0.76) |
| F | 0.00 (0.00) | -1.60 (-0.84) | -0.79 (-0.70) | -0.38 (-0.62) | -0.18 (-0.58) | -0.08 (-0.55) | -0.04 (-0.52) | -0.02 (-0.50) | -0.01 (-0.48) | -0.01 (-0.48) | -0.01 (-0.48) | -3,11 | (-0.73) |
| G45 | 0.00 (0.00) | 0.11 (0.02) | -0.08 (-0.12) | -0.06 (-0.25) | -0.03 (-0.34) | -0.02 (-0.36) | -0.01 (-0.37) | -0.00 (-0.36) | -0.00 (-0.35) | -0.00 (-0.35) | -0.00 (-0.35) | -0,83 | (-0.08) |
| G46 | 0.00 (0.00) | -3.51 (-0.66) | -1.13 (-0.56) | -0.50 (-0.54) | -0.22 (-0.51) | -0.10 (-0.49) | -0.05 (-0.46) | -0.02 (-0.44) | -0.01 (-0.42) | -0.01 (-0.42) | -0.01 (-0.42) | -5,55 | (-0.61) |
| G47 | 0.00 (0.00) | -1.02 (-0.37) | -0.45 (-0.48) | -0.20 (-0.49) | -0.09 (-0.48) | -0.04 (-0.46) | -0.02 (-0.44) | -0.01 (-0.42) | -0.00 (-0.40) | -0.00 (-0.40) | -0.00 (-0.40) | -1,85 | (-0.42) |
| H49 | 0.00 (0.00) | -0.94 (-0.56) | -0.76 (-0.54) | -0.43 (-0.54) | -0.22 (-0.53) | -0.11 (-0.51) | -0.05 (-0.49) | -0.03 (-0.47) | -0.01 (-0.46) | -0.01 (-0.46) | -0.01 (-0.46) | -2,55 | (-0.54) |
| H50 | 0.00 (0.00) | -0.04 (-0.78) | -0.03 (-0.57) | -0.02 (-0.54) | -0.01 (-0.52) | -0.00 (-0.49) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,1 | (-0.62) |
| H51 | 0.00 (0.00) | -0.01 (-0.72) | -0.01 (-0.59) | -0.01 (-0.55) | -0.00 (-0.54) | -0.00 (-0.52) | -0.00 (-0.49) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,03 | (-0.6) |
| H52 | 0.00 (0.00) | -0.59 (-0.64) | -0.58 (-0.55) | -0.32 (-0.55) | -0.16 (-0.53) | -0.08 (-0.51) | -0.04 (-0.49) | -0.02 (-0.47) | -0.01 (-0.45) | -0.01 (-0.45) | -0.01 (-0.45) | -1,79 | (-0.57) |
| H53 | 0.00 (0.00) | 0.14 (2.59) | -0.10 (-0.62) | -0.06 (-0.57) | -0.03 (-0.55) | -0.01 (-0.52) | -0.01 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,07 | (-0.17) |
| I | 0.00 (0.00) | -0.23 (-0.48) | -0.82 (-0.57) | -0.45 (-0.56) | -0.23 (-0.54) | -0.11 (-0.52) | -0.05 (-0.50) | -0.02 (-0.48) | -0.01 (-0.46) | -0.01 (-0.46) | -0.01 (-0.46) | -1,94 | (-0.54) |
| J58 | 0.00 (0.00) | -0.01 (-0.49) | -0.03 (-0.58) | -0.02 (-0.52) | -0.01 (-0.54) | -0.00 (-0.52) | -0.00 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,07 | (-0.54) |
| J59_60 | 0.00 (0.00) | -0.01 (-0.40) | -0.04 (-0.55) | -0.02 (-0.54) | -0.01 (-0.54) | -0.01 (-0.53) | -0.00 (-0.51) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,1 | (-0.51) |
| J61 | 0.00 (0.00) | -0.17 (-0.88) | -0.09 (-0.68) | -0.04 (-0.60) | -0.02 (-0.56) | -0.01 (-0.52) | -0.00 (-0.50) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,34 | (-0.73) |
| J62_63 | 0.00 (0.00) | -0.67 (-0.54) | -0.45 (-0.56) | -0.25 (-0.55) | -0.12 (-0.54) | -0.06 (-0.52) | -0.03 (-0.50) | -0.01 (-0.48) | -0.01 (-0.46) | -0.01 (-0.46) | -0.01 (-0.46) | -1,6 | (-0.54) |
| K64 | 0.00 (0.00) | -0.51 (-0.78) | -0.35 (-0.57) | -0.19 (-0.55) | -0.09 (-0.54) | -0.04 (-0.52) | -0.02 (-0.50) | -0.01 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -1,23 | (-0.63) |
| K65 | 0.00 (0.00) | -0.02 (-0.69) | -0.02 (-0.58) | -0.01 (-0.56) | -0.00 (-0.54) | -0.00 (-0.52) | -0.00 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,06 | (-0.59) |
| K66 | 0.00 (0.00) | -0.07 (-0.46) | -0.34 (-0.60) | -0.18 (-0.55) | -0.09 (-0.54) | -0.04 (-0.52) | -0.02 (-0.50) | -0.01 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,76 | (-0.55) |
| L | 0.00 (0.00) | -0.06 (-0.54) | -0.07 (-0.52) | -0.03 (-0.54) | -0.02 (-0.53) | -0.01 (-0.51) | -0.00 (-0.49) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,19 | (-0.53) |
| M69_70 | 0.00 (0.00) | -2.56 (-0.71) | -1.65 (-0.63) | -0.76 (-0.57) | -0.35 (-0.54) | -0.17 (-0.52) | -0.08 (-0.50) | -0.04 (-0.48) | -0.02 (-0.46) | -0.02 (-0.46) | -0.02 (-0.46) | -5,64 | (-0.64) |
| M71 | 0.00 (0.00) | -5.26 (-0.96) | -0.67 (-0.64) | -0.30 (-0.59) | -0.13 (-0.55) | -0.06 (-0.53) | -0.03 (-0.51) | -0.01 (-0.49) | -0.01 (-0.47) | -0.01 (-0.47) | -0.01 (-0.47) | -6,47 | (-0.87) |
| M72 | 0.00 (0.00) | -1.31 (-0.87) | -0.07 (-0.67) | -0.02 (-0.61) | -0.01 (-0.56) | -0.00 (-0.54) | -0.00 (-0.52) | -0.00 (-0.50) | -0.00 (-0.48) | -0.00 (-0.48) | -0.00 (-0.48) | -1,41 | (-0.84) |
| M73 | 0.00 (0.00) | -0.15 (-0.46) | -0.13 (-0.42) | -0.06 (-0.51) | -0.03 (-0.52) | -0.01 (-0.50) | -0.01 (-0.48) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,4 | (-0.46) |
| M74_75 | 0.00 (0.00) | -1.16 (-0.87) | -0.52 (-0.63) | -0.24 (-0.57) | -0.11 (-0.54) | -0.05 (-0.52) | -0.02 (-0.50) | -0.01 (-0.48) | -0.01 (-0.46) | -0.01 (-0.46) | -0.01 (-0.46) | -2,13 | (-0.71) |
| N77 | 0.00 (0.00) | -0.05 (-0.36) | -0.08 (-0.57) | -0.04 (-0.56) | -0.02 (-0.54) | -0.01 (-0.51) | -0.00 (-0.49) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,21 | (-0.49) |
| N78 | 0.00 (0.00) | 1.45 (1.40) | -0.91 (-0.52) | -0.36 (-0.52) | -0.16 (-0.51) | -0.07 (-0.49) | -0.03 (-0.47) | -0.02 (-0.46) | -0.01 (-0.44) | -0.01 (-0.44) | -0.01 (-0.44) | -0,13 | (-0.03) |
| N79 | 0.00 (0.00) | 0.00 (0.12) | -0.03 (-0.59) | -0.02 (-0.56) | -0.01 (-0.54) | -0.01 (-0.52) | -0.00 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,07 | (-0.49) |
| N80T82 | 0.00 (0.00) | -1.30 (-0.69) | -1.59 (-0.62) | -0.76 (-0.57) | -0.36 (-0.54) | -0.17 (-0.52) | -0.08 (-0.49) | -0.04 (-0.47) | -0.02 (-0.45) | -0.02 (-0.45) | -0.02 (-0.45) | -4,32 | (-0.61) |
| O84 | 0.00 (0.00) | -0.46 (-0.84) | -0.27 (-0.64) | -0.13 (-0.59) | -0.06 (-0.55) | -0.03 (-0.52) | -0.01 (-0.49) | -0.01 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,99 | (-0.69) |
| P85 | 0.00 (0.00) | -0.30 (-0.66) | -0.23 (-0.52) | -0.12 (-0.55) | -0.06 (-0.53) | -0.03 (-0.52) | -0.01 (-0.50) | -0.01 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,76 | (-0.57) |
| Q86 | 0.00 (0.00) | 0.29 (1.65) | -0.03 (-0.27) | -0.04 (-0.48) | -0.02 (-0.51) | -0.01 (-0.51) | -0.00 (-0.49) | -0.00 (-0.47) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | 0,18 | (0.41) |
| Q87_88 | 0.00 (0.00) | 0.02 (1.96) | -0.11 (-0.52) | -0.10 (-0.51) | -0.05 (-0.54) | -0.03 (-0.53) | -0.01 (-0.51) | -0.01 (-0.49) | -0.00 (-0.47) | -0.00 (-0.47) | -0.00 (-0.47) | -0,28 | (-0.47) |
| R90T92 | 0.00 (0.00) | -0.01 (-0.34) | -0.07 (-0.55) | -0.06 (-0.57) | -0.03 (-0.55) | -0.02 (-0.53) | -0.01 (-0.51) | -0.00 (-0.49) | -0.00 (-0.47) | -0.00 (-0.47) | -0.00 (-0.47) | -0,21 | (-0.53) |
| R93 | 0.00 (0.00) | -0.02 (-0.27) | -0.12 (-0.55) | -0.09 (-0.57) | -0.05 (-0.55) | -0.02 (-0.53) | -0.01 (-0.51) | -0.01 (-0.49) | -0.00 (-0.47) | -0.00 (-0.47) | -0.00 (-0.47) | -0,33 | (-0.51) |
| S94 | 0.00 (0.00) | -0.05 (-0.59) | -0.09 (-0.59) | -0.05 (-0.57) | -0.03 (-0.55) | -0.01 (-0.53) | -0.01 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,25 | (-0.57) |
| S95 | 0.00 (0.00) | -0.00 (-0.04) | -0.03 (-0.59) | -0.02 (-0.55) | -0.01 (-0.53) | -0.00 (-0.51) | -0.00 (-0.49) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,07 | (-0.43) |
| S96 | 0.00 (0.00) | -0.01 (-0.47) | -0.05 (-0.55) | -0.04 (-0.58) | -0.02 (-0.56) | -0.01 (-0.53) | -0.00 (-0.51) | -0.00 (-0.49) | -0.00 (-0.47) | -0.00 (-0.47) | -0.00 (-0.47) | -0,14 | (-0.55) |
| T | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| U | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | | (0.00) |
| Total | | | | | | | | | | | | -86,49 | (-0.43) |

Table 3.32: Change in the quantity of labour (in thousands of units) in Scenario 4 relative to the 'business as usual' scenario, by activation round. Each round corresponds to a term in the summation of Equation 3.1. Round zero denotes the variation in the final-demand vector for sector C29 only. The first round indicates the effect on suppliers closest to the automotive supply chain, the second round the effect on suppliers of those suppliers, and so forth. The last column reports the cumulative effect for each sector. Decimal points are shown in parentheses.

| Industry | Round 0 | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 | Round 6 | Round 7 | Round 8 | Round 9 | Round 10 | Total Δ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A01 | 0.00 (0.00) | -0.66 (-0.22) | -12.54 (-0.60) | -8.92 (-0.57) | -5.39 (-0.55) | -2.87 (-0.53) | -1.45 (-0.50) | -0.71 (-0.48) | -0.35 (-0.46) | -0.35 (-0.46) | -0.35 (-0.46) | -33,23 | (-0.55) |
| A02 | 0.00 (0.00) | -0.49 (-0.73) | -0.91 (-0.49) | -0.56 (-0.53) | -0.27 (-0.52) | -0.12 (-0.50) | -0.06 (-0.48) | -0.03 (-0.45) | -0.01 (-0.43) | -0.01 (-0.43) | -0.01 (-0.43) | -2,46 | (-0.54) |
| A03 | 0.00 (0.00) | -0.00 (-0.24) | -0.13 (-0.63) | -0.16 (-0.57) | -0.08 (-0.55) | -0.04 (-0.53) | -0.02 (-0.51) | -0.01 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,45 | (-0.57) |
| B | 0.00 (0.00) | -25.21 (-0.90) | -11.12 (-0.75) | -4.57 (-0.63) | -2.10 (-0.56) | -0.97 (-0.52) | -0.46 (-0.49) | -0.22 (-0.46) | -0.11 (-0.44) | -0.11 (-0.44) | -0.11 (-0.44) | -44,85 | (-0.78) |
| C10T12 | 0.00 (0.00) | -3.60 (-0.73) | -5.79 (-0.62) | -4.81 (-0.58) | -2.70 (-0.55) | -1.37 (-0.53) | -0.66 (-0.50) | -0.32 (-0.48) | -0.15 (-0.45) | -0.15 (-0.45) | -0.15 (-0.45) | -19,54 | (-0.6) |
| C13T15 | 0.00 (0.00) | -19.49 (-0.37) | -7.68 (-0.40) | -3.17 (-0.40) | -1.36 (-0.40) | -0.61 (-0.38) | -0.28 (-0.36) | -0.13 (-0.34) | -0.06 (-0.32) | -0.06 (-0.32) | -0.06 (-0.32) | -32,99 | (-0.38) |
| C16 | 0.00 (0.00) | -3.33 (-0.21) | -5.17 (-0.49) | -2.62 (-0.52) | -1.21 (-0.51) | -0.55 (-0.49) | -0.25 (-0.47) | -0.12 (-0.45) | -0.06 (-0.43) | -0.06 (-0.43) | -0.06 (-0.43) | -13,85 | (-0.37) |
| C17 | 0.00 (0.00) | -8.63 (-0.60) | -8.55 (-0.61) | -4.55 (-0.56) | -2.21 (-0.53) | -1.04 (-0.50) | -0.49 (-0.48) | -0.23 (-0.45) | -0.11 (-0.43) | -0.11 (-0.43) | -0.11 (-0.43) | -25,93 | (-0.58) |
| C18 | 0.00 (0.00) | -6.58 (-0.44) | -7.22 (-0.60) | -4.12 (-0.57) | -2.05 (-0.55) | -0.98 (-0.53) | -0.46 (-0.51) | -0.22 (-0.48) | -0.10 (-0.46) | -0.10 (-0.46) | -0.10 (-0.46) | -26,01 | (-0.44) |
| C19 | 0.00 (0.00) | -0.24 (-0.56) | -1.16 (-0.62) | -0.93 (-0.57) | -0.51 (-0.53) | -0.26 (-0.50) | -0.13 (-0.47) | -0.06 (-0.45) | -0.03 (-0.43) | -0.03 (-0.43) | -0.03 (-0.43) | -3,35 | (-0.56) |
| C20 | 0.00 (0.00) | -28.35 (-0.82) | -18.95 (-0.61) | -6.93 (-0.53) | -2.73 (-0.47) | -1.17 (-0.43) | -0.53 (-0.40) | -0.25 (-0.37) | -0.12 (-0.35) | -0.12 (-0.35) | -0.12 (-0.35) | -59,15 | (-0.66) |
| C21 | 0.00 (0.00) | -7.77 (-0.83) | -2.20 (-0.61) | -0.88 (-0.54) | -0.38 (-0.49) | -0.18 (-0.45) | -0.08 (-0.41) | -0.04 (-0.38) | -0.02 (-0.36) | -0.02 (-0.36) | -0.02 (-0.36) | -11,56 | (-0.72) |
| C22 | 0.00 (0.00) | -139.63 (-0.68) | -31.79 (-0.55) | -10.11 (-0.49) | -3.80 (-0.46) | -1.61 (-0.44) | -0.73 (-0.42) | -0.34 (-0.41) | -0.17 (-0.40) | -0.17 (-0.40) | -0.17 (-0.40) | -193,76 | (-0.6) |
| C23 | 0.00 (0.00) | -84.33 (-0.88) | -22.19 (-0.71) | -7.78 (-0.61) | -3.10 (-0.55) | -1.35 (-0.50) | -0.62 (-0.48) | -0.29 (-0.45) | -0.14 (-0.44) | -0.14 (-0.44) | -0.14 (-0.44) | -119,93 | (-0.8) |
| C24 | 0.00 (0.00) | -73.93 (-0.78) | -34.12 (-0.60) | -11.71 (-0.51) | -3.91 (-0.43) | -1.37 (-0.36) | -0.53 (-0.32) | -0.23 (-0.29) | -0.11 (-0.28) | -0.11 (-0.28) | -0.11 (-0.28) | -127,25 | (-0.65) |
| C25 | 0.00 (0.00) | -522.72 (-0.56) | -127.87 (-0.53) | -37.52 (-0.48) | -12.34 (-0.44) | -4.66 (-0.41) | -1.97 (-0.40) | -0.90 (-0.38) | -0.43 (-0.37) | -0.43 (-0.37) | -0.43 (-0.37) | -789,89 | (-0.48) |
| C26 | 0.00 (0.00) | -11.66 (-0.39) | -6.20 (-0.47) | -2.43 (-0.43) | -1.17 (-0.43) | -0.58 (-0.43) | -0.28 (-0.42) | -0.14 (-0.41) | -0.07 (-0.40) | -0.07 (-0.40) | -0.07 (-0.40) | -25,59 | (-0.38) |
| C27 | 0.00 (0.00) | 2.33 (0.02) | -5.58 (-0.22) | -2.49 (-0.26) | -1.20 (-0.29) | -0.60 (-0.31) | -0.30 (-0.32) | -0.15 (-0.33) | -0.08 (-0.33) | -0.08 (-0.33) | -0.08 (-0.33) | -37,96 | (-0.15) |
| C28 | 0.00 (0.00) | -58.62 (-0.48) | -21.16 (-0.40) | -7.46 (-0.36) | -2.93 (-0.34) | -1.27 (-0.33) | -0.59 (-0.32) | -0.29 (-0.32) | -0.14 (-0.31) | -0.14 (-0.31) | -0.14 (-0.31) | -170,85 | (-0.32) |
| C29 | -1254.36 (-0.24) | 27.99 (0.34) | 3.56 (0.12) | 0.83 (0.12) | 0.06 (0.02) | -0.08 (-0.07) | -0.07 (-0.13) | -0.05 (-0.18) | -0.03 (-0.21) | -0.03 (-0.21) | -0.03 (-0.21) | -1080,58 | (-0.23) |
| C30 | 0.00 (0.00) | -29.79 (-0.80) | -3.77 (-0.54) | -1.44 (-0.53) | -0.61 (-0.50) | -0.28 (-0.48) | -0.13 (-0.46) | -0.06 (-0.43) | -0.03 (-0.42) | -0.03 (-0.42) | -0.03 (-0.42) | -40,9 | (-0.59) |
| C31_32 | 0.00 (0.00) | -17.48 (-0.43) | -7.01 (-0.47) | -2.90 (-0.48) | -1.27 (-0.47) | -0.57 (-0.45) | -0.27 (-0.44) | -0.13 (-0.42) | -0.06 (-0.40) | -0.06 (-0.40) | -0.06 (-0.40) | -33,09 | (-0.41) |
| C33 | 0.00 (0.00) | -20.79 (-0.60) | -7.87 (-0.54) | -3.27 (-0.52) | -1.47 (-0.50) | -0.68 (-0.49) | -0.32 (-0.47) | -0.15 (-0.45) | -0.07 (-0.44) | -0.07 (-0.44) | -0.07 (-0.44) | -34,86 | (-0.56) |
| D35 | 0.00 (0.00) | -2.10 (-0.03) | -41.14 (-0.41) | -36.18 (-0.47) | -23.94 (-0.48) | -14.17 (-0.48) | -7.94 (-0.48) | -4.32 (-0.47) | -2.30 (-0.47) | -2.30 (-0.47) | -2.30 (-0.47) | -134,62 | (-0.37) |
| E36 | 0.00 (0.00) | -13.19 (-0.86) | -5.78 (-0.66) | -2.63 (-0.59) | -1.17 (-0.54) | -0.53 (-0.51) | -0.25 (-0.49) | -0.12 (-0.47) | -0.06 (-0.45) | -0.06 (-0.45) | -0.06 (-0.45) | -23,79 | (-0.72) |
| E37T39 | 0.00 (0.00) | -60.86 (-0.90) | -24.41 (-0.68) | -10.77 (-0.60) | -4.71 (-0.55) | -2.11 (-0.51) | -0.97 (-0.48) | -0.46 (-0.46) | -0.22 (-0.44) | -0.22 (-0.44) | -0.22 (-0.44) | -104,71 | (-0.76) |
| F | 0.00 (0.00) | -92.09 (-0.84) | -45.19 (-0.70) | -21.67 (-0.62) | -10.22 (-0.58) | -4.81 (-0.55) | -2.28 (-0.52) | -1.08 (-0.50) | -0.52 (-0.48) | -0.52 (-0.48) | -0.52 (-0.48) | -178,37 | (-0.73) |
| G45 | 0.00 (0.00) | 5.47 (0.02) | -4.06 (-0.12) | -2.91 (-0.25) | -1.62 (-0.34) | -0.81 (-0.36) | -0.40 (-0.37) | -0.19 (-0.36) | -0.10 (-0.35) | -0.10 (-0.35) | -0.10 (-0.35) | -40,79 | (-0.08) |
| G46 | 0.00 (0.00) | -302.47 (-0.66) | -97.62 (-0.56) | -42.86 (-0.54) | -18.88 (-0.51) | -8.54 (-0.49) | -3.95 (-0.46) | -1.87 (-0.44) | -0.90 (-0.42) | -0.90 (-0.42) | -0.90 (-0.42) | -477,98 | (-0.61) |
| G47 | 0.00 (0.00) | -46.40 (-0.37) | -20.24 (-0.48) | -9.20 (-0.49) | -4.25 (-0.48) | -1.98 (-0.46) | -0.93 (-0.44) | -0.45 (-0.42) | -0.22 (-0.40) | -0.22 (-0.40) | -0.22 (-0.40) | -83,89 | (-0.42) |
| H49 | 0.00 (0.00) | -80.33 (-0.56) | -64.35 (-0.54) | -36.23 (-0.54) | -18.44 (-0.53) | -9.08 (-0.51) | -4.44 (-0.49) | -2.17 (-0.47) | -1.07 (-0.46) | -1.07 (-0.46) | -1.07 (-0.46) | -217,19 | (-0.54) |
| H50 | 0.00 (0.00) | -1.81 (-0.78) | -1.23 (-0.57) | -0.63 (-0.54) | -0.30 (-0.52) | -0.14 (-0.49) | -0.07 (-0.46) | -0.03 (-0.44) | -0.02 (-0.42) | -0.02 (-0.42) | -0.02 (-0.42) | -4,25 | (-0.62) |
| H51 | 0.00 (0.00) | -0.81 (-0.72) | -0.92 (-0.59) | -0.49 (-0.55) | -0.24 (-0.54) | -0.12 (-0.52) | -0.06 (-0.49) | -0.03 (-0.47) | -0.01 (-0.45) | -0.01 (-0.45) | -0.01 (-0.45) | -2,68 | (-0.6) |
| H52 | 0.00 (0.00) | -55.77 (-0.64) | -54.41 (-0.55) | -29.80 (-0.55) | -14.77 (-0.53) | -7.09 (-0.51) | -3.38 (-0.49) | -1.62 (-0.47) | -0.79 (-0.45) | -0.79 (-0.45) | -0.79 (-0.45) | -168,4 | (-0.57) |
| H53 | 0.00 (0.00) | 7.15 (2.59) | -4.95 (-0.62) | -2.96 (-0.57) | -1.52 (-0.55) | -0.73 (-0.52) | -0.35 (-0.50) | -0.16 (-0.48) | -0.08 (-0.46) | -0.08 (-0.46) | -0.08 (-0.46) | -3,67 | (-0.17) |
| I | 0.00 (0.00) | -8.30 (-0.48) | -29.23 (-0.57) | -16.15 (-0.56) | -8.14 (-0.54) | -3.91 (-0.52) | -1.86 (-0.50) | -0.89 (-0.48) | -0.43 (-0.46) | -0.43 (-0.46) | -0.43 (-0.46) | -69,32 | (-0.54) |
| J58 | 0.00 (0.00) | -0.57 (-0.49) | -2.18 (-0.58) | -1.33 (-0.52) | -0.63 (-0.54) | -0.30 (-0.52) | -0.14 (-0.50) | -0.07 (-0.48) | -0.03 (-0.46) | -0.03 (-0.46) | -0.03 (-0.46) | -5,26 | (-0.54) |
| J59_60 | 0.00 (0.00) | -1.23 (-0.40) | -3.37 (-0.55) | -2.26 (-0.54) | -1.17 (-0.54) | -0.57 (-0.53) | -0.27 (-0.51) | -0.13 (-0.48) | -0.06 (-0.46) | -0.06 (-0.46) | -0.06 (-0.46) | -9,1 | (-0.51) |
| J61 | 0.00 (0.00) | -39.66 (-0.88) | -21.87 (-0.68) | -10.02 (-0.60) | -4.47 (-0.56) | -2.01 (-0.52) | -0.92 (-0.50) | -0.43 (-0.47) | -0.20 (-0.45) | -0.20 (-0.45) | -0.20 (-0.45) | -79,77 | (-0.73) |
| J62_63 | 0.00 (0.00) | -51.68 (-0.54) | -35.06 (-0.56) | -18.95 (-0.55) | -9.32 (-0.54) | -4.47 (-0.52) | -2.13 (-0.50) | -1.02 (-0.48) | -0.49 (-0.46) | -0.49 (-0.46) | -0.49 (-0.46) | -123,58 | (-0.54) |
| K64 | 0.00 (0.00) | -84.06 (-0.78) | -57.64 (-0.57) | -31.20 (-0.55) | -14.95 (-0.54) | -7.01 (-0.52) | -3.29 (-0.50) | -1.56 (-0.48) | -0.75 (-0.46) | -0.75 (-0.46) | -0.75 (-0.46) | -201,19 | (-0.63) |
| K65 | 0.00 (0.00) | -6.17 (-0.69) | -6.85 (-0.58) | -3.29 (-0.56) | -1.53 (-0.54) | -0.71 (-0.52) | -0.33 (-0.50) | -0.16 (-0.48) | -0.08 (-0.46) | -0.08 (-0.46) | -0.08 (-0.46) | -19,18 | (-0.59) |
| K66 | 0.00 (0.00) | -4.17 (-0.46) | -21.25 (-0.60) | -11.34 (-0.55) | -5.55 (-0.54) | -2.61 (-0.52) | -1.23 (-0.50) | -0.58 (-0.47) | -0.28 (-0.45) | -0.28 (-0.45) | -0.28 (-0.45) | -47,3 | (-0.55) |
| L | 0.00 (0.00) | -73.03 (-0.54) | -89.14 (-0.52) | -43.74 (-0.54) | -20.75 (-0.53) | -9.76 (-0.51) | -4.61 (-0.49) | -2.20 (-0.48) | -1.06 (-0.46) | -1.06 (-0.46) | -1.06 (-0.46) | -245,31 | (-0.53) |
| M69_70 | 0.00 (0.00) | -167.24 (-0.71) | -108.11 (-0.63) | -49.44 (-0.57) | -23.09 (-0.54) | -10.79 (-0.52) | -5.08 (-0.50) | -2.42 (-0.48) | -1.16 (-0.46) | -1.16 (-0.46) | -1.16 (-0.46) | -368,45 | (-0.64) |
| M71 | 0.00 (0.00) | -285.22 (-0.96) | -36.10 (-0.64) | -16.02 (-0.59) | -7.05 (-0.55) | -3.26 (-0.53) | -1.53 (-0.51) | -0.73 (-0.49) | -0.35 (-0.47) | -0.35 (-0.47) | -0.35 (-0.47) | -350,61 | (-0.87) |
| M72 | 0.00 (0.00) | -198.28 (-0.87) | -10.62 (-0.67) | -3.52 (-0.61) | -1.29 (-0.56) | -0.56 (-0.54) | -0.26 (-0.52) | -0.12 (-0.50) | -0.06 (-0.48) | -0.06 (-0.48) | -0.06 (-0.48) | -214,77 | (-0.84) |
| M73 | 0.00 (0.00) | -8.18 (-0.46) | -7.44 (-0.42) | -3.51 (-0.51) | -1.67 (-0.52) | -0.78 (-0.50) | -0.37 (-0.48) | -0.17 (-0.46) | -0.08 (-0.44) | -0.08 (-0.44) | -0.08 (-0.44) | -22,29 | (-0.46) |
| M74_75 | 0.00 (0.00) | -53.97 (-0.87) | -24.11 (-0.63) | -11.01 (-0.57) | -5.12 (-0.54) | -2.40 (-0.52) | -1.14 (-0.50) | -0.54 (-0.48) | -0.26 (-0.46) | -0.26 (-0.46) | -0.26 (-0.46) | -99,08 | (-0.71) |
| N77 | 0.00 (0.00) | -9.92 (-0.36) | -14.77 (-0.57) | -7.56 (-0.56) | -3.64 (-0.54) | -1.72 (-0.51) | -0.82 (-0.49) | -0.39 (-0.47) | -0.19 (-0.45) | -0.19 (-0.45) | -0.19 (-0.45) | -39,19 | (-0.49) |
| N78 | 0.00 (0.00) | 47.06 (1.40) | -29.60 (-0.52) | -11.84 (-0.52) | -5.32 (-0.51) | -2.41 (-0.49) | -1.11 (-0.47) | -0.52 (-0.46) | -0.25 (-0.44) | -0.25 (-0.44) | -0.25 (-0.44) | -4,24 | (-0.03) |
| N79 | 0.00 (0.00) | 0.04 (0.12) | -0.73 (-0.59) | -0.47 (-0.56) | -0.24 (-0.54) | -0.12 (-0.52) | -0.06 (-0.50) | -0.03 (-0.48) | -0.01 (-0.46) | -0.01 (-0.46) | -0.01 (-0.46) | -1,63 | (-0.49) |
| N80T82 | 0.00 (0.00) | -45.61 (-0.69) | -55.89 (-0.62) | -26.67 (-0.57) | -12.51 (-0.54) | -5.81 (-0.52) | -2.71 (-0.49) | -1.28 (-0.47) | -0.62 (-0.45) | -0.62 (-0.45) | -0.62 (-0.45) | -151,69 | (-0.61) |
| O84 | 0.00 (0.00) | -43.93 (-0.84) | -26.10 (-0.64) | -12.80 (-0.59) | -6.12 (-0.55) | -2.86 (-0.52) | -1.34 (-0.49) | -0.63 (-0.47) | -0.30 (-0.45) | -0.30 (-0.45) | -0.30 (-0.45) | -94,38 | (-0.69) |
| P85 | 0.00 (0.00) | -13.07 (-0.66) | -9.72 (-0.52) | -5.27 (-0.55) | -2.47 (-0.53) | -1.16 (-0.52) | -0.55 (-0.50) | -0.26 (-0.48) | -0.13 (-0.46) | -0.13 (-0.46) | -0.13 (-0.46) | -32,75 | (-0.57) |
| Q86 | 0.00 (0.00) | 17.22 (1.65) | -1.72 (-0.27) | -2.26 (-0.48) | -1.27 (-0.51) | -0.62 (-0.51) | -0.29 (-0.49) | -0.14 (-0.47) | -0.07 (-0.46) | -0.07 (-0.46) | -0.07 (-0.46) | 10,79 | (0.41) |
| Q87_88 | 0.00 (0.00) | 0.68 (1.96) | -3.04 (-0.52) | -2.75 (-0.51) | -1.47 (-0.54) | -0.72 (-0.53) | -0.34 (-0.51) | -0.16 (-0.49) | -0.08 (-0.47) | -0.08 (-0.47) | -0.08 (-0.47) | -7,95 | (-0.47) |
| R90T92 | 0.00 (0.00) | -0.74 (-0.34) | -4.77 (-0.55) | -3.68 (-0.57) | -2.12 (-0.55) | -1.08 (-0.53) | -0.52 (-0.51) | -0.25 (-0.49) | -0.12 (-0.47) | -0.12 (-0.47) | -0.12 (-0.47) | -13,39 | (-0.53) |
| R93 | 0.00 (0.00) | -1.05 (-0.27) | -5.24 (-0.55) | -3.84 (-0.57) | -2.08 (-0.55) | -1.03 (-0.53) | -0.49 (-0.51) | -0.23 (-0.49) | -0.11 (-0.47) | -0.11 (-0.47) | -0.11 (-0.47) | -14,19 | (-0.51) |
| S94 | 0.00 (0.00) | -1.88 (-0.59) | -3.43 (-0.59) | -2.01 (-0.57) | -1.04 (-0.55) | -0.51 (-0.53) | -0.24 (-0.50) | -0.12 (-0.48) | -0.06 (-0.46) | -0.06 (-0.46) | -0.06 (-0.46) | -9,35 | (-0.57) |
| S95 | 0.00 (0.00) | -0.06 (-0.04) | -1.25 (-0.59) | -0.62 (-0.55) | -0.31 (-0.53) | -0.15 (-0.51) | -0.07 (-0.49) | -0.03 (-0.47) | -0.02 (-0.45) | -0.02 (-0.45) | -0.02 (-0.45) | -2,53 | (-0.43) |
| S96 | 0.00 (0.00) | -0.28 (-0.47) | -1.91 (-0.55) | -1.50 (-0.58) | -0.73 (-0.56) | -0.34 (-0.53) | -0.16 (-0.51) | -0.07 (-0.49) | -0.04 (-0.47) | -0.04 (-0.47) | -0.04 (-0.47) | -5,06 | (-0.55) |
| T | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| U | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| Total | | | | | | | | | | | | -6589,14 | (-0.43) |

Table 3.33: Change in the value added (in millions of euros) in Scenario 4 relative to the 'business as usual' scenario, by activation round. Each round corresponds to a term in the summation of Equation 3.1. Round zero denotes the variation in the final-demand vector for sector C29 only. The first round indicates the effect on suppliers closest to the automotive supply chain, the second round the effect on suppliers of those suppliers, and so forth. The last column reports the cumulative effect for each sector. Decimal points are shown in parentheses.

| Industry | Round 0 | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 | Round 6 | Round 7 | Round 8 | Round 9 | Round 10 | Total Δ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A01 | 0.00 (0.00) | -0.02 (-0.26) | -0.30 (-0.61) | -0.21 (-0.57) | -0.13 (-0.54) | -0.07 (-0.52) | -0.03 (-0.49) | -0.02 (-0.47) | -0.01 (-0.45) | -0.01 (-0.45) | -0.01 (-0.45) | -0,8 | (-0.55) |
| A02 | 0.00 (0.00) | -0.01 (-0.75) | -0.01 (-0.50) | -0.01 (-0.52) | -0.00 (-0.51) | -0.00 (-0.49) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,03 | (-0.54) |
| A03 | 0.00 (0.00) | -0.00 (-0.28) | -0.00 (-0.64) | -0.01 (-0.57) | -0.00 (-0.55) | -0.00 (-0.52) | -0.00 (-0.50) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,01 | (-0.57) |
| B | 0.00 (0.00) | -0.07 (-0.90) | -0.03 (-0.74) | -0.01 (-0.62) | -0.01 (-0.55) | -0.00 (-0.51) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.43) | -0.00 (-0.43) | -0,13 | (-0.77) |
| C10T12 | 0.00 (0.00) | -0.05 (-0.74) | -0.08 (-0.63) | -0.07 (-0.58) | -0.04 (-0.55) | -0.02 (-0.52) | -0.01 (-0.49) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,28 | (-0.6) |
| C13T15 | 0.00 (0.00) | -0.39 (-0.40) | -0.15 (-0.42) | -0.06 (-0.41) | -0.03 (-0.40) | -0.01 (-0.38) | -0.01 (-0.36) | -0.00 (-0.33) | -0.00 (-0.31) | -0.00 (-0.31) | -0.00 (-0.31) | -0,65 | (-0.4) |
| C16 | 0.00 (0.00) | -0.07 (-0.25) | -0.09 (-0.49) | -0.05 (-0.51) | -0.02 (-0.50) | -0.01 (-0.47) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.41) | -0.00 (-0.41) | -0.00 (-0.41) | -0,26 | (-0.38) |
| C17 | 0.00 (0.00) | -0.10 (-0.61) | -0.09 (-0.61) | -0.05 (-0.55) | -0.02 (-0.52) | -0.01 (-0.49) | -0.01 (-0.46) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,28 | (-0.58) |
| C18 | 0.00 (0.00) | -0.12 (-0.47) | -0.13 (-0.61) | -0.07 (-0.57) | -0.03 (-0.54) | -0.02 (-0.52) | -0.01 (-0.49) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,47 | (-0.46) |
| C19 | 0.00 (0.00) | -0.00 (-0.58) | -0.01 (-0.63) | -0.01 (-0.56) | -0.00 (-0.52) | -0.00 (-0.49) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,02 | (-0.56) |
| C20 | 0.00 (0.00) | -0.23 (-0.82) | -0.15 (-0.59) | -0.05 (-0.51) | -0.02 (-0.45) | -0.01 (-0.41) | -0.00 (-0.38) | -0.00 (-0.36) | -0.00 (-0.34) | -0.00 (-0.34) | -0.00 (-0.34) | -0,47 | (-0.65) |
| C21 | 0.00 (0.00) | -0.05 (-0.84) | -0.01 (-0.60) | -0.01 (-0.53) | -0.00 (-0.48) | -0.00 (-0.43) | -0.00 (-0.40) | -0.00 (-0.37) | -0.00 (-0.34) | -0.00 (-0.34) | -0.00 (-0.34) | -0,07 | (-0.72) |
| C22 | 0.00 (0.00) | -1.62 (-0.64) | -0.37 (-0.51) | -0.12 (-0.47) | -0.04 (-0.44) | -0.02 (-0.42) | -0.01 (-0.40) | -0.00 (-0.39) | -0.00 (-0.38) | -0.00 (-0.38) | -0.00 (-0.38) | -2,26 | (-0.57) |
| C23 | 0.00 (0.00) | -1.08 (-0.89) | -0.28 (-0.70) | -0.10 (-0.59) | -0.04 (-0.53) | -0.02 (-0.49) | -0.01 (-0.46) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -1,52 | (-0.79) |
| C24 | 0.00 (0.00) | -0.77 (-0.77) | -0.34 (-0.56) | -0.11 (-0.47) | -0.04 (-0.39) | -0.01 (-0.33) | -0.01 (-0.29) | -0.00 (-0.26) | -0.00 (-0.25) | -0.00 (-0.25) | -0.00 (-0.25) | -1,29 | (-0.63) |
| C25 | 0.00 (0.00) | -7.01 (-0.51) | -1.71 (-0.47) | -0.51 (-0.44) | -0.17 (-0.41) | -0.06 (-0.38) | -0.03 (-0.37) | -0.01 (-0.36) | -0.01 (-0.35) | -0.01 (-0.35) | -0.01 (-0.35) | -10,9 | (-0.45) |
| C26 | 0.00 (0.00) | -0.09 (-0.31) | -0.06 (-0.44) | -0.02 (-0.41) | -0.01 (-0.41) | -0.01 (-0.41) | -0.00 (-0.40) | -0.00 (-0.39) | -0.00 (-0.38) | -0.00 (-0.38) | -0.00 (-0.38) | -0,23 | (-0.35) |
| C27 | 0.00 (0.00) | 0.20 (0.18) | -0.04 (-0.14) | -0.02 (-0.20) | -0.01 (-0.25) | -0.01 (-0.27) | -0.00 (-0.29) | -0.00 (-0.30) | -0.00 (-0.30) | -0.00 (-0.30) | -0.00 (-0.30) | -0,28 | (-0.09) |
| C28 | 0.00 (0.00) | -0.61 (-0.45) | -0.23 (-0.38) | -0.08 (-0.35) | -0.03 (-0.32) | -0.01 (-0.31) | -0.01 (-0.31) | -0.00 (-0.30) | -0.00 (-0.30) | -0.00 (-0.30) | -0.00 (-0.30) | -1,98 | (-0.33) |
| C29 | -19.12 (-0.28) | 0.31 (0.29) | 0.03 (0.08) | 0.01 (0.10) | 0.00 (0.02) | -0.00 (-0.06) | -0.00 (-0.13) | -0.00 (-0.17) | -0.00 (-0.19) | -0.00 (-0.19) | -0.00 (-0.19) | -16,61 | (-0.27) |
| C30 | 0.00 (0.00) | -0.36 (-0.80) | -0.05 (-0.53) | -0.02 (-0.52) | -0.01 (-0.49) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.40) | -0.00 (-0.40) | -0.00 (-0.40) | -0,51 | (-0.6) |
| C31_32 | 0.00 (0.00) | -0.29 (-0.43) | -0.11 (-0.46) | -0.05 (-0.46) | -0.02 (-0.45) | -0.01 (-0.44) | -0.00 (-0.42) | -0.00 (-0.40) | -0.00 (-0.39) | -0.00 (-0.39) | -0.00 (-0.39) | -0,55 | (-0.41) |
| C33 | 0.00 (0.00) | -0.36 (-0.57) | -0.14 (-0.52) | -0.06 (-0.51) | -0.03 (-0.49) | -0.01 (-0.47) | -0.01 (-0.45) | -0.00 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -0,61 | (-0.54) |
| D35 | 0.00 (0.00) | -0.01 (-0.08) | -0.07 (-0.42) | -0.06 (-0.46) | -0.04 (-0.47) | -0.02 (-0.47) | -0.01 (-0.47) | -0.01 (-0.46) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,22 | (-0.38) |
| E36 | 0.00 (0.00) | -0.11 (-0.87) | -0.05 (-0.65) | -0.02 (-0.57) | -0.01 (-0.53) | -0.00 (-0.50) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.43) | -0.00 (-0.43) | -0,2 | (-0.72) |
| E37T39 | 0.00 (0.00) | -0.83 (-0.90) | -0.33 (-0.68) | -0.14 (-0.59) | -0.06 (-0.53) | -0.03 (-0.49) | -0.01 (-0.46) | -0.01 (-0.44) | -0.00 (-0.42) | -0.00 (-0.42) | -0.00 (-0.42) | -1,41 | (-0.75) |
| F | 0.00 (0.00) | -1.62 (-0.85) | -0.79 (-0.70) | -0.38 (-0.62) | -0.18 (-0.57) | -0.08 (-0.54) | -0.04 (-0.51) | -0.02 (-0.48) | -0.01 (-0.46) | -0.01 (-0.46) | -0.01 (-0.46) | -3,11 | (-0.73) |
| G45 | 0.00 (0.00) | -0.24 (-0.04) | -0.10 (-0.14) | -0.06 (-0.26) | -0.03 (-0.33) | -0.02 (-0.35) | -0.01 (-0.35) | -0.00 (-0.35) | -0.00 (-0.34) | -0.00 (-0.34) | -0.00 (-0.34) | -1,31 | (-0.12) |
| G46 | 0.00 (0.00) | -3.59 (-0.68) | -1.11 (-0.55) | -0.48 (-0.53) | -0.21 (-0.50) | -0.10 (-0.47) | -0.04 (-0.45) | -0.02 (-0.43) | -0.01 (-0.41) | -0.01 (-0.41) | -0.01 (-0.41) | -5,58 | (-0.61) |
| G47 | 0.00 (0.00) | -1.11 (-0.41) | -0.44 (-0.47) | -0.20 (-0.48) | -0.09 (-0.47) | -0.04 (-0.45) | -0.02 (-0.43) | -0.01 (-0.40) | -0.00 (-0.38) | -0.00 (-0.38) | -0.00 (-0.38) | -1,92 | (-0.43) |
| H49 | 0.00 (0.00) | -0.98 (-0.58) | -0.76 (-0.55) | -0.42 (-0.53) | -0.21 (-0.52) | -0.10 (-0.50) | -0.05 (-0.48) | -0.02 (-0.46) | -0.01 (-0.44) | -0.01 (-0.44) | -0.01 (-0.44) | -2,59 | (-0.55) |
| H50 | 0.00 (0.00) | -0.04 (-0.79) | -0.03 (-0.57) | -0.02 (-0.54) | -0.01 (-0.51) | -0.00 (-0.48) | -0.00 (-0.45) | -0.00 (-0.42) | -0.00 (-0.40) | -0.00 (-0.40) | -0.00 (-0.40) | -0,1 | (-0.62) |
| H51 | 0.00 (0.00) | -0.01 (-0.73) | -0.01 (-0.60) | -0.01 (-0.55) | -0.00 (-0.53) | -0.00 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,03 | (-0.6) |
| H52 | 0.00 (0.00) | -0.61 (-0.66) | -0.59 (-0.56) | -0.31 (-0.55) | -0.15 (-0.53) | -0.07 (-0.50) | -0.03 (-0.48) | -0.02 (-0.46) | -0.01 (-0.44) | -0.01 (-0.44) | -0.01 (-0.44) | -1,81 | (-0.58) |
| H53 | 0.00 (0.00) | 0.13 (2.41) | -0.10 (-0.64) | -0.06 (-0.57) | -0.03 (-0.54) | -0.01 (-0.51) | -0.01 (-0.49) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,08 | (-0.2) |
| I | 0.00 (0.00) | -0.25 (-0.51) | -0.83 (-0.58) | -0.45 (-0.56) | -0.22 (-0.53) | -0.11 (-0.51) | -0.05 (-0.49) | -0.02 (-0.46) | -0.01 (-0.45) | -0.01 (-0.45) | -0.01 (-0.45) | -1,96 | (-0.55) |
| J58 | 0.00 (0.00) | -0.01 (-0.52) | -0.03 (-0.60) | -0.02 (-0.53) | -0.01 (-0.53) | -0.00 (-0.51) | -0.00 (-0.49) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,07 | (-0.55) |
| J59_60 | 0.00 (0.00) | -0.01 (-0.43) | -0.04 (-0.56) | -0.02 (-0.54) | -0.01 (-0.54) | -0.01 (-0.52) | -0.00 (-0.49) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,1 | (-0.52) |
| J61 | 0.00 (0.00) | -0.17 (-0.88) | -0.09 (-0.67) | -0.04 (-0.59) | -0.02 (-0.54) | -0.01 (-0.51) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.43) | -0.00 (-0.43) | -0.00 (-0.43) | -0,34 | (-0.72) |
| J62_63 | 0.00 (0.00) | -0.70 (-0.56) | -0.46 (-0.57) | -0.25 (-0.55) | -0.12 (-0.53) | -0.06 (-0.51) | -0.03 (-0.49) | -0.01 (-0.47) | -0.01 (-0.45) | -0.01 (-0.45) | -0.01 (-0.45) | -1,63 | (-0.55) |
| K64 | 0.00 (0.00) | -0.52 (-0.79) | -0.35 (-0.57) | -0.19 (-0.55) | -0.09 (-0.53) | -0.04 (-0.51) | -0.02 (-0.48) | -0.01 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -1,23 | (-0.63) |
| K65 | 0.00 (0.00) | -0.02 (-0.71) | -0.02 (-0.58) | -0.01 (-0.55) | -0.00 (-0.53) | -0.00 (-0.51) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,06 | (-0.6) |
| K66 | 0.00 (0.00) | -0.07 (-0.48) | -0.34 (-0.60) | -0.18 (-0.55) | -0.09 (-0.53) | -0.04 (-0.51) | -0.02 (-0.48) | -0.01 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,76 | (-0.55) |
| L | 0.00 (0.00) | -0.06 (-0.57) | -0.07 (-0.52) | -0.03 (-0.53) | -0.02 (-0.52) | -0.01 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,19 | (-0.53) |
| M69_70 | 0.00 (0.00) | -2.61 (-0.72) | -1.65 (-0.63) | -0.75 (-0.56) | -0.35 (-0.53) | -0.16 (-0.51) | -0.08 (-0.49) | -0.04 (-0.46) | -0.02 (-0.45) | -0.02 (-0.45) | -0.02 (-0.45) | -5,67 | (-0.64) |
| M71 | 0.00 (0.00) | -5.27 (-0.97) | -0.67 (-0.64) | -0.29 (-0.59) | -0.13 (-0.54) | -0.06 (-0.52) | -0.03 (-0.49) | -0.01 (-0.47) | -0.01 (-0.45) | -0.01 (-0.45) | -0.01 (-0.45) | -6,47 | (-0.87) |
| M72 | 0.00 (0.00) | -1.31 (-0.87) | -0.07 (-0.66) | -0.02 (-0.60) | -0.01 (-0.55) | -0.00 (-0.53) | -0.00 (-0.51) | -0.00 (-0.49) | -0.00 (-0.47) | -0.00 (-0.47) | -0.00 (-0.47) | -1,42 | (-0.85) |
| M73 | 0.00 (0.00) | -0.15 (-0.49) | -0.14 (-0.44) | -0.06 (-0.51) | -0.03 (-0.51) | -0.01 (-0.49) | -0.01 (-0.47) | -0.00 (-0.45) | -0.00 (-0.43) | -0.00 (-0.43) | -0.00 (-0.43) | -0,41 | (-0.47) |
| M74_75 | 0.00 (0.00) | -1.17 (-0.88) | -0.52 (-0.63) | -0.23 (-0.57) | -0.11 (-0.53) | -0.05 (-0.51) | -0.02 (-0.49) | -0.01 (-0.46) | -0.01 (-0.44) | -0.01 (-0.44) | -0.01 (-0.44) | -2,13 | (-0.71) |
| N77 | 0.00 (0.00) | -0.06 (-0.39) | -0.08 (-0.57) | -0.04 (-0.55) | -0.02 (-0.53) | -0.01 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,22 | (-0.49) |
| N78 | 0.00 (0.00) | 1.32 (1.28) | -0.89 (-0.51) | -0.35 (-0.51) | -0.16 (-0.50) | -0.07 (-0.48) | -0.03 (-0.46) | -0.02 (-0.44) | -0.01 (-0.42) | -0.01 (-0.42) | -0.01 (-0.42) | -0,22 | (-0.06) |
| N79 | 0.00 (0.00) | 0.00 (0.06) | -0.03 (-0.58) | -0.02 (-0.55) | -0.01 (-0.53) | -0.01 (-0.51) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,07 | (-0.49) |
| N80T82 | 0.00 (0.00) | -1.33 (-0.70) | -1.60 (-0.62) | -0.75 (-0.57) | -0.35 (-0.53) | -0.16 (-0.51) | -0.08 (-0.48) | -0.04 (-0.46) | -0.02 (-0.44) | -0.02 (-0.44) | -0.02 (-0.44) | -4,33 | (-0.61) |
| O84 | 0.00 (0.00) | -0.46 (-0.85) | -0.27 (-0.64) | -0.13 (-0.58) | -0.06 (-0.54) | -0.03 (-0.50) | -0.01 (-0.48) | -0.01 (-0.45) | -0.00 (-0.43) | -0.00 (-0.43) | -0.00 (-0.43) | -0,99 | (-0.69) |
| P85 | 0.00 (0.00) | -0.31 (-0.68) | -0.23 (-0.52) | -0.12 (-0.54) | -0.06 (-0.53) | -0.03 (-0.50) | -0.01 (-0.48) | -0.01 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,77 | (-0.58) |
| Q86 | 0.00 (0.00) | 0.27 (1.51) | -0.03 (-0.30) | -0.04 (-0.49) | -0.02 (-0.51) | -0.01 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | 0,15 | (0.35) |
| Q87_88 | 0.00 (0.00) | 0.02 (1.81) | -0.11 (-0.55) | -0.10 (-0.52) | -0.05 (-0.53) | -0.02 (-0.52) | -0.01 (-0.50) | -0.01 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,29 | (-0.48) |
| R90T92 | 0.00 (0.00) | -0.01 (-0.38) | -0.08 (-0.57) | -0.06 (-0.57) | -0.03 (-0.55) | -0.02 (-0.53) | -0.01 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.46) | -0.00 (-0.46) | -0,21 | (-0.54) |
| R93 | 0.00 (0.00) | -0.03 (-0.31) | -0.12 (-0.56) | -0.09 (-0.57) | -0.05 (-0.55) | -0.02 (-0.52) | -0.01 (-0.50) | -0.01 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,33 | (-0.52) |
| S94 | 0.00 (0.00) | -0.05 (-0.61) | -0.09 (-0.59) | -0.05 (-0.57) | -0.03 (-0.54) | -0.01 (-0.51) | -0.01 (-0.49) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,25 | (-0.57) |
| S95 | 0.00 (0.00) | -0.00 (-0.05) | -0.03 (-0.59) | -0.02 (-0.54) | -0.01 (-0.52) | -0.00 (-0.50) | -0.00 (-0.48) | -0.00 (-0.46) | -0.00 (-0.44) | -0.00 (-0.44) | -0.00 (-0.44) | -0,07 | (-0.42) |
| S96 | 0.00 (0.00) | -0.01 (-0.49) | -0.06 (-0.57) | -0.04 (-0.58) | -0.02 (-0.55) | -0.01 (-0.52) | -0.00 (-0.50) | -0.00 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,14 | (-0.55) |
| T | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (-1.41) |
| U | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | | (0.00) |
| Total | | | | | | | | | | | | -88,77 | (-0.44) |

Table 3.34: Change in the quantity of labour (in thousands of units) in Scenario 5 relative to the 'business as usual' scenario, by activation round. Each round corresponds to a term in the summation of Equation 3.1. Round zero denotes the variation in the final-demand vector for sector C29 only. The first round indicates the effect on suppliers closest to the automotive supply chain, the second round the effect on suppliers of those suppliers, and so forth. The last column reports the cumulative effect for each sector. Decimal points are shown in parentheses.

| Industry | Round 0 | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 | Round 6 | Round 7 | Round 8 | Round 9 | Round 10 | Total Δ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A01 | 0.00 (0.00) | -0.77 (-0.26) | -12.72 (-0.61) | -8.92 (-0.57) | -5.34 (-0.54) | -2.82 (-0.52) | -1.41 (-0.49) | -0.69 (-0.47) | -0.34 (-0.45) | -0.34 (-0.45) | -0.34 (-0.45) | -33,36 | (-0.55) |
| A02 | 0.00 (0.00) | -0.50 (-0.75) | -0.92 (-0.50) | -0.55 (-0.52) | -0.26 (-0.51) | -0.12 (-0.49) | -0.06 (-0.46) | -0.03 (-0.44) | -0.01 (-0.42) | -0.01 (-0.42) | -0.01 (-0.42) | -2,46 | (-0.54) |
| A03 | 0.00 (0.00) | -0.00 (-0.28) | -0.13 (-0.64) | -0.16 (-0.57) | -0.08 (-0.55) | -0.04 (-0.52) | -0.02 (-0.50) | -0.01 (-0.47) | -0.00 (-0.45) | -0.00 (-0.45) | -0.00 (-0.45) | -0,45 | (-0.57) |
| B | 0.00 (0.00) | -25.13 (-0.90) | -11.10 (-0.74) | -4.52 (-0.62) | -2.05 (-0.55) | -0.95 (-0.51) | -0.45 (-0.47) | -0.21 (-0.45) | -0.10 (-0.43) | -0.10 (-0.43) | -0.10 (-0.43) | -44,61 | (-0.77) |
| C10T12 | 0.00 (0.00) | -3.66 (-0.74) | -5.88 (-0.63) | -4.81 (-0.58) | -2.67 (-0.55) | -1.34 (-0.52) | -0.65 (-0.49) | -0.31 (-0.46) | -0.15 (-0.44) | -0.15 (-0.44) | -0.15 (-0.44) | -19,61 | (-0.6) |
| C13T15 | 0.00 (0.00) | -21.10 (-0.40) | -7.99 (-0.42) | -3.21 (-0.41) | -1.35 (-0.40) | -0.60 (-0.38) | -0.28 (-0.36) | -0.13 (-0.33) | -0.06 (-0.31) | -0.06 (-0.31) | -0.06 (-0.31) | -34,94 | (-0.4) |
| C16 | 0.00 (0.00) | -3.85 (-0.25) | -5.17 (-0.49) | -2.58 (-0.51) | -1.18 (-0.50) | -0.54 (-0.47) | -0.25 (-0.45) | -0.12 (-0.43) | -0.05 (-0.41) | -0.05 (-0.41) | -0.05 (-0.41) | -14,35 | (-0.38) |
| C17 | 0.00 (0.00) | -8.82 (-0.61) | -8.50 (-0.61) | -4.50 (-0.55) | -2.17 (-0.52) | -1.02 (-0.49) | -0.48 (-0.46) | -0.23 (-0.44) | -0.11 (-0.42) | -0.11 (-0.42) | -0.11 (-0.42) | -25,92 | (-0.58) |
| C18 | 0.00 (0.00) | -6.98 (-0.47) | -7.29 (-0.61) | -4.11 (-0.57) | -2.02 (-0.54) | -0.96 (-0.52) | -0.45 (-0.49) | -0.21 (-0.47) | -0.10 (-0.45) | -0.10 (-0.45) | -0.10 (-0.45) | -27,05 | (-0.46) |
| C19 | 0.00 (0.00) | -0.25 (-0.58) | -1.18 (-0.63) | -0.92 (-0.56) | -0.50 (-0.52) | -0.25 (-0.49) | -0.13 (-0.46) | -0.06 (-0.44) | -0.03 (-0.42) | -0.03 (-0.42) | -0.03 (-0.42) | -3,35 | (-0.56) |
| C20 | 0.00 (0.00) | -28.37 (-0.82) | -18.29 (-0.59) | -6.65 (-0.51) | -2.62 (-0.45) | -1.12 (-0.41) | -0.51 (-0.38) | -0.24 (-0.36) | -0.11 (-0.34) | -0.11 (-0.34) | -0.11 (-0.34) | -58,03 | (-0.65) |
| C21 | 0.00 (0.00) | -7.85 (-0.84) | -2.17 (-0.60) | -0.85 (-0.53) | -0.37 (-0.48) | -0.17 (-0.43) | -0.08 (-0.40) | -0.04 (-0.37) | -0.02 (-0.34) | -0.02 (-0.34) | -0.02 (-0.34) | -11,56 | (-0.72) |
| C22 | 0.00 (0.00) | -131.53 (-0.64) | -29.76 (-0.51) | -9.51 (-0.47) | -3.59 (-0.44) | -1.53 (-0.42) | -0.69 (-0.40) | -0.33 (-0.39) | -0.16 (-0.38) | -0.16 (-0.38) | -0.16 (-0.38) | -183,52 | (-0.57) |
| C23 | 0.00 (0.00) | -84.65 (-0.89) | -21.84 (-0.70) | -7.59 (-0.59) | -3.01 (-0.53) | -1.31 (-0.49) | -0.60 (-0.46) | -0.28 (-0.44) | -0.14 (-0.42) | -0.14 (-0.42) | -0.14 (-0.42) | -119,54 | (-0.79) |
| C24 | 0.00 (0.00) | -73.04 (-0.77) | -32.06 (-0.56) | -10.86 (-0.47) | -3.59 (-0.39) | -1.25 (-0.33) | -0.48 (-0.29) | -0.21 (-0.26) | -0.10 (-0.25) | -0.10 (-0.25) | -0.10 (-0.25) | -123,12 | (-0.63) |
| C25 | 0.00 (0.00) | -472.11 (-0.51) | -115.33 (-0.47) | -34.06 (-0.44) | -11.30 (-0.41) | -4.30 (-0.38) | -1.82 (-0.37) | -0.83 (-0.36) | -0.40 (-0.35) | -0.40 (-0.35) | -0.40 (-0.35) | -734,6 | (-0.45) |
| C26 | 0.00 (0.00) | -9.41 (-0.31) | -5.76 (-0.44) | -2.29 (-0.41) | -1.12 (-0.41) | -0.55 (-0.41) | -0.27 (-0.40) | -0.13 (-0.39) | -0.07 (-0.38) | -0.07 (-0.38) | -0.07 (-0.38) | -23,12 | (-0.35) |
| C27 | 0.00 (0.00) | 17.56 (0.18) | -3.61 (-0.14) | -1.93 (-0.20) | -1.01 (-0.25) | -0.52 (-0.27) | -0.27 (-0.29) | -0.14 (-0.30) | -0.07 (-0.30) | -0.07 (-0.30) | -0.07 (-0.30) | -24,66 | (-0.09) |
| C28 | 0.00 (0.00) | -55.54 (-0.45) | -20.35 (-0.38) | -7.11 (-0.35) | -2.78 (-0.32) | -1.21 (-0.31) | -0.56 (-0.31) | -0.27 (-0.30) | -0.13 (-0.30) | -0.13 (-0.30) | -0.13 (-0.30) | -178,89 | (-0.33) |
| C29 | -1455.52 (-0.28) | 23.47 (0.29) | 2.52 (0.08) | 0.71 (0.10) | 0.04 (0.02) | -0.07 (-0.06) | -0.07 (-0.13) | -0.04 (-0.17) | -0.03 (-0.19) | -0.03 (-0.19) | -0.03 (-0.19) | -1264,73 | (-0.27) |
| C30 | 0.00 (0.00) | -29.68 (-0.80) | -3.73 (-0.53) | -1.41 (-0.52) | -0.59 (-0.49) | -0.27 (-0.46) | -0.13 (-0.44) | -0.06 (-0.42) | -0.03 (-0.40) | -0.03 (-0.40) | -0.03 (-0.40) | -41,44 | (-0.6) |
| C31_32 | 0.00 (0.00) | -17.52 (-0.43) | -6.85 (-0.46) | -2.81 (-0.46) | -1.22 (-0.45) | -0.55 (-0.44) | -0.26 (-0.42) | -0.12 (-0.40) | -0.06 (-0.39) | -0.06 (-0.39) | -0.06 (-0.39) | -33,35 | (-0.41) |
| C33 | 0.00 (0.00) | -19.94 (-0.57) | -7.64 (-0.52) | -3.17 (-0.51) | -1.42 (-0.49) | -0.66 (-0.47) | -0.31 (-0.45) | -0.15 (-0.44) | -0.07 (-0.42) | -0.07 (-0.42) | -0.07 (-0.42) | -33,63 | (-0.54) |
| D35 | 0.00 (0.00) | -5.63 (-0.08) | -41.56 (-0.42) | -35.74 (-0.46) | -23.46 (-0.47) | -13.84 (-0.47) | -7.73 (-0.47) | -4.19 (-0.46) | -2.23 (-0.45) | -2.23 (-0.45) | -2.23 (-0.45) | -136,83 | (-0.38) |
| E36 | 0.00 (0.00) | -13.30 (-0.87) | -5.69 (-0.65) | -2.58 (-0.57) | -1.14 (-0.53) | -0.52 (-0.50) | -0.24 (-0.47) | -0.11 (-0.45) | -0.05 (-0.43) | -0.05 (-0.43) | -0.05 (-0.43) | -23,69 | (-0.72) |
| E37T39 | 0.00 (0.00) | -61.21 (-0.90) | -24.13 (-0.68) | -10.53 (-0.59) | -4.57 (-0.53) | -2.04 (-0.49) | -0.94 (-0.46) | -0.44 (-0.44) | -0.21 (-0.42) | -0.21 (-0.42) | -0.21 (-0.42) | -104,28 | (-0.75) |
| F | 0.00 (0.00) | -92.87 (-0.85) | -45.25 (-0.70) | -21.54 (-0.62) | -10.09 (-0.57) | -4.73 (-0.54) | -2.23 (-0.51) | -1.06 (-0.48) | -0.51 (-0.46) | -0.51 (-0.46) | -0.51 (-0.46) | -178,75 | (-0.73) |
| G45 | 0.00 (0.00) | -11.54 (-0.04) | -4.92 (-0.14) | -2.96 (-0.26) | -1.59 (-0.33) | -0.78 (-0.35) | -0.38 (-0.35) | -0.19 (-0.35) | -0.09 (-0.34) | -0.09 (-0.34) | -0.09 (-0.34) | -64,41 | (-0.12) |
| G46 | 0.00 (0.00) | -309.11 (-0.68) | -95.72 (-0.55) | -41.71 (-0.53) | -18.32 (-0.50) | -8.26 (-0.47) | -3.82 (-0.45) | -1.80 (-0.43) | -0.87 (-0.41) | -0.87 (-0.41) | -0.87 (-0.41) | -480,47 | (-0.61) |
| G47 | 0.00 (0.00) | -50.23 (-0.41) | -19.98 (-0.47) | -9.01 (-0.48) | -4.14 (-0.47) | -1.92 (-0.45) | -0.90 (-0.43) | -0.43 (-0.40) | -0.21 (-0.38) | -0.21 (-0.38) | -0.21 (-0.38) | -87,02 | (-0.43) |
| H49 | 0.00 (0.00) | -83.58 (-0.58) | -65.04 (-0.55) | -35.94 (-0.53) | -18.12 (-0.52) | -8.87 (-0.50) | -4.32 (-0.48) | -2.11 (-0.46) | -1.04 (-0.44) | -1.04 (-0.44) | -1.04 (-0.44) | -220,05 | (-0.55) |
| H50 | 0.00 (0.00) | -1.84 (-0.79) | -1.24 (-0.57) | -0.62 (-0.54) | -0.30 (-0.51) | -0.14 (-0.48) | -0.07 (-0.45) | -0.03 (-0.42) | -0.02 (-0.40) | -0.02 (-0.40) | -0.02 (-0.40) | -4,26 | (-0.62) |
| H51 | 0.00 (0.00) | -0.82 (-0.73) | -0.93 (-0.60) | -0.49 (-0.55) | -0.24 (-0.53) | -0.11 (-0.50) | -0.05 (-0.48) | -0.03 (-0.46) | -0.01 (-0.44) | -0.01 (-0.44) | -0.01 (-0.44) | -2,69 | (-0.6) |
| H52 | 0.00 (0.00) | -57.40 (-0.66) | -55.10 (-0.56) | -29.60 (-0.55) | -14.52 (-0.53) | -6.93 (-0.50) | -3.29 (-0.48) | -1.58 (-0.46) | -0.76 (-0.44) | -0.76 (-0.44) | -0.76 (-0.44) | -169,92 | (-0.58) |
| H53 | 0.00 (0.00) | 6.64 (2.41) | -5.05 (-0.64) | -2.96 (-0.57) | -1.50 (-0.54) | -0.71 (-0.51) | -0.34 (-0.49) | -0.16 (-0.46) | -0.08 (-0.44) | -0.08 (-0.44) | -0.08 (-0.44) | -4,22 | (-0.2) |
| I | 0.00 (0.00) | -8.76 (-0.51) | -29.62 (-0.58) | -16.08 (-0.56) | -8.02 (-0.53) | -3.82 (-0.51) | -1.81 (-0.49) | -0.86 (-0.46) | -0.41 (-0.45) | -0.41 (-0.45) | -0.41 (-0.45) | -69,78 | (-0.55) |
| J58 | 0.00 (0.00) | -0.60 (-0.52) | -2.23 (-0.60) | -1.35 (-0.53) | -0.62 (-0.53) | -0.29 (-0.51) | -0.14 (-0.49) | -0.06 (-0.46) | -0.03 (-0.44) | -0.03 (-0.44) | -0.03 (-0.44) | -5,34 | (-0.55) |
| J59_60 | 0.00 (0.00) | -1.32 (-0.43) | -3.46 (-0.56) | -2.27 (-0.54) | -1.16 (-0.54) | -0.56 (-0.52) | -0.26 (-0.49) | -0.12 (-0.47) | -0.06 (-0.45) | -0.06 (-0.45) | -0.06 (-0.45) | -9,27 | (-0.52) |
| J61 | 0.00 (0.00) | -39.72 (-0.88) | -21.57 (-0.67) | -9.82 (-0.59) | -4.37 (-0.54) | -1.95 (-0.51) | -0.89 (-0.48) | -0.41 (-0.46) | -0.19 (-0.43) | -0.19 (-0.43) | -0.19 (-0.43) | -79,11 | (-0.72) |
| J62_63 | 0.00 (0.00) | -53.75 (-0.56) | -35.56 (-0.57) | -18.92 (-0.55) | -9.20 (-0.53) | -4.38 (-0.51) | -2.07 (-0.49) | -0.99 (-0.47) | -0.47 (-0.45) | -0.47 (-0.45) | -0.47 (-0.45) | -125,78 | (-0.55) |
| K64 | 0.00 (0.00) | -85.29 (-0.79) | -57.62 (-0.57) | -30.81 (-0.55) | -14.66 (-0.53) | -6.84 (-0.51) | -3.20 (-0.48) | -1.51 (-0.46) | -0.72 (-0.44) | -0.72 (-0.44) | -0.72 (-0.44) | -201,36 | (-0.63) |
| K65 | 0.00 (0.00) | -6.31 (-0.71) | -6.85 (-0.58) | -3.24 (-0.55) | -1.50 (-0.53) | -0.69 (-0.51) | -0.32 (-0.48) | -0.15 (-0.46) | -0.07 (-0.44) | -0.07 (-0.44) | -0.07 (-0.44) | -19,22 | (-0.6) |
| K66 | 0.00 (0.00) | -4.43 (-0.48) | -21.38 (-0.60) | -11.23 (-0.55) | -5.45 (-0.53) | -2.55 (-0.51) | -1.20 (-0.48) | -0.57 (-0.46) | -0.27 (-0.44) | -0.27 (-0.44) | -0.27 (-0.44) | -47,32 | (-0.55) |
| L | 0.00 (0.00) | -76.19 (-0.57) | -89.44 (-0.52) | -43.20 (-0.53) | -20.36 (-0.52) | -9.53 (-0.50) | -4.48 (-0.48) | -2.13 (-0.46) | -1.02 (-0.44) | -1.02 (-0.44) | -1.02 (-0.44) | -247,34 | (-0.53) |
| M69_70 | 0.00 (0.00) | -170.74 (-0.72) | -108.03 (-0.63) | -48.95 (-0.56) | -22.69 (-0.53) | -10.55 (-0.51) | -4.95 (-0.49) | -2.34 (-0.46) | -1.12 (-0.45) | -1.12 (-0.45) | -1.12 (-0.45) | -370,46 | (-0.64) |
| M71 | 0.00 (0.00) | -285.73 (-0.97) | -36.04 (-0.64) | -15.87 (-0.59) | -6.93 (-0.54) | -3.19 (-0.52) | -1.49 (-0.49) | -0.71 (-0.47) | -0.34 (-0.45) | -0.34 (-0.45) | -0.34 (-0.45) | -350,63 | (-0.87) |
| M72 | 0.00 (0.00) | -199.78 (-0.87) | -10.55 (-0.66) | -3.48 (-0.60) | -1.27 (-0.55) | -0.55 (-0.53) | -0.25 (-0.51) | -0.12 (-0.49) | -0.06 (-0.47) | -0.06 (-0.47) | -0.06 (-0.47) | -216,11 | (-0.85) |
| M73 | 0.00 (0.00) | -8.66 (-0.49) | -7.71 (-0.44) | -3.48 (-0.51) | -1.63 (-0.51) | -0.76 (-0.49) | -0.36 (-0.47) | -0.17 (-0.45) | -0.08 (-0.43) | -0.08 (-0.43) | -0.08 (-0.43) | -22,93 | (-0.47) |
| M74_75 | 0.00 (0.00) | -54.37 (-0.88) | -24.06 (-0.63) | -10.91 (-0.57) | -5.04 (-0.53) | -2.35 (-0.51) | -1.11 (-0.49) | -0.53 (-0.46) | -0.25 (-0.44) | -0.25 (-0.44) | -0.25 (-0.44) | -99,15 | (-0.71) |
| N77 | 0.00 (0.00) | -10.82 (-0.39) | -14.72 (-0.57) | -7.47 (-0.55) | -3.57 (-0.53) | -1.68 (-0.50) | -0.79 (-0.48) | -0.38 (-0.46) | -0.18 (-0.44) | -0.18 (-0.44) | -0.18 (-0.44) | -39,8 | (-0.49) |
| N78 | 0.00 (0.00) | 42.93 (1.28) | -29.12 (-0.51) | -11.55 (-0.51) | -5.17 (-0.50) | -2.34 (-0.48) | -1.08 (-0.46) | -0.51 (-0.44) | -0.24 (-0.42) | -0.24 (-0.42) | -0.24 (-0.42) | -7,32 | (-0.06) |
| N79 | 0.00 (0.00) | 0.02 (0.06) | -0.72 (-0.58) | -0.47 (-0.55) | -0.24 (-0.53) | -0.12 (-0.51) | -0.05 (-0.48) | -0.03 (-0.46) | -0.01 (-0.44) | -0.01 (-0.44) | -0.01 (-0.44) | -1,63 | (-0.49) |
| N80T82 | 0.00 (0.00) | -46.68 (-0.70) | -56.09 (-0.62) | -26.38 (-0.57) | -12.27 (-0.53) | -5.67 (-0.51) | -2.64 (-0.48) | -1.24 (-0.46) | -0.59 (-0.44) | -0.59 (-0.44) | -0.59 (-0.44) | -152,13 | (-0.61) |
| O84 | 0.00 (0.00) | -44.32 (-0.85) | -26.09 (-0.64) | -12.63 (-0.58) | -6.00 (-0.54) | -2.79 (-0.50) | -1.30 (-0.48) | -0.61 (-0.45) | -0.29 (-0.43) | -0.29 (-0.43) | -0.29 (-0.43) | -94,31 | (-0.69) |
| P85 | 0.00 (0.00) | -13.41 (-0.68) | -9.79 (-0.52) | -5.21 (-0.54) | -2.43 (-0.53) | -1.14 (-0.50) | -0.53 (-0.48) | -0.25 (-0.46) | -0.12 (-0.44) | -0.12 (-0.44) | -0.12 (-0.44) | -32,99 | (-0.58) |
| Q86 | 0.00 (0.00) | 15.80 (1.51) | -1.89 (-0.30) | -2.29 (-0.49) | -1.26 (-0.51) | -0.61 (-0.50) | -0.29 (-0.48) | -0.13 (-0.46) | -0.06 (-0.44) | -0.06 (-0.44) | -0.06 (-0.44) | 9,21 | (0.35) |
| Q87_88 | 0.00 (0.00) | 0.62 (1.81) | -3.17 (-0.55) | -2.80 (-0.52) | -1.46 (-0.53) | -0.71 (-0.52) | -0.33 (-0.50) | -0.16 (-0.48) | -0.07 (-0.46) | -0.07 (-0.46) | -0.07 (-0.46) | -8,16 | (-0.48) |
| R90T92 | 0.00 (0.00) | -0.81 (-0.38) | -4.88 (-0.57) | -3.70 (-0.57) | -2.10 (-0.55) | -1.06 (-0.53) | -0.51 (-0.50) | -0.24 (-0.48) | -0.12 (-0.46) | -0.12 (-0.46) | -0.12 (-0.46) | -13,54 | (-0.54) |
| R93 | 0.00 (0.00) | -1.20 (-0.31) | -5.34 (-0.56) | -3.84 (-0.57) | -2.06 (-0.55) | -1.01 (-0.52) | -0.48 (-0.50) | -0.23 (-0.47) | -0.11 (-0.45) | -0.11 (-0.45) | -0.11 (-0.45) | -14,37 | (-0.52) |
| S94 | 0.00 (0.00) | -1.95 (-0.61) | -3.47 (-0.59) | -2.01 (-0.57) | -1.03 (-0.54) | -0.50 (-0.51) | -0.24 (-0.49) | -0.11 (-0.47) | -0.05 (-0.45) | -0.05 (-0.45) | -0.05 (-0.45) | -9,41 | (-0.57) |
| S95 | 0.00 (0.00) | -0.07 (-0.05) | -1.25 (-0.59) | -0.62 (-0.54) | -0.31 (-0.52) | -0.15 (-0.50) | -0.07 (-0.48) | -0.03 (-0.46) | -0.02 (-0.44) | -0.02 (-0.44) | -0.02 (-0.44) | -2,52 | (-0.42) |
| S96 | 0.00 (0.00) | -0.30 (-0.49) | -1.98 (-0.57) | -1.51 (-0.58) | -0.72 (-0.55) | -0.33 (-0.52) | -0.15 (-0.50) | -0.07 (-0.47) | -0.03 (-0.45) | -0.03 (-0.45) | -0.03 (-0.45) | -5,13 | (-0.55) |
| T | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| U | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0 | (0.00) |
| Total | | | | | | | | | | | | -6748,81 | (-0.44) |

Table 3.35: Change in the value added (in millions of euros) in Scenario 5 relative to the 'business as usual' scenario, by activation round. Each round corresponds to a term in the summation of Equation 3.1. Round zero denotes the variation in the final-demand vector for sector C29 only. The first round indicates the effect on suppliers closest to the automotive supply chain, the second round the effect on suppliers of those suppliers, and so forth. The last column reports the cumulative effect for each sector. Decimal points are shown in parentheses.

### 3.A.3 Model derivation connecting commodity final demand to industry output (industry-by-commodity total requirements matrix)

IO transactions can be organised in different tables that record flows over a given period, either in physical or monetary terms. The standard Leontief framework accounts for both sides of each market, allowing for discretionary final consumption and the use of non-produced primary factors. On the demand side, both intermediate and final components are included, while on the supply side production by firms is considered. In the present analysis we employ two types of input–output matrices, namely the Use and Make matrices.

Using Miller and Blair (2009) formalisation, the Use matrix can be written as $U_{c_x i} = [u_{ij}]$. It is a commodity-by-industry matrix in which each element denotes the monetary purchases of commodity $i$ made by industry $j$. The total of each row gives the total commodity output, equal to the sum of the use of commodity $i$ as an intermediate input by all sectors in the table plus final demand for that commodity. This quantity can be expressed as:

$$q_i = \sum_{j=1}^{n} u_{ij} + f_i \tag{3.14}$$

with $i = 1, .., n$.

The total of each column, instead, indicates the total industry output, which is defined as the column sum:

$$x_j = \sum_{i=1}^{n} u_{ij} \tag{3.15}$$

with $j = 1, .., n$.

The technical coefficients are determined as $b_{ij} = \frac{u_{ij}}{x_j}$ or in a matrix form as $B = U\hat{x}^{-1}$, dove $\hat{x}^{-1}$ is the matrix including total industry outputs in the main diagonal and zero, otherwise.

Each column of B contains elements that represent the input value of each commodity

per unit of output value produced by the sector corresponding to that column. The dimension of B is commodity-by-industry.

The Make matrix, which can be expressed as $V_{i\times c} = [v_{ij}]$, is an industry-by-commodity matrix[19] where each element denotes the monetary value of commodity $j$ output produced by industry $i$. The row total expresses the total industry output ($x_i$), while the column total indicates the total commodity output ($q_j$):

$$x_i = \sum_{j=1}^{n} v_{ij} \tag{3.16}$$

with con $i = 1, .., n$.

$$q_j = \sum_{i=1}^{n} u_{ij} \tag{3.17}$$

with con $j = 1, .., n$.

We can then define the so-called market shares as $d_{ij} = \frac{v_{ij}}{q_j}$ or, in matrix form, as $D = V\hat{q}^{-1}$, where $\hat{q}^{-1}$ is the diagonal matrix containing the total commodity outputs on the main diagonal and zeros elsewhere. Each element of D represents the fraction of total commodity output of commodity $j$ that is produced by sector $i$. Accordingly, the values in a given column indicate the market shares, i.e. the share of the commodity's value represented by that column that is produced by each sector in the table.

The equation (3.1) could be rewritten in its matrix form as:

$$q = Ui + f \tag{3.18}$$

Recalling the origina IO model with $n$ industries, the total gross production can be expressed in its matrix form as $X = Zi + f$, while the direct technical coefficients can be represented as $A = Z\hat{x}^{-1}$. By expliciting the latter by Z ($Z = A\hat{x}$) and substituting it in

[19]With respect to this mathematical formalisation, the Make matrices in FIGARO use the same row–column formatting — i.e. commodity-by-industry, like the Use matrices; consequently, if one wishes to apply the above formulations to FIGARO, one must take the inverse of the matrix U.

$X = Zi + f$, we get the relationship $x = (I - A)^{-1}f = Lf$.

The driving force is the exogenous vector of final demand for production in the sectors. In combination with the inverse Leontief matrix (total requirements matrix), $L = (I-A)^{-1}$, the industrial outputs necessary to satisfy final demand are determined. Similarly, starting from the Use matrix, we can rewrite $\mathbf{B} = \mathbf{U}\hat{\mathbf{x}}^{-1}$ as $U = B\hat{x}$. Substituting this latter relation into (3.5), we obtain the relation:

$$q = Bx + f \tag{3.19}$$

At this point, since obtaining the total requirement matrix is dependent on the decision to transform industry outputs x into commodity outputs q or commodity outputs q and e into industry outputs x, it is necessary to use the Make matrix. Using the D matrix, it is possible to derive the industry by commodity total requirements matrix as follows. Starting from: $D = V\hat{q}^{-1} \rightarrow D\hat{q} = V \rightarrow D\hat{q}i = Vi$. Considering that $x = Vi$ and replacing it in the previous equation, we get $D\hat{q}i = x$, from which $Dq = x$. Now, by pre-multiplying both sides in (6) by D, we get $Dq = D(Bx + f)$. Replacing $Dq = x$ in the last equation, we get $x = D(Bx + f)$ from which $x = (DB)x + Df$. By highlighting and making explicit x, we obtain:

$$x = [(I - DB)^{-1}D]f \tag{3.20}$$

That can be rewritten in its full form as:

$$x = [(I - (V\hat{q}^{-1})(U\hat{x}^{-1}))^{-1}V\hat{q}^{-1}]f \tag{3.21}$$

This formulation provides a response to changes in final demand f, transforming these changes into the levels of production x necessary to satisfy that demand, taking into account the relationships between sectors and market shares. If f changes, the result x will change linearly, based on the inverse of the inter-sectoral system $(I - DB)^{-1}$ and the

market shares D. In other words, f acts as the stimulus vector that is transformed through interactions between sectors (represented by DB) and market shares (represented by D).

### 3.A.4 Technical steps to derive the electric production recipe)

Technically, the following steps were applied to the Use tables:

1) Starting from the Use matrix for the reference year 2022, we aggregated along the rows by product, disregarding the country of origin of the product used as an input. Aggregation was performed by summing the monetary values across columns for each product. The resulting matrix therefore retains the original number of columns but has 64 rows, corresponding to the total number of products in the table. Primary attention was given to the column corresponding to sector C29 (China), which represents the production recipe of the Chinese automotive sector.

2) For the Use matrix in year 2012 we carried out the same procedure described in step 1), extracting exclusively the China column C29. We computed the technical coefficients for column C29 considering only the total intermediate inputs and explicitly excluding value added and adjustment items. These coefficients represent the composition of intermediate inputs used by the automotive sector and answer the question: what is the relative weight of each product in the total intermediate inputs of the automotive sector. This vector corresponds to $d^{ICE}_{chinese\ automotive,\ 2022}$.

3) We then computed $d^{EV}_{chinese\ automotive,\ 2022}$ by applying equation (3.13). This vector reflects the technical coefficients of products in the Use matrix calculated on the column totals, again excluding the components of value added and adjustments (such as taxes less subsidies on products, purchases from non-residents within the domestic territory, direct purchases abroad by residents, compensation of employees, other net taxes on production, and gross operating surplus). Consequently, it was necessary to normalize the vector so that the sum of the product technical coefficients together with the adjustments and value-added components equals 1. This normalization was performed by applying the following formula:

$$d^{EV\ *}_{chinese\ automotive,\ 2022} = \frac{d^{EV}_{chinese\ automotive,\ 2022}}{\left(d^{EV}_{chinese\ automotive,\ 2022}\ i + \ \phi_{chinese\ automotive,\ 2022}\ i\right)} \tag{3.22}$$

Where $\phi_{chinese\ automotive,\ 2022}$ is the sub-vector of value-added and adjustment coefficients[20]. This step implies that, for each unit of output produced, value added and the other items remain unchanged despite the shift from a mixed technology (internal combustion and electric) to a purely electric technology. In other words, the modelling approach assumes that the share of value added is invariant under both cost structures (EV and conventional), as also assumed by Ulrich and Lehr (2020); Leurent and Windisch (2015); Tamba et al. (2022). The primary motivation for this assumption is that, in the literature and in the data available to date, there is no clear evidence of systematically higher or lower value added in EV production.

At the end of this step, we obtain the vector corresponding to the Chinese electric-vehicle production recipe for 2022, which remains in an aggregated format of 64 industrial sectors (see Table 3.22 in the Appendix 3.A.1).

4.1) Once the Chinese electric production recipe has been obtained, we use it as the new production recipe for electric vehicles in the four European countries.

4.2) However, since we are interested in using the original value-added of the European automotive sectors, we replace in the aggregated Chinese production recipe the coefficients for the value-added items and the column-adjustment entries of the aggregated automotive columns with those from the four European countries, and then renormalise the column by dividing each entry by the column total so that the column sums again equal 1. (Table 3.23 in the Appendix 3.A.1 shows the Italian recipe for electric production.)

[20]Hence, in the denominator we get a scalar given by the sum of the elements of the vector $d^{EV}_{chinese\ automotive,\ 2022}$ and those of the vector $\phi_{chinese\ automotive,\ 2022}$. $i$ is the unit vector defined as $i = (1, .., 1)$. Therefore, the scalar product between the vector and the unit vector returns the column sum.

5.1) At this stage, we aim to disaggregate the electric production-recipe vector, thus returning to a table with the original size (M×N). First, starting from the initial Use 2022 table, for each of the four European countries we compute the technical coefficients of column C29 (automotive) using the column total — including value-added and adjustments — because the electric-vehicle production recipe vector calculated in point 4) was normalised taking into account the contribution of value added and adjustments.

5.2) We then consider only the portion of the coefficient vector pertaining to intermediate inputs and divide each coefficient that corresponds to a product supplied by a given country by the sum of the coefficients for the same product down the entire column. This yields the weight of each input in automotive production. Next, we multiply each element of this weight vector by the corresponding entry of the aggregated production-recipe vector, preserving a one-to-one product-to-product correspondence across all countries. For example, in Italy's C29 column, taking the C27 row for France, we multiply that entry by the C27 element of the aggregated vector to obtain the input coefficient that reflects the contribution of the French C27 sector to Italian automotive production. In this way, we obtain a recipe vector for electric vehicles for the four countries, balanced according to the specific contribution of each supplying country and sector to European producers.

5.3) Finally, we add to each of the four country vectors the six rows of value-added and adjustment coefficients; the column sums equal 1, confirming that the columns have been constructed correctly. Figure 3.9 below schematically illustrates the process for building the electric-vehicle production-recipe vector for the Italian automotive sector; the same procedure applies to the other European countries considered.

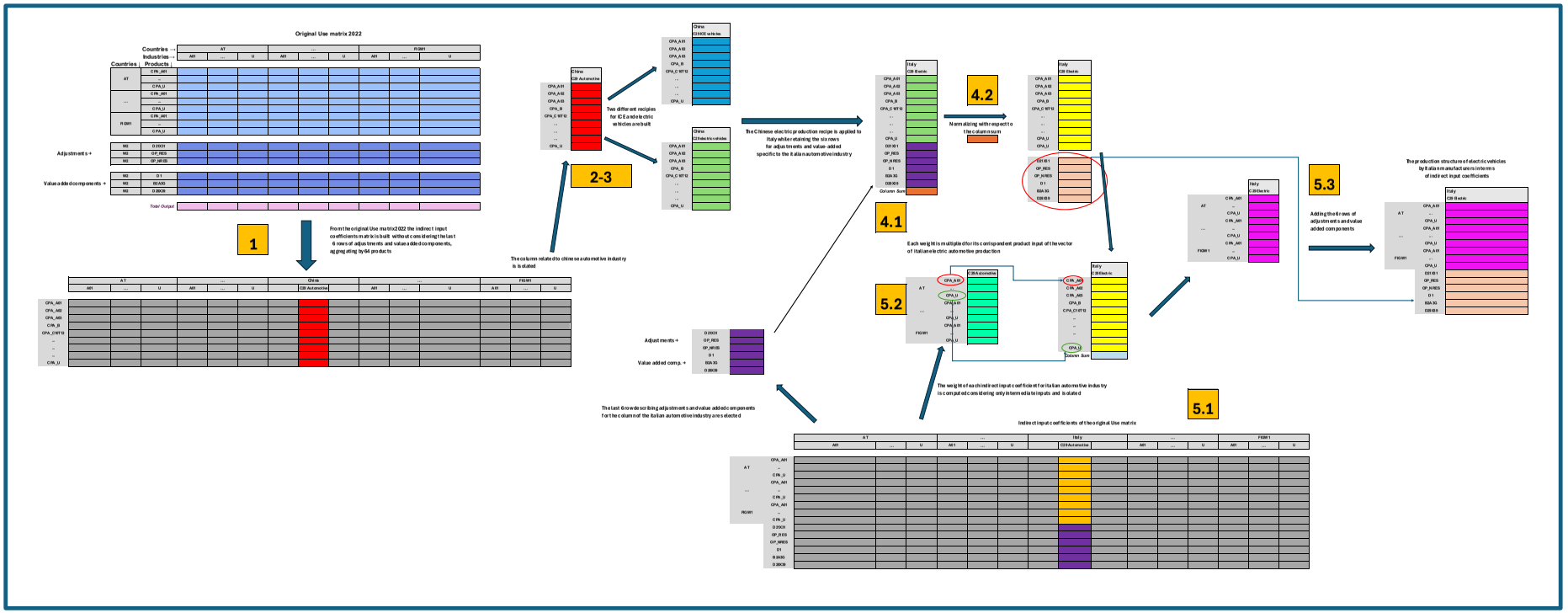



Figure 3.9: Construction of the electric production recipe for European producing countries. For illustrative purposes, the figure presents the main steps leading to the construction of the vector of technical direct coefficients of the Use matrix for the Italian automotive sector producing exclusively electric vehicles. The same procedure applies to the other three countries: Germany, Spain, and France.

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