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Labor Markets in Transition:

Evidence from Green Jobs, Automation, and the Great Resignation

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Introduction

The present thesis consists of three independent chapters, each addressing a distinct yet crucial aspect of labor market dynamics in the context of technological change, environmental sustainability, and post-pandemic transformations. While each chapter stands alone in its research question, methodology, and empirical focus, they collectively contribute to a broader understanding of how labor markets evolve in response to external shocks and structural transformations. Studying these dynamics is particularly relevant given the increasing pace and complexity of structural transformations affecting contemporary labor markets. By examining how technological innovation, environmental transition, and global health crises reshape employment patterns, this thesis aims to contribute to a deeper understanding of the mechanisms through which economies adapt to change. Such an understanding is essential not only for advancing academic knowledge, but also for informing policy strategies that promote resilience, equity, and long-term sustainability in the world of work.

The first chapter, *Measuring Green Jobs in Italy: A Task-Based Approach*, investigates the definition and measurement of Green Jobs, a concept that has become increasingly relevant in economic policy discussions. Despite the growing importance of Green Jobs, their quantification remains challenging due to the variety of definitions and methodologies proposed in the literature. This chapter contributes to the debate by introducing a novel task-based approach to measure Green Jobs in Italy, combining textual analysis and machine learning techniques to validate findings. Using the Italian Sample Survey on Professions (ICP), it identifies Green Tasks across different occupations and constructs continuous and binary indicators to assess the degree of greenness associated with each job. These indicators are then integrated with the *Comunicazioni Obbligatorie* dataset to analyze the distribution and characteristics of Green Jobs. The essential contribution of this chapter is methodological: it proposes a novel way to identify and measure Green Jobs by constructing an indicator directly based on the task content of occupations as described in the Italian context. Unlike previous studies that often rely on sectoral classifications or qualitative categorizations, this approach utilizes the Italian O*NET database (ICP) to develop a task-based indicator of job greenness. To the best of our knowledge, this is the first attempt to construct such an index for Italy using a direct mapping of Green Tasks onto occupational data at this level of detail. This methodological innovation allows for a more granular and dynamic representation of how environmental tasks are embedded in different professions.

The second chapter, *Robot, Trade, and Employment: Unraveling the Relationship Within the European Context*, is a co-authored work with Professor Chiara Franco from the University of Pisa and has been published in *Structural Change and Economic Dynamics*. This chapter examines the cross-border effects of robot adoption in the European labor market. Industrial robots have become a major technological innovation in manufacturing, with almost 4 million industrial robots operating worldwide as of 2022. The debate on their labor market impact is ongoing, with theories suggesting both positive productivity effects and negative displacement effects. While many studies have analyzed the impact of robots on employment at a national level, there is limited research on how robot adoption in one country affects employment dynamics in its trade partners. According to previous theoretical works, Robot adoption can influence trade partners employment dynamics in two opposite ways. On one hand, by lowering labor costs and encouraging firms to bring production back to their home country, it may reduce the demand for low-skilled labor in foreign economies. On the other hand, automation can lead to an expansion in production, increasing the need for intermediate goods, which may still be sourced from abroad and potentially boost employment in exporting countries. Nonetheless, robust empirical results are still lacking and often inconclusive. This chapter addresses this gap by constructing a novel indicator that captures both the penetration of industrial robots in the five largest European economies (France, Germany, Italy, Spain, and the UK) and the reliance of other European countries on these economies through trade linkages. Using the OECD Trade in Employment (TiM) dataset, the study explores whether robot adoption in these major economies influences employment outcomes in other European nations. Our research provides new insights into how technological change spreads its effects beyond national borders.

The third and last chapter, *The Italian Great Resignation: Just a Reallocation Trend?*, focuses on the post-pandemic labor market and the phenomenon of the *Great Resignation* (GR). Initially identified in the United States in 2021, the GR describes a surge in voluntary resignations that has disrupted labor markets worldwide. However, little research has explored whether this trend is a sign of widespread labor force exits or rather a reshuffling of workers across jobs. This chapter analyzes the Italian case using data from the Italian Labour Force Survey, assessing the extent to which resignations reflect labor force withdrawal versus job switching. After determining the appropriate measure to capture the trend, we compare two samples of representative Italian workers (pre- and post-Covid) and perform an econometric analysis to identify the underlying determinants of the GR. Finally, we enhance our study with decomposition and counterfactual analyses to assess the impact of unobservable psychological factors related to the pandemic, as well as to evaluate the role of wages in this context.

Overall, this dissertation contributes to the understanding of labor market transformations from three different perspectives: the green transition, technological change, and post-pandemic adjustments. What unites these three perspectives is their focus on how labor market dynamics are reshaped by profound transformations - whether triggered by sudden shocks such as the COVID-19 pandemic, driven by continuous processes like automation, or led by policy initiatives such as the European Green Deal - all of which feed into the broader debate on the future of work. By adopting novel methodologies and data-driven approaches, it provides insights that are relevant for both policymakers and researchers aiming to navigate the complexities of modern labor markets.

Chapter 1

Measuring Green Jobs in Italy: a Task-Based Approach

1.1 Introduction

The term Green Jobs has emerged as a key concept in economic policies over the past fifteen years. Starting with the Green Jobs Initiative in 2008, in which we found the first definition of Green Jobs (UNEP, 2008), many other national and international policies have placed this concept at the heart of their economic interventions. The European Green Deal and the Green Jobs Act in the US are just two examples of policies aimed at improving the green transition while maintaining GDP growth. Within Green Growth theory, these jobs are often seen as a mean of achieving both environmental and economic benefits by enhancing resilience and diversification. However, although international institutions and governments have financed specific policies to increase the number of Green Jobs, from an academic point of view, research has only started to develop recently (Peters, 2014; Stanef-Puică et al., 2022). To date, the literature has focused on two main challenges: the definition and measurement of Green Jobs.

As previously mentioned, the concept of Green Jobs is relatively new and is still evolving. Indeed, many institutions, such as the United Nations Environmental Program (UNEP), International Labour Office (ILO), and European Commission (EC), provide their definitions (Rutkowska-Podołowska et al., 2016). Although these definitions may appear similar, minor detectable differences might lead to divergent methods for counting Green Jobs. According to the literature, there are at least four different methods for measuring Green Jobs: green processes, green industries, green products and services, and green tasks (see Peters et al., 2011 for a comprehensive review). As explained in the second section, the first two methods tend to overestimate the number of Green Jobs, as they rely on firm-level data and therefore do not distinguish between green and non-Green Jobs within the same firm. On the other hand, the product and services approach will likely underestimate the total number of Green Jobs because it does not capture green activities that are not directly related to a specific green product (Consoli et al., 2016). A shared limitation of these three approaches is their inability to measure the greenness of a job at the occupational level.

The task approach developed by Autor et al. (2003) overcame this limitation. Indeed, by adopting a task approach is possible to accurately define the tasks carried out by each labor profession using specific databases. This strategy enables identifying workers who perform green tasks and, thus, measuring job greenness at an occupational level. This approach is widely used in the US, where the Occupational Information Networks (O*NET) launched the "Green Economy" programme, which primarily aims to identify the Green tasks and, subsequently, the Green Jobs in the US labor market (Dierdorff et al., 2009). The European Union also realized its own Green Task project, developing a list of 576 green tasks carried out by workers[1], but it could not link them to specific professions due to the lack of O*NET databases for European countries. However, the same European Union recommends using a task-based approach to identify Green Jobs in one of its report, despite the limitations of possible cross-walking from the US labor classification (Vona et al., 2021). Following this recommendation, the Italian *Agenzie Nazionali Politiche del Lavoro* (ANPAL) publishes an annual report on Green Jobs trends by measuring them through official decoding from US O*NET data.

This study aims to contribute to the literature by proposing a new greenness measure for Italian occupations that could also be extended to other European countries. By relying on the Italian Sample Survey on Professions (ICP), an O* NET-type dataset developed by the *Istituto Nazionale per l'Analisi delle Politiche Pubbliche* (INAPP), we identify a list of 204 green tasks performed by Italian workers out of 9,301 tasks. Our strategy is similar to that used by the European Union to create a list of green tasks. First, we conduct a text-content analysis of the European and US Green Tasks to identify the most frequent "green" words. Second, we manually label a task as green if it contains at least one "green" word and matches the definition of green skills suggested by the European Center for the Development of Vocational Training (Cedefop): "the knowledge, abilities, values, and attitudes needed to live in, develop and support a society that reduces the impact of human activity on the environment" (Cedefop, 2012). Third, we provide several robustness checks to confirm the quality of our manual labelling. Next, we compare our Green Job index to an index derived from the ANPAL report. It is essential to note the latter index is not exactly the ANPAL index but rather a reconstruction based on it. In the subsequent analysis, we highlight the noteworthy distinctions and advantages of employing an Occupational Information Network (O*NET) database customized specifically for Italy. Finally, we link our index to the *"Comunicazioni Obbligatorie"* dataset[2] to analyze the trends and characteristics of Green Jobs in terms of quality, location, sectoral distribution, gender and age dynamics.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on Green Jobs. Section 3 describes the construction of our Green Index and compares it with the reconstructed ANPAL index. Section 4 links our index to the *Comunicazioni Obbligatorie* dataset to provide statistical, comparative, and econometric evidence on Green Jobs. Finally, in section 5, we discuss potential policy implications.

[1]The complete list of the Green Tasks identified by the European Commission is available at the following link: https://esco.ec.europa.eu/en/use-esco/download

[2]Dataset provided by the *Instituto Nazionale della Previdenza Sociale* (INPS), which records all the employment contracts established in Italy from 2010 to 2020.

1.2 Literature

In this section, we provide a comprehensive framework for understanding Green Jobs. First, we introduce the concept of Green Growth and frame the role of Green Jobs within this theory. Second, we address two critical issues that are frequently encountered when studying the dynamics of Green Jobs: the definition and the measurement of these jobs. Here, we explain why the task approach should be preferred to accurately identify Green Jobs rather than relying on industry or occupation-based classification. Finally, we briefly review the task-approach literature by focusing on papers that employ this methodology to study Green Jobs.

1.2.1 From Green Growth to Green Jobs

In the current debate on environmental challenges, almost all economists agree that our planet is in danger and that we must radically transform the economic system to avoid unfixable consequences. One of the dominant perspectives for tackling global warming is the so-called Green Growth. The OECD defined *Green Growth* as "a way to pursue economic growth and development while preventing environmental degradation, biodiversity loss and unsustainable natural resource use" (OECD, 2011). Green Growth advocates argue that technological innovation can enable absolute decoupling of GDP growth from resource use and carbon emissions, making economic growth compatible with ecological limits (Hickel and Kallis, 2020). Over the last fifteen years, Green Growth has gained significant prominence in international political circles, as evidenced by the adoption of Green Growth principles by major global institutions such as the OECD, the World Bank, and the United Nations (Jacobs, 2013). However, this perspective has also encountered significant criticism from scholars who challenge its environmental effectiveness and potential social implications, such as unemployment and income inequality. For instance, Alexander and Rutherford (2019) question the environmental efficacy of Green Growth, while Hickel and Kallis (2020) argue that while absolute decoupling of GDP from emissions may be theoretically possible and empirically observable in a group of limited regions, it is not sufficient or feasible to meet the urgent climate targets. Therefore, they suggest that government policies, particularly in the richest nations, should focus on reducing production and consumption to tackle climate change effectively. The latter view of slowing down the pace of material production and consumption is consistent with the "Degrowth" theory, one of the most popular alternatives to Green Growth. This theory can be defined as a deliberate reduction in energy and resource consumption to align the economy with ecological limits and enhance social justice and human well-being (Latouche, 2009). According to Hickel (2021), Degrowth aims to reach a decrease in the throughput intentionally and does not necessarily seek to decrease GDP. However, an overall decrease in the throughput may still lead to a reduction of the GDP, which is not the intended outcome of Degrowth. Despite its popularity and relevance among academics, Degrowth has faced political resistance and public misunderstanding, partly due to its negative connotation and the wrong but frequent confusion of this concept with recession. Some scholars, such as Van den Bergh (2011), argue that the ambiguous nature of Degrowth makes it an ineffective political strategy to attract media attention and social support for environmental action. While the Degrowth theory offers an at-

tractive alternative perspective on tackling environmental challenges, its political feasibility and social acceptance remain uncertain.
Efforts to incorporate the social components into the concept of Green Growth have given rise to alternative approaches that aim to promote environmental sustainability while also addressing inequality and unemployment (D'Alessandro et al., 2020). Such strategies, which we can see as an extension of the Green Growth paradigm, have been reflected in significant government initiatives, including the US Green New Deal (Green New Deal, 2019). This political predominance highlights how, while the academic debate is still open, until now, the Green Growth theory has been the dominant paradigm in governmental institutions, which have integrated this concept into their sustainability and environmental agendas.
One significant outcome of the popularity of Green Growth has been the emergence of Green Jobs, which are the focus of this work. Green Jobs represent a key means of operationalizing the concept of Green Growth within labor markets. The UNEP first defined Green Jobs in 2008 (UNEP, 2008), and since then, economists have displayed a growing interest in analyzing their dynamics, quality, and growth, as evidenced by two recent literature reviews (Stanef-Puică et al., 2022; Apostel and Barslund, 2024). In the following paragraph, we examine two critical aspects of this branch of literature: the multiple definitions of Green Jobs and the different methods for measuring them.

1.2.2 Green Jobs' definitions and measures

As discussed in the previous paragraphs, Green Jobs has no a widely accepted definition. In their papers, Winter and Moore (2013) and Furchtgott-Roth (2012) enumerate several definitions provided by institutions, scholars and environmental associations. Although all the definitions share a similar focus on the sustainable use of resources, the development of renewable energy, and the preservation or restoration of the environment, some differences lead to several approaches to identifying Green Jobs. Indeed, definitions and measures are based on different observational levels, such as occupational, firm, product or process level. This lack of uniformity could cause contrasting estimations in the number of Green Jobs (Bowen and Kuralbayeva, 2015).
The first definition of Green Jobs used in the scientific literature dates back to 1999 when the OECD described environmental goods and services industries as "activities which produce goods and services to measure, prevent, limit, minimize or correct environmental damage to water, air and soil, as well as problems related to waste, noise and eco-systems. This includes technologies, products and services that reduce environmental risk and minimize pollution and resources" (OECD et al., 1999). Based on this definition, formulated at a sectoral level, several scholars and institutions have provided statistics on the number of employees in Green Activities (Marin and Vona, 2019; Cai et al., 2011). However, as we will show in the following, identifying Green Jobs at a sectoral level may lead to errors. In order to overcome this issue, in 2008, the UNEP stated the first formal definition of Green Jobs at an occupational-based level, providing a more precise definition. The UNEP defines Green Jobs as "work in agricultural, manufacturing, research and development (R&D), administrative, and service activities that contribute substantially to preserving or restoring environmental quality. Specifically, but not exclusively, this

includes jobs that help to protect ecosystems and biodiversity; reduce energy, materials, and water consumption through high efficiency strategies; decarbonize the economy; and minimize or altogether avoid generation of all forms of waste and pollution" (UNEP, 2008). Furthermore, the UNEP underlines the importance of Green Jobs being decent work with adequate wages, safe working conditions, job security, reasonable career prospects, and worker rights.

Following the UNEP definition, various institutions and scholars have formulated their own meaning of Green Jobs. The European Commission, in line with the UNEP, defines Green Jobs as those preserving and restoring the environmental quality (European Commission, 2012). In contrast, North American institutions, such as The Center of Excellence of California (COE) and the Environmental Careers Organization of Canada (ECO), emphasize occupations that minimize environmental impact (COE, 2009; ECO, 2010). Other institutions, including the Brooking Institutions and Statistics Canada, have adopted a different observational level, focusing on industries and processes that produce Green products or services and introducing new concepts such as the "clean economy"[3] (Muro et al., 2011; Winter and Moore, 2013). The latter concept of "clean" energy has led to further confusion in identifying Green Jobs. Indeed, some industries, such as nuclear energy, are considered clean and renewable in the US but not in Europe.

The previous paragraph is just a snapshot of all the definitions formulated over the last year. What is crucial for us is that all these various definitions have led to divergent methods of selecting Green Jobs. As proof of what we have just said, there are at least four different identification methodologies in the literature: Green Processes, Green Products and Services, Green Industries and Green Tasks (Peters et al., 2011). The Green Process approach selects occupations involved in green industrial processes, such as active waste management, treatment and recycling (van der Ree, 2019). However, since this method is based on firm-data level, it is not easy to make it compatible with current job classifications. The Green Product and Services method focuses on the products and services that contributing to environmental and conservation objectives. The whole workforce involved in their production or delivery is assumed to be Green. This approach is very popular in the US, where federal government officials maintain lists of green products or industries (US Department of Commerce, 2010). However, this method fails to capture green activities not directly associated with producing a particular green product or service, causing an underestimation of the total number of Green Jobs. The Green Industry technique selects industries displaying a high fraction of firms engaging in environmental and conservation objectives. However, since industrial classifications are not granular enough, it is not simple to distinguish green products and services from similar ones (Peters et al., 2011). In this case, as for the Process approach, there is a risk of overestimating the number of Green Jobs. Finally, the Task approach identifies green occupations based on the tasks carried out during the job. This evaluation is made possible by O*Net occupation-specific datasets, which list some of the most critical tasks required by workers and assign an importance score. In our opinion, this method has a double benefit. First, it allows identifying all the jobs that effectively include green tasks and computing the importance of the green

[3]The Brookings Institution defines the "clean economy" as economic activity "that provides goods and services with an environmental benefit or adds value to such products using skills or technologies that are uniquely applied to those products."

component of each profession. Second, it helps verify whether occupations carrying out green tasks also perform "brown tasks", defined by CEDEFOP as "knowledge and skills that increase the impact of human activity on the environment" (Cedefop, 2012).

1.2.3 Task Approach and Green Jobs

Autor et al. (2003) originally developed the task-based approach to explore the impact of Information and Communication Technologies spread on the US labor market. This theory differs from the previous predominant approach known as Skill Biased Technical Change (see Katz and Murphy, 1992; Acemoglu, 2002), in which workers are categorized by skills. Instead, in the task approach workers are classified by the degree of routine in the tasks performed in each job (Autor et al., 2003; Autor and Dorn, 2013). Acemoglu and Autor (2011) define a *task* as "a unit of work activity that produces output". In other words, the tasks are the actions carried out by workers during their job, which can be primarily classified by their degree of routine (routine vs non-routine) and the cognitive endowment required (manual vs cognitive). In the canonical version of the model, labor and capital are the inputs of the production function, which is articulated in tasks. Each task can be performed by capital or labor depending on economic convenience, ease of automation, and level of connection with other tasks (Sebastian and Biagi, 2018). Thanks to the availability of databases describing occupational tasks (such as the O*NET and the ICP), it is possible to conduct empirical analysis by ranking occupations based on their routine and manual levels. Over the last few years, the basic idea has been tested and expanded by many studies in different contexts beyond its original one studying the impact of digital technologies in the US labor market.
The Green Job literature is well-suited for the task-based approach, as both use occupations as the unit of analysis. Moreover, the O*NET-type databases contain a section that lists the most frequent and important tasks carried out by each professional code, along with their relative frequency/importance score. The presence of this section enables researchers to conduct text analysis to identify green tasks and their frequency/importance within occupations. In this regard, in 2009, the Occupational Information Network and the US Department of Labour launched the "Green Economy" programme to identify green tasks and the greenness of US occupations. As specified by the authors of the project, green activities are "related to reducing the use of fossil fuels, decreasing pollution and greenhouse gas emissions, increasing the efficiency of energy usage, recycling materials, and developing and adopting renewable sources of energy" (Dierdorff et al., 2009, p.11). In numerical terms, the programme identified 1,369 green tasks, referable to 138 jobs on a total of more than 1-thousand. The identified Green Jobs were categorized into three groups:

1. **Green demand**: Jobs that will grow greatly as the economy becomes more "green".

2. **Green enhanced skills**: existing occupations that will face significant transformations in their tasks.

3. **Green emerging**: new jobs that are created to meet the demands of the eco-friendly economy.

Having the opportunity of exploring these green tasks, some authors have studied Green Jobs within the US labor market. Consoli et al. (2016) conducted an empirical analysis comparing green and non-Green Jobs, revealing that the former require higher levels of skills, education and training. They also extended their analysis to the routine level of occupations, showing that Green Jobs display, on average, lower levels of routine than non-Green Jobs. Vona et al. (2019) created a continuous green task-measure that captures the amount of time spent on green activities by each profession. Their results show that Green Jobs are pro-cyclical, require high-skilled workers, provide a 4% wage premium, and are concentrated in specific areas of the US. Furthermore, the authors find a positive association between green employment and local green subsidies. Also Bowen et al. (2018) explore the O*NET green data, showing that most Green Jobs in the US have a low share of green tasks, with Green New and Emerging jobs displaying higher levels of greenness than Green Enhanced Skills jobs. They also find that workers from different occupations tend to shift to jobs with lower levels of greenness than those with higher levels.
In recent years, the task-based approach has also gained attention in Europe. In Germany, Janser (2018) developed a green job dictionary and employed the method of regular expressions to identify environment jobs within a German-specif database containing descriptions of occupations. His results reveal that in 2016 almost 10 percent of occupations had green requirements. Furthermore, Janser provide occupational, sectoral and regional distributions of the greenness and greening of jobs. Similarly, the European Commission has expressed interest in this approach, as evidenced by a report published in 2021. The report recommends that scholars and institutions adopt a task-based approach and continue measures instead of binary indicators. In the last section of the work, it explicitly suggests using cross-walking from the US O*NET data, given the lack of similar databases at a European level (Vona et al., 2021, p. 33).
Regarding Italy, ANPAL publishes an annual report that measures firms' demand for Green Jobs (ANPAL, 2019). Following the recommendations of the European Commission report, ANPAL adopts a task indicators that is created through a series of cross-walking from the US O*NET data. This report aims to provide statistics on the trends and diffusion of Green Jobs by attaching the index to data on future job demand by Italian firms. While this approach aligns with the previous European Commission's guidelines, it needs several areas for improvement, including its binary construction.
To address this issue, we propose a new task-based indicator that captures the greenness of Italian occupations. Using the ICP, a database that describes Italian occupational tasks, we develop continuous and binary indices to measure the frequency and importance of green actions within each occupation. Our new indicators represent a qualitative improvement in identifying Italian Green Jobs and the greenness level of each job. In addition, given that the labor markets in other European countries share more similarities with Italy than the US, our task indicator could also be applied to provide comparative analyses within the European Union. In the following section, we describe our index's computation and compare it with the reconstructed index formulated by ANPAL. Our contribution to the literature aims to provide a more accurate measure of Green Jobs in Italy to help policymakers and researchers better understand the dynamics of the green economy in the country.

1.3 Green Job index

In this section, we delineate the construction of our new index and draw a comparison with the indicator reconstructed from ANPAL's work, which we shall henceforth refer to as the "transcoded index". First, given the lack of a list of green occupations in ANPAL's work, we attempt to replicate their indicator based on the guidelines provided in their report. Subsequently, we thoroughly analyze this reconstructed index, highlighting its shortcomings. Second, we present the development process of our green index and perform some robustness tests to assess its quality. Lastly, we conduct a first comparison of the two indicators.

1.3.1 The Transcoded Green Job index

The first index we present in this paragraph is constructed based on the instruction provided by the ANPAL report to build their index (ANPAL, 2019, p. 9). The primary data source for the index is the US O*Net Green Task file[4]. As outlined in the previous chapter, the "Green Economy" programme is a project developed by the U.S. O*Net development center to identify all the green tasks in the U.S. labour market. The project identified 1,369 green tasks, attributable to 138 jobs on more than 1-thousand. In order to create an equivalent index for Italy, we started by identifying the jobs labelled as green by the O*NET resource center. Next, by using official decoding, we passed from the US Standard Occupational Classification (2010 SOC) to the International Standard Classification of Occupation[5] (ISCO-08), and then to the Italian Classification[6] (CP2011). As mentioned above, our methodology is similar to that used by ANPAL to construct its indicator. However, there is a significant difference since they convert Green Jobs to the European Standard Classification of Occupation (ESCO) before reaching the CP2011 classification. We skipped this intermediate step for two reasons: we believe that adding a crosswalk could increase the likelihood of incorrect couplings, and there is no official decoding available online for the transition from the ESCO classification to the CP2011.
Since each classification exhibits a different level of granularity, we refined the matching process by using the formal definitions of jobs available in the U.S. and Italian databases. Therefore, we only matched two codes where the decoded process led to two identical jobs. Our analysis reveals a total of 110 green occupations out of 796. Although our purpose was to recreate the ANPAL index as closely as possible, since their report does not provide a complete list of the jobs identified as green in the CP2011 classification, we can only comment on the results we obtained replicating their methodology.
Although the ANPAL report's effort to map Italian Green Jobs is commendable, we have identified several shortcomings in using this methodology:

1. The SOC classification level of detail is more granular than the ISCO and CP2011 classifications, making it difficult to identify corresponding Italian

[4] The U.S. green tasks file can be accessed at https://www.onetcenter.org/reports/GreenTask.html

[5] The crosswalk between the 2010 SOC and the 2008 ISCO is available at https://www.bls.gov/soc/soccrosswalks.htm

[6] The crosswalk between the 2008 ISCO and the CP2011 is available at https://www.istat.it/it/archivio/18132

professions. For instance, the CP2011 does not include occupations such as wind energy operation managers and industrial ecologists.

2. Due to the multiple transcoding processes, some Italian occupations that are evidently green are not detected, such as environmental control technicians and waste collection technicians.

3. Some occupations detected as green in the Italian classification, such as carpenters, stockbrokers and asphalters, raise some concerns.

4. The Transcoded Index does not provide a continuous measure of the greenness of occupations.

In light of these weaknesses, we present a new indicator to capture Green Jobs in the next section.

1.3.2 The Content Green Job Index

In this section, we introduce our Content Green Job Index, which is created using three distinct data sources. First, we perform a content analysis on the 1,369 green tasks detected by the O*NET Resource Center to identify the most frequent "green" words. In Figure 1.1, we report a wordcloud graph illustrating the relative frequency of these words. We also conduct a similar analysis on the 576 green tasks listed by ESCO[7] to collect the most frequent green words encountered in these tasks. These preliminary steps are essential to understanding the meaning of Green Tasks for two of the most important international institutions. Subsequently, we conduct a manual search for similar green tasks within the Italian ICP survey, focusing on the most updated version of 2013. The ICP survey includes a free-form section where a panel of respondents from each of the 796 5-digit CP groups describe approximately twelve work activities that best describe their occupation. In total, there are more than 9,300 tasks contained within the survey. We individually analyze each task to search for the translation of the most frequent green words found in the US O*Net Green task file and the ESCO Green tasks' list. After examining each task containing "green" words to exclude false positives, we identified 204 "green" tasks. According to our results, out of 769 5-digit Italian occupations, 84 jobs include at least a green task. The procedure described above has already been employed in the scientific literature to develop a digital task index by Cirillo et al. (2021).

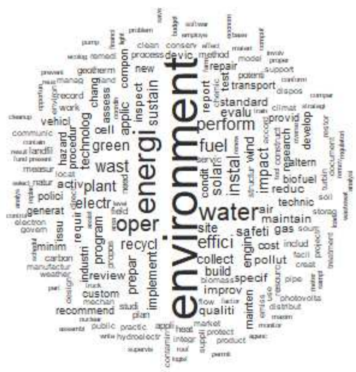


Figure 1.1: Wordcloud graph of the U.S. Green Tasks

Furthermore, we develop two continuous indices since each task included in the ICP dataset has a score that indicates its importance and frequency in performing the

[7]The complete list of the green tasks identified by the European Commission is available at the following link: https://esco.ec.europa.eu/en/use-esco/download

work,

$$\textbf{Green Importance}_i = \frac{\sum \textit{Imp. Green Task}_i}{\sum \textit{Imp. Task}_i} \tag{1.1}$$

$$\textbf{Green Frequency}_i = \frac{\sum \textit{Freq. Green Task}_i}{\sum \textit{Freq. Task}_i} \tag{1.2}$$

The first index measures the importance of green tasks within each i occupation, dividing the sum of the importance score of the green tasks by the total sum of the importance scores of all tasks for that occupation. If a profession has no green tasks, the numerator will be equal to 0. The second indicator is constructed similarly but serves as a proxy for the time spent on green activities. Indeed, it is based on the values of the frequency score instead of the importance ones.
As a first robustness check, we examine the 84 occupations displaying at least one green task and checked for the simultaneous presence of brown tasks. We discover seven jobs exhibiting this issue and proceed to eliminate them from our list. Indeed, for jobs such as mining engineers or agricultural tractor operators, the green components appears to be present merely to mitigate the environmental damage caused by performing the main tasks of the job[8].
To further validate our approach, we compute an association matrix based on the Green Tasks developed by ESCO. We choose to focus on this source because it has an official Italian translation and is directly comparable with the ICP dataset. In addition, ESCO's green tasks list draws from various sources, including the O*NET green task list, making it a reliable tool. Primarily, we process both the ESCO and ICP tasks by converting them to lowercase, removing Italian stopwords, and lemmatizing words. We then create a list of green lemmas, consisting of the 400 most used words in the ESCO tasks and keeping only those directly connected to the green concept. This process result in a green dictionary containing 168 green words (see Table 1.1). In the first place, more than 80% of our manual labelled green tasks display at least one green word in the dictionary. Furthermore, we verify that all of the remaining 38 tasks included a synonymous of ESCO green words. To confirm the accuracy of our green identification, we collect the seven most associated words for each ESCO green word and conduct an association check. We find that more than a quarter of our tasks simultaneously display a green word and one of its most associated words. This check further confirms the effectiveness and the pertinence of our green identification approach.

As a final validation step, we conduct a Jaccard similarities analysis to assess the correlation between our green tasks and those listed by ESCO. The Jaccard index, a measure of set similarity, compares the size of the intersection of sets to the size of their union, yielding values between 0 and 1. A score of 0 implies no similarity, while 1 signifies complete identity. Comparing the values for green tasks listed by ESCO with our green and non-green tasks, we observed a statistically significant higher similarity for the former (0.1 vs. 0.02). This suggests that our green tasks are semantically closer to ESCO's green skills.
We also develop a dummy indicator to identify High-Green occupations. An occupation qualifies for this designation if it involves at least two tasks classified as

[8] In our empirical sample, we identify 23,267 workers performing jobs that involve both green and brown tasks simultaneously. Although these workers are included in the count of green jobs, they represent less than 5% of the total, which amounts to 482,995 green jobs.

Table 1.1: ESCO Green Dictionary

rifiuti	energia	ambientale	ambientali
impatto	acqua	fattibilità	inquinamento
riscaldamento	piante	alimentari	smaltire
energetico	animali	edifici	solare
risorse	acque	sostenibili	sostenibile
naturali	alberi	ambiente	riciclaggio
calore	oceaniche	benessere	salute
ridurre	consumo	elettrica	fauna
eoliche	turbine	conservazione	selvatica
solari	sprechi	pannelli	biogas
raffreddamento	trasporto	contaminazione	trattamento
acquacoltura	suolo	sostenibilità	sviluppo
biorisanamento	biomassa	agricoltura	foreste
habitat	natura	raccolta	urbanistica
alimenti	biologia	sociale	rischi
protette	protezione	parchi	energetica
prevenzione	idrogeno	alimentare	biologica
sicurezza	energetiche	riduzione	risparmio
biodiversità	colture	antiparassitari	fotovoltaici
verde	climatici	assorbimento	climaticamente
fanghi	teleraffreddamento	teleriscaldamento	selvaggina
silvicoltura	aria	elettrico	malattie
naturale	specie	ecologia	eolici
idriche	elettriche	cogenerazione	termica
ecologici	ecologica	prevenire	tutela
efficienza	risanamento	conservare	flora
contaminati	territorio	marea	terreno
isolante	agricole	cambiamenti	organici
coltivazione	irrigazione	depurazione	geotermiche
marina	ventilazione	riciclare	ecosostenibili
raccogliere	fonte	smaltimento	emissioni
riciclo	nocivi	pozzi	patrimonio
geotermici	purificazione	ecologiche	siti
sito	allevamento	agricola	microclimi
albero	verdi	legno	energie
rinnovabili	edilizio	piovana	animale
mare	ecosistemi	curare	convertitori
ondoso	eolico	salvaguardare	geotermica
responsabile	trattare	falda	botanica
geochimici	eolica	coltivare	forestali
fotovoltaico	meteorologiche	fermentazione	scaldacqua
elettricità	circolare	silvicola	veterinario

"green". Furthermore, both the importance and frequency of at least one green task within that occupation must surpass the median value calculated across the entire ICP (Occupational Information Network) database. This approach aims to select occupations that not only involve more than one environmentally friendly task, but also emphasize their significance and occurrence in comparison to the broader spectrum of occupations in the database. As a result of applying these criteria, we identify 24 occupations as High-Green (we report all the 24 occupations and their values in Table A1).

1.3.3 First macro comparison

This paragraph analyses the primary macro-level differences between the Content Index and the Transcoded Index. Table 1.2 collects all the 5-digit green occupations categorized by macro-occupation categories (1-digit CP2011). The distribution reveals some differences, but both indices display the highest portion of Green Jobs among professionals, technicians and skilled workers. In particular, the Transcoded Index green occupations are concentrated among professionals (27%), which are highly skilled workers responsible for analyzing and making decisions on complex issues. Similarly, within the Content Index, professionals account for over a quarter of the green occupations, but in this case, the highest concentration of Green Jobs is observable within technicians and associate professionals (27%). As expected, clerical supporter workers, services and sales workers, and elementary occupations display the lowest concentrations in both indices.

The main difference between the two classifications is the total number of Green Jobs. The Transcoded Index shows 33 green occupations more than the Content Index. In addition, when overlapping the two indicators, only 29 occupations are green in both cases, indicating a low level of intersection. This evidence may suggest that one of the two indices is not accurately capturing the greenness of jobs. Specifically, it appears that the Transcoded Index could overestimate the number of green occupations since it assumes that the tasks carried out by a specific occupation in the US are identical in Italy. However, this assumption may not hold, as the Italian labour market differs significantly from the US labour market.

In the next section, we will attach these two indicators to a labour force database to further explore their differences.

Occupation - 1 digit	**Percentage D.I.**	**Percentage C.I.**
Legislator and managers	15%	8%
Professionals	27%	26%
Technicians and Associate Professionals	18%	27%
Clerical Support Workers	2%	0%
Services and Sales Workers	2%	6%
Craft, Skilled Workers and Farmers	19%	21%
Machine Operators and Vehicle Drivers	13%	6%
Elementary Occupations	5%	5%
Total Value	**110**	**77**

Table 1.2: Distribution of Green occupations across 1-digit macro-occupations

1.4 Descriptive Analysis

In this section, we provide a comprehensive overview of the data source employed for our descriptive and econometric analysis. Subsequently, we will present a set of fundamental descriptive analyses to highlight the distinctions between our indices and the Transcoded Green Job index.

1.4.1 *Comunicazioni Obbligatorie*

To provide the comparison and highlight the disparities between the two indices, we access the administrative micro-data provided by the *Comunicazioni Obbligatorie* (COB). This unique dataset covers the period from 2010 to 2020[9], offering comprehensive information regarding all job contracts established in this time-frame. It is important to emphasize that in Italy, the private firms have to communicate all the information concerning their employees' contracts to the Ministry of Labour. Consequently, each record within the dataset contains essential details regarding both the employee and the employer. This includes the firm's location, sector of activity, occupation, age gender, nationality and level of education. Notably, the occupational information is available at the highest detailed level, the 5th digit, enabling an exact association with our Content Green Job index. To the best of our knowledge, this is the only dataset displaying such a level of granularity for Italy.
Furthermore, this dataset allows us to study workers' employment history, providing us with the opportunity of tracing their initial hiring position, the duration of their employment and the eventual subsequent transformation of their initial contracts over time. To accurately account for the effective duration of each job, we adopt the concept of *Unità di Lavoro/Anno* (ULA), in which each contract is transformed into an equivalent unit equal to 1 for full-time workers employed for an entire year. In this framework, part-time work and seasonal work are therefore fractions of a complete ULA. This approach allows us to properly weight each record within the dataset based on the duration of the corresponding job. We have the capability to track the status and developments of each record over the next two years, allowing each record to contribute a maximum of 2 ULA. The richness of our data enables

[9] To avoid issues related to the economic shock caused by Covid-19, we restrict our analysis to the period from 2010 to 2019.

us to identify instances where permanent or temporary jobs conclude before their expected termination. In this analysis, we have opted to exclude a specific green occupation categorized under agricultural laborers (8.3.1.1.0). The reason behind this exclusion lies in the fact that, while some of the tasks associated with this occupation are unequivocally identified as green[10] and this profession does not explicitly list brown tasks in its job activity descriptions within the ICP, there is a high likelihood that individuals in this occupation may also encounter tasks associated with pollution. Furthermore, the seasonal nature of this profession contributes to several activations in the COB, potentially introducing confusion in our analysis. Nevertheless, for those interested, we are willing to provide the analysis results if we decide to incorporate this occupation into the green occupations category.

1.4.2 Descriptive Evidence

In Panel A of Figure 1.2, we present the trend analysis of the Transcoded Index, the Content Index[11], and the High-Green Index. In Panel a, we illustrate the proportion of green ULAs relative to the total, while in Panel b, we depict the annual activation volume of green ULAs.

Examining the figure, the Transcoded Index shows an upward trend over time, particularly evident in the activated volumes. The latter displays some deviations, such as the peak in 2015, which is also observable in smaller measures in the other two indices. Conversely, the Content Index exhibits a relatively stable pattern throughout our period of analysis, both in terms of proportions and volumes. Interestingly, if we focus on the High-Green Index, our dummy indicator for the greenest occupations, we observe a decisive increase over the observed period (from 40,000 activations in 2010 to around 56,000 in 2019).

(a) Proportion of green ULAs relative to the total over time. The right axis is relative to the High-Green Index.

(b) Annual activation volume of green ULAs over time. The right axis is relative to the High-Green Index.

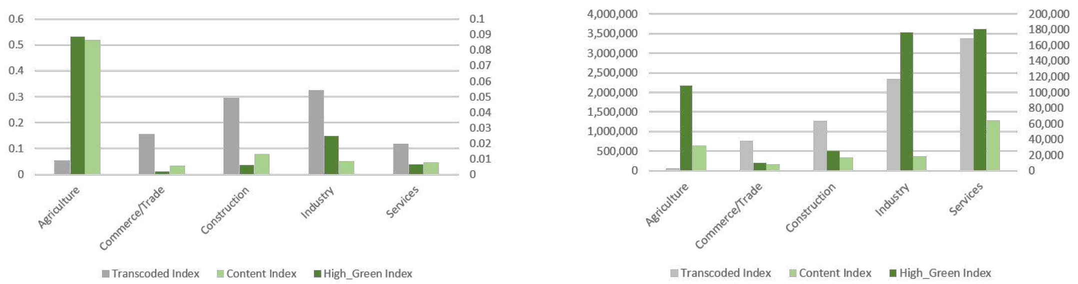
Figure 1.2: Trend of green ULAs

Examining the sectoral distribution of the three indices reveals a diverse landscape (refer to Figure 1.3). When considering the proportion of green ULAs relative to the total, the Content and High-Green indicators exhibit their highest levels in agriculture (0.5 and 0.09, respectively). Conversely, the Transcoded Index indicates

[10] The tasks identified as green are: 1) plant trees or plants; 2) Prune the trees; 3) Monitor the growth and health of plants.

[11] For this index, we classify a job as green if it involves at least one green task.

that the highest proportion of Green ULAs is observable in the industry and construction sectors, accounting for around 32% and 27% of the total, respectively. Analyzing the volumes of ULAs activated, the results show more similarities among the indicators, yet some distinctions persist. While the services sector consistently sees the highest number of ULAs activated across all measures, the Content Index displays a relatively low number in the industry sector. However, the most significant differences emerge in agriculture, where the Content and High-Green indices demonstrate high values of activations, whereas the Transcoded Index is close to zero.



(a) Proportion of green ULAs relative to the total over economic sectors. The right axis is relative to the High-Green Index.

(b) Annual activation volume of green ULAs over sectors. The right axis is relative to the High-Green Index.

Figure 1.3: Sectoral distribution of green ULAs

These preliminary findings are sufficient to demonstrate that the indices capture distinct proxies. However, we delve deeper into our analysis by providing descriptive evidence related to gender, age, geographical dimension, and educational level.

Regarding demographic dimensions, all three indices exhibit the highest volumes of activations among males. Nevertheless, differences emerge when examining the workers' ages. While the transcoded index shows the highest ULA values among the youngest workers (18-29 years), our indicators concentrate their activations among workers aged between 40 and 49 years (refer to Figure A1 in the appendix). The geographical dimension is one of the most interesting results (refer to Figure 1.4). While all three indices show their highest volumes in *Lombardia*, the Transcoded index suggests that green ULAs are located almost exclusively in the northern regions. In contrast, our two indicators reveal a heterogeneous distribution, with high values observable also in central and southern regions, such as *Campania* and *Tuscany*. This divergence is likely connected to the previous findings on the sectoral distribution of the indices. Finally, with regard to the educational levels of green ULAs, an interesting pattern emerges (see Figure 1.5). The Content Index exhibits a noticeable polarization, showcasing the highest relative values among workers holding either only a middle school diploma or a university degree, compared to the Transcoded Index that display high proportion among workers holding high-school diploma. On the other hand, when examining the High-Green Index, a different trend appears where the percentage of low-educated workers seems to predominate, with a limited representation of highly-educated individuals.

Figure 1.4: Geographical distribution of the green ULAs actived by regions.

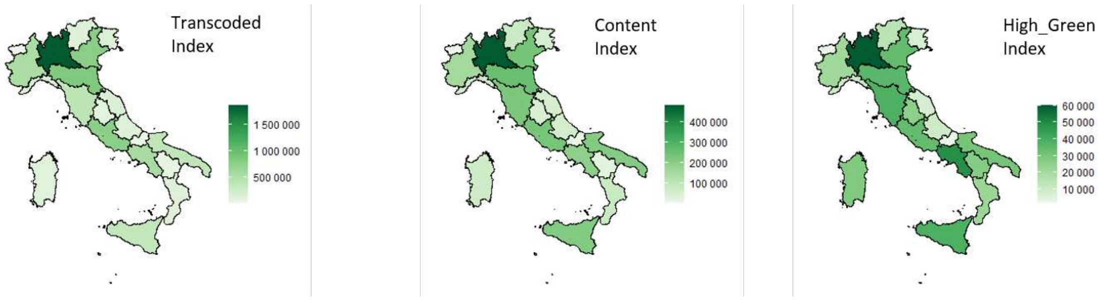
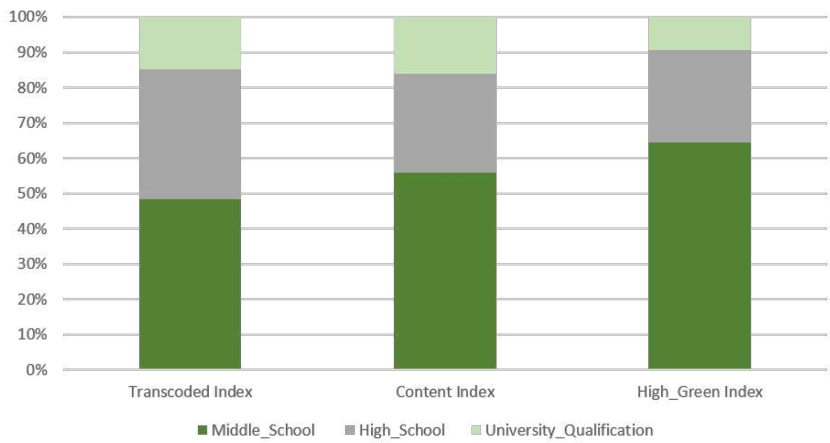


Figure 1.5: Educational levels among green workers for the different indices.



In conclusion, it is noteworthy to emphasize that our approach, directly grounded in an exploration of the tasks performed by Italian workers, yields distinct results when compared to the transcoded index, which relies on transcodifications from the US list of Green Jobs. Our findings appear to be more aligned with the data from ISTAT on eco-industries[12], exhibiting similar patterns to our content indicator. As a result, in the subsequent analysis, we exclusively consider our novel indicators.

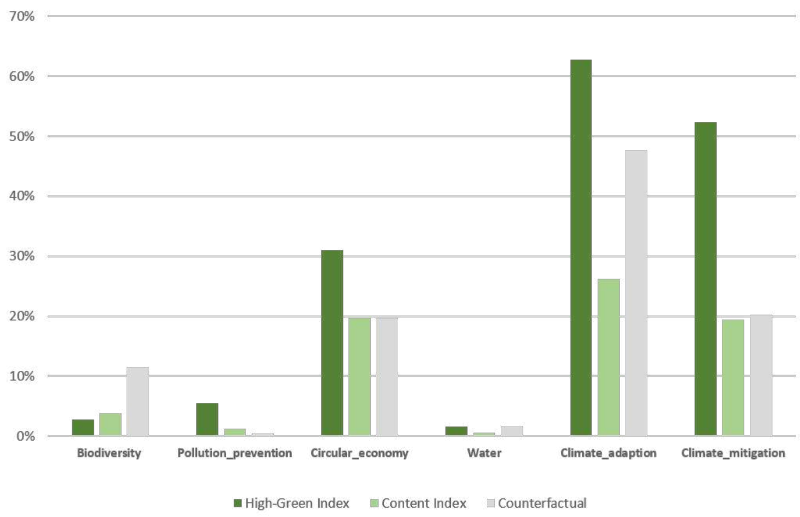
1.4.3 The Green Jobs within the EU taxonomy framework

In 2020, the EU taxonomy for sustainable activities become law. According to the European legislator, this classification is essential to identify sustainable economic activities and to canalize investments in the green sectors. The underlying goal is reaching a net zero trajectory by 2050, therefore the identification of these sectors is fundamental to help companies and investors in their investment decisions. The taxonomy regulation recognizes six environmental goals: climate change mitigation, climate change adaption, sustainable use and protection of water, transition to a circular economy, pollution prevention and control, protection and restoration of biodiversity and ecosystem. An environmentally sustainable economic activity should largely contribute to at least one environmental goal, while not harming any other objective.

[12] available at the following website: https://www.istat.it/it/archivio/291997

In this section, we gather information on the sectors included in the taxonomy regulation and we add six dummies to our COB database, indicating whether a worker carries out their job in a sustainable sector[13]. As shown in Figure 1.6, although the percentages of content and counterfactual workers[14] involved in the six taxonomy objectives are similar, High-Green workers appear to be the most engaged in environmental goals in proportion. Notably, of the total High-Green workers, more than 60% work in sectors that make a substantial contribution to the climate adaptation goal. High percentages are also observed for the climate mitigation and circular economy objectives, with 52.4% and 31%, respectively. Compared to the counterfactual, the only taxonomy goal for which our High-Green index shows a lower proportion of workers is biodiversity. However, this result could be related to the way sectors are identified in the EU taxonomy for this specific objective, where only three ATECO codes are recognized as making a substantial contribution, all of which refer to touristic activities. In conclusion, this final analysis confirms again the reliability of our High-Green index in capturing green jobs, suggesting that we should primarily focus on it in the econometric section.

Figure 1.6: Distribution of the indices among EU environmental economic activities



[13]The list of the environmental economic activities as defined by the EU taxonomy is available at: https://ec.europa.eu/sustainable-finance-taxonomy/taxonomy-compass/the-compass

[14]In this paragraph, counterfactual workers are defined as those who, according to our previous content analysis, do not perform any green tasks.

1.5 Econometric analysis

In this section, we first explore the characteristics of green workers by adopting a logistic model. Secondly, in connection to the initial definition of Green Jobs that explicitly mentions job security (UNEP, 2008), our objective is to assess the impact of greenness levels on this labor proxy. Subsequently, employing the exact matching methodology, we aim to determine whether holding High-Green Jobs is associated with a greater likelihood of having permanent positions. In the econometric analysis, following the approach by Consoli et al. (2016), we restrict our focus to 3-digit CP macro-occupation categories that include at least one green profession at their subsequent levels. This step is necessary to avoid comparing professions that are too different in terms of characteristics. By imposing this condition, we obtain a unique dataset of 1,780,338 workers spanning from 2010 to 2019.

1.5.1 Features of Green Jobs

In this analysis, we utilized logistic regression to identify the key characteristics of workers newly employed in green occupations. Within this framework, we define individuals as "green" based on their prior identification as High-Green workers.

To preliminary explore the associations between our categorical predictors and High-Green worker status, we generate stacked barplots illustrating the distinctions between green and non-green workers (refer to Figure 1.7). In relative terms, the features most strongly associated with Green Jobs include being male, holding a temporary job, working in the southern regions of Italy or on the islands, and possessing a lower level of education.

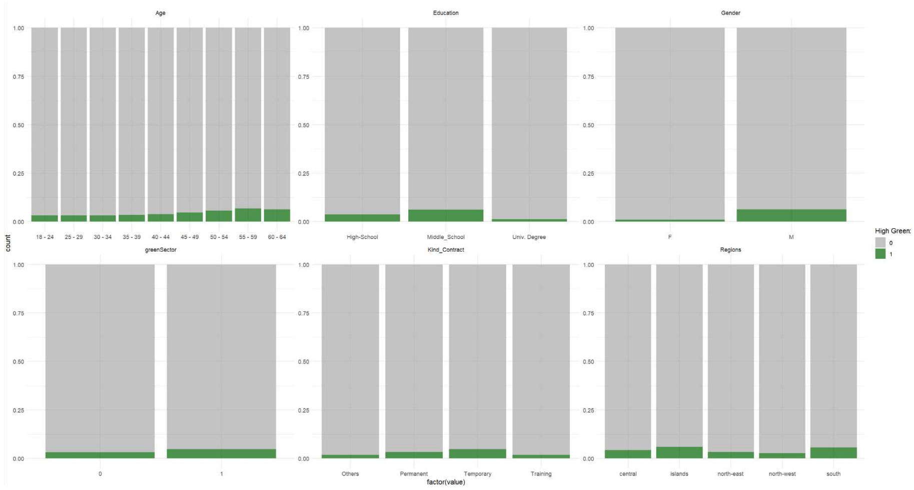


Figure 1.7: Stacked barplots of our categorical predictors

In the logit model, we maintain the same variables while also introducing a comprehensive set of dummy variables representing the 3-digit Italian occupation categories and the 2-digit ATECO codes (refer to Table A2). All the variables considered yield statistically significant results, affirming that males have a higher probability than females of being employed in Green Jobs. Additionally, this initial analysis reveals that Green Jobs are frequently associated with temporary positions and are primarily undertaken by relatively older workers with lower levels of education (lower than middle-school diploma), although the probability is higher for people holding a degree than a high-school diploma. The proportion of green workers is notably higher in the southern regions of Italy and for people employed in sustainable ATECO sectors as identified by the EU taxonomy.

1.5.2 Are Green Jobs also steady jobs?

In this analysis, we explore our continuous green indicators by employing an approach similar to that adopted by Consoli et al. (2016) in their study, which aims to reduce the heterogeneity deriving from comparing vastly different macro-occupations. The regression equation is as follows:

$$Y_i = \beta_0 + \beta_1 Green\_Continuous_i + \beta_2 X_i + CP3_i + ATE2D_i + \epsilon_i \tag{1.3}$$

Here, Y_i represents a dummy variable indicating the type of employment contract (permanent vs temporary jobs, where permanent = 1). $Green\_Continuous_i$ is a continuous variable that alternately refers to the importance and frequency values of the Content Green Job index. X represents a set of control variables including individual and occupational characteristics of each worker, such as gender, level of education, geographical location and age. Lastly, $CP3$ is a comprehensive set of dummy variables for the 3-digit Italian occupation categories, and $ATE2D$ refers to the ATECO economic sector at the second-digit level.
Our goal is to understand the relationship between the greenness level of an occupation and the probability of obtaining a permanent position. As shown in Table 1.3, higher levels of both Green Frequency and Green Importance are associated with a decreased probability of having a permanent job. All three models we employ (OLS, logistic, and probit) confirm a negative and statistically significant relationship. Consistent with expectations, being male, having a university degree, and being older increase the likelihood of securing a permanent job. Additionally, working in a sector identified as sustainable under the EU Taxonomy is associated with a lower probability of having a permanent job.

Table 1.3: Continuous regressors

	Dependent variable: Permanent Job					
Variables	*OLS*	*logistic*	*probit*	*OLS*	*logistic*	*probit*
GT_frequency	−0.117***	−0.793***	−0.448***			
	(0.005)	(0.029)	(0.017)			
GT_Importance				−0.120***	−0.826***	−0.470***
				(0.005)	(0.030)	(0.017)
Male	0.020***	0.147***	0.087***	0.020***	0.148***	0.087***
	(0.001)	(0.005)	(0.003)	(0.001)	(0.005)	(0.003)
High_School	−0.005***	−0.036***	−0.017***	−0.005***	−0.036***	−0.017***
	(0.001)	(0.005)	(0.003)	(0.001)	(0.005)	(0.003)
University_Degree	0.022***	0.161***	0.094***	0.022***	0.160***	0.094***
	(0.001)	(0.008)	(0.004)	(0.001)	(0.008)	(0.004)
age25-29	0.043***	0.442***	0.237***	0.043***	0.442***	0.237***
	(0.001)	(0.010)	(0.005)	(0.001)	(0.010)	(0.005)
age30-34	0.090***	0.792***	0.430***	0.090***	0.792***	0.430***
	(0.001)	(0.009)	(0.005)	(0.001)	(0.009)	(0.005)
age35-39	0.098***	0.860***	0.468***	0.098***	0.860***	0.468***
	(0.001)	(0.009)	(0.005)	(0.001)	(0.009)	(0.005)
age40-44	0.104***	0.908***	0.497***	0.104***	0.908***	0.497***
	(0.001)	(0.010)	(0.005)	(0.001)	(0.010)	(0.005)
age45-49	0.105***	0.918***	0.502***	0.105***	0.918***	0.502***
	(0.001)	(0.010)	(0.005)	(0.001)	(0.010)	(0.005)
age50-54	0.110***	0.954***	0.522***	0.110***	0.954***	0.522***
	(0.001)	(0.010)	(0.006)	(0.001)	(0.010)	(0.006)
age55-59	0.113***	0.979***	0.536***	0.113***	0.979***	0.536***
	(0.001)	(0.011)	(0.006)	(0.001)	(0.011)	(0.006)
age60-64	0.071***	0.632***	0.343***	0.071***	0.632***	0.343***
	(0.001)	(0.013)	(0.007)	(0.001)	(0.013)	(0.007)
greenSector	−0.011***	−0.082***	−0.049***	−0.011***	−0.082***	−0.049***
	(0.003)	(0.017)	(0.010)	(0.003)	(0.017)	(0.010)
Constant	0.330***	−2.207***	−1.104***	0.329***	−2.214***	−1.108***
	(0.010)	(0.053)	(0.030)	(0.010)	(0.053)	(0.030)
Controls	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	1,755,109	1,755,109	1,755,109	1,755,109	1,755,109	1,755,109
Adjusted R^2	0.164			0.164		

Notes: standard errors in parentheses are robust. Sector, macro-profession and regions fixed effects included in all models. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

1.5.3 A matching analysis

In continuation of the previous analysis, and in an effort to address potential sources of bias comprehensively, we extend our investigation by employing exact matching. Specifically, we match "High-Green" workers with similar characteristics to "no-green" workers, utilizing variables such as gender, age class, education level, macro-region, 3-ISCO digit categories, and belonging to EU taxonomy sustainable sectors. With a substantial dataset comprising around 1.8 million workers, approximately 71,936 are identified as "High-Green." Following exact matching, any units in sub-classes lacking either treated or control units are excluded. Despite discarding 22,862 High-Green observations due to the exact matching criteria, this step is justified. Indeed, post-matching analysis reveals that over 17,000 of the excluded workers belong to the CP-3 digit 8.3.1 category, where there are no "no-green" workers. Eliminating this specific group is deemed appropriate, as they likely differ significantly from others.

Exact matching is a non-parametric method that ensures perfect balance in observed covariates by creating matched groups with identical characteristics. This approach eliminates bias from measured confounders, making it a powerful tool for causal inference. However, it comes at the cost of reduced sample size, as observations without exact matches are discarded. This trade-off between balance and efficiency is particularly relevant when working with large datasets, as seen in our study. While exact matching minimizes model dependence, it does not account for unobserved confounders, which could still bias our estimates.

The mean difference between the treated and control groups is -0.028 (95% CI [-0.0363; -0.0336], $p < 2.2e-16$), suggesting that, on average, being a High-Green worker leads to a slight reduction in the probability of obtaining a permanent job. One possible explanation is that High-Green jobs might be concentrated in roles characterized by more flexible contracts. Furthermore, the relative novelty of some of these occupations may result in extended transition periods before workers secure permanent employment.

To confirm our findings, we also conducted 1:1 nearest neighbor matching without replacement, which yielded a mean difference of -0.01 (95% CI [-0.0089; -0.0015], p = 0.0058). While this alternative method preserves a larger sample size, it may introduce imbalances in covariates compared to exact matching. Nevertheless, the direction of the effect observed with exact matching is confirmed, reinforcing the robustness of our results.

As a latter robustness check, we exclude from the counterfactual group the observation that results to be green jobs according to the Transcoded Index. In this case, we compare the average difference in the proportion of permanent employment between treated and control units at the subclass level, following exact matching. Consistently with previous findings, the result indicates a statistically significant negative effect of High-Green jobs on the probability of having a permanent contract of of -0.024 (95% CI [–0.0390, –0.0100], p = 0.0009). This suggests that, on average, High-Green jobs holders have a 2.4 percentage point lower likelihood of holding a permanent position within matched subclasses.

Although the difference in means between High-Green and non-High-Green workers is relatively small, making it difficult to assert a definitive causal negative effect on the probability of obtaining a permanent job, our analysis provides no evidence supporting a positive association between High-Green status and job stability. These findings contribute to the broader discussion on green jobs by highlighting potential labor market frictions faced by workers in sustainable sectors, emphasizing the need for further investigation into job quality and career trajectories within these fields.

Table 1.4: Whole sample stratified by highGreen

	0	1	SMD
n	1708402	71936	
genere = M (%)	976389 (57.2)	64302 (89.4)	0.782
macro_regione (%)			0.312
north-west	428905 (25.1)	11461 (15.9)	
north-east	377920 (22.1)	12639 (17.6)	
central	353418 (20.7)	15493 (21.5)	
south	384780 (22.5)	22282 (31.0)	
islands	163379 (9.6)	10061 (14.0)	
classe_eta (%)			0.285
18-24	202787 (11.9)	6647 (9.2)	
25-29	224466 (13.1)	7094 (9.9)	
30-34	245302 (14.4)	7866 (10.9)	
35-39	248562 (14.5)	8695 (12.1)	
40-44	239856 (14.0)	9580 (13.3)	
45-49	208518 (12.2)	10050 (14.0)	
50-54	156363 (9.2)	9326 (13.0)	
55-59	102166 (6.0)	7319 (10.2)	
60-64	80382 (4.7)	5359 (7.4)	
istruzione (%)			0.583
middle_school	735664 (43.1)	47636 (66.2)	
high_school_diploma	512132 (30.0)	18634 (25.9)	
university_degree	460606 (27.0)	5666 (7.9)	
isco_3 (%)			2.488
1.1.2	4652 (0.3)	3 (0.0)	
1.3.1	7988 (0.5)	0 (0.0)	
2.1.1	30489 (1.8)	496 (0.7)	
2.2.1	12043 (0.7)	0 (0.0)	
2.2.2	1827 (0.1)	343 (0.5)	
2.3.1	12297 (0.7)	676 (0.9)	
2.4.1	11850 (0.7)	0 (0.0)	
2.5.1	54637 (3.2)	89 (0.1)	
2.5.3	5516 (0.3)	11 (0.0)	
2.6.3	257381 (15.1)	0 (0.0)	
3.1.1	6853 (0.4)	0 (0.0)	
3.1.3	35998 (2.1)	0 (0.0)	
3.1.4	1552 (0.1)	427 (0.6)	
3.1.6	4186 (0.2)	0 (0.0)	
3.1.8	3120 (0.2)	2289 (3.2)	
3.2.1	74756 (4.4)	0 (0.0)	
3.2.2	2558 (0.1)	93 (0.1)	
3.4.1	28632 (1.7)	0 (0.0)	
3.4.6	289 (0.0)	5 (0.0)	
5.4.8	69174 (4.0)	1 (0.0)	
6.1.3	84034 (4.9)	2013 (2.8)	
6.1.4	15041 (0.9)	0 (0.0)	
6.1.5	141385 (8.3)	982 (1.4)	
6.2.1	77839 (4.6)	0 (0.0)	
6.2.4	55364 (3.2)	0 (0.0)	
6.4.1	170020 (10.0)	0 (0.0)	
6.4.3	846 (0.0)	0 (0.0)	
6.4.4	617 (0.0)	7585 (10.5)	
6.5.3	54605 (3.2)	0 (0.0)	
7.1.5	6421 (0.4)	0 (0.0)	
7.1.6	1463 (0.1)	1800 (2.5)	
7.3.2	18214 (1.1)	0 (0.0)	
7.4.3	18183 (1.1)	2984 (4.1)	
8.1.4	432138 (25.3)	22130 (30.8)	
8.3.1	0 (0.0)	17393 (24.2)	
8.3.2	6434 (0.4)	12616 (17.5)	

1.6 Conclusions

In this work, we have proposed a new approach to selecting Green Workers and continuously evaluating their level of "greenness" within the Italian labor market. Building on previous research based on the U.S., we developed a set of new task indicators aimed at identifying High-Green Jobs and measuring their greenness levels in terms of both importance and frequency. This approach represents a novelty within the Italian context, as until now, the only available measures were based on transcriptions from U.S. occupation codes. In this paper, we directly compare the two approaches, showing that our proposed indicators appear to better identify green occupations. While our measures already demonstrate a higher degree of accuracy compared to previously used institutional statistics, we believe that future research could further enhance their efficiency by adopting more advanced machine learning techniques.
Additionally, in this work, we conducted an econometric analysis of the Italian labor market using the COB dataset. By dividing our sample into High-Green and non-High-Green workers, we first explored the characteristics of High-Green workers in Italy. Contrary to expectations based on the formal UNEP definition, green workers appear to be more frequently associated with lower levels of education and temporary employment. Furthermore, we observe a higher percentage of males, predominantly concentrated in the poorer regions of Italy. To address the issue of job security, we performed an analysis using various econometric specifications to explore the association between the greenness level of an occupation and the likelihood of being employed in a permanent position. Surprisingly, all the relationships between our continuous green indicators and the dummy variable indicating permanent positions were negative. Lastly, to refine the previous analysis, we conducted a matching analysis based on a High-Green dummy, selecting only workers highly involved in green tasks as green. While the negative effect was slightly reduced in this case, there was still a negative and statistically significant association with the probability of holding a permanent job.
From a political perspective, this result could pose a significant challenge. In a labor market like the Italian one, which has undergone progressive reforms over the past decades to increase job flexibility Cirillo et al. (2017), *ceteris paribus*, green jobs appear to be characterized by an additional layer of precariousness. This presents a dual concern. On one hand, while a minority of workers may actively prefer temporary positions, the majority accept them primarily due to the scarcity of stable employment opportunities (Morris and Vekker, 2001). As a result, green jobs risk being perceived as less attractive compared to alternative career paths. On the other hand, from a firm-level perspective, empirical studies on Italy suggest that temporary contracts negatively affect workers' motivation and effort, ultimately reducing firm productivity (Boeri and Garibaldi, 2007; Battisti and Vallanti, 2013). These findings underscore the need for targeted policy interventions to ensure that green jobs contribute to both environmental sustainability and labor market stability.

In conclusion, our work represents a methodological innovation in the study of Green Jobs. For the first time, we propose a set of green measures directly built on Italian task data, allowing us to explore the real characteristics of each Italian profession. Additionally, our applied analysis is crucial in understanding that, while Green Jobs are popular in political and economic discussions, their characteristics may not be as favorable for Italian workers.

Chapter 2

Robot, Trade and Employment: unravelling the relationship within the European context[1]

2.1 Introduction

Industrial robots stand as one of the most widespread technological innovations within the manufacturing sectors. According to the latest report by the International Federation of Robotics, in 2022 there were almost 4 million industrial robots operating worldwide (IFR, 2023). With such high numbers of worldwide robot adoption together with the increasing adoption of technologies like Artificial Intelligence (AI) and Internet of Things (IoT), the issue of how new technologies impact the labor market arises once again. The concept of "technological unemployment" often takes centre stage when significant technological advancements occur over the history (Keynes, 1930).

After the alarming projections put forward by the seminal paper by Frey and Osborne (2017) with respect to potential job losses caused by computerization, later explorations of the data did not report unanimous results. In particular, focusing our attention on robots' effect, a blurred picture emerges. Most of the papers investigating the amount of their labour-replacing effects, report both positive and negative results (Acemoglu and Restrepo 2020; Graetz and Michaels 2018; Adachi et al. 2024). As evidenced by Filippi et al. (2023) not unanimous results depend on the heterogeneity of the countries analyzed (e.g., the US vs. European countries or Japan) as well as the different levels of analysis (country vs. sector or firm-level data).

From a theoretical point of view, as discussed by Aghion et al. (2022) and firstly evidenced in the paper by Acemoglu and Restrepo (2019), the adoption of robots can lead to two opposing effects. On one side, productivity could rise, resulting in increased labour demand and higher wages. Conversely, we could observe displacement effects due to the substitution of labour with machines: this effect could partially be more relevant for low-skilled workers.

[1]This work is co-authored with Professor Chiara Franco from the University of Pisa and has been published in *Structural Change and Economic Dynamics*. Franco, C., & Suppressa, F. (2025). Robot, trade and employment: Unravelling the relationship within the European context. *Structural Change and Economic Dynamics*, 73, 407-422.

Furthermore, the impact of robot is not confined only to internal production activities but also to international ones, such as exports (DeStefano and Timmis 2024; Alguacil et al. 2022). Nevertheless, a still not wide literature has started to investigate whether the robot adoption can have effects not only on exports or employment dynamics within the adopting countries, but also on other trade-connected countries following the lines of Global Value Chain (GVC) relationships. In this respect, the channels producing the final effect are still twofold. Firstly, robot adoption can enhance the competitiveness of adopters, primarily by reducing labor costs. This can lead to the domestic sourcing of goods, mainly intermediate goods, that were previously imported from less developed countries where they were produced at a lower cost. It means that production (or part of production) abroad may be substituted with production at home (Rodrik, 2018), possibly generating a decrease in demand for low-skilled labor force, which previously constituted the bulk of demand in developing countries. Secondly, robotization may also expand the production scale, leading to greater demand for input sources, especially intermediates, that can come from abroad (Baur et al., 2022). Conversely, this should act as a boost to the foreign employment dynamics.

From an empirical point of view, these channels have been proved to be at work in some studies investigating whether robot investment in developed countries may generate adverse employment impacts on developing or emerging countries (e.g., Faber 2020; Stemmler 2023; Kugler et al. 2020; Carbonero et al. 2020; Gravina and Pappalardo 2022; Díaz Pavez and Martínez-Zarzoso 2024). It is confirmed that negative employment impacts can occur on trade partners: as developed countries invest in automation, they might choose to bring back previously offshored production, potentially reducing employment in developing nations.

Still, a comprehensive analysis on whether this phenomenon can hold for the overall European context is missing.

To address the limitations evidenced above, in this paper we put ourselves into the stream of literature dealing with the impact of robot adoption on employment, but considering how trade relationships may play a role. In this perspective, our first contribution is to develop an innovative measure of robots diffusion through GVC linkages. It represents a comprehensive indicator that can concurrently assess the level of industrial robot penetration in the five major European economies (France, Germany, Italy, Spain and the UK) and the extent to which other European nations export to these five top countries satisfying their final demand. Using this novel indicator built through OECD Trade in Employment (TiM) dataset, we estimate the effects of robot investments in the Top 5 European economies on the employment dynamics of other European countries. Specifically, robot adoption for each Top5 country is weighted through a measure of GVC relationship characterized by the novelty of accounting for employment content: in particular, it describes the proportion of a country's workforce that is employed to meet final demand from the Top 5 economies, relative to its total workforce involved in export activities. This approach has never been adopted so far also in those studies adopting a GVC perspective (e.g. Gravina and Pappalardo 2022).

A second contribution is the perspective we use to analyze the European context: as evidenced before, most of the studies using the GVC approach, investigate the impact of robot adoption in developed countries with respect to developing countries. Instead, we focus on an intra-European perspective involving mainly developed nations: we specifically focus on these five countries firstly because, from an economic point of view, they accounted for around 63% of the total GDP produced by the European countries selected in our study in 2018. In addition, in terms of imports, these countries represented more than half of the EU total[2]. On the other side, they are also the leaders in terms of robotization. Focusing on 2018, their operational stocks accounted for around 72% of the total in our sample, while at the beginning of the period under observation (1995), their share was up to 83%. In sum, these countries represent within Europe the most important productive and large trade hub.

Our main results point to a positive impact of robot investments in the Top five European economies in affecting the change in employment. We think that this impact can be generated by a couple of motivations: the first is that the task composition of labour of countries and sector that participate in the GVC are different, thus the amount of employment can be higher where the task composition of job is biased towards low skilled or routine occupations. Not surprisingly, in line with the results reached by Graf and Mohamed (2024), the sensitivity analysis we run shows that this impact is mainly driven by low-income European countries. A second motivation, refers to the evidence of higher GVC integration of European countries which is not matched by a converging trend of functional specialisation. It means that also within a quite homogeneous group of countries, the trade-related employment impacts can still vary because of production and technological structures that mirror a hierarchical positioning of European countries.

The remainder of this paper is organized as follows. Section 2 gives an overview of the existing literature on the impact of robotization on employment within and outside the adopting country. Section 3 describes the data we use in our empirical analysis and the construction of our novel indicator. Section 4 and 5 provide our main estimation results and further analyses. Finally, in section 6, we discuss our findings and we offer some conclusive remarks.

[2] Authors' computations based on Eurostat data available at the following link: https://ec.europa.eu/eurostat/databrowser/view/nama_10_gdp__custom_11396345/default/table?lang=en, refers to Figure B1 in the appendix.

2.2 Overview of the Literature

2.2.1 Robot and Employment

The role industrial robots may play in affecting employment dynamics has been extensively analyzed. The heterogeneity of the results is evidenced in recent literature reviews (e.g., Filippi et al. 2023), in which it is explained how different research methods and level of analysis as well as the types of industries and countries studied can greatly affect the findings in these investigations. These divergent outcomes highlight the complexity of the relationship between industrial robot adoption and employment dynamics. Even though in their descriptive work Fernandez-Macias et al. (2021) claim that the potential to be a disruptive technology seems not so relevant in Europe, except in a few sectors, still this impact needs to be carefully evaluated.

As evidenced in the introduction, the theoretical mechanisms at the base of the robot-employment nexus are rooted into the “displacement” vs “productivity” effect: as Acemoglu and Restrepo (2019) explain, on the one side, automation may negatively impact employment because of higher number of tasks that can substitute labour with capital. On the other side, automation may also generate and increase in productivity that may further enhance labour demand for those tasks that are not substituted.[3] Which of the two effects is going to prevail remains an empirical matter. Aghion et al. (2022) confirm these two opposing view in their review but also providing firm-level empirical evidence for France in favour of the most positive one.

Indeed, most of the research conducted at the country-sectoral, regional or firm level in various countries has generated mixed results. The European case is the most studied. Graetz and Michaels (2018) is the first work utilizing a sectoral approach in the analysis of the European labour market: they observe no notable connections between the adoption of industrial robots and overall employment levels even though observing a decline in the share of low-skilled labour. Klenert et al. (2023) reveal partially different findings for Europe as their work does not yield significant evidence concerning the reduced share of low-skilled workers but, instead, shows a positive association between total employment and robot adoption[4]. Similarly,Reljic et al. (2023) evidence how the impact of robotization in Europe is not homogeneous as we may expect, but, instead, positive employment effect can be found only in core and service oriented countries, while the peripheral countries are not affected by such trend. Similarly, Chen and Frey (2024) through a comparison over eight European countries, report for Italy, Norway, and the UK significant employment losses while Germany, Denmark, Finland, and Spain do not show significant results.

In contrast, Acemoglu and Restrepo (2020)’ study on the United States adopts a different approach, concentrating on the local labor market as the unit of analysis. Their results indicate that an additional robot per thousand workers corresponds to

[3] They go further in considering this effect not just a simple “productivity effect” but they call it a “reinstatement effect” as it may create new tasks potentially altering the balance between labor and capital in favor of labor.

[4] Anton et al. (2022) focus on Europe as well, but adopting a regional perspective highlighting two different patterns: during the initial analysis period from 1995 to 2005, they observed a negative association between robotization and European employment levels but this relationship evolved into a positive association in the following period from 2005 to 2015.

a decline of 0.39 percentage points in the local employment-to-population ratio. A rather different picture, using a similar econometric methodology, emerges for the Japanese case: Adachi et al. (2024) shoe an increase in employment following robot adoption.

Further streams of the literature offer an overview of this multifaceted phenomenon that can help in focusing the channels at work: for example, De Vries et al. (2020) adopting the perspective concerning the types of jobs affected by robotization, show that workers employed in non-routine cognitive tasks are those gaining the highest benefits to the detriment of those employed in routine tasks. However, mainly high-income countries within Europe display such effect. A further in depth cross-country analysis in this line of research with reference to the European case is performed by Bachmann et al. (2024) who study: by assigning two-digit industry level data into two-digit occupation specific data they are able to study the mechanisms behind the final impact on employment at the workers' level. They reveal how decomposition of job tasks is a crucial factor to consider together with labour costs: in countries, like those of Central and Eastern Europe, where the labour costs is low or average, robot exposure is favourable for workers employed in occupation intensives in routine manual or routine cognitive tasks.

Giving emphasis to the perspective dealing with the impact on workers are a couple of papers on single countries: Dauth et al. (2021) using administrative data set show that in Germany exposure to robots generates in displacement effects within the manufacturing sector. However, these job losses are completely compensated for by the creation of new jobs in the service industry[5]. Dottori (2021) explores the case of Italy finding that robotization does not have a negative impact on overall employment even though it has reduced the likelihood of new workers entering the manufacturing sector.

At the firm level, several studies indicate a positive association between robot adoption and both productivity and employment levels. Koch et al. (2021), using a panel data set of Spanish manufacturing firms, show that an increase in the output is accompanied by a net increase in job creation at a rate of 10%. They also underline substantial job losses among companies that choose not to adopt robots, leading to a productive redistribution of labour from non-adopting firms to adopting ones. Focusing on French manufacturing firms, Domini et al. (2021) find similar evidence on employment dynamics that can be attributed to both an increased rate of hiring and a decreased rate of employee separations. Similarly to the German case, Kariel (2021) evidences that in the UK jobs lost in manufacturing are recovered in services. However, not all firm level studies are unanimous in finding positive results (see Acemoglu et al. 2020). China is a specific case analyzed because of its massive and still increasing rate of adoption: Zhang et al. (2023) show a large positive effect on overall employment.

In this quite large and still evolving literature, despite the heterogeneity of results the common empirical focus is on the mechanisms through which robotization mainly generates possible impacts within the country of adoption. From our point of view, it is interesting to note that the European case can not be considered as homogeneous group of countries, but the production structure and the sectoral specificity of each country may generate different effects. We underline this point because, in our

[5]Furthermore, the study indicates that robotization leads to the emergence of new roles and responsibilities for workers within their original manufacturing plants

interconnected world, there is another side of the coin that needs to be explored: to comprehend the intricacies of the relationship between robots and employment, it is fundamental to consider also whether the impact of robots can go beyond borders as a consequence of globalization of production. This may be relevant to study in our sample of countries considering that Europe is highly commercially connected within itself.

2.2.2 Robot and Employment in a trade context

While the widespread adoption of industrial robots has primarily been observed in high-income countries, the effects of robotization extend far beyond national borders: the increasing fragmentation of production deploying through GVC also causes robots to impact trade related countries. From a theoretical point of view, we can discern two primary channels through which robotization can impact employment dynamics through trade. The first pathway regards a shift of relative production costs: automation adoption could reduce production costs for high-income nations, eroding the labour cost advantage traditionally held by less developed countries in the production of labour-intensive goods. Consequently, a phenomenon often referred to as "re-shoring" may emerge, involving the relocation of production units from developing countries to high-income nations. Naturally, this dynamic could reduce imports and negatively affect employment in less developed countries (Rodrik, 2018). On the other side, a contrasting trend may emerge as well: as robot adoption frequently leads to increased productivity, adopting firms often requires more intermediate inputs that can be sourced from third countries. A greater demand of intermediate inputs thus generates great benefits also in terms of employment (Artuc et al., 2023). This theoretical ambiguity reflects heterogeneity in the empirical results. Adopting a macroeconomic approach to explore the presence of a reshoring effect Krenz et al. (2021) and Krenz and Strulik (2021) both find positive results in developed and emerging countries, but without estimating whether reshoring can cause a loss in employment from sourcing countries[6]. A step toward the understanding of the impact on employment dynamics is offered by Carbonero et al. (2020) who show that robot diffusion has caused a general reduction in global employment, especially concentrated in emerging economies. Specifically, focusing on cross-country effects, robot adoptions in high-income countries negatively affect developing countries' labour markets, suggesting a possible pattern of re-shoring. Reinforcing the evidence on the reshoring channel is the paper by Gravina and Pappalardo (2022) who employ an approach similar to ours: by building an index accounting for the spreading of robots through GVC at the country-sector level, they point out that robotization in Europe negatively impacts emerging countries' employment share, especially for Asian economies.[7] Studies accounting for the case of emerging countries are increasing as well: Díaz Pavez and Martínez-Zarzoso (2024) find that foreign

[6] Similarly, the paper by De Backer and DeStefano (2021) reveals that investments in robots reduce the need for offshoring from developed countries but without finding an emerging pattern of reshoring. The impact on employment dynamics is not examined as well.

[7] In both papers, the approach is different from our measure; first, the exposure to foreign robots is calculated using a trade-weighted average of robots from developed countries without considering the employment content of exports; secondly it is not considered whether exports satisfy the final demand of destination countries, reflecting a GVC linkage that with trade data can be underestimated.

exposure to robots have negative impacts on employment and labour share rather than the amount of robots adopted locally. Similarly to Carbonero et al. (2020) they provide a trade-weighted measure of the foreign exposure. Different and contradicting results come from studies at the firm level: for example, Stapleton and Webb (2020) investigate the consequences of automation in Spain on imports and multinational operations, including nations with lower income levels. Their findings reveal that companies adopting robots in Spain tend to increase both the value of imports from lower-income countries and the establishment of new affiliates in those regions. This result proves that the second channel identified, that of productivity, can be at work as the integration of robotic technology positively influences the extensive margin of trade and multinational projects[8]. Analyzing the same country, Cilekoglu et al. (2024) find similar results as robot adoption positively impact on the amount of foreign rather than local sourcing. The occurrence of the productivity effect is confirmed both at the sectoral level (e.g. Graetz and Michaels 2018) but also at the firm level. Stiebale et al. (2024)find that only large firms (superstar) increase their productivity. Similar results are found by Bonfiglioli et al. (2024), who evidence that for France there are labour productivity increases as well as higher demand for high-skill professions. Beyond European case, this positive effect has been detected also for the Chinese case. Duan et al. (2023) find that through improvements in both the human capital structure and the innovation capability of firms, productivity can rise (especially in non-state-owned and small scale firms).[9] In line with the work by Graetz and Michaels (2018), Fu et al. (2021) using country level data report that higher labor productivity induced by robot adoption is shown in developed countries but not developing ones.

Further evidence, but rather confirming the first channel of the likely reshoring effect, comes from Faber (2020) who examines the impact of robot adoption in the US on employment dynamics in Mexico. The study confirms that an increasing rate of robot adoption in the United States leads to decreasing employment opportunities in Mexico while simultaneously increasing the number of employees in the US. Stemmler (2023) for Brazil find comparing results for manufacturing sectors in Brazil while a positive effect is detected for sectors producing raw materials. Kugler et al. (2020) evidence that reshoring back production is again one of the main motivation for the negative employment impact for those sectors that in Colombia are most exposed to US automation adoption.[10]

In conclusion, different studies report different parts of the story about the linkage between the adoption of robots in a country (or groups of countries) and their impact on trade-connected countries. For this reason, the need to account for the

[8] Still connected with the trade topic but conducting an analysis on the direct impact on export is the work by Alguacil et al. (2022) who demonstrated that in Spain, firms using robots experience a substantial increase in their probability of exporting, export sales and the proportion of exports in their overall output.

[9] This positive relationship in the Chinese case has been detected in other related studies (Wang et al., 2024; Zhang et al., 2023).

[10] Even though not directly estimating the employment impact on foreign countries, Fontagné et al. (2023) further explores the relationship between technology adoption, GVC and labor dynamics across European countries. Their main findings reveal that, while robot adoption does not have a direct impact on labour share, they have, instead, an indirect effect altering the GVC position by increasing the degree of upstreamness of production tasks. This works puts into evidence that automation adoption and international production dynamics are strictly interrelated to explain employment dynamics.

high fragmentation of production that GVCs have brought, giving a more precise measure of the likely effect of spreading of technology through trade linkage, can become relevant for the final effect to occur. One step in this direction is done by Graf and Mohamed (2024): examining only the German case they estimate whether domestic robot adoption can impact employment content of countries that export to Germany over the years 2004-2015. They acknowledge a positive effect especially guided by low-tech sectors and non-OECD countries. We go a step further by adopting a similar perspective and enlarging our analysis on the Top five European economies through the same data as Graf and Mohamed (2024), but using them to build a different trade-weighted measure of exposure to foreign robots.

2.3 Data

This section provides a comprehensive overview of the data sources employed in this study and the original database we built based on them. Subsequently, we present a new indicator designed to simultaneously measure the level of industrial robot penetration in the five major European economies (France, Germany, Italy, Spain and the UK) and assess the extent to which other European nations rely on these Top five economies for their exports.

2.3.1 Data Sources

In this work, we integrate various sources of data at the country-sectoral level.
One of our primary sources is the Trade in Employment (TiM) database provided by the OECD[11]. This database provides a collection of labour market indicators designed to clarify the complexities of global production networks and supply chains. Indeed, looking at the estimation of workers embodied in foreign final demand, we can estimate the extent to which a specific country-sector workforce depends on and integrates with foreign economies. All the indicators are developed starting from the 2021 OECD's Inter-Country Input-Output (ICIO) Tables[12]. In addition, recent estimates of employment and employees' compensation by industrial activity, taken from official sources, are integrated into the computation. The TiM database provides indicators for 45 individual industries, categorized according to the ISIC Rev.4 classification, across approximately 50 countries. The period spans from 1995 to 2018. This database has never been employed before (with the exception of Graf and Mohamed 2024) to investigate such a research question: we think this is particularly suitable to this purpose as it catches the amount of work embodied in trade flows.

The second source, from which we extrapolate data on industrial robots, is the International Federation of Robotics (IFR) database. This dataset contains comprehensive information on industrial robot stocks at the country-sector level. The robots cataloged in this dataset fall within the definition established by the International Standards Organisation. According to this definition, a robot is characterized as "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment" (ISO, 2012)[13]. IFR offers annual statistics on the operational stock of industrial robots by country and industry, starting from 1993.

Lastly, to incorporate control variables into our econometric estimations, we extract indicators such as GDP, labour costs, fixed capital, hours worked and imports from China from the Database for Structural Analysis (STAN) developed by the OECD. Economic sectors are classified based on the ISIC Rev.4 classification, like in the TiM database.

[11] We refer to the 2021 version of the database, available at the following link: https://stats.oecd.org/Index.aspx?DataSetCode=TIM_2021

[12] see http://oe.cd/icio

[13] These machines are primarily tailored for functions such as material handling, machine tending, welding, soldering, assembly, and disassembly. The industries are classified following the International Standard Industrial Classification for all economic activities, reaching a three-digit level for manufacturing industries.

We need to properly merge the three datasets described above to conduct our analysis. Specifically, we focus on 22 European countries (in our work, Europe is defined by its geographical dimension rather than economic union) and 20 economic sectors. In Table 2.1, we report a comprehensive list of the countries utilized in our analysis, while in Table B1 there are the selected IFR sectoral code and the corresponding ISIC code. To transition from the IFR sectoral code to the ISIC classification, we employ the conversion table outlined in Jurkat et al. (2022). By merging the three data sources, we obtain a unique panel database containing 11,040 observations covering a time-period from 1995 to 2018.

Table 2.1: List of European Countries included in our analysis

Selected Countries	Austria; Belgium; Bulgaria; Croatia; Czech Republic; Denmark; Estonia; Finland; Greece; Hungary; Ireland; Latvia; Lithuania; Netherlands; Norway; Poland; Romania; Slovakia; Slovenia; Sweden; Switzerland; Turkey
Top 5 Economies	France; Germany; Italy; Spain; United Kingdom

2.3.2 Top5 Robot Adoption and Export Dependence Index

One of the major novelty in this study is the introduction of the Top5 Robot Adoption and Export Dependence (TRAED) Index. As discussed extensively in the literature review, understanding the intricate interplay between robots, employment, and trade is a difficult task. While analyzing the separate relationships between robots and employment and robots and trade could simplify the analysis, it may also result in a fragmented perspective. The TRAED index, by design, avoids this fragmentation by integrating both dimensions into a single indicator serves a dual purpose: it quantifies the level of industrial robot penetration in the Top five European economies while also evaluating the extent to which other European nations rely on these dominant economies for their export activities.

For each economic sector i, country c and time t, the TRAED indicator is defined as follows:

$$\text{TRAED}_{c,i,t} = \log[(\frac{\text{FFD\_DEM\_Top5}_{c,i,1995}}{\sum_p \text{FFD\_DEM}_{c,i,p,1995}} \times \text{RD\_Top5}_{i,t}) + 1] \tag{2.1}$$

where:

- $\mathbf{FFD\_DEM\_Top5_{c,i,1995}}$: The Domestic Employment Embodied in Foreign Demand of Top 5 countries represents the number of persons (in thousands) in country c and industry i employed to meet the foreign final demand in the Top five European economies in 1995. To build this measure, we have taken the sum of the workers of country c embodied in the foreign demand of Germany, France, Italy, Spain, and the UK ;
- $\mathbf{FFD\_DEM_{c,i,p,1995}}$: the Domestic Employment Embodied in Foreign Demand is the number of persons (in thousands) engaged in industry i in country c to fulfil final demand for goods and services in country p (set of all the countries commercially related to country c). It refers to 1995;

- **RD_Top5**: the robot density in the Top five European economies is calculated as the number of robots per 1,000 workers.

The fraction $\frac{\text{FFD\_DEM\_Top5}_{c,i,1995}}{\sum_p \text{FFD\_DEM}_{c,i,p,1995}}$, within our equation, represents the weight assigned to each country; henceforth, we will refer to it as "Top 5 dependence". This variable quantifies the proportion of workers engaged in the production of final products for the Top 5 European economies relative to the total workforce involved in export activities during the initial period. We fix the export-dependence shares to 1995 for several reasons:

- **Data availability**: 1995 is the first year available in the OECD's TiM dataset.

- **Avoiding endogeneity**: By fixing the shares to a single year, we avoid potential endogeneity and serial correlation between changes in trade patterns and changes in robot adoption in subsequent years. Fixing the index to 1995 ensures that the initial trade structure is not influenced by robotization dynamics, which were not yet significant at that time.

- **Low robot penetration in 1995**: In 1995, the diffusion of industrial robots was still relatively low. This allows us to assume that robots had not yet significantly affected employment and trade linkages, ensuring that the index captures the effects of subsequent robotization, rather than being influenced by pre-existing robot-driven dynamics.

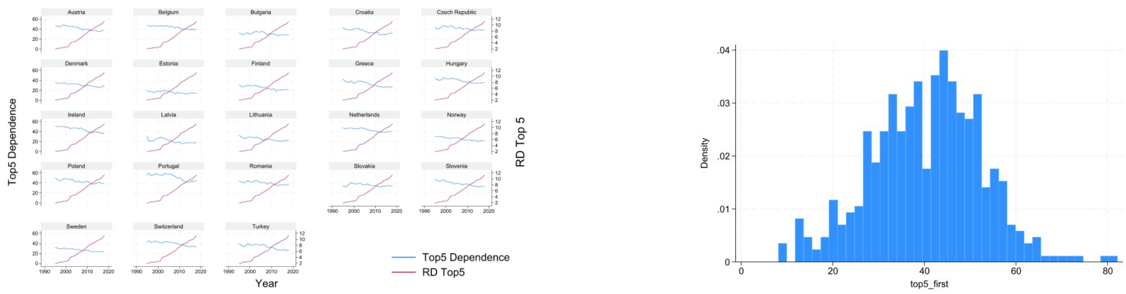
By multiplying this dependence by robot density (RD_Top5), the index captures the degree to which increasing robotization in the Top 5 economies might affect employment in other European countries via trade linkages. The TRAED Index is critical for our analysis because it provides a nuanced view of how robot adoption in the most technologically advanced European countries influences employment dynamics in other European economies through trade dependencies. This approach is particularly valuable in a context like Europe, where economies are deeply interconnected, and traditional measures of robot adoption may not fully capture these cross-border effects. By employing this measure, built using OECD Tim database, we also go beyond previous approaches in measuring GVC involvement of countries, as we take into consideration the employment content of trade flows in value added.

By combining robot adoption with export dependence, the index helps to uncover indirect channels through which automation might influence employment patterns across borders, offering insights into the broader impacts of technological change within integrated economic systems.

However, as observable in Panel A of Figure 2.1, if we plot the averaged change across industries categorized by country for the Top 5 dependence measure and the RD component, the technological component is clearly the one introducing variation in the TRAED index. On the contrary, the fraction of our equation appears to be quite steady over the period of analysis.
Next, in line with Artuc et al. (2023), we add 1 within the logarithmic function to prevent issues with zero values. Panel B of Figure 2.1 displays the distribution of the Top5 dependence within our equation, illustrating the weights of all country-sector combinations. The mean value is 40.46, with a standard deviation of 12.09. This indicates that, on average, around 40% of the workers are involved in exports towards the Top 5 European countries. Therefore, we have reason to believe that in such

integrated labour markets, the adoption of robots by major economies may provoke significant effects on other European nations. In Figure B2 in the appendix, we present the distribution of our TRAED index by country. The multiple plots reveal a remarkable degree of similarity in its distribution across European countries. Only a closer examination of the data reveals that Portugal's economic sectors exhibit the highest TRAED values, while Baltic and Scandinavian countries appear to have the lowest exposure.

Figure 2.1: Decomposition of the two component of the TRAED index by country (Panel A) and distribution of the Top5 dependence (Panel B)



(a) Panel A   **(b)** Panel B

However, the picture changes significantly when we shift our focus to the heterogeneity of distribution among economic sectors. As shown in Table B2 in the appendix, the TRAED index values display considerable variation among different economic sectors. For instance, sectors such as Motor vehicles, Rubber and plastics products, and products of wood and cork consistently exhibit the highest levels of the TRAED indicator on average. In contrast, sectors like Construction, Electricity services, coke manufacturing and refined petroleum products consistently have the lowest average values. This divergence is not surprising and primarily stems from heterogeneous levels of robot adoption across sectors. A second major motivation is the heterogeneous degree of trade openness of sectors.

2.3.3 Descriptive Analysis

This section presents some initial descriptive findings as a prelude to our econometric analysis. We begin by showing the mean and standard deviations of the key variables employed in our study, as depicted in Table 2.2. These statistics are provided for the whole sample, the initial year of observation and the last available period, allowing us to discern time patterns in the data. The main variables in our analysis are as follows: the TRAED index, described in detail in the previous paragraph. Measures of domestic robotization, including robot density, robot installation, and robot stock, pertain to the 23 European countries in our study and are sourced from the IFR dataset. Labour Cost includes employees' wages and salaries paid by employers, along with supplements such as contributions to social security, private pensions, health insurance, life insurance, and similar schemes. We normalize this cost based on the number of workers in each country-sector combination. All the data related to employment (employment, employment embodied in exports, and share of employment) are taken from the TiM database and are available at the country-sector level. Lastly, the value added deflator, also calculated at the country-sector level, is set to 100 for the year 2015 as the reference period. Remarkably, each variable exhibits a distinct trajectory over time. On the one hand, the TRAED index, the value-added deflator, the export workers' share, labour cost, and robot density all reveal upward trends. The substantial percentage increase in the TRAED index is particularly noteworthy, surpassing 70% during this period, keeping the Top 5 dependence variable constant. In parallel, we see a significant boost in the 23 Robot Density across the countries of our sample.

On the other hand, we observe a decrease in variables such as employment, and employment share. The reduction in total employment and employment share aligns with expectations, given our primary focus on the manufacturing sectors.

We then explore potential patterns associated with country heterogeneity to establish a connection between our paper and the existing literature. In Panel A of Figure 2.2, we present data on the GDP per capita of the 23 countries included in our analysis. While making a clear distinction between developed and developing countries in the European context is challenging, we can discern the presence of at least two major groups, which we will henceforth refer to as "high-income" and "low-income" countries.

Notably, when we examine the correlation between our TRAED index and changes in employment since 1995, we observe a contrasting relationship for these two groups (as shown in Figure 2.2, Panel B). Our initial findings suggest that adopting robots in the Top 5 EU countries positively impacts employment dynamics in less prosperous nations. In contrast, the effect on richest countries appears negligible or negative.

This preliminary result, which we further investigate in the econometric section, hints at the existence of a pattern linked to a country's income status. Importantly, it implies a direction contrary to what the majority of previous empirical literature has found. This divergence in dynamics is also apparent when we consider the correlation between the TRAED index and changes in the number of workers involved in exports (as shown in Figure B3).

Table 2.2: Descriptive Statistics

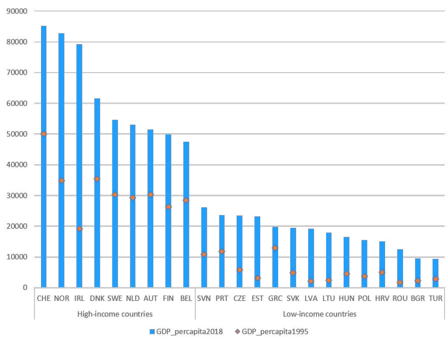
Variable	Mean (Standard Deviations)		
	Whole Sample	1995	2018
TRAED Index	3.893	2.819	4.813
	(2.205)	(2.214)	(1.921)
Robot Density	1.922	0.244	5.553
	(6.328)	(1.458)	(12.370)
Robot Installation	11.130	0.783	29.515
	(54.975)	(6.294)	(95.938)
Robot Stock	72.839	8.907	243.378
	(296.755)	(66.000)	(687.630)
Empl. Embodied in Foreign Demand	30.266	28.105	36.351
	(60.441)	(56.486)	(74.959)
Share of Export Workers	0.507	0.444	0.576
	(0.227)	(0.220)	(0.222)
Labour Cost	25.339	15.318	35.808
	(23.987)	(14.171)	(24.133)
Employment	97.974	108.672	94.478
	(344.787)	(420.217)	(310.299)
Value Added Deflator	93.857	88.705	106.237
	(52.478)	(137.872)	(27.433)
Share of Employment	1.817	2.104	1.564
	(3.025)	(3.626)	(2.323)
Observations[14]	11.040	240	240

As a final step of our descriptive analysis, we analyze the connection between our robot-related metrics and the variables of interest at the sectoral level throughout the analyzed period. Initially, we aggregate our data at the sectoral level, incorporating all 23 European countries in our study into a single comprehensive geographical unit. To achieve this, we take sum of the various robot-related metrics, the employment variable, and the number of workers involved in exports. Subsequently, since after aggregating the 23 European countries it is no longer possible to examine every bilateral relation, we reconstruct our TRAED index by computing a weighted average of the Top five dependencies, factoring in the workforce composition of each sector.
In Figure 2.3, we illustrate the correlation between the TRAED Index and changes in employment compared to 1995. Although we encounter some divergent results, such as in the Electrical Equipment sector, there is a clear overall positive association between the robotization of the Top 5 countries and the employment trends in the other European nations. The same positive relationship is also observable in the context of the correlation between the TRAED Index and changes in Export Workers (as depicted in Figure B4). In the appendix, we also present scatter plots illustrating the association between the domestic robot density of the 23 countries and changes in employment and export workers. This analysis displays a positive relationship, suggesting a more pronounced productivity-enhancing effect than a

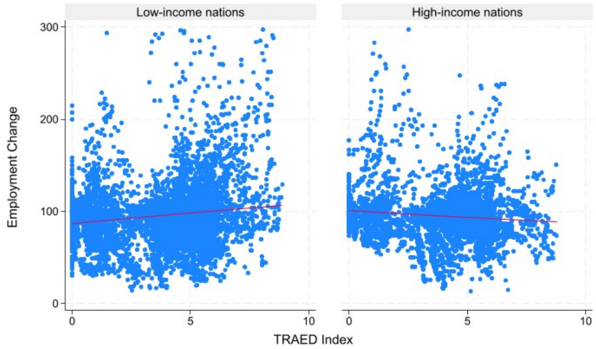
[14]The total observations for Value Added Deflator and Labour Cost are 7.999

displacement effects at the European level (see Figure B5).

Figure 2.2: Segmentation of the countries analyzed based on their GDP per capita (Panel A) and correlation between the TRAED Index and Employment change by macro-groups (Panel B)

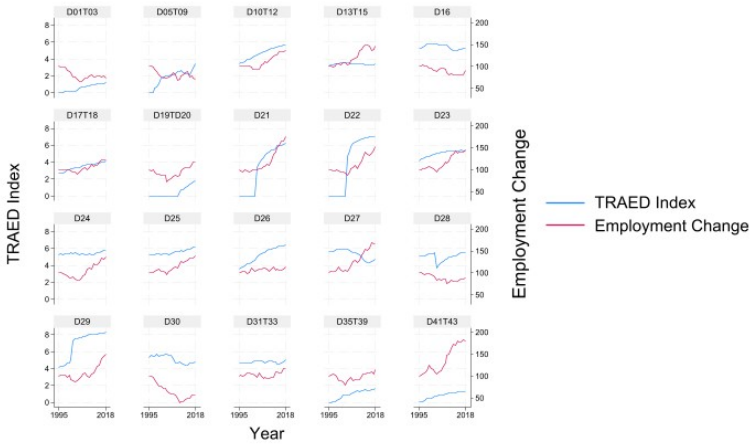


(a) Panel A



(b) Panel B

Figure 2.3: Correlation between the TRAED Index and the Employment Change by sector



2.4 Econometric analysis and results

Our baseline model for estimating the impact of the Top 5 robot adoptions on the labour outcomes in other European countries is as follows:

$$Y_{ict} = \alpha + \beta TI_{ict} + \gamma X_{ict} + \lambda_c + \delta_i + \eta_t + \epsilon_{ict}$$

where Y is the dependent variable (change in total employment). In our baseline model, following the paper by Fernandez-Macias et al. (2021), we normalize the initial year's dependent variable to a scale of 100, after which we calculate the annual changes for each subsequent year. TI is our TRAED index, as specified in the previous section. Then, X is a vector of covariates: value added deflator, cost of labour and domestic robotization. We have already described the value-added deflator and the cost of labour in the previous section. In addition, we include domestic robotization as a dummy variable, indicating whether domestic robots are present in a specific country-sector-year combination[15]. Lastly, λ_c, δ_i and η_t denote, respectively, country, sector and year fixed effects[16].

Table 2.3 shows the baseline estimates for the relationship between the TRAED index and the change in total employment relative to 1995: we observe positive and highly significant coefficients using both the OLS and the FE estimators (col 1 and 3 respectively). In the same Table in col 2 and 4 we include our control variables: with the exception of labour costs that are not significant, value added deflator as well as the role of domestic robotization positively impact on our main dependent variable. Our core dependent variable remains positively significant. This results stands for the fact that, as found in previous literature, the robot adoption in the Top 5 generates an increase in the employment of countries that are in trade relationship with them: in particular it means that the employment content is affected by the augmented Top 5 robotization as a productivity enhancement effect is going to occur. However, due to the strong integration among European nations, these benchmark results may be affected by endogeneity. This may stem from the potential reverse causality in the relationship between robot adoption and labor market outcomes. For instance, as highlighted in other studies utilizing our framework, firms might adopt robots in response to a decline in the workforce caused by rising labor costs. In the same way, sectors experiencing growth may invest more in robots rather than expanding their labor force. Additionally, our estimations could be influenced by omitted variable bias, such as the role of human capital. Therefore, following the approach of Acemoglu and Restrepo (2020), we employ an Instrument Variable (IV) approach, using the robot density in Japan as an instrument for the TRAED index. The rationale behind this instrument is to identify a country ahead of the Top 5 European nations in robot adoption, thus isolating the source of variation resulting from global technological advances[17]. Furthermore, despite their close technological ties, the commercial relationships between Japan and Europe are relatively minimal.

[15] As a robustness check, we also tried using quartiles of domestic robot density. The results are consistent with those presented in this section.

[16] In a robustness check, we have also included a control variable for imports from China within the Top5 sectors and a variable capturing the inward multinational activity as the change in the number of enterprises under foreign control. The results remain consistent with those of our baseline model.

[17] In Figure B6, we present the time trend of the operational robot stock for Japan and the Top 5 European countries.

Consequently, we can reasonably assume that this instrument is not correlated with unobserved European labour market conditions that could influence our dependent variables.

Referring to columns 5 and 6 of Table 2.3, the instrumental approach appears to validate the robustness of our findings[18]. In particular, in column 6, we can interpret these results as indicating that a one percent increase in our TRAED index, on average, leads to a 0.04 percentage point increase in employment compared to the year 1995. Regarding the control variables, both the VA deflator and the domestic robotization are positively associated with the change in employment.

Table 2.3: Dependent var: Change in Total Employment

	OLS		**FE**		**IV**	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TRAED Index	4.722***	4.226***	4.006***	3.608***	4.269**	4.061**
	(1.076)	(1.258)	(1.113)	(1.346)	(1.692)	(1.933)
Domestic Robot		6.925**		7.942***		6.955**
		(3.104)		(2.855)		(3.035)
Value Added Deflator		0.0730*		0.0792*		0.0729*
		(0.0399)		(0.0458)		(0.0399)
Labour Cost		0.337		0.963**		0.337
		(0.255)		(0.473)		(0.253)
Constant	96.09***	64.67***	93.62***	81.84***	94.74***	64.62***
	(1.426)	(9.936)	(3.511)	(7.226)	(1.536)	(11.45)
Observations	11,040	7,999	11,040	7,999	11,040	7,999
R-squared	0.374	0.415	0.097	0.143	0.374	0.415
Kleibergen-Paap F-statistics					126.489	97.569

Notes: Standard errors in parentheses are clustered at the country-industry level. Year dummies included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

We then proceed to assess the influence of the TRAED index on various indicators of changes in workers embodied in exports. As shown in Table 2.4, all our model specifications reveal a positive and statistically significant relationship as in the benchmark estimates. Our IV specification consistently reinforces these findings, displaying results close to the fixed effects (FE) specification. Comparing employment embodied in exports of final and intermediate products, the coefficients both display positive and significant impact generated by the TRAED Index. However, the notable increase in employment is exceptionally high in the case of employment embodied in exports of intermediate products, suggesting a rise in demand for this specific product category. This reinforces the fact that as found in the firm-level literature, the channel of the productivity effect may generate higher demand of

[18] In Table B3, we report the first stage IV regressions in which we see that the variable measure japanese robotization is positive and highly significant as expected.

intermediates from trade-connected countries. A further channel that could drive the final result is relative to the impact of robot adoption on the kind of tasks that they are going to substitute or complement. While we did not follow the approach of decomposing labour according to the different tasks performed by workers, we can make the hypothesis that, as put into evidence by Bachmann et al. (2024), the positive impact generated by robot exposure is particularly relevant for workers whose occupations mainly imply routine tasks (cognitive or manual) that are those implied in the production of intermediate inputs to satisfy final demand in Top 5 countries.

Table 2.4: Dependent var: Change in workers embodied in exp. of intermediate and final inputs

	Work. embodied in Interm. Input			*Work. embodied in Final Input*		
Variables	(OLS)	(FE)	(IV)	(OLS)	(FE)	(IV)
TRAED Index	17.48***	17.77***	21.22***	13.31***	13.18***	11.69***
	(4.17)	(4.88)	(5.09)	(3.23)	(3.51)	(4.42)
Constant	3.067	54.99*	13.34	47.62	85.09***	43.51
	(67.83)	(29.84)	(56.09)	(39.88)	(16.46)	(37.89)
Controls	YES	YES	YES	YES	YES	YES
Observations	7,975	7,975	7,975	7,975	7,975	7,975
R-squared	0.283	0.082	0.283	0.287	0.091	0.287
Kleibergen-Paap F-stat.			97.585			97.585

Notes: Standard errors in parentheses are clustered at the country-industry level. Year, sector, and country fixed effects included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

In conclusion, when considering the impacts generated by robot adoption at the European level, we observe a positive effect on several employment outcomes. While this could suggest that reshoring might be occurring within this integrated economic market (Rodrik, 2018), only an analysis at the firm level could give us more insights on such a phenomenon. In addition, highly robotized sectors may be less vulnerable to competition from developing countries outside Europe, primarily due to the absence of competitive advantage in labour costs[19].

Subsequently, we aim to discern distinct patterns associated with the income status of the countries under examination. Typically, the prevailing approach in the literature is to investigate the influence of robotization in highly developed countries on less developed commercial partners. In our study, we classify the 23 European countries in our sample into two groups based on their GDP per capita levels, as previously shown in Figure 2.2 (panel A). Even though our countries all belong to common geographical and cultural areas, there are still differences when considering income levels. Not surprisingly we find that most of those belonging to the group of low income countries refer to Central and East European countries.

Our baseline model yields contrasting results for these two groups. As evident in Table 2.5, the positive impact of the Top 5 robotization disappears in the case

[19]In our analysis, we find that the country-sector units with the highest level of robotization tend to have the lowest wage-capital ratio.

of high-income countries, where the instrumental variable (IV) regression fails to reveal any significant effects. Conversely, when focusing on low-income countries, the impact is of greater magnitude than the entire sample, indicating that this category drives the previous findings. For this specific group of nations, the coefficients consistently exhibit statistical significance. We can think of some possible motivations for such result: the first is that, as evidenced before, the Central and East European countries belong to this group. In this regard, as Bachmann et al. (2024) found, where labour costs were lower the highest improvement has been for routine workers that represent the bulk of labour force in those countries. In our framework, even though not controlling for occupation content we can hypothesis that such channel may be at work. Moreover, the degree of functional specialisation of those countries, characterized by a large share of blue collars can directly be implied in a larger share of production for final demand in higher income countries (De Vries et al., 2020).

Table 2.5: Dependent var: Change in total Employment

	High-Income Countries			*Low-Income Countries*		
Variables	(OLS)	(FE)	(IV)	(OLS)	(FE)	(IV)
TRAED Index	2.162**	1.771*	1.534	4.870***	5.102***	6.234**
	(1.043)	(0.992)	(1.742)	(1.763)	(1.819)	(2.623)
Domestic Robot	-6.325*	-1.284	-6.117	10.50***	8.295**	10.28***
	(3.803)	(3.533)	(3.878)	(3.617)	(3.198)	(3.546)
Value Added Deflator	0.216***	0.273***	0.214***	0.0268	0.0359	0.0269
	(0.0676)	(0.0770)	(0.0683)	(0.0382)	(0.0420)	(0.0380)
Labour Cost	0.386*	0.339	0.390*	1.336**	2.014**	1.326**
	(0.206)	(0.271)	(0.203)	(0.608)	(0.869)	(0.604)
Constant	60.14***	63.97***	60.41***	74.04***	88.82***	74.23***
	(10.49)	(11.94)	(10.50)	(9.297)	(5.703)	(9.201)
Observations	3,428	3,428	3,428	4,571	4,571	4,571
R-squared	0.529	0.262	0.529	0.440	0.176	0.440
Kleibergen-Paap F-stat.			97.769			48.060

Notes: Standard errors in parentheses are clustered at the country-industry level. Year, sector and country fixed effects included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

In the appendix (refer to Table B4), we present the effects of the TRAED index on changes in workers embodied in exports for the two groups. Once again, we observe a consistent pattern. Significant effects are exclusively noticeable in the context of low-income countries, whereas the impact on high-income nations is essentially negligible. All these results reinforces the idea that the productivity effect is prevailing among the European area.

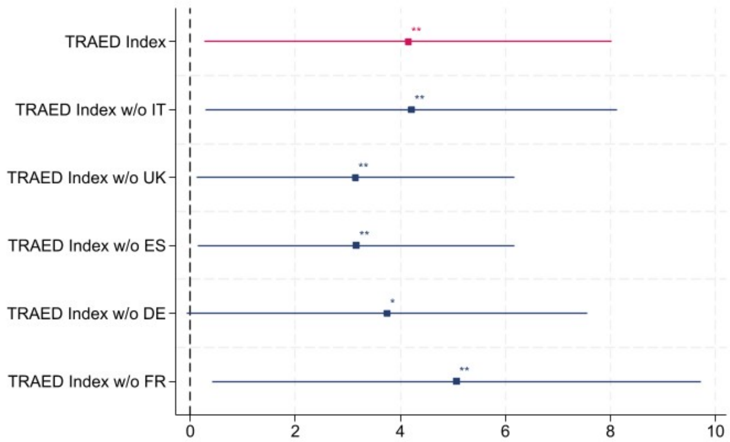
2.5 Further Analysis

In this chapter, we present several supplementary analyses. We aim to assess the robustness of the primary estimates and provide additional perspectives on the impact of robotization on the European labour market. Firstly, we decompose our composite indicator to determine if our results are driven by one of the Top 5 countries. Secondly, we change our dependent variable to investigate whether our overall positive results are valid also when considering as a dependent variable the number of hours worked. Lastly, we restrict our sample to manufacturing sectors, excluding ATECO codes of different industries. [20].

2.5.1 Decomposing the TRAED Index

Our objective here is to decompose the TRAED index to determine whether our results are sensitive to the exclusion of any one of the Top five countries. In Figure 2.4, we present the coefficients of modified versions of the TRAED index, considering different subgroups of countries[21]. The red line represents the results obtained using the complete TRAED Index for reference. Notably, even when Germany is excluded from the TRAED index, a positive association with employment change remains evident, though it is less statistically significant. All other subgroups yield results similar to the baseline model, consistently showing positive and significant effects on the employment levels of other European countries. This sensitivity analysis confirms that our findings are robust and not dependent on the evolving economic trend of specific countries.

Figure 2.4: Decomposed contribution to the TRAED index



Notes: ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

[20]Following Fernandez-Macias et al. (2021), we also split our sample into two different time periods (1995-2005 vs 2006-2018). The results are consistent with their analysis of European domestic robotization, showing higher positive effects in the first period. In addition, to assess the robustness of our results, we conducted also a series of tests by changing the starting year for calculating the total change in employment. Specifically, we used 1995, 2000, 2005, and 2010 as alternative starting points. The results remain consistent and statistically significant across these different starting years, with the TRAED_Index coefficient retaining its significant effect. This confirms the robustness of our findings, regardless of the chosen reference year

[21]In the figure, we report the coefficients related to the IV specifications with controls.

As a further robustness check of our index, we modify the approach used in equation (1) by focusing on the bilateral trade relationships between the countries under analysis and each of the top 5 European economies. Here, we have revisited the construction of the TRAED Index to ensure that it accurately captures the heterogeneity in Domestic Employment Embodied in Foreign Final Demand linkages and robot intensity across countries. The original aggregation method treated the Top 5 trade partners as a single unit, potentially overlooking variations in the distribution of linkages and automation intensity among individual trade partners. To address this, we have implemented a bilateral approach that computes the indicator separately for each country-top 5 pair and then aggregates these values weighted by the share of FFD_DEM for each partner. This refined method allows for a more nuanced analysis while maintaining the robustness of the results.
Mathematically, instead of aggregating the variables FFD_DEM and RD at the sectoral level as in equation (1), where the emphasis was mainly on sector-level interactions, we now compute a bilateral trade index toward each of the top 5 countries individually. Specifically, for each combination of country, sector, and year, we calculate five distinct bilateral TRAED indices, one for each of the top 5 European economies.

For each country c, sector i, and year t, the bilateral trade index with country j (one of the top 5) is calculated as follows:

$$\text{TRAED}_{c,j,i,t} = \log\left[\left(\frac{\text{FFD\_DEM}_{c,j,i,1995}}{\sum_p \text{FFD\_DEM}_{c,p,i,1995}} \times \text{RD}_{j,i,t}\right) + 1\right]$$

Here:

- $\text{FFD\_DEM}_{c,j,i,1995}$ represents the Domestic Employment Embodied in Foreign Demand from country j (one of the top 5 economies) for country c in sector i in the base year 1995.

- $\sum_p \text{FFD\_DEM}_{c,p,i,1995}$ is the total Domestic Employment Embodied in Foreign Demand from all partners p for country c in sector i in 1995.

- $\text{RD}_{j,i,t}$ is the robot density for country j in sector i and year t.

Once these bilateral indices are computed for each of the five top economies, we then take a weighted average of these indices, using the FFD_DEM variable as weights, to obtain a new aggregated version of the TRAED index. This revised approach allows us to capture the trade connections between countries more precisely by incorporating individual bilateral relations.
In Table 2.6, we present a series of IV regressions, where we replace the original specification of the TRAED index (as introduced in section 2) with the new version. Importantly, the results from section 4 remain robust, indicating that both specifications capture similar effects. Also for the change in total employment in high-income countries, as noted previously, we do not find any statistically significant coefficients. Overall, even with this modification of the TRAED index, which highlights the bilateral relationships with the Top 5 economies, the positive impact of robotization in these leading economies on employment changes in the 23 European countries analyzed is confirmed.

Table 2.6: Previous regressions with the new specification of the TRAED Index

	Whole Sample			*Subsample change in total workers*	
Variables	tot. empl.	interm. input	final input	Less-income	High-income
New_Traed_Index	4.042*	21.24***	11.59**	6.096*	1.553
	(2.111)	(7.101)	(5.319)	(3.156)	(1.831)
Labour_Cost	0.340	0.436	0.249	1.323**	0.381*
	(0.254)	(1.000)	(0.570)	(0.616)	(0.201)
GDP_Deflator	0.0745*	0.00706	-0.00460	0.0308	0.214***
	(0.0406)	(0.177)	(0.0966)	(0.0391)	(0.0687)
Domestic_Robotization	6.753**	0.851	-9.238	9.490***	-6.007
	(3.081)	(12.35)	(10.17)	(3.624)	(3.852)
Constant	64.19***	2.988	47.35	73.38***	60.14***
	(9.928)	(67.48)	(39.74)	(9.229)	(10.66)
Observations	7,999	7,975	7,975	4,571	3,428
R-squared	0.414	0.284	0.288	0.443	0.531
Kleibergen-Paap F-statistics	26.885	26.889	26.889	13.551	34.943

Notes: Standard errors in parentheses are clustered at the country-industry level. Year dummies included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

2.5.2 Hours Worked

In this section, as an additional robustness check, we use the change in hours worked compared to the first observed year as the dependent variable. The results are presented in Table 2.7. Although this additional analysis is limited to a smaller sample, as the STAN database provides data on hours worked for only a subset of our selected countries, the findings reported in Table 2.3 are generally corroborated. The TRAED index maintains its positive and significant impact on the dependent variable, suggesting a prevalence of the productivity effect at the European level. However, when focusing on the IV specification, for the whole sample we do not observe significant effects. In Table B5, we replicate the same analysis by categorizing countries based on their GDP levels. In this case, even in the IV regression, we observe positive and significant impacts for low-income countries. Conversely, and in line with expectations, we report non significant effects for high-income countries.

Table 2.7: Dependent var: Change in Hours Worked

	OLS		FE		IV	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TRAED Index	5.077***	5.048***	4.348***	4.002***	3.146*	3.344
	(1.205)	(1.280)	(1.226)	(1.263)	(1.907)	(2.137)
Domestic Robot		5.650**		8.250***		5.734**
		(2.715)		(2.395)		(2.803)
Value Added Deflator		0.0338		0.0162		0.0438
		(0.025)		(0.031)		(0.032)
Labour Cost		-0.235		0.498*		-0.218
		(0.215)		(0.260)		(0.220)
Constant	103.5***	104.1***	97.10***	91.68***	103.9***	103.7***
	(8.407)	(9.782)	(5.584)	(6.319)	(8.615)	(10.28)
Observations	6,394	6,175	6,394	6,175	6,036	5,841
R-squared	0.324	0.340	0.140	0.169	0.326	0.342
Kleibergen-Paap F-statistics					73.646	71.267

Notes: Standard errors in parentheses are clustered at the country-industry level. Year dummies included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

2.5.3 Sub-sample Analysis

In this last econometric exercise, we restrict our sample to manufacturing industries only. Out of the 20 economic sectors included in our analysis, three are not manufacturing industries (Agriculture, forestry, fishing; Electricity, gas, water supply; Construction). We remove these three sectors from our econometric specifications to ensure that our results are not driven by them. As shown in Table 2.8, all our previous results are confirmed by this robustness check. For the new sample, the positive and significant effect of the TRAED index appears even more statistically robust, particularly if we focus on the IV specification. Additionally, the previously observed divergent results between high- and low-income countries are further confirmed by this supplementary analysis.

Table 2.8: Dependent var: Change in total Employment for manufacturing sectors

	Whole Sample			*High-Income Countries*			*Low-Income Countries*		
Variables	(OLS)	(FE)	(IV)	(OLS)	(FE)	(IV)	(OLS)	(FE)	(IV)
TRAED Index	4.320***	4.479***	3.600***	0.728**	0.961	-0.993	6.083***	6.517***	6.205***
	(0.509)	(1.228)	(0.926)	(0.309)	(0.901)	(0.622)	(0.745)	(1.813)	(1.360)
Constant	86.90***	87.21***	89.54***	95.01***	86.67***	102.4***	80.51***	77.83***	80.07***
	(2.965)	(5.288)	(4.273)	(2.326)	(6.349)	(3.455)	(3.905)	(7.920)	(5.941)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,645	6,645	6,645	2,852	2,852	2,852	3,793	3,793	3,793
R-squared	0.281	0.136	0.281	0.547	0.414	0.543	0.296	0.132	0.296
Kleibergen-Paap F-stat.			97.602			212.585			122.585

Notes: Standard errors in parentheses are clustered at the country-industry level. Year, sector and country fixed effects included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

2.6 Conclusions

Despite the level of empirical analysis, when considering the robot-employment nexus scholars are primarily interested in the impact generated within the country of adoption (Acemoglu and Restrepo, 2020; Koch et al., 2021; Klenert et al., 2023). Still, a small part of this literature is also concerned in addressing the impact on other trade-related countries: it means that adoption of robots can generate an impact on countries that are connected with the adopting country through trade relationships. These papers are mainly devoted to understand what happens to employment dynamics in developing countries (Faber, 2020). However, the empirical evidence remains marked by significant contradictions, mainly due to the difficulties in understanding which kind of channel is at work to generate the final impact. Both displacement and productivity effects can be at work, thus potentially affecting employment negatively and positively respectively. Moreover, the diversity in empirical approaches and levels of analysis introduces additional complexity to the relationship.

The main aim of our paper is providing an alternative country-sector perspective in the examination of the robot impact in a highly trade-integrated market focusing on the European experience. As extensively discussed in the literature review, understanding the relationship between robots, employment, and trade is a complex challenge. A straightforward analysis of robots and employment, or robots and trade separately, would simplify the task but risk missing the broader picture. For this reason, we develop a new trade-weighted index (TRAED index) measuring the indirect impact of Top 5 European economies robot adoption on different measures of employment in the rest of Europe.

The introduction of this novel index allows us to investigate the repercussions of robotic investments on employment trends in European countries that are commercially linked to our Top 5 Economies, while featuring a new measurement of GVC relationships that takes into consideration the employment content tied to fulfilling the final demand of these leading economies.

This is particularly relevant as accounting for employment content of trade has never been done before. Only a study specifically focused just on Germany adopts a similar perspective, but with different methodologies (Graf and Mohamed, 2024). Instead, we provided a new perspective by furnishing empirical evidence on the impacts of robot adoption finding that cross-border effect may still be at work even within a quite homogeneous economic area.

Our main results indicate a positive association between this index and the various employment measures. Furthermore, the instrumental variable strategy confirms the robustness of our findings, highlighting a positive and significant causal relationship of the TRAED index on employment outcomes. This fact suggests that, within the strongly integrated European market, the productivity effect deriving from robot adoption outweighs any potential re-shoring effect. It is also a confirmation of the literature finding a positive effect generated by robot adoption through higher productivity (e.g. Bonfiglioli et al. 2024; Duan et al. 2023).

It seems quite relevant also that when extending the analysis, positive results are more significant in lower income levels. This may stand for the fact that intermediate input needs in high-income countries are satisfied mainly by workers in low-income countries, thus positively influencing their employment dynamics. This finding appears to be unique to the European case, as contrasting results are evident in other economic contexts (see, for example, Díaz Pavez and Martínez-Zarzoso 2024). As clearly described in a recent paper by Bontadini et al. (2024), European countries exhibit a structure characterized by headquarters and factory economies, where central economies can purchase intermediate products at lower prices from Eastern European countries. This evidence aligns well with our results, suggesting that an increase in productivity in top economies, driven by robot adoption, leads to a subsequent increase in employment in low-income countries. According to our estimations, the latter result seems to be pulled by workers embodied in the exports of intermediate inputs. Among the policy implications that can be drawn from these results two mainly stand out: the first is that it is not enough to care about the effects of automation investments within the same country of adoption as the consideration of international linkages of the country may generate effects that can be relevant as well. The second, which is connected to the first, refers to the idea that the technological policy of a country needs to be intertwined with the consideration of the employment dynamics of countries that are productively connected.

As a final remark and as a way to open further lines of research, we evidence that our framework and new empirical approach can be extended also to consider trade linkages outside Europe, to understand whether the positive effect of employment can still hold considering other country-sector contexts. We could potentially consider other countries within the Top 5, including for example US or Japan but the analysis would lose its regional perspective. A second important research avenue to be explored in the future is relative to the use of firm level data. It would allows two kinds of literature advancement: firstly, it would foster the development of a more nuanced comprehension of the economic impact of robot adoption, secondly it would enable to leave out the assumption that every single firm operating within a particular sector possesses an identical capacity and willingness to embrace robotic technologies as well as being impacted by it. As also evidenced by Klenert et al. (2023), we recognize that using firm level data has the advantage of diminishing the significance of measurement error within the overall variation. At the same time, through the use of firm level data it would be possible to achieve a different and complementary perspective of the robot adoption approach: the possibility of disentangling the displacement effect from the effects describing the creation of new tasks and productivity effects would be feasible. As Seamans and Raj (2018) point out, the need for more firm level studies depicting the behavior of firms with respect to robot adoption is urgent. At the same time, through the analysis at the firm level impact is not possible to achieve a complete picture, as the reallocation effect is not so evident as when employer-employee data are use (e.g. Dauth et al. 2021). Thus, the two levels of analysis can result as complementary. However, in our framework, working with firm level data is so far not feasible as we catch not only the amount of export activities but also the employment content. Finally, although these data and the index we built have many advantages, we do not have available data that account for robot adoption at the occupation-sector level by incorporating also the employment content of exports. The approach followed by Bachmann et al. (2024) can be a promising avenue for further research as it would help measuring more precisely and follow the employment dynamics at the workers level.

Chapter 3

The Italian Great Resignation: just a Reallocation trend?

3.1 Introduction

The Covid-19 pandemic has profoundly transformed labor markets worldwide (Cortes and Forsythe, 2023), leaving a lasting impact on various aspects of human life. Much of the existing literature has explored the asymmetric effects on employment levels across and within countries (Fana et al., 2020), as well as the heterogeneous consequences for firms' performance (Shen et al., 2021).

Among the various labor-related topics connected to the Pandemic, one phenomenon has gained significant attention in the media but remains relatively underexplored in economic literature: the so-called "Great Resignation" (GR). The term was first proposed in May 2021 by Klotz (2021) to describe the unprecedented increase in workers' voluntary resignations observed in the U.S. labor market.[1] To illustrate the magnitude of this trend, data released by the U.S. Bureau of Labor Statistics (BLS) show that in November 2021 and in March 2022, 4.5 million American workers voluntarily left their jobs, marking the highest levels ever recorded (Bureau of Labor Statistics, 2022b,a). This unprecedented wave of voluntary resignations, which reached record levels in the United States, has also been observed - albeit on a smaller scale — in other countries, such as Australia, Germany, and France, reflecting a broader shift in labor market dynamics (Horowitz, 2022). Concerning Italy, our case of study, the phenomenon of the GR was brought to the fore by the popular-science book: "*Le grandi dimissioni. Il nuovo rifiuto del lavoro e il tempo di riprenderci la vita*" written by the sociologist Francesca Coin. In the book, the author provides a comprehensive overview of the GR as a global phenomenon, with a particular focus on Italy, adopting mainly a qualitative approach based on workers' interviews. In terms of quantitative analysis, although some official statistics sources and a working paper offer preliminary insights into the phenomenon (Brunetta et al., 2022; Ministero del Lavoro e delle Politiche Sociali, 2023), confirming its relevance also in the Italian context, a comprehensive multivariate analysis is still lacking.

The few researchers who have attempted to understand this multifaceted phenomenon have primarily focused on two key dimensions: identifying its underlying

[1] This phenomenon has also been referred to as the "Big Quit" by Curtis (2021) in a popular article on Forbes.

determinants and exploring whether it reflects a true rise in quitting or rather a shift toward job switching. Regarding the causes of the GR, some scholars have highlighted factors closely tied to workers' sentiments about their jobs, such as persistent issues with low wages, lack of recognition for achievements, feelings of disrespect, toxic or negative workplace cultures, and the pursuit of professional satisfaction and purpose (Formica and Sfodera, 2022; Parker and Horowitz, 2022). Others have emphasized the role of the Covid-19 pandemic itself, arguing that the phenomenon was more systemic and predictable by analyzing pre-pandemic labor market trends[2] (Fuller and Kerr, 2022). Finally, some studies have investigated potential connections between the Great Resignation and the rise of remote work, suggesting that increased flexibility may have contributed to reshaping workers' decisions (Barrero et al., 2021). Secondly, beyond identifying the underlying causes, a smaller body of research has also focused on disentangling whether the GR is primarily characterized by workers quitting the labor force altogether or by a large-scale reallocation of labor through job switching (Brunetta et al., 2022; Thompson, 2021). According to Birinci and Amburgey (2022), the Great Resignation is primarily driven by a trend of Great Reallocation, characterized by job-to-job transitions. In contrast, Lambert (2023) highlights that while quit rates in the U.S. began rising alongside an increase in job openings, data reveals a persistent gap between job vacancies and job seekers. This could suggests that some individuals have left their jobs without seeking new employment. However, the existing literature on this topic remains limited, highlighting the need for further research to provide new evidence and deeper insights.

In this work, we contribute to the literature by providing evidence for the Italian case through a multivariate econometric analysis. Using official statistics data from the Italian Ministry of Labour, we begin by identifying the questions within the Italian Labour Force Survey that can isolate the phenomenon. This allows us to investigate whether the Italian GR is more closely related to job switching or outright quitting. After establishing the appropriate measure to capture the trend, we compare two sample of representative Italian workers (before- and post-Covid) and we conduct an econometric analysis to identify the underlying determinants of the GR. Finally, we complement our study with decomposition and counterfactual analyses to assess the role of unobservable psychological factors linked to the pandemic, as well as to evaluate the influence of wages in this context.

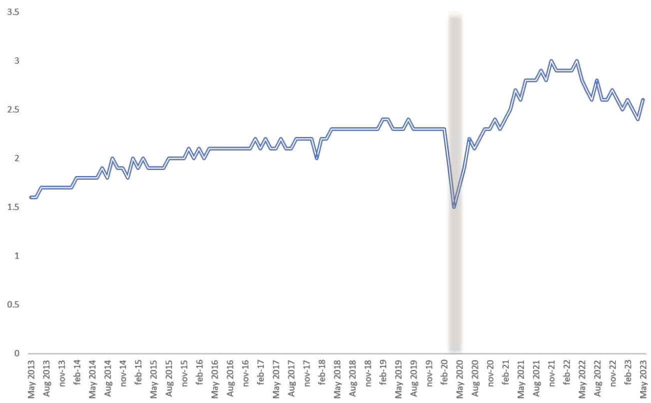
The remainder of the paper is structured as follows: Section 2 outlines the existing literature. Section 3 compares two indicators to capture the GR in Italy and, after presenting the data and variables used in the empirical analysis, it provides some preliminary descriptive evidence. Section 4 describes the empirical strategy and discusses the econometric results. Finally, Section 5 concludes and explores the implications of the findings.

[2]This perspective, however, has been partially challenged by recent data from the Bureau of Labor Statistics, showing low quit rates in subsequent years (Bureau of Labor Statistics, 2025).

3.2 Literature Review

The term Great Resignation refers to the unprecedented wave of voluntary resignations among U.S. workers that began in the spring of 2021. As mentioned in the Introduction, Klotz (2021) coined this term to describe the phenomenon, while Curtis (2021) refers to the same trend using the expression Big Quit. As shown in Figure 3.1, data from the Bureau of Labor Statistics indicate that resignation rates have reached their highest levels in at least a decade. During the COVID-19 pandemic (the shaded area in the graph), the quit rate dropped to its lowest point between 2013 and 2023. However, following the most critical phase of the pandemic, as economic activity resumed, voluntary resignations surged. In the U.S., the peak was recorded in November 2021 and March 2022, when approximately 4.5 million American workers voluntarily left their jobs. Although an increase in resignations is relatively normal after a recession, the study by Amanor-Boadu (2022) shows that, even when controlling for economic growth, the quit rates following the COVID-19 shock were statistically higher than in previous cases, such as the Great Recession. This suggests that the phenomenon is not driven solely by economic recovery, but may be influenced by factors specific to the pandemic itself.

Figure 3.1: Authors' elaboration based on data from the Bureau of Labor Statistics, U.S. Department of Labor (2023)



In support of the exceptional nature of this event and its strong connection to the Pandemic, it is worth noting that, during the same period, another phenomenon emerged in the labor market—widely discussed in both media and academic literature as Quiet Quitting (QQ)[3] Thir term refers to employees performing only their formal job duties, indicating low commitment and reduced engagement. While scholars generally agree that both trends (RR and QQ) are linked to the aftermath of the COVID-19 pandemic, there is no consensus on whether they were directly caused

[3]The term QQ refers to the practice of employees fulfilling only the minimum requirements of their job without taking on additional tasks beyond their formal job description (Yıldız, 2023). It reflects a low level of commitment to work, where individuals disengage from organizational goals and refrain from exceeding their assigned duties (Formica and Sfodera, 2022). Although the term was originally coined by economist Mark Boldger at the Texas A&M Economics Symposium in 2009, it gained widespread attention in 2022, in the wake of the GR. In the US, in the second quarter of 2022, the ratio of engaged to actively disengaged employees was 1.8 to 1, with 32% classified as engaged and 18% as actively disengaged; the lowest level of engagement recorded in the past decade (Harter, 2022).

by pandemic-related restrictions (Formica and Sfodera, 2022). Some authors argue that COVID-19 acted as a catalyst, accelerating preexisting workplace trends, but it is indisputable that the pandemic—particularly through governmental restrictions—had profound psychological and social effects on workers, fundamentally reshaping work-life balance (Yıldız, 2023).

Another key issue is determining whether the Great Resignation was merely a wave of job switching or a lasting exit from the labor market. As Lambert (2023) explains, post-recession recoveries typically see rising quit rates and job openings, encouraging job switching. However, after COVID-19 in the U.S., a persistent gap between job seekers and vacancies suggests many who quit did not seek new employment. A Goldman Sachs report (November 2021) estimates that 3.4 million Americans over 55 and 800,000 aged 25–54 left the workforce without plans to return (Goldman Sachs, 2021). Notably, younger workers who resigned were more likely to refrain from job searching. Birinci and Amburgey (2022) find that in leisure and hospitality, quits were driven by job-to-job transitions, whereas in manufacturing and construction, most were not. Meanwhile, Fuller and Kerr (2022) emphasize reshuffling and early retirement, aligning with Thompson (2021), who highlight job switching and moderate early retirements. Outside the U.S., Brunetta et al. (2022) suggest that Italy's trend was primarily job-to-job transitions.

Having outlined the labor context of the GR, the following discussion will examine the key factors identified in the literature as explanations for the GR. By reviewing existing studies, we aim to highlight the main economic, psychological, and organizational drivers behind this phenomenon. Finally, we will briefly present the Italian context during the pandemic to better define the setting for our empirical analysis.

3.2.1 Determinants of the Great Resignation

To better understand the Great Resignation, it is essential to examine the key factors identified in the literature that have contributed to this unprecedented wave of voluntary resignations. Scholars have explored various economic, psychological, and organizational drivers behind this phenomenon, shedding light on the underlying motivations that led millions of workers to leave their jobs. Applying a moral economic framework and employing BERTopic analysis, Varavallo et al. (2023) identify three key dimensions underlying the Great Resignation: "Work and Employment" (organizational dynamics), "Social Justice and Activism" (community-driven factors), and "Health, Well-being, and Lifestyle" (individual motivations). Their findings emphasize drivers such as flexibility, meaningful work, social responsibility, and self-care, basically the same factors that Nikolova (2024) found in her study on Dutch representative data. While their study provides valuable insights by making use of social media data, the authors themselves recommend future research using micro-level data to refine the understanding of the mechanisms behind this phenomenon. Consistently, survey data from Parker and Horowitz (2022) indicate that the majority of workers who left their jobs in 2021 cited low wages (63%), lack of career advancement opportunities (63%), and workplace disrespect (57%) as primary reasons. Nearly half pointed to childcare responsibilities (48% among those with children under 18), inflexible work schedules (45%), or inadequate benefits such as health insurance and paid leave (43%). Furthermore, findings from the survey highlight demographic disparities in resignation rates, with younger workers and lower-income individuals being more likely to leave their jobs. Across educational levels, individuals with postgraduate degrees reported the lowest likelihood of having resigned in 2021 (13%), compared to 17% of those with a bachelor's degree, 20% of those with some college education, and 22% of those with a high school diploma or lower. These findings collectively illustrate the multifaceted nature of the Great Resignation, driven by structural, social, and individual-level factors.

Several scholars have tried to specifically determine whether COVID-19 played a significant role in driving the Great Resignation. Formica and Sfodera (2022) argue that the pandemic primarily acted as a catalyst, accelerating preexisting trends in specific industries, such as hospitality. In addition, in their study, they highlight key contributing factors, including low wages, poor working conditions, toxic workplace cultures, lack of meaningful work, and feelings of disrespect. Similarly, Lambert (2023) adopts a labor market segmentation approach, analyzing U.S. data dating back to 2003. His findings suggest that resignation rates had already been increasing in certain sectors since the early 2000s, indicating that the Great Resignation is part of a longer-term pattern rather than a sudden anomaly. Also Fuller and Kerr (2022) do not believe that the Great Resignation began with the pandemic; rather, they argue that it represents the continuation of a long-term trend. To explain the underlying factors driving this phenomenon, they developed the theory of the five Rs: Retirement, Relocation, Reconsideration, Reshuffling, and Reluctance. Their analysis suggests that, unlike in previous recessions, the pandemic accelerated the exit of older workers from the labor force, prompting earlier retirements. They find no significant evidence of large-scale relocation across U.S. states, though there is clear indication of a widespread reassessment of work-life balance. Moreover, their findings suggest that the trend is better characterized as reshuffling rather than mass resignation, as data from the Bureau of Labor Statistics (BLS) indicate that hiring rates in several sectors have exceeded quit rates. Finally, some workers also exhibit reluctance to return to in-person work.
However, two studies published in the Monthly Labor Review challenge this perspective, arguing that the Great Resignation is, in fact, an anomaly within the long-term trends of the labor market. Gittleman (2022), using historical data, demonstrates that while recent quit rates are not the highest in recorded history, they have surged more rapidly in the 21st century than what would be expected from labor market trend alone. In addition, the study calls for further research to assess whether workers are exiting the labor force entirely or transitioning to better job opportunities. Similarly, Amanor-Boadu (2022) finds that, even after controlling for economic growth, the quit rates observed during the pandemic were statistically distinct from those recorded during the Great Recession and the dot-com downturn, underscoring the unique nature of this phenomenon and its strong link to COVID-19. A key question that arises is why the pandemic might have fundamentally altered individuals' attitudes toward work. One possible explanation is the widespread adoption of remote work, which reshaped employee expectations and workplace norms (Yıldız, 2023).

During the COVID-19 pandemic, governments worldwide imposed quarantine and isolation measures, requiring many businesses to rapidly transition to remote operations, albeit with significant variations across industries (Bartik et al., 2020). While according to some studies remote work negatively impacted employee motivation and severely disrupted work-life balance (Vyas, 2022), also contributing to increased family conflict (Prime et al., 2020), the majority of workers came to view it as an essential benefit (Barrero et al., 2021). Findings from the June Survey of Working Arrangements and Attitudes, analyzed by Barrero et al. (2021), highlight the pivotal role of remote work preferences in driving the Great Resignation. According to their results, 58% of surveyed employees indicated they would comply with their employer's directive to return to full-time, in-person work. However, 36% stated they would comply while actively seeking a job that allows remote work, and 6% reported they would quit rather than return to full-time office work. Additionally, 56% of workers expressed a higher likelihood of considering a new job if it offered a hybrid work arrangement. Before we, in turn, examine in a more systematic way the Italian data to investigate the specific determinant factor for this country, it is important to consider and explore the specific circumstances this country faced during the COVID-19 crisis.

3.2.2 The Italian Case

Italy was one of the first European countries to experience the outbreak of COVID-19, leaving little time for preparation. In response to the rapid spread of the virus, the Italian government implemented sectoral lockdowns in March 2020. However, excess mortality remained high, likely due in part to the demographic structure of Italy, characterized by a high proportion of older adults compared to younger individuals[4]. Maida et al. (2024) analyze excess mortality by comparing average mortality rates from March to May in the years 2015–2019 with those recorded in the same period in 2020 at the local labor market level, revealing that actual cases of COVID-19 were significantly higher than official data suggested. In this period, Italian workers faced significant challenges both in terms of economic stability and health risks. Barbieri et al. (2022) analyze the heterogeneous effects of the pandemic in different sectors, highlighting that while healthcare workers were the most exposed to contagion, other sectors such as leisure and trade, in the case of professions that require physical proximity, also faced substantial infection risks. In this complex and evolving scenario, Italy also experienced an increase in voluntary resignations. In the second semester of 2021, resignations increased by 37% compared to the previous semester, 85% compared to the same period in 2020, and remained 10% higher than in the same semester of 2019 (Armillei, 2021).

A detailed and qualitative analysis of the Italian "Great Resignation" is provided in the book *Le Grandi Dimissioni* by sociologist Francesca Coin. Through a combination of different sources and personal interviews, Coin examines the profound challenges faced by workers during COVID-19, particularly in three key sectors deeply affected by the Pandemic: healthcare, food services, and large-scale retail. Her picture is strikingly dramatic, revealing how many Italian workers experienced exhausting shifts, the absence of vacation time, elevated risks of contagion, and work environments characterized by racism and male chauvinism. In numerous cases documented in the book, workers were compelled to resign, either seeking employment abroad —- especially in the healthcare sector—or transitioning to different industries. Coin's analysis underscores the persistence of deep-rooted structural issues in the Italian labor market, while also suggesting that the COVID-19 pandemic may have served as a catalyst, prompting workers to become more aware of their con-

[4] See https://noi-italia.istat.it/pagina.php?id=3&categoria=3&action=show&L=0

ditions and take steps toward change (Francesca Coin, 2023). Focusing exclusively on 2021 and drawing on official INPS data, Brunetta et al. (2022) demonstrate that the observed rise in resignations is primarily driven by a job-switching trend, as the data also reveal a simultaneous increase in worker mobility. Furthermore, Brunetta et al. (2022) report that voluntary resignations in 2021 increased by 11.6% compared to 2020, whereas in 2020, they had declined by 14.9% relative to 2019. Therefore, the authors suggest that the surge in resignations in Italy reflects a phenomenon of "postponed resignations", as many workers were unable to leave their jobs in 2020 due to the labor market freeze. However, given the newly available data for 2022, which show that resignation rates have remained consistently above 2021 levels, it is evident that this trend cannot be attributed solely to a delayed wave of mass resignations. To this end, we aim to provide a more detailed quantitative analysis that not only explores whether the Italian Great Resignation is merely a case of job switching or rather indicative of a more permanent quitting trend but also seeks to identify the key determinants behind workers' decision to resign.

3.3 GR Indicators and Descriptive Evidence

3.3.1 GR Indicators

In Italy, the official data source for tracking resignations is the *Communicazioni Obbligatorie* (COB) dataset, an administrative database managed by the Ministry of Labor, which contains all job activations and terminations. Within job terminations, it is also possible to trace the cause and therefore identify workers' voluntary resignations. However, while this represents a fundamental source for analyzing trends and measuring the extent of the Italian Great Resignation (GR), the COB cannot be directly used in our multivariate analysis because it lacks detailed worker-level characteristics, which are essential for understanding the determinants of a complex phenomenon like the GR. Therefore, to explore this complexity, we rely on the Italian Labour Force Survey (ILFS), a quarterly dataset provided by ISTAT that is representative of the Italian workforce.

The ILFS provides a range of worker-specific variables essential for conducting a robust econometric analysis. Although it does not include a direct indicator for resignations, we construct two indices based on survey responses, following the two distinct approaches discussed in the literature: job quitting and job switching. The Switching indicator is a binary variable that takes the value of 1 if a worker meets specific conditions based on three ILFS survey questions:

1. **COND3** – What is your professional status?
2. **F1** – Are you looking for another job?
3. **F2** - Are you seeking a new job or an additional one?

Specifically, the indicator equals 1 when individuals report being employed (**COND3**) and actively searching for another job (**F1**), but explicitly states that they are looking to replace their current job rather than seeking additional employment (**F2**). This distinction is crucial, as those looking for supplementary work represent a different phenomenon unrelated to the GR.

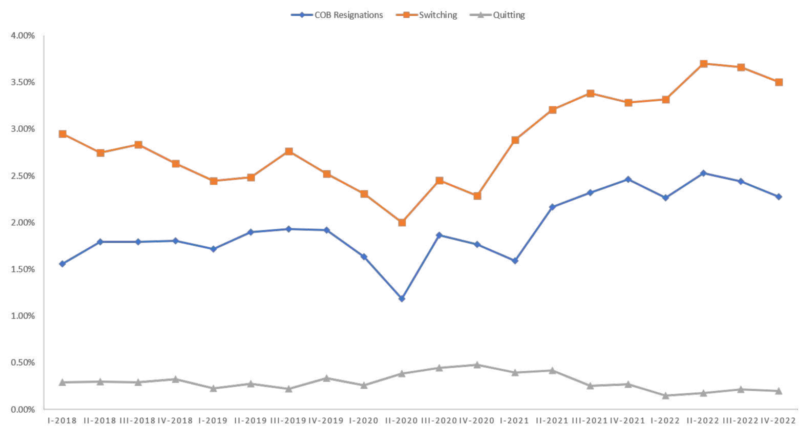
Conversely, the Permanent Quitting indicator is based on the following ILFS survey questions:

1. **COND3** – What is your professional status?
2. **E1** - Have you ever had a job in your life?
3. **E2** - In which year did you stop working?
4. **E14/E15** - What was the reason for leaving your last job/working activity?

Similar to the Switching indicator, the Permanent Quitting indicator is also a binary variable. It takes the value of 1 for individuals who are no longer employed (**COND3**) but reported having held a job within the past year (**E1**). However, to ensure that the indicator captures voluntary resignations rather than other forms of job separation, we exclude individuals who left the workforce due to retirement, were dismissed (including cases of firm closures), or whose contracts simply expired (**E14/E15**). This approach allows us to better isolate cases of voluntary job quitting, which are more directly linked to the phenomenon of the GR.

In Figure 3.2, we present the trend of the two indices over the period 2018–2022 (the timeframe analyzed in our econometric section), expressed as rates relative to the total employed population and broken down by quarter. For comparison, we also include the official trend of resignations derived from the COB dataset.[5]

Figure 3.2: Comparison of trends between official Italian resignation statistics and our reconstructed proxies.



A first observation of the graph reveals a striking similarity between our Switching indicator and the official trend of the GR, while the Permanent Quitting indicator appears to capture a distinct phenomenon. What is particularly noteworthy, however, is that this visual impression is strongly corroborated by the correlation analysis: the Switching index exhibits an exceptionally high positive correlation (0.86) with the COB trend on resignations. Given the complexity of job transitions and the multiple factors influencing career mobility, such a strong alignment was far from guaranteed. This finding suggests that our index not only captures this dynamic but does so with remarkable precision. The difference in absolute numerical rates can largely be explained by the fact that not all workers seeking to change jobs successfully secure new employment, as quitting without an alternative is particularly risky in the Italian labor market.

Conversely, the visual representation already suggests that the Permanent Quitting indicator does not align with the official resignation trend. Instead, it serves as a proxy for a different aspect of labor market dynamics, displaying a negative correlation with the COB data (-0.51). This distinction is crucial in addressing the open question of whether resignations primarily reflect professional mobility or labor force withdrawal. Our findings suggest that, at least in Italy, the GR is better interpreted as a reallocation trend rather than a widespread exit from the labor market. Assuming our Switching indicator is a reliable proxy, we further provide descriptive evidence on the underlying reasons why workers seek to leave their current jobs in pursuit of better opportunities.

[5] The data on resignations come from the COB dataset, while the official number of employed individuals is taken from ISTAT's quarterly series on employment, available at the following link: http://dati.istat.it/Index.aspx?DataSetCode=DCCV_OCCUPATITDE1.

3.3.2 Variables

In the final dataset, we divide the sample into two groups: pre-Covid and post-Covid. The pre-Covid group includes the ILFS quarters from 2018 and 2019, while the post-Covid group consists of the quarters from 2021 and 2022. We exclude observations from 2020, the year Covid-19 reached Italy and significantly disrupted the Italian labor market. We end up with approximately 729,000 workers, well distributed across the two different periods of analysis.

Since our econometric analysis aims to understand the determinants of the Italian GR, our dependent variable is the Switching Indicator, previously introduced in the last section. Given the high correlation displayed between the Switching Indicator and the official COB trend, we are confident that our measure works as a reliable proxy for the GR phenomenon. We then incorporate a set of explanatory variables that may influence the decision to quit a job. The first is a dummy variable equal to one for workers interviewed in the post-Covid period. By including this dummy, we hypothesize that, after controlling for other potential confounders, if this variable retains a statistically significant impact on resignation decisions, it might capture individual psychological and unobservable factors related to the pandemic.

Next, we examine the relationship between job resignation and several individual characteristics, including gender, years of education, age, and partnership status. We also account for job-related features particularly relevant in this context, such as working hours, contract type (permanent vs. temporary) and firm-size. Additionally, we include fixed effects for both the worker's sectoral code and the macro-region where the job is located.

Following the task-based literature, which explores how occupation-specific characteristics influence workers' sense of meaningfulness and, consequently, their decision to quit (Nikolova and Cnossen, 2020), we incorporate five continuous task indicators: work autonomy (WA), routine manual (RM), routine cognitive (RC), social intelligence (SI), and flexibility. These indicators are reconstructed using the 2013 edition of the *Indagine Campionaria sulle Professioni* (ICP), an Italian O*Net-type database. Our indicators are based on classical task measures widely discussed in the economic literature (Autor and Dorn, 2013; Goldin, 2014; Frey and Osborne, 2017). Table C1 lists all the ICP questions used to construct these task indicators, which are linked to the ILFS at the 4th ISCO digit level.

As highlighted in the literature, another potential determinant of resignation decisions is the feasibility of remote work. To account for this, we compute an additional task index based on the indicator proposed for the U.S. by Dingel and Neiman (2020). Using multiple O*Net questions, the authors developed a binary indicator to identify occupations that cannot be performed from home. A detailed description of the ICP questions used to reconstruct the remote work (RW) indicator is provided in Table C1.

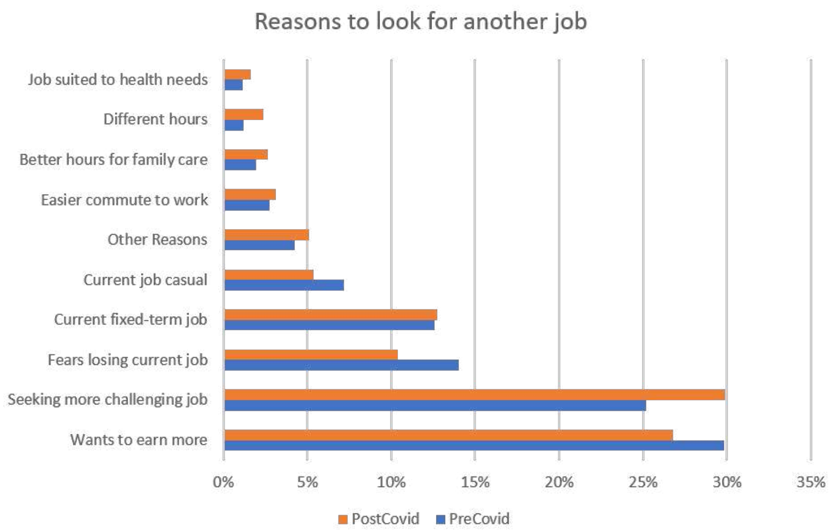
Finally, we introduce a proxy for net monthly wages. Unfortunately, this variable is only observable for the pre-Covid period. To address this limitation, we impute values for the post-Covid observations by calculating the median wage based on the 4th digit ISCO code, the macro-sectoral code, and the macro-region where the work is performed.

3.3.3 Descriptive Analysis

In Table C2, we present the means and standard deviations (SD) of our key variables, stratified by individuals interviewed before and after the COVID-19 pandemic. The only variable exhibiting a notable change between the two groups is the Switching indicator. Specifically, the proportion of workers seeking alternative employment was 2.9% in the pre-COVID period, rising to 3.5% in the post-pandemic period. Regarding other individual and job-related characteristics, the two samples appear well-balanced in terms of gender, age, years of education, cohabitation with a partner, and hours worked. Notably, the remote working indicator reveals that approximately 60% of Italian workers are employed in occupations requiring constant physical presence at the workplace. Overall, the two groups exhibit remarkably similar values across most variables, suggesting minimal compositional differences. Nevertheless, in the econometric analysis, we further investigate the potential influence of compositional effects on the dynamics of the Italian GR through a decomposition analysis.

To better understand the drivers of this phenomenon, Figure 3.3 presents the reasons for seeking new employment (based on question F3 of the ILFS), stratified by individuals interviewed before and after the COVID-19 pandemic. The most striking finding from this descriptive analysis is the shift in primary motivations. In the pre-pandemic period, the predominant reason for seeking new employment was the desire to increase one's wage. However, in the post-pandemic era, the primary motivation has shifted significantly toward the pursuit of more fulfilling work, better aligned with individuals' skills and competencies. These preliminary results suggest a growing emphasis on meaningful work and overall well-being among workers, reflecting a potential psychological shift in labor market priorities. This hypothesis is further supported by the observed increase in the percentage of respondents citing reasons related to achieving a better work-life balance, such as the need to spend more time on family care or to reduce commuting time. Additionally, a notable decline is observed in the fear of losing one's current job, a trend that could align with the economic recovery following a period of significant recession. In the econometric section, we further explore the role of monetary incentives through a counterfactual analysis.

Figure 3.3: Comparison of reasons for seeking new employment among individuals interviewed before and after the Covid-19 Pandemic.



3.4 Econometric Analysis

3.4.1 Multivariate Analyses: What Are the Determinants of the Italian GR?

In this section, to provide initial insights into the determinants of the Italian GR, we apply the following logit model:

$$\text{Logit}(Y_i) = \beta_0 + \beta_1 \text{PostCovid} + X_i\beta + \gamma_j + \delta_r \tag{3.1}$$

where Y represents our *Switching_Indicator*, as described in detail in Section 3.1. The variable PostCovid is a dummy indicating individuals interviewed in 2021 and 2022, while the vector X includes all the variables described in Section 3.2 that could potentially act as concurrent determinants of this phenomenon. Lastly, γ_j and δ_r represent fixed effects of sectors and Italian regions respectively.

The estimation results for our five logit models are reported in Table 3.1, where we progressively introduce additional potential determinants. In column (1), we include only the variable PostCovid, which already exhibits a positive and significant effect on the probability of quitting one's current job. As we sequentially incorporate individual characteristics and regional fixed effects (column 2), job characteristics (column 3), and task characteristics, wage proxies, and sectoral fixed effects (column 4), the structural and positive effect attributable to the pandemic remains significant.

Moreover, as expected, we find that higher wages, having a permanent contract, being in a relationship, and increasing age reduce resignation propensity. Conversely, being male and having more years of education increase switching desire.

Among the task-related indicators, workers in occupations characterized by greater flexibility, routine cognitive tasks, social interactions, and autonomy exhibit a lower probability of resigning from their job. The negative impact of working hours may reflect the desire of individuals working fewer hours to secure a full-time position. Notably, our smart-working proxy suggests that workers who cannot perform their job remotely face a higher probability of changing jobs.

In column (5), we also introduce controls for firm-size[6]. While this inclusion results in a loss of approximately 100,000 observations (compared to column 4), we observe a significant increase in McFadden's pseudo R^2, indicating an improvement in the model's goodness of fit[7]. However, we do not observe substantial changes in the signs of our coefficients.

[6] We classify firms into micro, small, medium, and large based on the number of employees: micro firms have fewer than 10 employees, small firms have between 10 and 49 employees, medium firms have between 50 and 249 employees, and large firms have 250 or more employees.

[7] As a robustness check, we re-estimated the models presented in columns (1)–(4) using the sample available in column (5). The McFadden pseudo R^2 remains approximately the same as in Table 1, suggesting that the observed difference is due to the inclusion of firm-size fixed effects rather than sample selection.

Table 3.1: Logit Analysis of the determinants of the Italian GR

	Dependent variable:				
	Switching_Indicator				
	(1)	(2)	(3)	(4)	(5)
Post_Covid	0.219***	0.245***	0.266***	0.348***	0.312***
	(0.013)	(0.014)	(0.014)	(0.014)	(0.016)
Years_Educ		−0.002	0.024***	0.060***	0.063***
		(0.002)	(0.002)	(0.003)	(0.003)
Gender_M		−0.096***	0.163***	0.287***	0.298***
		(0.014)	(0.016)	(0.017)	(0.018)
Partnered		−0.490***	−0.462***	−0.426***	−0.403***
		(0.022)	(0.022)	(0.023)	(0.024)
Age		−0.054***	−0.044***	−0.038***	−0.038***
		(0.001)	(0.001)	(0.001)	(0.001)
Hours_Worked			−0.039***	−0.026***	−0.024***
			(0.001)	(0.001)	(0.001)
Permanent_Work			−0.550***	−0.625***	−0.631***
			(0.015)	(0.016)	(0.018)
Work_Autonomous				−0.009***	−0.006***
				(0.001)	(0.001)
Routine_Manual				0.0005	−0.001
				(0.001)	(0.002)
Routine_Cognitive				−0.015***	−0.014***
				(0.002)	(0.002)
Social_Intelligence				−0.010***	−0.009***
				(0.001)	(0.001)
Smart_Working				0.046*	0.050*
				(0.024)	(0.026)
Flexibility				−0.022***	−0.020***
				(0.001)	(0.002)
log_Wage				−0.709***	−0.775***
				(0.023)	(0.025)
Constant	−3.524***	−0.829***	−0.026	6.297***	6.505***
	(0.010)	(0.044)	(0.061)	(0.181)	(0.197)
Observations	729,215	723,117	723,117	691,833	588,625
Regional F.E.	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Sectoral F.E.	*No*	*No*	*Yes*	*Yes*	*Yes*
Firm-Size Dummies	*No*	*No*	*No*	*No*	*Yes*
McFadden Pseudo R^2	0.001	0.051	0.086	0.135	0.251

Note: *p<0.1; **p<0.05; ***p<0.01 . Robust standard errors in parenthesis.

To provide a quantitative interpretation of our findings, in the appendix (Table C3 and Table C4), we report the marginal effects for the specifications in columns (4) and (5) of Table 3.1. Focusing on the average marginal effects from model (4), we find that being interviewed in the post-COVID period increases the Switching

Propensity by approximately 1 percentage point. A 10% increase in wages reduces the probability of changing jobs by 0.27 percentage points. Being male increases the propensity by 0.85 percentage points, whereas being in a relationship decreases it by 1.27 percentage points. The results for the marginal effects in column (5) are quite similar.

3.4.2 Subsample Analysis

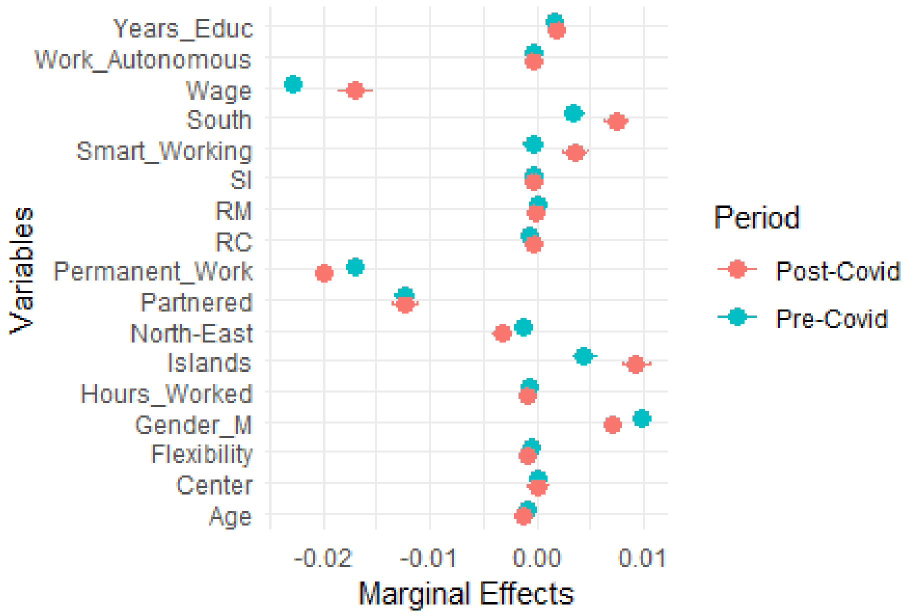
While the previous logit analysis has provided a preliminary overview of the factors leading Italian workers to quit their jobs, a more refined empirical approach is needed to determine whether specific characteristics differentiate the pre- and post-Covid periods. Additionally, the significant effect of the PostCovid dummy may reflect differences in how certain determinants influence resignation propensity across the two time spans.

To address this, we split our sample into the two periods and separately estimate the specification of column (4) in Table 3.1. The results of the separate logit regressions are reported in Table C5. However, to better capture differences in the impact of individual coefficients between the two periods, Figure 3.4 presents the marginal effects of all our regressors[8].

Among the most notable variations, the effect of the dummy variable indicating the impossibility of working from home stands out: it has no impact in the pre-Covid period but becomes significant and positively associated with resignation propensity in the post-Covid period. A strong variation in marginal effects is also observed for regional factors: Italian regions historically facing greater job market challenges (such as the South and the Islands) see a further increase in their impact on the likelihood of seeking alternative employment. Finally, an important result emerges from the wage proxy, which sees a decline in its effect on reducing resignation probability while remaining strongly significant. This might suggest that the Great Resignation goes beyond a mere intensification of pre-existing trends related to low-paid jobs and difficult working conditions.

[8]For space reasons, we exclude sectoral fixed effects. However, we observe changes in statistical significance for manufacturing (from not significant to positive), construction (sign change from positive to negative), and social services (from not significant to positive).

Figure 3.4: Comparison of reasons for seeking new employment among individuals interviewed before and after the Covid-19 Pandemic.



3.4.3 Di Nardo, Fortin and Lemieux Decomposition

To further analyze the change in resignation propensity before and after the COVID-19 pandemic, we apply the Di Nardo, Fortin, and Lemieux (DFL) decomposition (DiNardo et al., 1996). This method allows us to separate observed differences into two key components: a composition and a structural effect. The former captures the impact of changes in the distribution of observable characteristics (e.g., industry, education, gender, job stability) between the pre- and post-COVID periods. Differently, the structural effect reflects shifts in the relationship between these characteristics and resignation propensity, indicating changes in behavior, preferences, or labor market conditions. Essentially, we construct a counterfactual pre-Covid population that retains the same sectoral distribution, occupation, contract types, age, gender composition, and task characteristics as the post-Covid workforce, but with a switching propensity reflecting pre-Covid behavior. As discussed in D'Ambrosio et al. (2022), the DFL approach can be seen as a generalization of mean decomposition methods, such as Oaxaca-Blinder. While both methodologies yield similar insights, the key advantage of DFL lies in its ability to reweight the entire distribution rather than focusing solely on the mean. Moreover, the high prevalence of zeros in our binary dependent variable makes quantile regression an unsuitable alternative.

Formally, in the DFL framework, we can express the density of switching propensity y as a function of the time period T, where $T = 1$ indicates the post-Covid period and $T = 0$ refers to the pre-Covid period. Additionally, we define a set of observable characteristics X, including sector, occupation, contract type, age, gender, and task characteristics. Based on the definition of conditional probabilities, we obtain:

$$f(y|T=1) = \int f(y|X)h(X|T=1)dX$$

$$f(y|T=0) = \int f(y|X)h(X|T=0)dX$$

In our study, $f(y|T = 1)$ represents the distribution of switching propensity in the post-Covid period, while $f(y|T = 0)$ corresponds to the pre-Covid period. The counterfactual switching propensity distribution that would have prevailed in the pre-Covid period if the distribution of characteristics had been the same as in the post-Covid period can be written as a reweighted distribution of the observed pre-Covid density:

$$\int f(y|X)h(X|T=1)dX = \int w_X f(y|X)h(X|T=0)dX$$

The weights w_X are defined as the ratio of the density of characteristics X across the two time periods. Intuitively, they represent the ratio of the probability of observing a given characteristic in the post-Covid period to the probability of observing it in the pre-Covid period:

$$w_X = \frac{h(X|T=1)}{h(X|T=0)} = \frac{P(T=1|X)}{1-P(T=1|X)} \cdot \frac{P_0}{P_1}$$

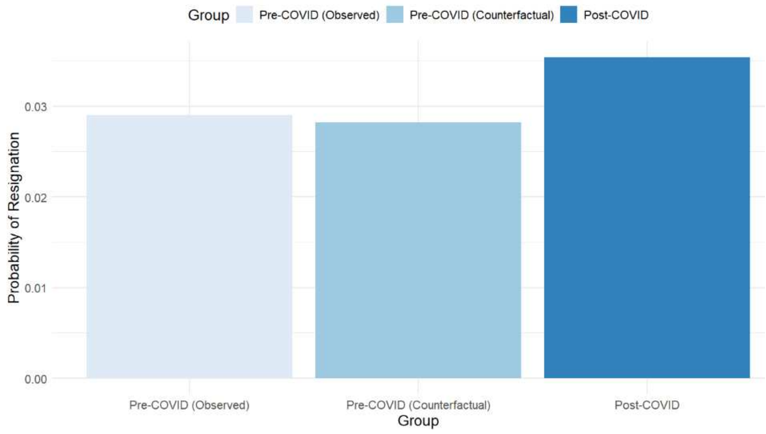
where the second equality derives from Bayes' law. Since the direct estimation of $h(X|T)$ is hampered by dimensionality issues, the conditional probability $P(T = 1|X)$ can be estimated using binary choice models such as logit or probit. The terms P_0 and P_1 correspond to the share of individuals in the pre-Covid and post-Covid periods, respectively. Basically, w_x assign more relevance to pre-Covid interviewed workers more similar in terms of characteristics to the post-Covid surveyed workers. In the next section, we adopt an extension of this methodology to estimate the counterfactual concentration curve for the wages.

To provide a visual representation of our results, in Figure 3.5 we plot the percentage of people aiming at change their jobs in the observed pre- and post-Covid periods, along with the counterfactual pre-Covid group. As we can observe, the counterfactual and observed pre-Covid groups display almost the same probability of switching, indicating that the composition effect is quite small.

Our results confirm that the overall change in switching propensity is positive, meaning that the switching indicator rates increased after the pandemic. However, when we decompose the results, the composition effect appears to be negative (-0.0008), implying that differences in observable characteristics (such as industry shifts, workforce demographics, or contract types) would have led to a slightly lower resignation rate.

Conversely, the structural effect is strongly positive (0.0072), suggesting that the main driver of the increased switching rate is a change in the relationship between covariates and switching propensity. This could reflect a shift in worker preferences, with employees placing greater importance on job flexibility or work-life balance. Another possible explanation could be related to changes in labor market conditions after the pandemic, such as increased job opportunities leading to higher voluntary turnover. More generally, the structural effect could capture a post-pandemic reevaluation of job satisfaction, prompting more individuals to leave their jobs despite unchanged personal characteristics.

Figure 3.5: DFL Decomposition



3.4.4 Concentration Curve

As a final step in our analysis, we examine the relationship between wages and job transitions, focusing on whether resignation patterns differ before and after the pandemic. To construct a counterfactual wage distribution, we apply the DiNardo et al. (1996) reweighting approach, allowing us to compare observed and counterfactual resignation trends. More precisely, we first normalize wages to ensure comparability across different periods. We then estimate an inverse probability weighting (IPW) model using a logistic regression, where the probability of belonging to the post-pandemic period is predicted based on a set of individual and job-related characteristics. Then, for each pre-Covid observation, we compute the probability of belonging to the post-pandemic period and derive the weights.

Observations with invalid or extreme weights (NA, infinite, or negative values) are removed to ensure stability in the reweighting process. The pre-Covid sample is then resampled using these weights to generate a counterfactual dataset that resembles the post-Covid wage distribution in terms of observable characteristics.

Once the counterfactual distribution is constructed, we apply the concept of the *concentration curve* (Wagstaff et al., 2007) to examine the cumulative distribution of switching relative to the cumulative sum of wages. This approach allows us to assess whether switching are more concentrated among low-wage workers or are evenly distributed across wage levels. Specifically, we compute:

$$S_i = \sum_{j \leq i} \frac{w_j}{\sum w}; \quad Q_i = \sum_{j \leq i} \frac{d_j}{\sum d} \tag{3.2}$$

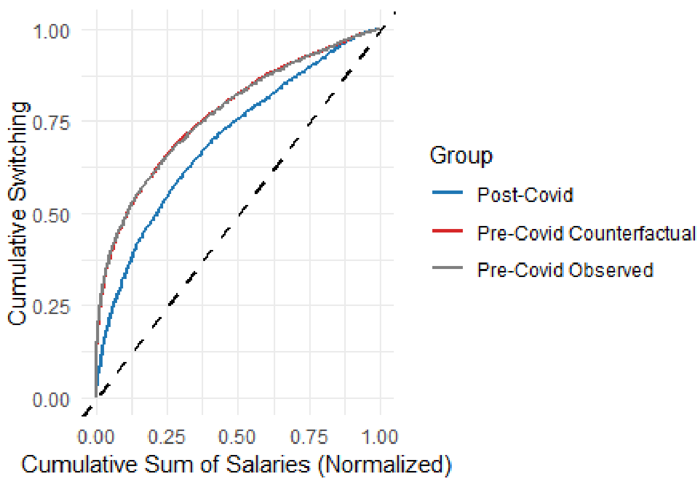
where S_i represents the cumulative proportion of salaries (normalized), and Q_i represents the cumulative proportion of switching.

We then visualize these trends using the concentration curve (Wagstaff et al., 2007), which plots the cumulative percentage of resignations (y-axis) against the cumulative sum of wages, ranked in increasing order (x-axis). If resignation rates were uniformly distributed across wage levels, the concentration curve would align with the 45-degree line. Conversely, if quitting is more prevalent among lower-wage workers, the curve would lie above this line.

Our results reveal two key insights (refers to Figure 3.6. First, the near-identical pre-Covid observed and counterfactual curves confirm that compositional effects do not drive the resignation trend; instead, structural factors play a decisive role. Second, the post-Covid curve rises more gradually, suggesting that resignations have become more widespread across different wage levels, including higher earners. This supports the evidence from our subsample analysis.

While wages remain a significant predictor of job transitions, they do not primarily explain the rise in Italy's quit rate. Instead, other underlying factors must account for this shift,

Figure 3.6: Wage Counterfactual Analysis



3.5 Conclusions

In this study, we provide a quantitative contribution to the growing literature on the Great Resignation. By analyzing the Italian case—a context that has received limited attention in the scientific literature—we offer new insights into this phenomenon.

By comparing official resignation data from the Ministry of Labor, we constructed an indicator that closely replicates the trend observed in the ILFS. This validation allowed us to proceed with the analysis and derive several key findings.

First, our study confirms that in Italy, the Great Resignation primarily manifested as job-to-job transitions rather than widespread labor market exits. This is evident from the strong alignment between the quit trend observed in official COB data and our Switching Indicator within the ILFS. Second, our multivariate and subsample analyses help identify the key drivers of this trend. In the Italian labor market, the intention to quit is more prevalent among highly educated individuals, young workers, men, those without a partner, and those in temporary positions. Regarding job characteristics, we find that workers engaged in routine cognitive and social interaction tasks, as well as those with greater flexibility and autonomy, are less likely to resign. Additionally, our subsample analysis highlights the increasing role of remote work. While teleworking was not a significant factor before the pandemic, it emerged as a crucial determinant of quitting decisions in the post-pandemic period.

Third, our decomposition analysis reveals that the Great Resignation in Italy is not driven by compositional effects but rather by structural changes. These shifts likely reflect evolving individual work preferences, leading to a reassessment of work-life balance priorities. Finally, our counterfactual analysis based on the concentration curve demonstrates that the rise in job transitions cannot be solely attributed to Italy's longstanding issues related to low wages. While compensation remains an important factor influencing job-switching decisions, the increasing propensity to switch jobs is driven by a more complex interplay of factors, including job-task characteristics and broader work-life balance considerations.

From a methodological perspective, our study has certain limitations. The comparison groups (pre- and post-Covid workers) represent two distinct snapshots of the Italian labor force. Due to data constraints, we are unable to conduct a longitudinal analysis to assess whether Covid had a direct impact on individuals' propensity to switch jobs or to examine how the effects of various factors evolved over time. Future research should explore these dynamics further, ideally adopting longitudinal data to provide a deeper understanding of the structural transformations underlying the worldwide Great Resignation.

In conclusion, our study provides quantitative evidence that the Great Resignation (GR) was indeed a significant phenomenon in Italy — a finding that was far from obvious. Despite a series of labor market reforms implemented in recent decades to increase workplace flexibility (Barbieri and Scherer, 2009; Cirillo et al., 2017), finding a new job in Italy remains challenging, and leaving one's current position without securing another is highly risky.

Our analysis confirms this intuition, highlighting a distinctive feature of the Italian case: the GR primarily manifested as job switching rather than large-scale exits from the labor market. As shown by our results, the trend in our Switching

Indicator closely mirrors that of official resignation data. The fact that the Switching Indicator is higher in percentage terms may suggest that a substantial share of workers considered leaving their jobs but ultimately refrained from doing so without the security of alternative employment.

This underscores the unique dynamics of the Italian labor market, where structural rigidities and risk aversion shape resignation behavior.

Conclusions

This work has explored three distinct yet interconnected labor market dynamics, each contributing to a deeper understanding of structural shifts and policy challenges within the Italian and broader European context. By examining Green Jobs, Robotization, and the Great Resignation, this research provides novel insights into employment trends, methodological advancements, and policy implications. From a scientific standpoint, each chapter addresses specific gaps in the existing literature, not only by developing new measurement tools and exploring new empirical context, but also by investigating research questions that remain largely unanswered. In doing so, this work advances both the methodological and empirical foundations for understanding how structural transformations affect employment dynamics.

In the first chapter, we introduced a new approach to defining and measuring Green Jobs within the Italian labor market. Our task-based indicators represent a significant methodological improvement compared to previous transcriptions from U.S. occupation codes, offering a more precise assessment of job "greenness." By directly comparing our indicators with existing indicators, we demonstrated their superior accuracy in identifying green occupations. Our econometric analysis provided surprising insights: contrary to expectations, Green Jobs in Italy tend to be associated with lower levels of education, a higher prevalence of male workers, and a concentration in economically disadvantaged regions. Moreover, workers in these roles are more likely to hold temporary contracts, revealing an additional layer of labor market precariousness. This result challenges the UNEP definition that suggests Green Jobs offering stable and high-quality employment opportunities. From a policy perspective, ensuring that the transition to a greener economy does not reinforce labor market instability is crucial. Future research could refine our measures through advanced machine learning techniques to further improve the identification and classification of Green Jobs and explore policy interventions that mitigate the precariousness associated with them.

The second chapter expanded the perspective to an international scale, analyzing the employment effects of robot adoption in the Top 5 European economies on other European countries. By introducing the novel TRAED index, we provided empirical evidence that automation investments in leading economies generate positive employment spillovers in trade-connected countries. Our findings suggest that, within the highly integrated European market, the productivity effects of automation outweigh potential reshoring effects, leading to an overall increase in employment. This is particularly evident in lower-income European countries, where the demand for intermediate inputs from high-income economies sustains employment levels. This result aligns with previous works in the literature, showing that European countries exhibit a structure characterized by headquarters and factory economies, where central economies can purchase intermediate products at lower prices from Eastern

European countries.

Our results contribute to the debate on automation's employment effects by emphasizing the importance of considering international trade relationships rather than solely focusing on domestic labor market impacts. Future research should explore the implications of automation beyond Europe, potentially extending the analysis to global trade networks and firm-level data to better capture heterogeneous responses to technological change.

Finally, the third chapter examined the Great Resignation phenomenon in Italy, offering one of the first in-depth empirical analyses of this trend in the economic literature. Our results indicate that, rather than reflecting widespread labor force exits, the Italian Great Resignation is primarily characterized by job-to-job transitions. Highly educated young workers in temporary positions are the most likely to switch jobs, with post-pandemic shifts in job preferences and remote work playing an increasingly significant role. Our multivariate analysis highlights that quitting is more prevalent among men, those without a partner, and individuals who perform jobs that do not allow remote work opportunities. Furthermore, our decomposition analysis reveals that the increase in resignations is not driven by compositional changes in the workforce but rather by structural transformations in job preferences. Specifically, the growing emphasis on work-life balance and job flexibility appears to be a key driver of mobility decisions. While low wages remain an important factor influencing job-switching behavior, our counterfactual analysis suggests that monetary compensation alone does not fully explain the trend. Instead, a more complex interplay of job-task characteristics and evolving worker preferences has emerged in the post-pandemic labor market. These findings highlight the need for companies and policymakers to rethink labor market strategies, taking into account workers' growing demand for flexibility, autonomy, and career development opportunities. Future research should utilize longitudinal data to explore whether these trends are temporary responses to the pandemic or indicative of a more permanent transformation in employment relationships.

Taken together, the findings of this dissertation underscore the complex interplay between technological change, job quality, and worker preferences in shaping contemporary labor markets. Policymakers must address the precarious nature of Green Jobs, recognize the cross-border employment effects of automation, and consider the shifting workforce expectations in the wake of the Great Resignation. Future research should build on these insights by incorporating longitudinal data and firm-level analyses to deepen our understanding of these structural labor market changes and their long-term implications.

Appendix Chapter 1

Table A1: Distribution of Green occupations across 1-digit macro-occupations

Occupational Code	**Greenness Importance**	**Greenness Frequency**	**Description**
1.1.2.3.2	20%	17%	Superintendents of cultural heritage
2.1.1.6.4	59%	61%	Meteorologists
2.1.1.6.5	57%	57%	Hydrologists
2.2.2.1.2	52%	55%	Specialists in territory recovery and conservation
2.3.1.1.5	43%	47%	Botanists
2.3.1.1.7	39%	48%	Ecologists
2.3.1.3.0	54%	53%	Agronomists and foresters
2.5.1.1.3	18%	20%	Specialists in public safety
2.5.3.2.3	21%	29%	Geographers
3.1.4.1.4	38%	37%	Technicians of water treatment plants
3.1.8.3.1	64%	61%	Environmental control technicians
3.1.8.3.2	54%	58%	Technicians of waste collection and treatment and environmental reclamation
3.2.2.1.2	80%	82%	Forestry technicians
3.4.6.3.2	58%	54%	Technicians of the security services of firefighters
3.4.6.3.3	71%	73%	Technicians of the security services of the forest corps
5.4.8.3.3	45%	43%	Forest corps agents
6.1.3.1.0	17%	16%	Roofers and waterproofers
6.1.5.2.0	37%	34%	Workers responsible for the maintenance of sewerage systems
6.4.4.1.1	40%	34%	Reforestators
7.1.6.2.1	58%	61%	Operators of waste recovery and recycling plants
8.1.4.5.0	67%	69%	Ecological operators and other waste collectors and separators
8.3.1.1.0	26%	24%	Agricultural laborers
8.3.1.2.0	34%	35%	Unskilled personnel engaged in green maintenance
8.3.2.1.0	42%	38%	Unskilled forest personnel

Table A2: Logit Model

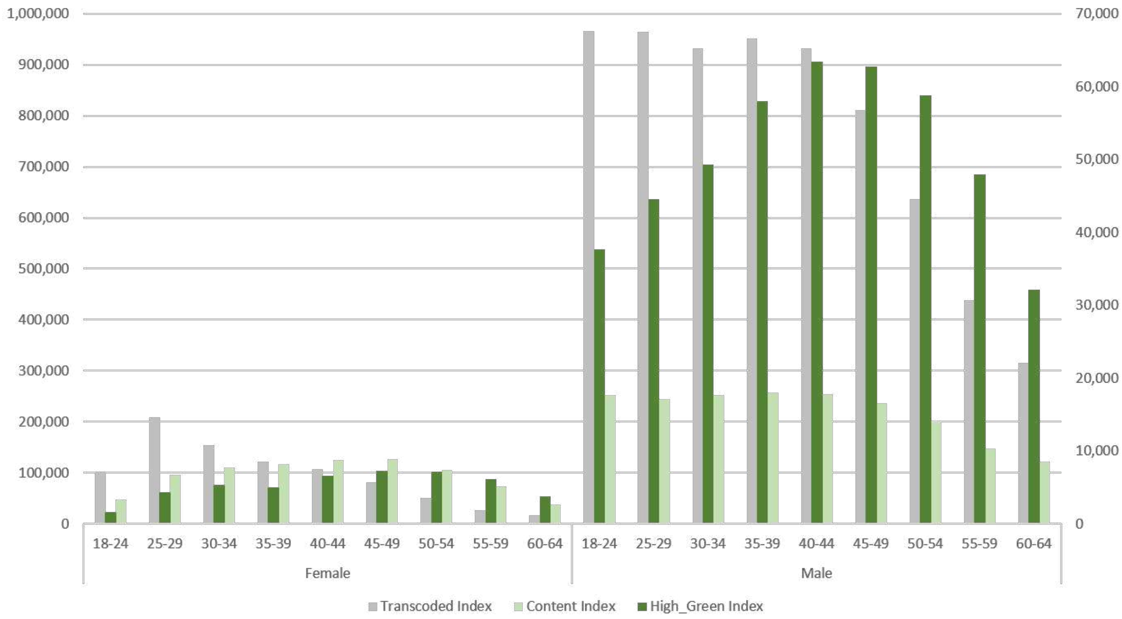
	Estimate	Std. Error	z value	Pr(>|z|)	OddsRatio
(Intercept)	11.917	0.584	20.394	0	0.00001
gender_male	1.790	0.021	84.864	0	5.987
fixed_term_contract	0.769	0.032	24.328	0	0.464
training_contract	0.453	0.059	7.716	0	06
temporary_contract	0.332	0.029	11.582	0	0.717
North_East	0.246	0.024	10.322	0	1.279
Center	0.165	0.024	6.883	0	1.180
South	0.661	0.022	29.731	0	1.937
Islands	0.222	0.028	7.814	0	1.249
Age25 - 29	0.237	0.033	7.143	0	1.267
Age30 - 34	0.226	0.033	6.785	0	1.254
Age35 - 39	0.216	0.033	6.574	0	1.242
Age40 - 44	0.318	0.033	9.700	0	1.375
Age45 - 49	0.425	0.033	12.919	0	1.530
Age50 - 54	0.461	0.034	13.360	0	1.585
Age55 - 59	0.563	0.037	15.224	0	1.755
Age60 - 64	0.498	0.040	12.525	0	1.645
High_school	0.210	0.018	11.505	0	0.811
University_degree	0.095	0.029	3.232	0.001	0.909
GreenSector	0.115	0.080	1.432	0.152	1.122

In the logit, we also insert dummy variables for CP 3-digit categories (worker-ISCO Italian Classification).

Table A3: Stratified by HighGreen

	0	1	SMD
n	604,911	49,074	
gender = M (%)	374,771 (62.0%)	44,645 (91.0%)	0.728
macro_region (%)			0.402
north-west	156,462 (25.9%)	7,868 (16.0%)	
north-east	136,425 (22.6%)	7,107 (14.5%)	
central	130,439 (21.6%)	11,098 (22.6%)	
south	129,801 (21.5%)	16,488 (33.6%)	
islands	51,784 (8.6%)	6,513 (13.3%)	
age_class (%)			0.284
18 - 24	84,794 (14.0%)	4,359 (8.9%)	
25 - 29	77,168 (12.8%)	5,162 (10.5%)	
30 - 34	85,091 (14.1%)	5,746 (11.7%)	
35 - 39	86,450 (14.3%)	6,063 (12.4%)	
40 - 44	84,542 (14.0%)	6,975 (14.2%)	
45 - 49	75,393 (12.5%)	6,869 (14.0%)	
50 - 54	54,932 (9.1%)	6,444 (13.1%)	
55 - 59	33,656 (5.6%)	4,302 (8.8%)	
60 - 64	22,885 (3.8%)	3,154 (6.4%)	
education (%)			0.182
up to middle school	352,736 (58.3%)	32,914 (67.1%)	
high school	187,747 (31.0%)	12,016 (24.5%)	
university	64,428 (10.7%)	4,144 (8.4%)	
greenSector (mean (SD))	0.52 (0.50)	0.82 (0.39)	0.673
isco_3 (%)			1.169
1.1.2	23 (0.0%)	3 (0.0%)	
1.3.1	0 (0.0%)	0 (0.0%)	
2.1.1	22,186 (3.7%)	494 (1.0%)	
2.2.1	0 (0.0%)	0 (0.0%)	
2.2.2	1,337 (0.2%)	290 (0.6%)	
2.3.1	10,363 (1.7%)	601 (1.2%)	
2.4.1	0 (0.0%)	0 (0.0%)	
2.5.1	11,231 (1.9%)	89 (0.2%)	
2.5.3	279 (0.0%)	10 (0.0%)	
2.6.3	0 (0.0%)	0 (0.0%)	
3.1.1	0 (0.0%)	0 (0.0%)	
3.1.3	0 (0.0%)	0 (0.0%)	
3.1.4	1,287 (0.2%)	413 (0.8%)	
3.1.6	0 (0.0%)	0 (0.0%)	
3.1.8	2,956 (0.5%)	2,231 (4.5%)	
3.2.1	0 (0.0%)	0 (0.0%)	
3.2.2	464 (0.1%)	76 (0.2%)	
3.4.1	0 (0.0%)	0 (0.0%)	
3.4.6	2 (0.0%)	1 (0.0%)	
5.4.8	0 (0.0%)	0 (0.0%)	
6.1.3	81,171 (13.4%)	2,012 (4.1%)	
6.1.4	0 (0.0%)	0 (0.0%)	
6.1.5	38,939 (6.4%)	982 (2.0%)	
6.2.1	0 (0.0%)	0 (0.0%)	
6.2.4	0 (0.0%)	0 (0.0%)	
6.4.1	0 (0.0%)	0 (0.0%)	
6.4.3	0 (0.0%)	0 (0.0%)	
6.4.4	593 (0.1%)	5,695 (11.6%)	
6.5.3	0 (0.0%)	0 (0.0%)	
7.1.5	0 (0.0%)	0 (0.0%)	
7.1.6	1,377 (0.2%)	1,620 (3.3%)	
7.3.2	0 (0.0%)	0 (0.0%)	
7.4.3	16,400 (2.7%)	2,798 (5.7%)	
8.1.4	410,990 (67.9%)	22,130 (45.1%)	
8.3.1	0 (0.0%)	0 (0.0%)	
8.3.2	5,313 (0.9%)	9,629 (19.6%)	

Figure A1: Annual activation volume of green ULAs over age and gender. The right axis is relative to the High-Green Index.



Appendix Chapter 2

Table B1: Matching between IFR and TiM sectoral classifications

Industry IFR	Industry TiM
All Industries	D01: TOTAL
Agriculture, forestry, fishing	D01T03: Agriculture, hunting, forestry and fishing
Mining and quarrying	D05T09: Mining and quarrying
Food and beverages	D10T12: Food products, beverages and tobacco
Textiles	D13T15: Textiles, textile products, leather and footwear
Wood and furniture	D16: Wood and products of wood and cork
Paper	D17T18: Paper products and printing
Other chemical products n.e.c.	D19TD20: Manufacture of coke and refined petroleum prod.
Pharmaceuticals, cosmetics	D21: Pharmaceutic, medicinal chemical and botanical prod.
Rubber and plastic products (non-automotive)	D22: Rubber and plastics products
Glass, ceramics, stone, mineral products (non-auto	D23: Other non-metallic mineral products
Basic metals	D24: Basic metals
Metal products (non-automotive)	D25: Fabricated metal products
Household/domestic appliances	D26: Computer electronic and optical equipment
Computers and peripheral equipment	D26: Computer electronic and optical equipment
Info communication equipment, domestic and prof.	D26: Computer electronic and optical equipment
Electronic components/devices	D26: Computer electronic and optical equipment
Semiconductors, LCD, LED	D26: Computer electronic and optical equipment
Medical, precision, optical instruments	D26: Computer electronic and optical equipment
Electrical machinery n.e.c. (non-automotive)	D27: Electrical equipment
Electrical/electronics unspecified	D27: Electrical equipment
Industrial machinery	D28: Machinery and equipment, nec
Motor vehicles, engines and bodies	D29: Motor vehicles, trailers and semi-trailers
Metal (AutoParts)	D29: Motor vehicles, trailers and semi-trailers
Other vehicles	D30: Other transport equipment
All other manufacturing branches	D31T33: Manufacturing nec; repair and installation of machinery and equipment
Electricity, gas, water supply	D35T39: Electricity, gas, water supply, sewerage, waste and remediation services
Construction	D41T43: Construction

Table B2: TRAED indicator statistics among economic sectors

Sector	Mean	SD	p50	Min	Max
D01T03	0.6757567	0.5079043	0.6910621	0.0169006	1.658163
D05T09	1.900035	0.9959935	2.148016	0	3.989504
D10T12	4.6464	0.8577306	4.662709	2.313164	6.219182
D13T15	3.388786	0.3678649	3.498498	2.123282	4.02737
D16	5.648199	0.2753295	5.649137	4.988023	6.12007
D17T18	3.601499	0.5629145	3.638733	2.150225	4.799051
D19TD20	0.4807417	0.694381	0	0	2.302366
D21	3.262909	2.649779	4.348192	0	6.916811
D22	4.078481	3.225952	5.95226	0	7.647594
D23	5.127626	0.5367926	5.194301	3.501414	5.998357
D24	5.535183	0.3332425	5.551691	4.562799	6.314025
D25	5.612494	0.4634903	5.552483	4.506002	6.645398
D26	5.162432	1.093738	5.301649	2.017534	7.095385
D27	5.258816	0.6176682	5.377066	3.268099	6.17011
D28	5.087703	0.5950501	5.207024	2.818625	6.170329
D29	6.773282	1.710798	7.549074	2.632556	8.882624
D30	5.035353	0.5683227	5.065981	3.59664	5.977674
D31T33	4.723168	0.2766377	4.723446	4.053992	5.489874
D35T39	0.9930088	0.6344654	1.062679	0	2.115421
D41T43	0.8656387	0.4891277	0.896636	0.0166976	1.771202

Table B3: First stage IV regression

Variables	(1)	(2)
Japan RD	0.053***	0.053***
	(0.004)	(0.005)
Domestic Robot		0.164***
		(0.049)
Value Added Deflator		-0.0001
		(0.0004)
Labour Cost		0.0017
		(0.0014)
Constant	-0.060	-0.165*
	(0.058)	(0.0699)
Observations	11,040	7,999
R-squared	0.374	0.415

Notes: Standard errors in parentheses are clustered at the country-industry level. Year dummies included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

Table B4: Dependent var: change in Workers Embodied in Exports

	High-Income Countries			*Low-Income Countries*		
Variables	(OLS)	(FE)	(IV)	(OLS)	(FE)	(IV)
TRAED Index	3.996**	4.150**	4.374	15.48***	15.81***	16.96***
	(1.734)	(1.805)	(2.700)	(4.609)	(4.636)	(6.053)
Domestic Robot	-4.348	0.0252	-4.474	12.93**	11.53**	12.69**
	(5.211)	(6.255)	(5.181)	(6.416)	(5.625)	(6.329)
Value Added Deflator	0.269***	0.343***	0.270***	-0.0419	-0.0427	-0.0418
	(0.0722)	(0.0862)	(0.0734)	(0.0538)	(0.0599)	(0.0535)
Labour Cost	-0.220	-0.522*	-0.222	1.854**	1.772	1.843**
	(0.198)	(0.266)	(0.195)	(0.751)	(1.096)	(0.747)
Constant	72.40***	73.04***	72.23***	66.45***	80.42***	66.64***
	(11.26)	(10.33)	(11.33)	(18.39)	(10.22)	(18.22)
Observations	3,428	3,428	3,428	4,571	4,571	4,571
R-squared	0.492	0.133	0.492	0.278	0.167	0.278
Kleibergen-Paap F-stat.			97.862			48.022

Notes: Standard errors in parentheses are clustered at the country-industry level. Year dummies included in all models. Controls include GDP; EU membership and cost of labor. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

Table B5: Impact on hours worked by workers divided by GDP levels

	High-Income Countries			*Low-Income Countries*		
Variables	(OLS)	(FE)	(IV)	(OLS)	(FE)	(IV)
TRAED Index	2.150*	1.738	1.510	5.763***	5.704***	5.550*
	(1.110)	(1.116)	(1.885)	(1.818)	(1.855)	(2.847)
Domestic Robot	-1.794	2.461	-1.102	11.75***	10.67***	11.44***
	(3.796)	(3.590)	(4.356)	(2.756)	(2.528)	(2.808)
Value Added Deflator	0.141**	0.191***	0.167**	-0.00286	-0.0123	-0.00268
	(0.0582)	(0.0658)	(0.0741)	(0.0246)	(0.0295)	(0.0320)
Labour Cost	0.141	-0.0269	0.215	0.674	1.231*	0.704
	(0.226)	(0.274)	(0.234)	(0.470)	(0.674)	(0.474)
Constant	97.19***	78.96***	94.12***	89.30***	95.54***	90.34***
	(8.415)	(11.46)	(9.639)	(8.501)	(7.098)	(8.627)
Observations	3,212	3,212	3,045	2,963	2,963	2,796
R-squared	0.374	0.124	0.378	0.441	0.256	0.445
Kleibergen-Paap F-stat.			90.650			33.490

Notes: Standard errors in parentheses are clustered at the country-industry level. Year, sector and country fixed effects included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

Table B6: Foreign robot impact by macro-sectors

	Manufacturing Sectors			*Other Sectors*		
Variables	(OLS)	(FE)	(IV)	(OLS)	(FE)	(IV)
TRAED Index	4.320***	4.479***	3.600***	-7.152*	-12.96**	-108.9**
	(0.509)	(1.228)	(0.926)	(3.649)	(6.118)	(44.15)
Domestic Robot	7.849***	6.746***	8.142***	6.368**	5.997	9.107***
	(1.292)	(2.531)	(1.321)	(2.923)	(3.728)	(3.498)
Value Added Deflator	-0.020***	-0.018	-0.021***	0.376***	0.279***	0.377***
	(0.006)	(0.024)	(0.006)	(0.045)	(0.062)	(0.061)
Labour Cost	-0.141***	-0.237	-0.135**	0.950***	2.259***	0.937***
	(0.0528)	(0.229)	(0.0531)	(0.135)	(0.578)	(0.153)
Constant	86.90***	87.21***	89.54***	36.97***	78.85***	35.04***
	(2.965)	(5.288)	(4.273)	(7.260)	(8.275)	(10.63)
Observations	6,645	6,645	6,645	1,354	1,354	1,354
R-squared	0.281	0.136	0.281	0.626	0.366	0.443
Kleibergen-Paap F-stat.			93.853			29.897

Notes: Standard errors in parentheses are robusts. Year, sector and country fixed effects included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

Figure B1: Share of Imports within the EU in 2018, based on Eurostat data

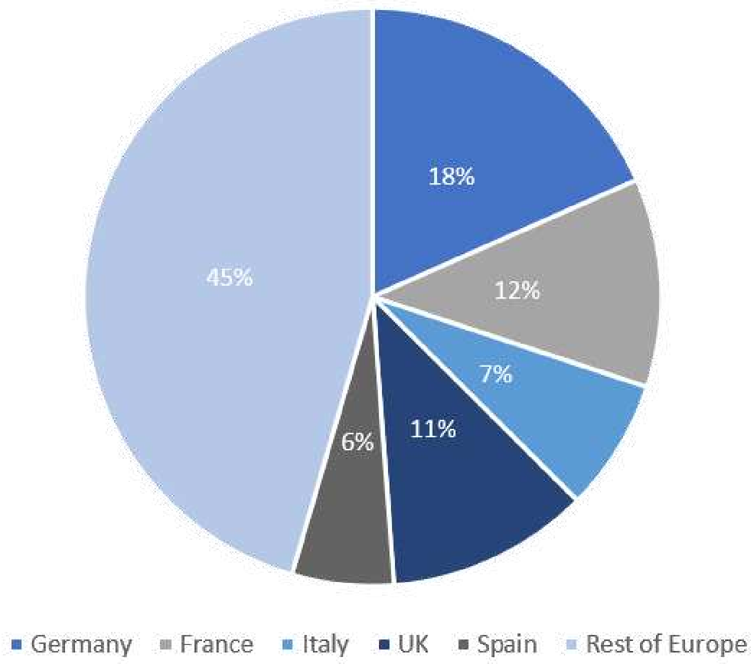


Figure B2: Distribution of the TRAED index by country

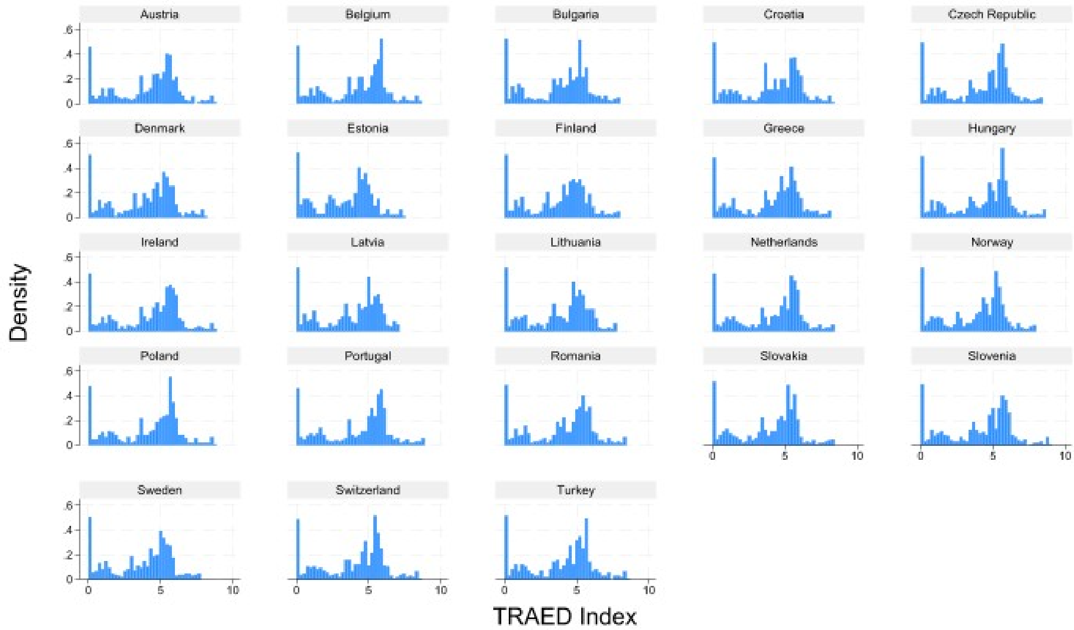


Figure B3: correlation between the TRAED Index and the Change in workers embodied in Exports compared to 1995

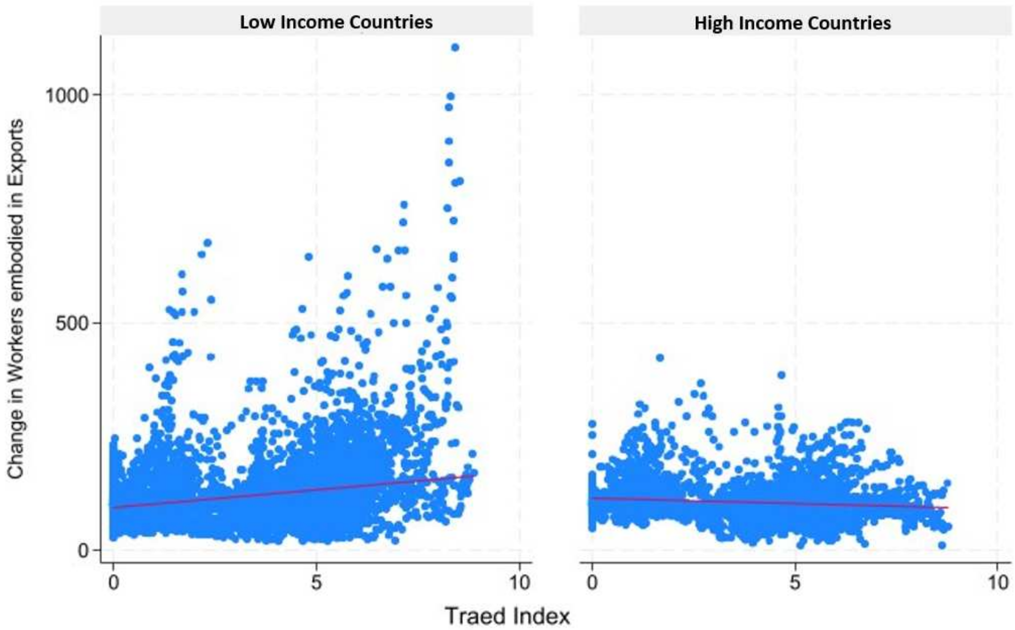


Figure B4: Correlation between the TRAED Indes and changes in workers embodied in exports by countries

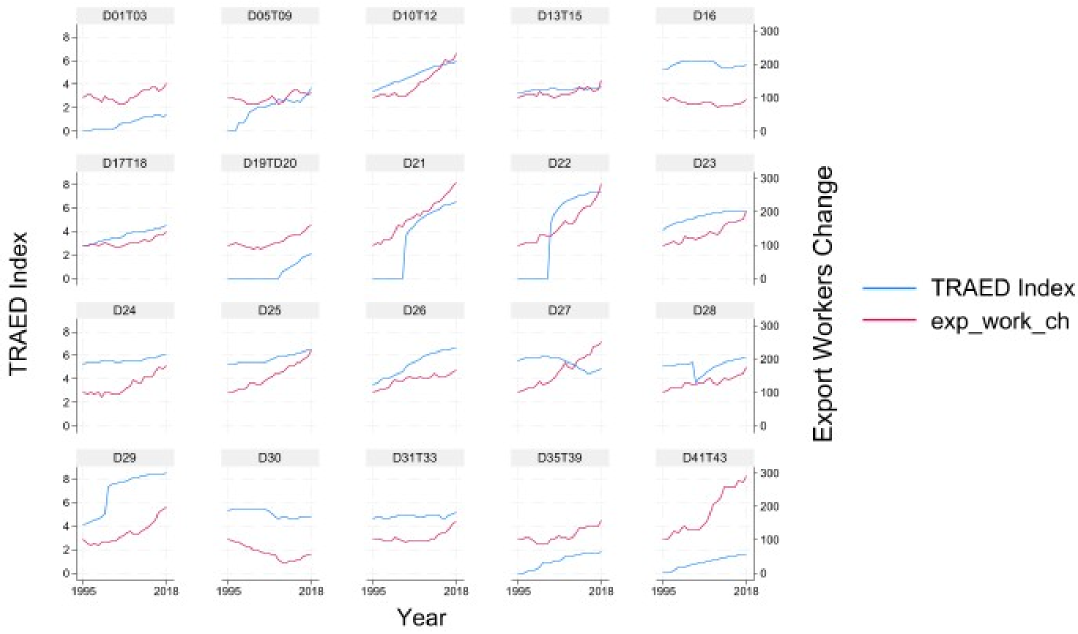
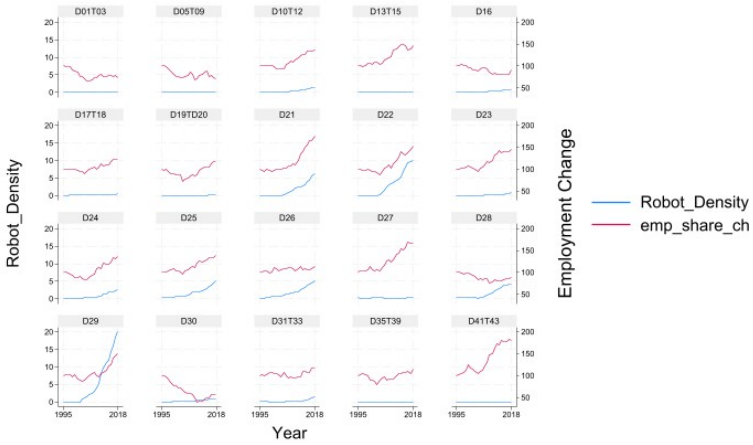
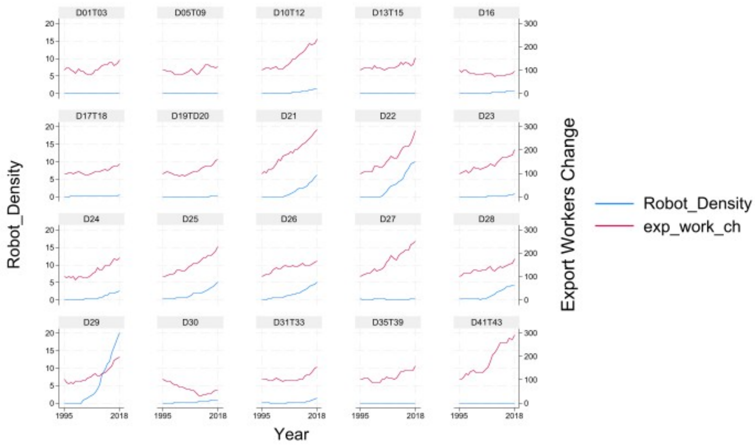


Figure B5: Association between the robot density of the 23 countries and changes in employment and export workers

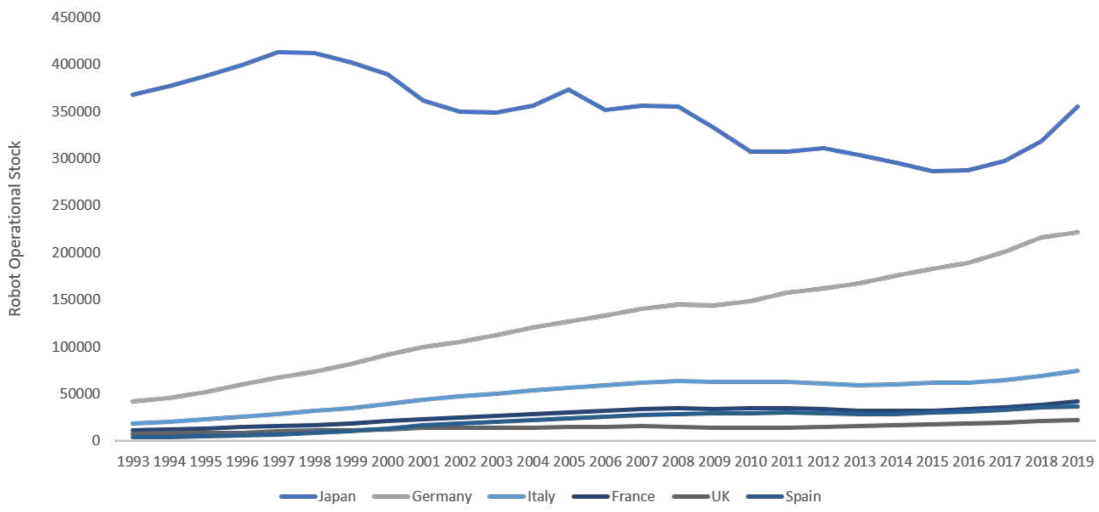


(a) Panel A



(b) Panel B

Figure B6: time trend of the operational robot stock for Japan and the Top 5 European countries



Note: The data pertains to the operational stocks of all economic sectors in both Japan and the Top five European countries.

Instrumental Variable (IV) Estimation

The IV estimation involves two main steps:

First Step: Instrumental Variable Regression

In the first step, we regress the endogenous variable (TRAED_Index) on the instrument (Robot_Density_Japan) and any exogenous controls:

$$\text{TRAED\_Index} = \alpha_0 + \beta_1 \text{Robot\_Density\_Japan} + \beta_2 \text{X} + \epsilon \tag{3}$$

Where:

- TRAED_Index is the endogenous variable.
- Robot_Density_Japan is the instrumental variable.
- X include other relevant factors that may influence the TRAED_Index such as countries, economic sectors, GDP deflator and labour costs.
- ϵ is the error term.

Second Step: Outcome Regression

In the second step, we use the predicted values from the first step to estimate the main equation:

$$\text{Change\_Emp} = \beta_0 + \beta_1 \text{TRAE}\hat{\text{D}}\text{\_Index} + \beta_2 \text{X} + u \tag{4}$$

Where:

- TRAE$\hat{\text{D}}$_Index are the predicted values obtained from the first step.
- Change_Emp is the dependent variable representing total changes in employment.
- X include other relevant factors that may influence the TRAED_Index such as countries, economic sectors, GDP deflator and labour costs.
- u is the error term in this regression.

Appendix Chapter 3

Table C1: ICP Indicators and Variables

Indicators	ICP variables	ICP questions
Routine Manual (RM)	Rhythm determined by machinery	D.28
	Control	C.25
	Importance of repetitive tasks	H.51, H.42
Perception and Manipulation (PM)	Finger dexterity	D.24
	Hand dexterity	D.23
	Confined spaces	H.26
Social Intelligence (SI)	Social perceptiveness	C.11
	Negotiation	C.14
	Persuasion	C.13
	Assisting and caring for others	G.29
Work_Autonomy	Independent planning	E.20
	Autonomous decision-making	E.21
Flexibility	Interpersonal Relationship	G.28, H.6
	Autonomous decision-making	H.48
	Task-autonomy	H.52
	Deadline pressure	H.54
Remote Working (RW)	Email frequency	H.4
	Violent encounters	H.14
	Weather exposure	H.17, H18
	Disease exposure	H.29
	Minor injuries exposure	H.33
	Walking/running duration	H.36
	Safety gear time-use	H.43, H.44
	Full-body physical activity	G.16
	Hand-arm manipulation	G.17
	Machine operation control	G.18
	Vehicle/equipment operation	G.20
	Public Interaction	G.32
	Mechanical equipment maintenance	G.22, G.23
	Equipment inspection	G.4

Table C2: Summary Statistics

	Pre-COVID	Post-COVID
Variable	Mean	Mean
	(sd)	(sd)
Switching_Indicator	0.029	0.035
	(0.17)	(0.18)
Years_Educ	12.00	13.00
	(3.90)	(3.70)
Gender	0.56	0.55
	(0.50)	(0.50)
Partnered	0.88	0.90
	(0.33)	(0.30)
Age	46	46
	(12.00)	(12.00)
Hours_Worked	37.00	37.00
	(11.00)	(11.00)
Permanent_Work	0.64	0.66
	(0.48)	(0.47)
Work_Autonomy	64.00	64.00
	(11.00)	(11.00)
Routine_Manual	29.00	28.00
	(11.00)	(11.00)
Routine_Cognitive	49.00	49.00
	(5.30)	(5.20)
Social_Intelligence	37.00	37.00
	(13.00)	(13.00)
RW	0.62	0.60
	(0.49)	(0.49)
Flexibility	43.00	43.00
	(6.50)	(6.50)
Wage	1336.00	1337.00
	(502.00)	(406.00)

Table C3: Marginal Effects of Table 1 columns 4

Variable	AME	SE	z	p	Lower	Upper
Work_Autonomous	-0.0003	0.0000	-10.2864	0.0000	-0.0003	-0.0002
Hours_Worked	-0.0008	0.0000	-35.9002	0.0000	-0.0008	-0.0007
Permanent_Work	-0.0186	0.0005	-40.1005	0.0000	-0.0195	-0.0177
Years_Educ	0.0018	0.0001	24.3743	0.0000	0.0016	0.0019
Age	-0.0011	0.0000	-57.6334	0.0000	-0.0012	-0.0011
Flexibility	-0.0006	0.0000	-15.9337	0.0000	-0.0007	-0.0006
Gender_M	0.0085	0.0005	17.3524	0.0000	0.0076	0.0095
Smart_Working	0.0014	0.0007	1.9327	0.0533	-0.0000	0.0028
log_Wage	-0.0211	0.0007	-30.9187	0.0000	-0.0225	-0.0198
Post_Covid	0.0104	0.0004	23.9234	0.0000	0.0095	0.0112
Routine_Cognitive	-0.0005	0.0001	-6.6469	0.0000	-0.0006	-0.0003
Routine_Manual	0.0000	0.0000	0.3378	0.7355	-0.0001	0.0001
Social_Intelligence	-0.0003	0.0000	-10.0140	0.0000	-0.0003	-0.0002
Partnered	-0.0127	0.0007	-18.2700	0.0000	-0.0140	-0.0113

Table C4: Marginal Effects Estimates of Table 1 column 5

Variable	AME	SE	z	p	Lower	Upper
Work_Autonomous	-0.0002	0.0000	-6.6481	0.0000	-0.0002	-0.0001
Hours_Worked	-0.0007	0.0000	-30.1614	0.0000	-0.0008	-0.0007
Permanent_Work	-0.0192	0.0005	-36.9984	0.0000	-0.0202	-0.0182
Firm_Size(Medium)	-0.0002	0.0011	-0.1492	0.8814	-0.0024	0.0020
Firm_Size(Micro)	-0.0071	0.0010	-6.7519	0.0000	-0.0091	-0.0050
Firm_Size(Small)	-0.0025	0.0010	-2.3592	0.0183	-0.0045	-0.0004
Years_Educ	0.0019	0.0001	23.7760	0.0000	0.0018	0.0021
Age	-0.0011	0.0000	-51.9966	0.0000	-0.0012	-0.0011
Flexibility	-0.0006	0.0000	-13.6709	0.0000	-0.0007	-0.0005
Gender_M	0.0091	0.0005	16.7950	0.0000	0.0080	0.0101
Smart_Working	0.0015	0.0008	1.9272	0.0540	0.0000	0.0030
log_Wage	-0.0236	0.0008	-31.2079	0.0000	-0.0250	-0.0221
Post_Covid	0.0095	0.0005	19.6132	0.0000	0.0085	0.0104
Routine_Cognitive	-0.0004	0.0001	-5.4393	0.0000	-0.0006	-0.0003
Routine_Manual	-0.0000	0.0000	-0.0423	0.9663	-0.0001	0.0001
Social_Intelligence	-0.0003	0.0000	-8.7629	0.0000	-0.0003	-0.0002
Partnered	-0.0123	0.0008	-16.2910	0.0000	-0.0137	-0.0108

Table C5: Subsample logit analysis

	Dependent variable:	
	Switching_Indicator	
	(Pre_Covid)	(Post_Covid)
Years_Educ	0.063***	0.057***
	(0.004)	(0.004)
Gender_M	0.363***	0.213***
	(0.024)	(0.023)
Partnered	−0.458***	−0.374***
	(0.031)	(0.034)
Age	−0.035***	−0.041***
	(0.001)	(0.001)
Hours_Worked	−0.022***	−0.029***
	(0.001)	(0.001)
Permanent_Work	−0.631***	−0.606***
	(0.023)	(0.022)
Work_Autonomous	−0.008***	−0.010***
	(0.001)	(0.001)
Routine_Manual	0.001	−0.0004
	(0.002)	(0.002)
Routine_Cognitive	−0.023***	−0.008***
	(0.003)	(0.003)
Social_Intelligence	−0.010***	−0.010***
	(0.001)	(0.001)
Smart_Working	−0.015	0.109***
	(0.034)	(0.034)
Flexibility	−0.017***	−0.026***
	(0.002)	(0.002)
log_Wage	−0.843***	−0.518***
	(0.029)	(0.047)
Constant	7.084***	5.351***
	(0.231)	(0.346)
Observations	371,153	320,680
Regional F.E.	*Yes*	*Yes*
Sectoral F.E.	*Yes*	*Yes*
Note:	*p<0.1; **p<0.05; ***p<0.01	

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