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Three Essays on Technological Change and Labour-Market Dynamics

by

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Contents

List of Figures

List of Tables

Abstract

This thesis examines how innovation and technological change shape aggregate growth and labour-market outcomes, and how policy mediates the attendant trade-offs. The first essay develops a Schumpeterian dynamic general equilibrium model with creative destruction and search-and-matching frictions that distinguishes skilled R&D from unskilled production labour. Calibrated to U.S. data (2003–2019), the model delivers a transparent growth–unemployment trade-off under innovation policy. Both R&D tax credits and direct wage subsidies raise the innovation arrival rate and TFP growth, while increasing separations and steady-state unemployment. Welfare comparisons favour direct R&D wage subsidies: doubling the subsidy from 10% to 20% yields a 1.47% consumption-equivalent gain versus 0.36% for doubling a 6% incremental credit. In contrast, a broad corporate-profit tax cut from 33% to 30% reduces innovation and welfare despite a slight decline in unemployment.

The second essay studies within-occupation skill obsolescence. Using vacancy-text-based task measures merged with multidimensional individual skills, it constructs worker-specific exposure to skill obsolescence and shows that higher exposure predicts lower earnings, longer non-employment, and greater occupational mobility. On the other hand, workers whose primary skill becomes obsolete but possess offsetting strengths are more likely to adapt in place. The third essay analyses displaced workers using an event–study difference-in-differences design and finds large, persistent earnings losses concentrated on weeks worked. However, losses are heterogeneous in terms of exposure to skill obsolescence. Non-exposed workers lose about 20% in year one and recover within three years, whereas highly exposed workers lose about 30% and remain below baseline eight years later. Overall, the results support a portfolio of innovation instruments, adjusted to objectives and fiscal constraints, and complemented by adjustment policies for the most exposed, and therefore most vulnerable workers.

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Chapter 1

Introduction

Technological progress is the main engine of productivity growth, yet its labour-market consequences are varied and sometimes dramatic. Policies that stimulate innovation can accelerate growth but may also intensify creative destruction and strain frictional labour markets. In parallel, technological shifts reweight the skills demanded within occupations, exposing some workers to obsolescence and altering the incidence and persistence of earnings losses when jobs are destroyed. This thesis brings these macro and micro perspectives together in three essays.

The analysis is based on a Schumpeterian view of growth: new varieties and quality improvements raise productivity but displace incumbents, endogenising job turnover (Aghion and Howitt, 1992). When job creation and destruction meet search-and-matching frictions, unemployment responds not only to cyclical conditions but also to the pace of innovation. At the worker level, technological change is reflected in shifting skill demands within occupations. Workers whose endowments are misaligned with these shifts face skill obsolescence and, upon displacement, more difficult reallocation.

The first essay (**Chapter 2**) builds a DSGE model that embeds creative destruction in a frictional labour market with segmented labour types (skilled R&D versus unskilled production). Policy experiments quantify steady-state and transition dynamics under targeted R&D support versus broad profit-tax changes. Both R&D tax credits and direct wage subsidies increase the innovation arrival rate and TFP growth, but also raise separations and unemployment in the new steady state. Welfare comparisons favour direct wage subsidies over incremental tax credits (e.g., a doubling of the subsidy delivers larger consumption-equivalent gains), while broad corporate-tax cuts reduce innovation and welfare despite a small decline in unemployment.

The second essay **(Chapter 3)** moves to the micro roots of adjustment by constructing a worker-level measure of exposure to within-occupation skill obsolescence. The essay merges occupation-year task measures with individuals' multidimensional skills, classifying workers into high exposure, primary-skill obsolescence, and no exposure. Our estimates show robust penalties for high-exposure and primary-skill groups. Higher exposure is associated with lower earnings, longer non-employment, and greater occupational mobility, indicating that within-occupation demand shifts translate into lower pay and slower re-employment for exposed workers.

The third essay **(Chapter 4)** studies the consequences of job loss under within-occupation changes in task content, our measure of skill obsolescence. Using an event-study difference-in-differences design with staggered timing and NLSY79 data linked to a vacancy-based occupation–task map, I show that displacement causes large and persistent earnings losses. These losses operate mainly through the extensive margin (fewer weeks worked), with little role for weekly hours. There is a pronounced heterogeneity with respect to exposure status. Non-exposed workers experience losses that abate within several years, whereas highly exposed and primary-skill exposed workers suffer larger and more persistent declines. Conditional wage effects are modest for the non-exposed but more persistent for the highly exposed.

The macro essay is quantitatively disciplined by U.S. aggregates on unemployment, TFP growth, R&D labour, and wage premia. The micro essays exploit (i) panel data with weekly work histories, displacement timing, and multidimensional test scores for constructing cognitive, manual, and interpersonal skill endowments; and (ii) occupation-year skill demands derived from vacancy text that map into standard task taxonomies. The interaction of these sources yields an operational measure of individual exposure to within-occupation obsolescence.

At the macro level, well-designed, targeted R&D support raises growth but should be evaluated against its unemployment consequences. In the model, direct subsidies deliver larger welfare gains than incremental tax credits, while broad corporate-tax cuts are an inefficient innovation policy. At the micro level, the evidence that exposure to obsolescence amplifies and prolongs displacement costs underscores a role for targeted active labour-market policies: retraining aligned with emerging skill requirements, improved matching services, and earnings insurance that recognises longer non-employment spells among the exposed.

Chapter 2

Economic Growth and Employment under Innovation Policies

2.1 Introduction

The significance of innovations in raising productivity and thus fostering economic growth places innovation policies at the heart of modern growth strategies. In recent decades, innovation efforts in advanced economies have been fueled by direct subsidies and tax incentives for research and development. With these increased efforts, gross domestic spending on R&D has risen from approximately 1.95% of GDP in 1995 to 2.7% in 2022 across OECD countries (OECD, 2024). Considering this rise in R&D intensity, we question whether policies that stimulate this wave of innovation can raise long-run growth without worsening unemployment in frictional labour markets.

Even though its benefits are substantial, innovation may carry labour-market costs. The most distinct and crucial cost might be the high and persistent unemployment (Zagler, 2009). The new technologies arising from innovative activities not only create new job opportunities, but they may also lead to job losses through the process of creative destruction. Understanding how innovation affects both growth and unemployment is therefore essential for designing effective policy.

These concerns intensified after the global financial crisis, when global productivity slowed and policymakers again relied on R&D support (Akcigit et al., 2022a). A substantial body of literature finds that such policies boost productivity and output (Hall and Van Reenen, 2000; Akcigit et al., 2018). However, many quantitative assessments either abstract from labour–market outcomes or assume full employment while studying macro effects of innovation policies or structural reforms (Roeger et al., 2008; Varga and in 't Veld, 2011; Varga and Roeger, 2014). That modelling choice risks understating displacement and the role of frictions.

Investigating the macroeconomic impact of innovation policies in a frictionless labour market, however, might be misleading in the sense that it risks overlooking their possible adverse effects on the labour market. This is because when the labour market is frictionless, job creation and destruction can balance each other, bringing the labour market into full employment. However, the existence of search and matching frictions between firms and workers leads to what is called 'technological unemployment' (Chu et al., 2021).

This paper, then, constructs a Dynamic Stochastic General Equilibrium (DSGE) model where growth results from Schumpeterian creative destruction and considers a frictional labour market to analyse the possible impact of innovation policies on driving growth and labour market dynamics. The use of search and matching frictions in this model is based on the idea that when jobs are destroyed and new ones are created due to innovations, the workers who lose their jobs often lack the necessary skills or human capital that can be applied to the new jobs. Therefore, it becomes harder for them to be matched with new jobs, and thus, the spell of unemployment can be more prolonged for these workers. In this context, this study focuses on two counteracting effects of innovation-driven growth in line with the Schumpeterian equilibrium unemployment literature: 'capitalisation' and 'creative destruction' (Aghion and Howitt, 1994; Mortensen and Pissarides, 1998; Mortensen, 2005). The former reinforces the creation of more vacancies and reduces equilibrium unemployment, whereas the latter increases it by destroying jobs due to higher growth.

Against this backdrop, this study examines two common innovation–enhancing policies—R&D *subsidies* and *tax credits*—and studies their effects on both growth and unemployment when labour markets feature search and matching frictions. Moreover, our setup will enable us to examine the impact of labour market frictions on the effectiveness of innovation policies. The rest of the paper is then organised as follows. Section 2.2 provides a review of the various strands of literature related to our study, while Section 2.3 develops the model. Section 2.4 presents the calibration and the quantitative analysis. Finally, the fifth section concludes the research.

2.2 Literature Review

The determinants of long-run economic growth have long been examined. Among the possible sources, the growth of technology or total factor productivity (TFP) has been largely emphasised in the theoretical literature in recent decades. In his ground-breaking contribution on the growth theory, Solow (1956) pointed out the significance of technology in economic growth by claiming that there can be no growth in the long run without technology. However, the role of technical change in long-run growth received much more attention after the emergence of endogenous (or new) growth theories, where technology is not accepted as manna from heaven anymore, but it is determined endogenously (Romer, 1986; Lucas, 1988; Romer, 1990).

The endogenous growth models based on the neoclassical framework, however, were not sufficient to explain the major role of R&D and innovations in persistent technological progress observed in the last two centuries (Akcigit, 2017). Thus, this led to the rise of innovation-based endogenous growth models initiated by Romer (1990), Grossman and Helpman (1991) and Aghion and Howitt (1992). In these models, new technologies emerge as a consequence of R&D efforts of individuals and firms. These new technologies can be introduced either in the form of a new product variety, as in Romer (1990), or as a better version of existing ones, as in Grossman and Helpman (1991) and Aghion and Howitt (1992), based on the premise of Schumpeterian creative destruction. In either case, innovations lead to higher productivity and thus to economic growth. In addition to these seminal works, Jones (1995) introduced a "semi-endogenous" growth model where he challenged the prediction of "scale effects" in these models. He demonstrated that although growth is generated endogenously by R&D, the rate of growth in the long run depends on the population growth rate. Our study relates to that of Schumpeterian growth literature.

The importance of innovation and thus technical change implied by these models brought attention to the policies to incentivise firms' R&D efforts. A great deal of work focused on the impact of such policies in the form of tax incentives or direct subsidies on the R&D investments (Hall and Van Reenen, 2000; Bloom et al., 2002; Harris et al., 2009; Rao, 2016). Bloom et al. (2002), for instance, finds that tax incentives are instrumental in boosting the R&D intensity, especially in the long run, using panel data of nine OECD countries over the period of 1979-1997. Rao (2016) investigates the impact of US federal R&D tax credit between the years 1981-1991 and shows that a 10% decline in costs leads to nearly a 20% increase in R&D intensity in the short run. Akcigit et al. (2018) also examines the impact of the US federal R&D tax credit introduced in 1981 by building a dynamic general equilibrium growth model. One of the main results of their work is that the US federal R&D tax credit policy was an effective response to foreign competition since it raised the technological competitiveness of US firms by making them more innovative.

None of these works, however, focused on ex ante impact assessment of innovation policies. In this context, the pioneer work of Comin and Gertler (2006), which integrated the DSGE model with innovation-led growth, paved the way for making an analysis of potential innovation-enhancing policies or structural reforms on various macroeconomic indicators. Thus, several studies tried to shed light on the interactions between such policies or reforms and various macroeconomic dynamics by using a DSGE model with endogenous growth properties (Roeger et al., 2008, 2009; Varga and in 't Veld, 2011; Cacciatore et al., 2012; Di Comite and Kancs, 2015). Most of the analysis in this framework is based on the simulation-based model developed by the European Commission (QUEST III model), where the endogenous growth is based on the product variety paradigm of Romer (1990) but in a semi-endogenous growth setting of Jones (1995).

Within this framework, Roeger et al. (2008) examines the macroeconomic impact of 10 different structural reform scenarios for the EU region. They find an important positive impact of both reforms on TFP and GDP in the long run. Moreover, Varga and in 't Veld (2011) investigates the potential macroeconomic impact of EU Cohesion Policy, which provides large-scale fiscal transfers to support R&D, human capital and infrastructure in the EU region. Their results indicate that fiscal transfers towards human capital and R&D investments are found to have a strong and permanent impact on productivity in the medium term. Similar analyses were also done for single country cases, such as for Italy (Annicchiarico et al., 2013) and for Portugal, Spain, Italy and Greece (Varga and Roeger, 2014). Recently, the models have been extended to include technology diffusion (European Commission DGRI, 2017) and firm heterogeneity in order to better understand the role of innovation policies (Benedetti-Fasil et al., 2021)

The existing studies regarding the impact of innovation policies, however, have not considered their effects on labour market dynamics. The current models in this area of research assume frictionless labour markets and, thus, full employment. Therefore, the interactions among innovation, growth and employment have remained uncovered. In this regard, we aim to contribute to the existing literature by examining the growth and labour market outcomes under innovation policies. To do so, we model the economy in which the growth is determined endogenously based on Schumpeterian creative destruction, and the labour market is subject to search and matching frictions. In doing so, we closely follow the literature on Schumpeterian innovation-led growth and equilibrium unemployment (Aghion and Howitt, 1994;

Mortensen and Pissarides, 1998; Şener, 2000; Mortensen, 2005).

In this strand of literature, Aghion and Howitt (1994) made one of the first contributions where they analyse the relationship between economic growth and long-run unemployment by using a search model of equilibrium unemployment. The authors indicate that growth can decrease unemployment through the 'capitalisation' effect, but it may also raise it through 'creative destruction'. Mortensen and Pissarides (1998) add to this literature and show that employment is negatively affected by higher productivity growth when the cost of upgrading the existing technology exceeds a unique critical level, and the impact is positive otherwise.

Pissarides (2000), on the other hand, emphasises the 'capitalisation effect' and argues that faster productivity growth results in higher labour demand and thus lower unemployment. More recently, Aghion et al. (2016) created a simple model of Schumpeterian growth and unemployment to examine the impact of creative destruction on the well-being of workers. Chu et al. (2021) examines the relationship among inflation, innovation and unemployment in a Schumpeterian growth model with frictional labour markets. We intend to contribute to this literature by building a DSGE model in such a way as to analyse the impact of innovation policies on these dynamics.

Another strand of literature considers the impact of macroeconomic policies in the presence of labour market frictions. Yashiv (2004), for instance, examines the consequences of macroeconomic policy for labour market outcomes in the presence of labour market frictions and presents how policy might be useful to alleviate frictions as well as how it may create adverse outcomes. However, the paper did not feature endogenous growth as in our study. Chen et al. (2011) investigate the effectiveness of some human capital policies in the presence of labour market frictions by introducing an endogenous growth model with search and matching frictions. Cacciatore and Fiori (2016) study the macroeconomic impact of deregulating the goods and labour market in an otherwise-standard RBC model where there is endogenous product creation and labour market frictions. In a similar vein, Cacciatore et al.

(2016) analyses the impact of labour and product market reforms in a New Keynesian DSGE framework. This paper deviates from these studies as well in terms of modelling the endogenous growth in the Schumpeterian framework and studying innovation policies.

2.3 Model

The baseline model of this study builds on the simple model of Aghion et al. (2016), where growth results from Schumpeterian creative destruction, but it also leads to endogenous obsolescence of firms and jobs. Unlike their study, we differentiate labour into two categories: skilled and unskilled.[1]. Skilled labour is employed by entrepreneurs in order to increase the probability of innovating a higher quality product, whereas unskilled labour is used to produce differentiated intermediate goods. The market for the latter is assumed to be frictional. The presence of these frictions causes equilibrium unemployment.

The government encourages the innovation efforts of entrepreneurs by providing them direct subsidies and tax credits towards decreasing their cost of investment in research. The existence of this support raises the R&D investments of these firms and increases the rate of creative destruction. On the one hand, new innovations create new jobs and thus new employment opportunities. On the other hand, they drive more firms to exit the market, and workers of these firms join the pool of unemployed people. Once a new innovation is discovered, the entrepreneur cannot match with a suitable production worker immediately. Instead, he needs to search for production workers to produce this higher quality product and cannot realise the monopolistic profits until he matches with an employee. When he finds his workers, he collects the monopolistic profits until the arrival of the next innovation.

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[1] Chu et al. (2021) use a similar structure where people can work as production workers or as R&D workers

2.3.1 Households

The population is a unit continuum of risk-sharing households. A share of $\lambda \in (0,1)$ of households is skilled while the remaining, $1-\lambda$, is unskilled. Each skilled worker is endowed with one unit of productive time per period. The household chooses the share, $n_{r,t} \in [0,1]$ of that endowment that is devoted to research work. Therefore, aggregate skilled hours are represented as

$$L_{r,t} = \lambda n_{r,t} \tag{2.1}$$

Unskilled individuals, however, either hold a production job or are unemployed, and we normalised hours per employed worker to one. Let u_t be the unemployment rate. Aggregate unskilled hours are then

$$L_{p,t} = (1-\lambda)(1-u_t) \tag{2.2}$$

Because unskilled hours already scale one-for-one with headcount employment, we do not introduce a separate hour choice, $n_{p,t}$. Throughout the paper, we refer to $L_{r,t}$ and $L_{p,t}$ as skilled and unskilled labour inputs; both are expressed as shares of the labour force time endowment and are directly comparable. [2]

Households derive utility from consuming a homogeneous final good, suffer disutility from supplying labour and maximise their lifetime utility:

$$\mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \left(\ln C_t - \Psi_p \frac{L_{p,t}^{1+\chi}}{1+\chi} - \Psi_r \frac{L_{r,t}^{1+\chi}}{1+\chi} \right) \tag{2.3}$$

C_t stands for final consumption, $L_{p,t}$ and $L_{r,t}$ represent the labour supplied for

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[2] Allowing an hours choice for unskilled workers would complicate the Nash-bargaining block without affecting the model's mechanism: empirical variation in hours per production worker is an order of magnitude smaller than variation in their employment status. We therefore normalise hours per match to one and focus on the extensive margin u_t.

production and research, respectively. $\beta \in (0,1)$ is the subjective discount factor whereas χ stands for the inverse of the Frisch elasticity. Finally, $\Psi_p > 0$ and $\Psi_r > 0$ are scale parameters measuring disutilities of unskilled and skilled labour.

Skilled workers face no matching frictions, so any hours the family wants to supply are employed. Thus, unemployment u_t pertains only to the unskilled labour, who receive benefits, b_t. Households face the following budget constraint, where we denominate all the factor prices by the price of final goods, which is chosen as numeraire:

$$C_t = w_{r,t}L_{r,t} + w_{p,t}L_{p,t} + b_t u_t + (1-\tau)\Pi_t - T_t \tag{2.4}$$

where $w_{r,t}$ and $w_{p,t}$ are the real wages of skilled labour, $L_{r,t}$, and unskilled labour, $L_{p,t}$, respectively. Moreover, b_t stands for unemployment benefits, which are assumed to be proportional to output, $b_t = \bar{b}Y_t$, where $\bar{b} \in (0,1)$ is an exogenous unemployment benefit parameter. Finally, $(1-\tau)\Pi_t$ is the after-tax aggregate profits, in which τ represents the corporate taxes and T_t is the lump-sum taxes paid by households.

Households' optimisation problem yields the stochastic discount factor and labour supply conditions.

$$\Lambda_{t,t+1} = \beta \frac{C_t}{C_{t+1}} \tag{2.5}$$

$$\omega_t = \Psi_p C_t L_{p,t}^{\chi} \tag{2.6}$$

$$w_{r,t} = \Psi_r C_t L_{r,t}^{\chi} = \Psi_r C_t (\lambda n_{r,t})^{\chi} \tag{2.7}$$

However, we note that market wages of production workers are set by bargaining due to the matching frictions faced by production workers. Therefore, equation (2.6) resulting from the first order conditions does not represent the actual wage paid for production workers but stands for the shadow price of leisure below which a worker prefers leisure over supplying labour. For future reference, we call this shadow value ω_t. Moreover, combining unemployment benefits b_t with this shadow value yields the reservation wage:

$$w_t^{res} = b_t + \omega_t \tag{2.8}$$

2.3.2 Final Goods

The final good is produced under perfect competition, as a Cobb-Douglas aggregate of a continuum of intermediates indexed on $[0, 1]$. That is,

$$Y_t = \exp\left(\int_0^1 \ln y_{j,t} dj\right) \tag{2.9}$$

where Y_t is the final good and $y_{j,t}$ is the quantity of the intermediate good j used in production. Profit maximisation yields the demand for intermediate goods as:

$$y_{j,t} = \frac{Y_t}{p_{j,t}} \tag{2.10}$$

where $p_{j,t}$ is the price of intermediate goods and the price index is normalised to 1, that is $\exp\left(\int_0^1 \ln p_{j,t} dj\right) = 1$. Thus, the equation (2.10) implies that the final good producer spends the same amount of the final good on each variety j.

2.3.3 Intermediate Goods, Entrepreneurs and Innovation

Unlike the final good sector, there is monopolistic competition in the intermediate goods sector. The continuum of differentiated goods is produced using the following linear technology:

$$y_{j,t} = A_{j,t} l_{p,j,t} \tag{2.11}$$

where $A_{j,t}$ is the productivity of the sector j at time t and $l_{p,j,t}$ is the unskilled labour working in the production of the intermediate good j. Productivity, $A_{j,t}$, evolves depending on the success of innovation efforts and is the only source of growth in this economy. Innovations, however, depend on the R&D efforts of entrepreneurs who employ skilled workers to engage in innovation within an industry, thereby increasing their chances of success in inventing a higher-quality product. Upon the success of an entrepreneur, he replaces the incumbent and becomes the new monopolist in his sector. The successful entrepreneur continues to produce until another entrepreneur replaces him. Following a discovery, the productivity of sector j improves as follows

$$A_{j,t+1} = \begin{cases} \gamma A_{j,t} & \text{with probability } x_{j,t} \\ A_{j,t} & \text{with probability } 1 - x_{j,t} \end{cases} \tag{2.12}$$

where $\gamma > 1$ is the step size of innovations. In every period, sector-specific productivity improves with probability $x_{j,t}$. It becomes $\gamma A_{j,t}$ or continues to produce with the current level of technology with probability $1 - x_{j,t}$. We also define the productivity index of the economy as

$$A_t \equiv \int_0^1 A_{j,t} dj \tag{2.13}$$

The probability of success,$x_{j,t}$, depends on the research productivity and the skilled labour employed in R&D. Therefore, we define the success probability as

$$x_{j,t} = \min\{(\mu_t l_{r,j,t})^{\phi}, 1\} \tag{2.14}$$

where $\phi \in (0, 1)$, and $l_{r,j,t}$ denotes the skilled labour hours devoted to research in sector j at time t, $\mu_t > 0$ is a constant exogenous parameter that stands for the productivity of research.

2.3.4 Determining Wages and Profits

As it is clear from equation (2.11), intermediate good producers use only production workers to produce their goods. The labour market for production workers is frictional, and the wages of production workers are determined through a generalised Nash Bargaining process. To do so, we follow set up of Mortensen (2005) as it allows a much simpler setting than using a more general Nash bargaining through value functions.[3] However, in this setting, we assumed that the outside option of the workers is the reservation wage w_t^{res}, whereas the employer has no outside option. Thus, we can define the Nash bargaining on wages as follows:

$$w_{p,t} = \arg\max_{w_{p,t}} (w_{p,t} - w_t^{res})^{\alpha} \left(p_{j,t}A_{j,t} - w_{p,t}\right)^{1-\alpha} \tag{2.15}$$

As can be seen, the surplus of firms is defined as the difference between the marginal revenue product $p_{j,t}A_{j,t}$ and the cost of labour $w_{p,t}$. The fact that productivity, $A_{j,t}$, is endogenous can complicate the bargaining process, as both the firm and workers will negotiate by considering the potential productivity growth. For the sake of tractability, we assume that both parties take the productivity as given when they start the negotiation. In other words, we assume that the firm's current productivity level $A_{j,t}$ is known by both parties at the time of wage bargaining and that agents form their expectations about future productivity levels based on all available information. The outcome of this bargaining process is then as follows:

$$w_{p,t} = \alpha p_{j,t}A_{j,t} + (1-\alpha)w_t^{res} \tag{2.16}$$

where the bargained wage is the average between the marginal revenue product and

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[3] In a similar setting, Chu et al. (2021) argues that using a more general bargaining condition with the value functions of employment and unemployment adds complexity without providing new insight. (see also Stepanok (2016))

the reservation wage. The worker and the firm need to commit to this wage schedule throughout the life cycle of the firm.

As stated above, the arrival of innovation increases productivity by γ. Firms in the intermediate good sector compete a la Bertrand, and their pricing decision is static. Due to the threat of the follower, the leader sets the price of the intermediate good to the markup over the marginal cost of the follower, which is:

$$p_{j,t} = \gamma \frac{w_{p,t}}{A_{j,t}} \tag{2.17}$$

By combining this price rule with the wage schedule (2.16), we can define the wage of the production workers as[4]

$$w_{p,t} = \frac{(1-\alpha) w_t^{res}}{(1-\alpha\gamma)} \tag{2.18}$$

and the price of intermediate goods can now be expressed as

$$p_{j,t} = \gamma \frac{(1-\alpha) w_t^{res}}{(1-\alpha\gamma) A_{j,t}} \tag{2.19}$$

Moreover, using the (2.19) and (2.10) the the demand for intermediate goods is now

$$y_{j,t} = \frac{(1-\alpha\gamma) A_{j,t}}{(1-\alpha)\gamma w_t^{res}} Y_t \tag{2.20}$$

where the (2.20) uses (2.8). Using the price rule in (2.17), we can find the monopolistic profits as

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[4] It is important to note that the wage cannot be determined when $\alpha\gamma \geq 1$. Thus, in order for the wage to be determined, we need to put a parameter restriction so that $\alpha\gamma < 1$.

$$\begin{aligned} \pi_{j,t} &= \left(p_{j,t} - \frac{w_{p,t}}{A_{j,t}}\right) y_{j,t} \\ &= \left(\gamma\frac{w_{p,t}}{A_{j,t}} - \frac{w_{p,t}}{A_{j,t}}\right) y_{j,t} \\ &= \left(\frac{\gamma - 1}{\gamma}\right) Y_t \end{aligned} \tag{2.21}$$

where the last equality uses (2.20).

As the profit is the same across industries, we assume that the arrival of innovation is also the same across sectors, i.e. $x_{j,t} = x_t$, to simplify the analysis and focus on symmetric equilibrium following the standard treatment in the literature.

2.3.5 Labour Market

The labour market for production workers in the model economy suffers from search and matching frictions. In contrast, the market for research labour is assumed to be frictionless as in Şener (2000). Indeed, the evidence shows that skilled workers generally experience considerably lower rates of unemployment relative to unskilled labour (Nickell and Bell, 1995; Cairó and Cajner, 2018).[5] Although this does not necessarily mean that skilled labour does not suffer from any frictions, it documents a significant difference in being exposed to matching frictions in the labour market between these groups. We will use this assumption for simplicity in this baseline model.

In the labour market, jobs are separated by the arrival of new innovations and job matches are determined by the aggregate matching function and job market tightness. The matching function is, then, defined as:

$$m(u_t, v_t) = \kappa u_t^{\eta} v_t^{1-\eta} \tag{2.22}$$

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[5] Cairó and Cajner (2018) argues that lower rates of unemployment of skilled labour are due to lower separation rates.

where κ is the matching efficiency, u_t is the number of unemployed workers at time t, and v_t is the number of vacancies at time t. The matching technology has the standard assumptions of being increasing, concave, and homogeneous of degree one in u_t and v_t. Therefore, the probability that an unemployed worker finds a job (the job-finding rate) can be defined as

$$\rho_t = \frac{m(u_t, v_t)}{u_t} = \kappa\theta^{1-\eta} \tag{2.23}$$

and the probability that a vacancy is filled, i.e. job-filling rate, is:

$$\nu_t = \frac{m(u_t, v_t)}{v_t} = \kappa\theta^{-\eta} \tag{2.24}$$

where $\theta = \frac{v_t}{u_t}$ is the labour market tightness.

Given separations that occur with the arrival of innovation and matches that occur through the matching function, unemployment evolves according to

$$u_{t+1} \;=\; u_t + x_t\, L_{p,t} - \rho_t\, u_t \;=\; (1-\rho_t)u_t + x_t\big(1-u_t\big).$$

2.3.6 Value Functions

The workers are at risk of losing their jobs due to creative destruction. Therefore, the job separation in this model occurs at the arrival rate of innovations, x_t. On the other hand, any unemployed worker finds a job with probability ρ_t. In this regard, the value of an employed worker is:

$$J_t = w_{p,t} + \Lambda_{t,t+1}\mathbb{E}_t\{[x_t U_{t+1} + (1-x_t)J_{t+1}]\} \tag{2.25}$$

where $\Lambda_{t,t+1} = \beta\frac{C_t}{C_{t+1}}$ is the stochastic discount factor derived from households' maximisation problem. The intuition behind the equation (2.25) is that the value of being employed at time t (J_t) is equal to the real wage she can earn from her work and expected discounted value of continuing the work in the next period or the value of being unemployed if the job is subject to creative destruction with the arrival rate of x_t. In a similar manner, the value of being unemployed at time t is:

$$U_t = w_t^{res} + \Lambda_{t,t+1}\mathbb{E}_t[\rho_t J_{t+1} + (1-\rho_t)U_{t+1}] \tag{2.26}$$

The equation (2.26) states that the present value of being unemployed equals the reservation wage, and the value of being employed in the next period, plus the value of staying unemployed.

On the firm's side, there are three different states of the firm: entrant, incumbent before hiring a production worker, and incumbent after hiring a production worker. First of all, a firm must innovate in order to enter the market and replace the incumbent. Thus, the first state is the entry state in which the entrepreneur tries to innovate. At this stage, the prospective entrant tries to maximise the discounted value of becoming the incumbent in the next period and thus decides on his research effort, $l_{r,j,t}$. The value of an entrant firm before it has successfully innovated is:

$$E_{j,t} = \max_{l_{r,j,t}} -\psi w_{r,t} l_{r,j,t} + \Lambda_{t,t+1}\mathbb{E}_t\left[x_t I_{j,t+1}\right] \tag{2.27}$$

where $\psi = (1-s)(1-\tau)\big[1 - \frac{\tau_r \tau}{1-\tau}\big]$ stands for the subsidies and R&D tax credits provided by the government towards decreasing the cost of research and $w_{r,t}$ is the wage for skilled labour, which is determined in a competitive market.[6] Assuming free entry to research, i.e. $E_{j,t} = 0$, we can derive the optimal R&D decision of the entrant as follows:

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[6] Following Benedetti-Fasil et al. (2021), we model the R&D tax credit as a rebate that scales with the corporate tax rate; consequently the effective marginal R&D cost includes a term proportional to τ.

$$\psi w_{r,t} = \phi \frac{x_t}{l_{r,j,t}} \Lambda_{t,t+1} \mathbb{E}_t \left[I_{j,t+1} \right] \tag{2.28}$$

where the marginal costs of adding an additional skilled hour, the wage costs $\psi w_{r,t}$, are balanced with the expected marginal benefits, which is the expected discounted value of innovation.

Following a successful discovery, the firm moves into the incumbent state and needs to hire production workers to start production and earn monopolistic profits. Thus, the value of an incumbent firm, $I_{j,t}$, after a successful innovation and before hiring unskilled labour, would be the expected discounted value of becoming a productive firm.

$$I_{j,t} = \Lambda_{t,t+1} \mathbb{E}_t \left[\nu_t V_{j,t+1} + (1 - \nu_t) I_{j,t+1} \right] \tag{2.29}$$

where ν_t is the probability of filling a vacancy and $V_{j,t+1}$ is the value of a firm in the production stage at time $t + 1$. If the firm is successful in hiring unskilled labour (which happens with probability ν_t), it moves to the production stage with value $V_{j,t+1}$. If the firm is not successful in hiring (which happens with probability $1 - \nu_t$), it remains an incumbent firm with value $I_{j,t+1}$.

Posting a vacancy costs a *fraction* of the production wage, $c_{v,t} = \sigma_v w_{p,t}$ with $\sigma_v > 0$. Free entry, therefore, requires

$$c_{v,t} \;=\; \Lambda_{t,t+1}\, \nu_t \left[V_{j,t+1} - I_{j,t+1} \right]. \tag{2.30}$$

Finally, the last stage is the production stage, where a firm in the incumbent state successfully hired a production worker and started production. Therefore, the value of a firm in the production stage, $V_{j,t}$, is the profit of the firm net of corporate taxes plus the expected future value of the firm. This can be expressed as follows.

$$V_{j,t} = (1-\tau)\pi_{j,t} + \Lambda_{t,t+1}\mathbb{E}_t\left[(1-x_{t+1})V_{j,t+1}\right] \tag{2.31}$$

The value functions defined above reflect the life cycle of a firm in this model: a new entrant firm hires skilled labour to innovate, if successful, it becomes an incumbent firm and hires unskilled labour to produce, and it continues production until the job is destroyed due to creative destruction. The firm's decision to enter the market and to hire skilled labour for research is driven by the expected value of becoming an incumbent and moving to the production stage. The firm's decision to hire unskilled labour for production is driven by the expected value of production. The rate of job destruction x_t in the production stage depends on the success of new entrepreneurs in the innovation stage.

2.3.7 Government

In the presence of innovation policies, the government finances its budget through taxing corporate profits (excluding tax credits) and lump-sum taxes on households. We assume that the budget is balanced each period, and it is thus defined as:

$$G_t = \tau\Pi_t + T_t \tag{2.32}$$

where G_t is total government expenditure on subsidies and tax credits. Equation (2.32) can also be written as:

$$(s + \tau_r\tau)w_{r,t}L_{r,t} + b_t u_t = \tau\Pi_t + T_t. \tag{2.33}$$

2.3.8 Aggregation and Market Clearing

In this baseline model, the economy is closed and all costs regarding production and R&D are in terms of labour, and the only other real expenditure is the vacancy-posting cost, c_v, which is paid in units of the final good. Therefore, the market clearing for the aggregate output implies:

$$Y_t = C_t + c_{v,t}\theta_t u_t \tag{2.34}$$

Moreover, market clearing for skilled labour is:

$$L_{r,t} = \int_0^1 l_{r,j,t} dj \tag{2.35}$$

where the demand for skilled labour can be derived by using (2.28) as:

$$l_{r,j,t} = \left(\frac{\phi \mu_t^{\phi} \Lambda_{t,t+1} \mathbb{E}_t I_{j,t}}{\psi w_{r,t}} \right)^{\frac{1}{1-\phi}} \tag{2.36}$$

The long-run growth in this economy comes from the quality improvements in the intermediate goods reflected by the increase in the productivity index, A_t. In every period, a measure $x_t \in [0, 1]$ of varieties succeeds in R&D and their quality jumps by γ. By the law of large numbers, the aggregate index, A_t, evolves deterministically

$$A_{t+1} = x_t(\gamma A_t) + (1 - x_t)A_t \tag{2.37}$$

rearranging equation (2.37), we get the rate of productivity growth:

$$g \equiv \frac{A_{t+1}}{A_t} - 1 = x_t(\gamma - 1) \tag{2.38}$$

The growth rate basically depends on the rate at which innovation arrives and the step size of innovations.

2.4 Quantitative Analysis

In this section, we provide the quantitative analysis of the model. We start by presenting the parameter calibration and data used. Then, we discuss the comparative statics implications regarding the change in innovation policies. Finally, we examine the transitional dynamics based on permanent changes in innovation policies.

2.4.1 Calibration

Household parameters. We calibrate the model for the US economy for the period between 2003 and 2019. We set the discount factor, β, to 0.96, which implies an annual real interest rate of 4%. We set the Frisch elasticity of labour supply to 0.5 for both labour types following Chetty et al. (2011). Robustness to alternative Frisch elasticities is reported in Appendix 2.C.3. The disutility weights, Ψ_p and Ψ_r of unskilled and skilled labour are chosen so that the model reproduces the wage premium of about 1.8 and the share of labour force time for R&D of nearly 1% for the period of interest based on Business Enterprise Research and Development (BERD) Survey.[7]

Innovation block. The step size of innovations is set to, $\gamma = 1.2$, implying that each innovation raises the productivity by 20%. The parameter regarding the R&D elasticity, $\phi = 0.5$, is chosen based on the microeconometric estimates in the literature (Blundell et al., 2002; Akcigit et al., 2018). Moreover, we set the research productivity parameter, $\mu = 0.10$, so that the model matches the average TFP growth of 0.69% over the period 2003-2019 in the US, which corresponds to the BLS data on

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[7] The skilled-labour share is fixed at $\lambda = 0.30$ considering the Bureau of Labour Statistics (BLS) data on workers with a bachelor's degree or higher, which averaged nearly 30% of the labour force between 2003 and 2019. The use of an education level of a Bachelor's degree and higher reflects the R&D-capable labour in the economy.

Table 2.1: Calibrated Parameters

Parameter	Symbol	Value
Household discount factor	β	0.96
Innovation step size	γ	1.2
R&D success elasticity	ϕ	0.5
Worker Nash bargaining weight	α	0.5
Matching efficiency parameter	κ	0.5
Matching elasticity w.r.t. unemployment	η	0.5
Vacancy-posting cost share	σ_v	0.03
Research productivity	μ	0.10
Unemployment-benefit replacement rate	$\bar{b}$	0.035
Disutility weight: unskilled labour	Ψ_p	1.85
Disutility weight: skilled labour	Ψ_r	32.6
Frisch elasticity of labour supply	χ	0.5
Skilled-worker population share	λ	0.3
Baseline corporate-profit tax rate	τ	0.33
Baseline direct R&D subsidy rate	s	0.1
Baseline R&D tax-credit rate	τ_r	0.06

multifactor productivity.

Labour market. Following Epstein and Shapiro (2017), we set the bargaining power of the production workers, α, the elasticity of matching, η and the matching efficiency, κ, to 0.5. Furthermore, we the vacancy posting cost share, σ_v is set to 0.03 to match the average unemployment rate of 6.1% between 2003 and 2019.

Government. We set the unemployment benefit parameter, $\bar{b} = 0.035$, such that the share of unemployment benefits in GDP stays close to the average of the time period. The corporate tax rate is set to 33% using OECD's Corporate Income Tax Rates Database. [8] Finally, we set statutory rates for the tax credits, τ_r, and direct subsidies, s, as 6% and 10%, respectively, based on the R&D tax incentives database of OECD.

The Table 2.2 presents the targets and model fit under the calibrated parameters. Although the model is stylised, it is still able to match some key moments well.

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[8] Until 2018, the corporate tax rates were 35% in the US. Following the US tax reform known as the Tax Cuts and Jobs Act, corporate taxes were reduced to 21%.

Table 2.2: Calibration targets and model fit (annual U.S. data 2003–2019)

Moment	**Model**	**Target (Data)**	**Source**
TFP growth g (pct/yr)	0.69	0.69	BLS MFP
Unemployment rate u (%)	6.1	6.1	BLS CPS
R&D labour share L_r (% of LF hours)	1.16	1.0	NSF BERD (FTE)
Relative wage w_r/w_p	1.83	1.82	BLS OEWS

2.4.2 Comparative Statics

We study how the balanced–growth allocation responds when each R&D–policy instrument is varied separately around the baseline $(\tau_r, s) = (0.06, 0.10)$. At every grid point we recompute the full general-equilibrium steady state. Figure 2.1 plots the long-run TFP growth rate g (left axis) and the steady-state unemployment rate u (right axis).

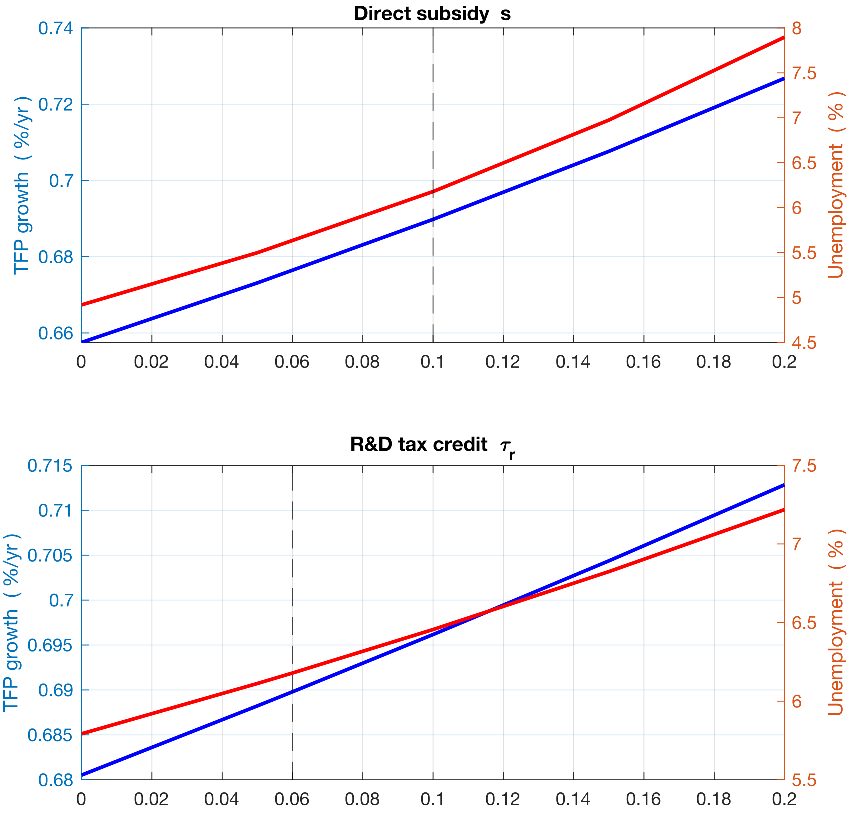

Figure 2.1: Comparative Statics

Raising either the incremental tax credit τ_r or the direct wage subsidy s lowers the effective R&D cost wedge

$$\psi(\tau_r, s) \;=\; (1-s)\,(1-\tau)\left[1-\tfrac{\tau_r\,\tau}{1-\tau}\right],$$

which increases R&D effort, the innovation arrival rate x, and long-run growth $g = x(\gamma - 1)$. At the same time, an increase in x heightens separations through the process of creative destruction and, by means of the vacancy free-entry condition, lowers the equilibrium tightness. Mechanically, this implies a lower job-finding rate and a higher job-filling rate. In steady state, unemployment therefore rises due to both a higher inflow (greater x) and a weaker outflow (lower job-finding), resulting in the familiar Schumpeterian growth–unemployment trade-off.

Holding the subsidy fixed, ψ is *affine* in τ_r; accordingly, (τ_r, g) and (τ_r, u) are nearly linear. When s varies, ψ moves multiplicatively, and both g and u inherit *convexity*: each extra percentage point of subsidy has a larger marginal effect than the previous one.

Local elasticities at the baseline. Differentiating at $(\tau_r, s) = (0.06, 0.10)$ gives:

Table 2.3: Proportional elasticities at the baseline $\big(\tau_r, s\big) = \big(0.06, 0.10\big)$.

Instrument	ε_u $\dfrac{\partial(u)/u}{\partial X/X}$	ε_g $\dfrac{\partial(g)/g}{\partial X/X}$
Tax credit τ_r	0.067	0.014
Wage subsidy s	0.24	0.05

A 1% increase in s is therefore about $\frac{0.24}{0.067} \approx 3.6$ times more potent for unemployment and $\frac{0.05}{0.014} \approx 3.6$ times more potent for growth than an equally proportional increase in τ_r. Taken together, the comparative statics show that both instruments raise growth but at the cost of higher unemployment, with subsidies delivering larger marginal effects per percentage change in the instrument. [9]

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[9] Cost-effectiveness per fiscal dollar is assessed separately in the welfare analysis.

2.4.3 Transitional Dynamics

In this section, we examine the response of the model's variables following a permanent policy change over the 50-year horizon. All reforms are *pre-announced* at date 0 and implemented in period 1 unless otherwise stated. We focus on two targeted policies, an increase in direct subsidies and tax credits, and a nontargeted policy, corporate tax reduction.

Targeted Policies: Subsidies and Tax Credits

We analyse the effects of an increase in tax credits and direct subsidies separately. Figure 2.2 depicts the transitional dynamics regarding a permanent change of direct subsidies from 10% to 20%. A permanent rise in direct grants raises the hours supplied by skilled workers to R&D by almost 12% and skilled wages by 6%. This, in turn, boosts innovation efforts and results in a nearly 0.25 percentage point increase in innovation probability, leading to an almost 0.04 percentage point increase in TFP growth. On the other hand, higher innovation increases job separation and raises unemployment by more than two percentage points.

In the case of tax credits, we observe relatively weaker effects on the model's variables compared to the increase in the direct subsidies. Figure 2.3 documents the model's response to a permanent change in tax credits from 6% to 12%. Doubling of tax credits raises the hours supplied by skilled workers by around 3%, which increases the success probability of innovations by only around 0.06 percentage points. This leads to a modest increase in TFP growth of just 0.01 percentage points and a nearly 0.5 percentage point increase in unemployment.

Under the current structure of the model with frictionless R&D labour, the innovation probability $x_t = (\mu L_{r,t})^{\phi}$ and therefore $g_t = x_t(\gamma - 1)$ adjust one-for-one with the cost wedge. Therefore, the doubling of subsidies and tax credits leads TFP growth to settle down to a new BGP almost immediately after the policy comes into force. Instead, unemployment rises gradually, and it takes around 5 years to adjust

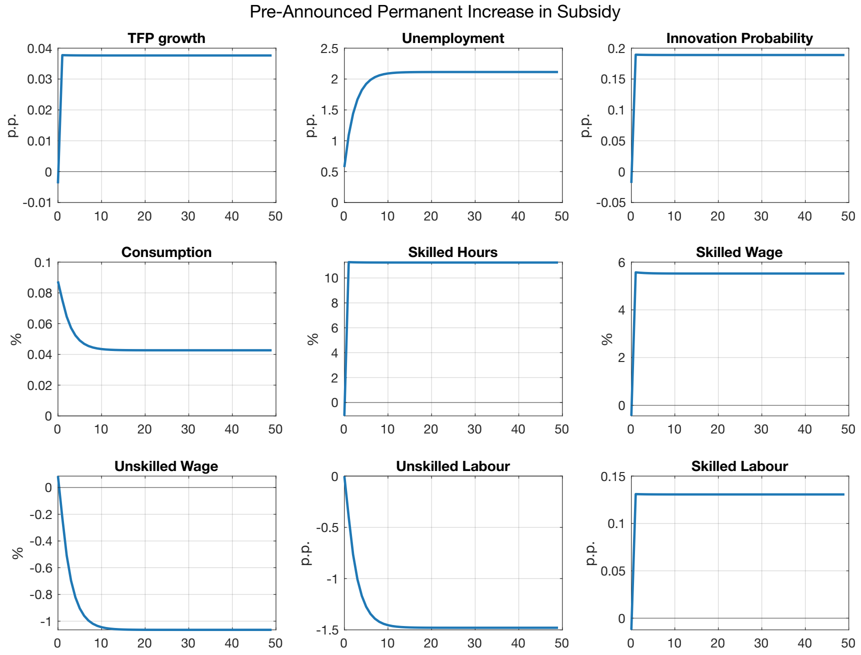

Figure 2.2: Permanent Increase in Direct Subsidy s from 10 % to 20 %

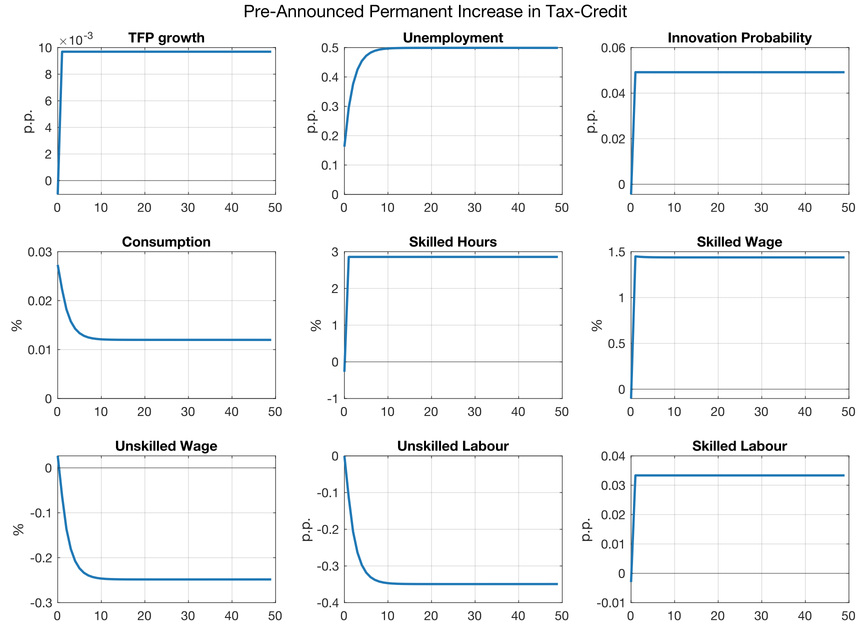

Figure 2.3: Permanent Increase in Tax Credits τ_r from 6% to 12%

to its new level due to frictions in the unskilled labour market.

The initial declines in skilled hours, wages, and thus TFP growth observed in both figures at $t = 0$ are related to anticipation effects. As the policy is pre-announced at $t = 0$, the cost of R&D is expected to be lower from the next period on, which lowers demand for skilled labour and thus decreases TFP growth initially. On impact, we observe that TFP growth reaches its peak before declining slightly and settles on the new BGP.

Because profits—and therefore the household dividend base—rise immediately with the expected future productivity, the net effect on after-tax income is positive despite higher lump-sum taxes, so consumption increases on impact.

Nontargeted Policy: Corporate Tax Cuts

So far, we have focused on the policies that are targeted to increase innovation efforts. However, there are also policies aimed at boosting economic growth without directly targeting innovation incentives. A crucial instrument in this fashion is corporate tax reduction. In the US, for instance, a new legislation regarding corporate tax reform came into force under the Tax Cuts and Jobs Act at the end of 2017. Under the new law, corporate taxes are reduced from 35% to 21%, aiming mainly to bolster the competitiveness of US companies and stimulate economic growth and job creation.

The effectiveness of such general taxation policies in fostering innovation, however, is controversial, as they are not specifically targeted for that purpose (Stantcheva, 2021). However, like any other economic activity, innovation also hinges on the time and material inputs devoted to it. Thus, corporate taxes are likely to have an impact on the returns those investments generate (Akcigit et al., 2022b). In this regard, we are interested in how corporate tax cuts affect TFP growth and unemployment dynamics in our model economy. To examine this, we run another policy experiment in which corporate taxes are permanently reduced by three percentage points. Figure 2.4 shows the transitional dynamics in our model regarding this policy change.

The model's response to a permanent corporate tax reduction suggests that re-

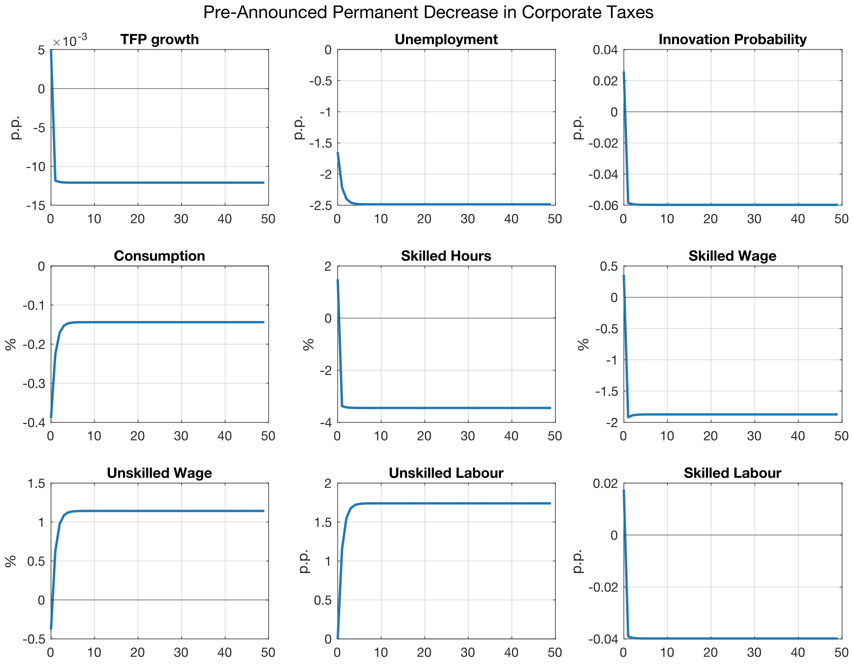

Figure 2.4: Permanent Decrease in Corporate Taxes τ from 33% to 30%

ducing the broad corporate tax rate in our economy discourages innovation, as it removes two implicit subsidies to research: wage deductibility and the R&D tax credit refund. Both are proportional to τ, so the cost wedge ψ rises when τ falls. Entrants therefore hire fewer skilled hours, the innovation arrival rate drops, and long-run TFP growth falls by more than 0.01 percentage points. Because job separations equal the innovation rate, a decrease in innovation success reduces the risk of creative destruction. Thus, unemployment also declines, but at the cost of slower growth and a larger lump-sum tax to offset the lost profit-tax revenue.

2.4.4 Welfare Analysis

We now evaluate the present discounted welfare effects of the three permanent policy reforms. Throughout, welfare is computed with the household's objective

$$U_0 = \sum_{t=0}^{\infty} \beta^t \Big[\ln C_t - \tfrac{\Psi_p}{1+\chi} L_{p,t}^{1+\chi} - \tfrac{\Psi_r}{1+\chi} L_{r,t}^{1+\chi} \Big],$$

In our quantitative implementation all real quantities are in stationary units (we normalize the final-good price index and Y_t to one), so flow utility is time invariant along a balanced–growth path (BGP). If (C, L_p, L_r) are the stationary BGP values, lifetime welfare on that BGP is

$$W^{\text{BGP}} \;=\; \frac{\ln C - \frac{\Psi_p}{1+\chi} L_p^{1+\chi} - \frac{\Psi_r}{1+\chi} L_r^{1+\chi}}{1-\beta}. \tag{2.39}$$

For a deterministic policy path $\{C_t, L_{p,t}, L_{r,t}\}_{t=0}^{T}$ followed by its terminal BGP, overall welfare equals

$$W^{\text{dyn}} \;=\; \sum_{t=0}^{T} \beta^t \Big[\ln C_t - \tfrac{\Psi_p}{1+\chi} L_{p,t}^{1+\chi} - \tfrac{\Psi_r}{1+\chi} L_{r,t}^{1+\chi} \Big] \;+\; \beta^{T+1} W_T^{\text{BGP}}.$$

To express welfare differences in intuitive units, we compute the constant proportional change in *baseline* consumption that makes the household indifferent between two allocations. Let W_0 be welfare under the status quo and W_i under policy i. We compute the consumption equivalent (CE) gain ξ_i solves $U_0\big((1+\xi_i)C_t\big) = W_i$ and, with log utility

$$\xi_i \;=\; \exp\!\big\{(1-\beta)\,(W_i - W_0)\big\} - 1. \tag{2.40}$$

A positive (negative) ξ_i means the representative household would accept a permanent rise (cut) of that percentage in baseline consumption as compensation for forgoing (adopting) policy i.

Table 2.4: Consumption–equivalent welfare effects of permanent policy changes

Policy shock	CE gain (%)	PV fiscal cost (% GDP)
$s:$ 0.10 → 0.20 (wage subsidy)	**1.47**	14.2
$\tau_r:$ 0.06 → 0.12 (tax credit)	**0.36**	2.7
$\tau:$ 0.33 → 0.30 (corp. tax cut)	**-2.64**	9.1

Doubling the direct subsidies raises growth by 0.04 percentage points and, despite a two percentage point rise in unemployment, yields a dynamic CE gain of 1.47%. With the same statutory doubling, the incremental credit cuts the cost wedge by just 3%, so growth rises one-third as much and welfare only 0.36%. Lowering τ from 33% to 30% reduces deductibility, increases the effective R&D wage, and *lowers* long-run growth. The CE loss is as high as 2.64%, even though unemployment falls; broad tax cuts thus seem an inefficient innovation policy.

Dividing CE by the present-value cost (second column) shows that every 1% of GDP spent on direct wage subsidies buys 0.10% CE welfare, against 0.13% for tax credits and a negative return for profit-tax cuts about -0.29%. This result indicates that although targeted R&D subsidies deliver the largest welfare boost, tax credits are more cost-effective.

2.5 Conclusion

Innovation policies have gained prominence in the policy agendas of advanced economies, as innovation has been regarded as the main catalyst of productivity and, by extension, economic growth. However, technological change is also believed to entail costs. In this paper, we study the impact of innovation policies not only on economic growth but also on unemployment. In doing so, we try to shed light on the debate on the economic growth-unemployment trade-off by embedding a Schumpeterian growth model with a frictional production-worker labour market.

The model evaluates two targeted policy instruments, direct subsidies and tax credits, which are commonly used by governments to foster R&D activities. In addition, it also analyses the effect of a corporate tax cut as a nontargeted policy for innovation. Because job creation and destruction are endogenous, the model delivers a transparent growth–unemployment trade-off: stronger innovation policies raise TFP but also accelerate creative destruction and thus increase separation risk.

Calibrated to US data for 2003-2019, the economy reproduces the key moments it targets, i.e., TFP growth, unemployment, the STEM wage premium, and the R&D labour share. Comparative statics and perfect-foresight simulations indicate that R&D subsidies dominate tax credits in raw welfare terms. Doubling the direct wage subsidy raises long-run TFP growth by 0.04 pp and delivers around 1.5% consumption-equivalent (CE) gain, more than four times the gain from a revenue-equivalent doubling of the incremental tax credit.

Tax credits, however, are more cost-efficient. Once the present value fiscal outlay is netted out, credits buy about 0.13% of annual consumption for each %-of-GDP they cost, versus 0.10% for subsidies. On the other hand, a broad profit tax cut is not an effective tool for boosting innovation. Lowering the corporate rate from 33% to 30% raises the R&D wage wedge, reduces the success probability, and ultimately lowers growth. The representative household would accept a permanent 2.64% drop in consumption to avoid such a reform despite a short-run fall in unemployment.

The findings indicate that well-designed, transparent subsidies remain the most effective tool for policy implementation when fiscal space is ample. On the other hand, well-designed tax credits outperform when budgets are tight. A nontargeted profit-tax cut, by contrast, is dominated on both growth and welfare grounds.

The current model, however, is abstracted from endogenous entry costs for new research lines and matching frictions for skilled workers. Adding either margin would moderate the growth response and could tilt cost-effectiveness further toward tax credits. Empirically, exploring state-level R&D programs where variation in credits is larger would allow a direct test of the model's welfare rankings. Both extensions are left for future research.

Appendices to Chapter 2

2.A Model Derivations

The final good is a Cobb–Douglas (log) aggregate of a unit measure of intermediates:

$$Y_t = \exp\Big(\int_0^1 \ln y_{j,t}\, dj\Big), \qquad \text{with} \quad \exp\Big(\int_0^1 \ln p_{j,t}\, dj\Big) = 1. \tag{2.41}$$

A competitive final-good producer chooses $\{y_{j,t}\}$ to minimize $\int_0^1 p_{j,t} y_{j,t}\, dj$ subject to (2.41). The Lagrangian implies $p_{j,t} y_{j,t} = \text{const}$ across j; normalizing the log price index to one yields

$$y_{j,t} = \frac{Y_t}{p_{j,t}}, \qquad \int_0^1 p_{j,t} y_{j,t}\, dj = Y_t. \tag{2.42}$$

Hence the final-good producer spends the same amount on each variety in every period.

2.A.1 Pricing against the follower and profits

Intermediate technology is $y_{j,t} = A_{j,t}\, l_{p,j,t}$. With Bertrand competition against the immediate follower, the leader prices at the follower's marginal cost markup:

$$p_{j,t} = \gamma\, \frac{w_{p,t}}{A_{j,t}}. \tag{2.43}$$

Combining (2.42) and (2.43), firm j's profit is

$$\begin{aligned}\pi_{j,t} &= \Big(p_{j,t} - \tfrac{w_{p,t}}{A_{j,t}}\Big) y_{j,t} = \Big(\gamma\, \tfrac{w_{p,t}}{A_{j,t}} - \tfrac{w_{p,t}}{A_{j,t}}\Big) \cdot \frac{Y_t}{p_{j,t}} = \Big(\gamma - 1\Big) \frac{w_{p,t}}{A_{j,t}} \cdot \frac{Y_t}{\gamma\, w_{p,t}/A_{j,t}} \\ &= \frac{\gamma - 1}{\gamma} Y_t \;\equiv\; \pi_t. \end{aligned} \tag{2.44}$$

Thus profits are uniform across varieties and proportional to aggregate expenditure.

2.A.2 Nash bargaining and the production wage

The generalized Nash problem is

$$\max_{w_{p,t}} \, (w_{p,t} - w_t^{res})^{\alpha} \big(p_{j,t}A_{j,t} - w_{p,t}\big)^{1-\alpha}.$$

The FOC gives $\frac{\alpha}{w_{p,t}-w_t^{res}} = \frac{1-\alpha}{p_{j,t}A_{j,t}-w_{p,t}}$, hence

$$w_{p,t} = \alpha \, p_{j,t}A_{j,t} + (1-\alpha)\, w_t^{res}. \tag{2.45}$$

Using (2.43) so that $p_{j,t}A_{j,t} = \gamma w_{p,t}$ and rearranging,

$$w_{p,t} = \frac{(1-\alpha)}{1-\alpha\gamma}\, w_t^{res}, \qquad \text{requiring} \quad \alpha\gamma < 1. \tag{2.46}$$

2.A.3 Vacancy free entry and tightness

Let the resource cost of posting a vacancy be a fraction of the production wage in final-good units $c_{v,t} = \sigma_v w_{p,t}$. Free entry into vacancy posting equates the cost and the expected discounted gain from moving an incumbent-without-worker firm to production:

$$\sigma_v w_{p,t} = \Lambda_{t,t+1}\, \nu_t \big(V_{t+1} - I_{t+1}\big). \tag{2.47}$$

The aggregate matching function is $m(u_t, v_t) = \kappa u_t^{\eta} v_t^{1-\eta}$. Let $\theta_t = v_t/u_t$ denote tightness. Then

$$\rho_t = \frac{m}{u_t} = \kappa\theta_t^{1-\eta}, \qquad \nu_t = \frac{m}{v_t} = \kappa\theta_t^{-\eta}. \tag{2.48}$$

2.A.4 Value functions and closed forms on the BGP

With constant per-period profit $\pi_t = \pi$ and constant x, ν on a balanced-growth path (BGP), the production value satisfies

$$V = (1-\tau)\pi + \beta(1-x)\,V \;\Rightarrow\; V = \frac{(1-\tau)\pi}{1-\beta(1-x)}. \tag{2.49}$$

The incumbent-without-worker value satisfies

$$I = \beta\big[\nu V + (1-\nu)I\big] \;\Rightarrow\; I = \frac{\beta\nu}{1-\beta(1-\nu)}\,V. \tag{2.50}$$

Therefore

$$V - I = \frac{1-\beta}{1-\beta(1-\nu)}\,V = \frac{1-\beta}{1-\beta(1-\nu)} \cdot \frac{(1-\tau)\pi}{1-\beta(1-x)}. \tag{2.51}$$

Plugging (2.51) into (2.47) yields the BGP vacancy free-entry condition in observables.

2.A.5 Stationarization and balanced growth

Quality improvements are the only source of trend growth:

$$A_{t+1} = x_t\,\gamma A_t + (1-x_t)A_t \quad\Rightarrow\quad g_t \equiv \frac{A_{t+1}}{A_t} - 1 = x_t(\gamma - 1). \tag{2.52}$$

We work in stationary (quality-deflated) units, dividing growing variables by A_t:

$$\tilde{X}_t \equiv \frac{X_t}{A_t}, \qquad X \in \{Y, C, w_p, w_r, w^{res}, \pi\}.$$

Objects that are shares or probabilities (e.g. $u_t, \theta_t, \rho_t, \nu_t, L_{p,t}, L_{r,t}$) are stationary. On a BGP with constant x and thus constant g, $\tilde{X}_t$ is constant and the SDF reduces to $\Lambda_{t,t+1} = \beta$.

2.A.6 Unemployment dynamics and the steady state

Matches arrive at rate ρ_t to each unemployed worker; separations occur at the innovation rate x_t for each occupied production job. With $L_{p,t}$ denoting employed unskilled hours, the headcount law of motion is

$$u_{t+1} = (1-\rho_t)u_t + x_t\big((1-\lambda) - u_t\big). \tag{2.53}$$

When u_t is defined as a *rate among unskilled*, this reduces to

$$u_{t+1} = (1-\rho_t)u_t + x_t(1-u_t). \tag{2.54}$$

In steady state, $u = \frac{x}{x+\rho}$.

2.A.7 Government budget and present-value fiscal cost

Per-period budget balance is

$$(s+\tau_r\tau)\, w_{r,t}L_{r,t} + b_t u_t = \tau\,\Pi_t + T_t, \qquad b_t = \bar{b}\,Y_t, \quad \Pi_t = \int_0^1 \pi_{j,t}\,dj = \pi_t. \tag{2.55}$$

Let $G_t \equiv (s+\tau_r\tau)w_{r,t}L_{r,t} + b_t u_t$ and $R_t \equiv \tau\Pi_t$ denote outlays and revenues (excluding T_t). For a deterministic policy path relative to baseline, the present-value (PV) fiscal cost we report is

$$\text{PV Cost} = \sum_{t=0}^{T} \Lambda_{0,t}\big[G_t - R_t\big] \; - \; \sum_{t=0}^{T} \Lambda_{0,t}\big[G_t^{\text{base}} - R_t^{\text{base}}\big], \tag{2.56}$$

where $\Lambda_{0,t} = \prod_{s=0}^{t-1} \Lambda_{s,s+1}$ is the model SDF. In stationary units (or under $Y_t \equiv 1$), we express (2.56) as a share of baseline GDP.

2.A.8 Entrant FOC and the effective R&D cost wedge

Entrants hire skilled hours $l_{r,j,t}$ to draw innovations with arrival $x_{j,t} = (\mu l_{r,j,t})^{\phi}$. Let the effective marginal cost of R&D embody direct subsidies and tax credits:

$$\psi \equiv (1-s)(1-\tau)\Big(1-\frac{\tau_r \tau}{1-\tau}\Big). \tag{2.57}$$

Under free entry ($E_{j,t} = 0$), the FOC is

$$\psi\, w_{r,t} = \phi\, \frac{x_{j,t}}{l_{r,j,t}}\, \Lambda_{t,t+1}\, \mathbb{E}_t\big[I_{j,t+1}\big] = \phi\, \mu^{\phi}\, l_{r,j,t}^{\phi-1}\, \Lambda_{t,t+1}\, \mathbb{E}_t\big[I_{j,t+1}\big]. \tag{2.58}$$

In symmetry, $x_{j,t} = x_t$ and $l_{r,j,t} = L_{r,t}$.

2.A.9 Stationary BGP system (unknowns and equations)

On a BGP with constant (τ, τ_r, s) and $Y \equiv 1$, a convenient unknown set is

$$\{u, \theta, L_r, x, C, w_p, w_r, w^{res}\}.$$

The defining equations are:

(i) Skilled wage: $w_r = \Psi_r \, C \, L_r^{\chi}$. (A.S1)

(ii) Shadow price & Res. wage: $\omega = \Psi_p \, C \, L_p^{\chi}, \quad w^{res} = b + \omega, \quad b = \bar{b},\ L_p = (1-\lambda) - u.$ (A.S2)

(iii) Nash wage: $w_p = \dfrac{(1-\alpha)}{1-\alpha\gamma} \, w^{res}, \quad (\alpha\gamma < 1).$ (A.S3)

(iv) Matching: $\rho = \kappa\theta^{1-\eta}, \quad \nu = \kappa\theta^{-\eta}.$ (A.S4)

(v) Unemployment: $u = \dfrac{x}{x+\rho}.$ (A.S5)

(vi) Innovation: $x = (\mu L_r)^{\phi} \in (0,1).$ (A.S6)

(vii) Goods market: $1 = C + \sigma_v w_p \, \theta \, u.$ (A.S7)

(viii) Vacancy free-entry: $\sigma_v w_p = \beta \, \nu \, \dfrac{1-\beta}{1-\beta(1-\nu)} \cdot \dfrac{(1-\tau)\pi}{1-\beta(1-x)}, \quad \pi = \dfrac{\gamma-1}{\gamma}.$ (A.S8)

Equations (A.S1)–(A.S8) pin down the BGP tuple for any (τ, τ_r, s).

2.A.10 Welfare objects and consumption equivalents

Per-period utility in stationary units is

$$u(C, L_p, L_r) = \ln C - \frac{\Psi_p}{1+\chi} L_p^{1+\chi} - \frac{\Psi_r}{1+\chi} L_r^{1+\chi}. \tag{2.59}$$

BGP welfare is

$$W^{\text{BGP}} = \frac{\ln C - \frac{\Psi_p}{1+\chi} L_p^{1+\chi} - \frac{\Psi_r}{1+\chi} L_r^{1+\chi}}{1-\beta}. \tag{2.60}$$

For a deterministic transition $\{C_t, L_{p,t}, L_{r,t}\}_{t=0}^{T}$ followed by its terminal BGP,

$$W^{\text{dyn}} = \sum_{t=0}^{T} \beta^t \, u(C_t, L_{p,t}, L_{r,t}) + \beta^{T+1} \, W_T^{\text{BGP}}. \tag{2.61}$$

The consumption-equivalent (CE) gain ξ of a policy relative to baseline solves $U_0((1+\xi)C_t) = W^{\text{dyn}}$; with log utility,

$$\xi = \exp\big\{(1-\beta)\,(W^{\text{dyn}} - W^{\text{base}})\big\} - 1. \tag{2.62}$$

Discounting convention. Welfare uses β-discounting of flow utility as in (2.61). Present-value fiscal costs use the model SDF $\Lambda_{t,t+1} = \beta\, C_t/C_{t+1}$ as in (2.56).

2.B Data, Calibration and Solution Method

2.B.1 Data sources and construction (US, 2003–2019)

Final list of target moments.

- **TFP growth** $g^{\text{data}} = 0.0069$ (pct/yr): BLS Multifactor Productivity (private nonfarm business). Annual log-difference averaged 2003–2019.
- **Unemployment rate** $u^{\text{data}} = 0.061$: BLS CPS (annual average).
- **R&D labour share** $L_r^{\text{data}} \approx 0.010$: NSF Business Enterprise R&D (BERD/BRDIS), full-time equivalent (FTE) R&D personnel divided by total labour hours (employment × average hours). Reported as a share of labour-force time.
- **Wage premium** $(w_r/w_p)^{\text{data}} \approx 1.82$: BLS OEWS. w_r is the mean hourly wage across STEM/R&D-intensive occupation groups (Computer & Mathematical; Architecture & Engineering; Life/Physical/Social Scientists). w_p is the mean hourly wage for Production Occupations. Ratio averaged 2003–2019.

Policy parameters and fiscal ratios.

- **Corporate tax rate** τ: OECD Corporate Income Tax Rates (statutory combined). Baseline $\tau = 0.33$ reflects 35% through 2017 and 21% from 2018, averaged over the sample.
- **R&D instruments** (s, τ_r): OECD R&D Tax Incentives Database. Baseline $s = 0.10$, $\tau_r = 0.06$ (statutory).
- **Unemployment benefits**: BEA NIPA (Unemployment insurance). We calibrate the replacement parameter $\bar{b}$ to reproduce the average benefits-to-GDP ratio given u^{data} (see B.2).

2.B.2 Parameter targeting and calibration steps

We target four moments with *four* parameters $\{\mu, \sigma_v, \Psi_p, \Psi_r\}$, holding the rest fixed at literature values or statutory rates. The calibration proceeds as follows.

Step 1: Match trend TFP growth with research productivity μ. On a BGP, growth satisfies $g = x(\gamma - 1)$ with $x = (\mu L_r)^{\phi}$. Hence

$$x^{\text{target}} \;=\; \frac{g^{\text{data}}}{\gamma - 1}, \qquad \mu \;=\; \frac{\left(x^{\text{target}}\right)^{1/\phi}}{L_r}, \tag{2.63}$$

evaluated at the BGP L_r that results from Steps 3–4. In practice we either (i) iterate on μ jointly with Steps 3–4 until g matches, or (ii) update μ by (2.63) after each inner equilibrium solve.

Step 2: Match steady unemployment with vacancy cost share σ_v. Given all other parameters and policy (τ, τ_r, s), choose σ_v to hit u^{data} on the BGP. Operationally, solve the scalar root

$$\Phi(\sigma_v) \;\equiv\; u^{\text{model}}(\sigma_v) - u^{\text{data}} = 0,$$

where u^{model} is computed from the stationary system (A.S1)–(A.S8). A simple bisection or Brent method is robust.

Step 3: Match the R&D hours share with Ψ_r. Using the skilled-labour FOC $w_r = \Psi_r \, C \, L_r^{\chi}$ and the equilibrium value of w_r implied by the firm and policy blocks, choose Ψ_r so that the model BGP satisfies $L_r = L_r^{\text{data}}$. We implement this by solving the scalar equation

$$\Xi_r(\Psi_r) \;\equiv\; L_r^{\text{model}}(\Psi_r) - L_r^{\text{data}} = 0,$$

with the BGP recomputed at each trial Ψ_r.

Step 4: Match the wage premium with Ψ_p. Market wages for production workers satisfy $w_p = \frac{1-\alpha}{1-\alpha\gamma} \, w^{res}$ with $w^{res} = b + \omega$, where $b = \bar{b}Y$ and $\omega = \Psi_p \, C \, L_p^{\chi}$. Choose Ψ_p to hit the wage premium target:

$$\Upsilon(\Psi_p) \;\equiv\; \log\!\left(\frac{w_r}{w_p}\right)^{\text{model}} - \log\!\left(\frac{w_r}{w_p}\right)^{\text{data}} \;=\; 0. \tag{2.64}$$

Steps 3 and 4 can be solved jointly with a 2D root finder in (Ψ_r, Ψ_p) using the two moments $\{L_r, (w_r/w_p)\}$.

Step 5: Calibrate the benefit parameter $\bar{b}$. With $b_t = \bar{b}\, Y_t$ and $Y_t \equiv 1$, the model's benefits-to-GDP ratio equals $\bar{b}\, u$ (in headcount units). Given the observed average ratio UI/GDP and u^{data}, set

$$\bar{b} \;=\; \frac{(\text{UI/GDP})^{\text{data}}}{u^{\text{data}}}. \tag{2.65}$$

This ensures the government budget composition mirrors the data on average.

Outer–inner algorithm (summary).

1. Fix (τ, τ_r, s) and literature parameters $\{\alpha, \chi, \kappa, \eta, \phi, \gamma, \beta, \lambda\}$.

2. Outer loop over $\{\Psi_r, \Psi_p, \sigma_v, \mu\}$ to hit $\{L_r, (w_r/w_p), u, g\}$.
3. Inner loop: solve the BGP system (A.S1)–(A.S8) at each parameter guess.

2.C Robustness and Sensitivity

2.C.1 Local Elasticities at the Baseline

We compute symmetric proportional elasticities at $(\tau_r, s) = (0.06, 0.10)$ using ±1% multiplicative perturbations, re-solving the BGP each time:

$$\varepsilon_{Y,X} \equiv \frac{\partial \ln Y}{\partial \ln X} \approx \frac{\ln Y(X \cdot 1.01) - \ln Y(X \cdot 0.99)}{\ln(1.01) - \ln(0.99)}, \qquad Y \in \{u, g\},\ X \in \{\tau_r, s\}.$$

(Values are very close to those reported in the main text: $\varepsilon_{u,\tau_r} \approx 0.07$, $\varepsilon_{g,\tau_r} \approx 0.01$, $\varepsilon_{u,s} \approx 0.24$, $\varepsilon_{g,s} \approx 0.05$.)

2.C.2 Parameter Perturbations

For $p \in \{\phi, \alpha, \eta, \kappa, \chi\}$ we set $p' = p \times \{0.90, 1.10\}$, keep (Ψ_p, μ) at their baseline calibrated values, and re-solve the BGP. We then compute steady-state (BGP-only) consumption-equivalent (CE) gains for three permanent policies: (i) $s: 0.10 \to 0.20$, (ii) $\tau_r: 0.06 \to 0.12$, and (iii) $\tau: 0.33 \to 0.30$. Table 2.C.1 reports headcount unemployment u (%) and annual TFP growth g (pp/yr) in the perturbed baseline, and CE gains (%).

Because baseline $\mu L_r < 1$, lowering ϕ *raises* $x = (\mu L_r)^\phi$ (a smaller exponent on a base < 1 increases the value), which boosts growth g but also separation risk, pushing u sharply up; the opposite holds when ϕ increases. This also amplifies the gains from targeted R&D support and the (negative) CE from a broad profit-tax cut.

Table 2.C.1: Sensitivity to parameter perturbations (±10%). BGP-only CE gains (%).

	Baseline BGP		CE gain (%)		
Parameter shock	u (%)	g (pp/yr)	$\Delta s:\ 0.10\to 0.20$	$\Delta \tau_r:\ 0.06\to 0.12$	$\Delta \tau:\ 0.33\to 0.30$
$\phi \times 0.90$	22.726	1.0020	1.7962	0.4831	-4.5091
$\phi \times 1.10$	1.0993	0.4377	-0.0591	-0.0171	-0.3447
$\alpha \times 0.90$	3.8373	0.6806	1.0208	0.2361	-1.6960
$\alpha \times 1.10$	10.6710	0.6973	2.2554	0.5840	-4.5575
$\eta \times 0.90$	6.2876	0.6895	1.8971	0.4685	-3.2515
$\eta \times 1.10$	5.9189	0.6905	1.6015	0.3850	-2.5755
$\kappa \times 0.90$	6.7248	0.6883	1.7207	0.4235	-2.9497
$\kappa \times 1.10$	5.5797	0.6914	1.7804	0.4302	-2.8564
$\chi \times 0.90$	4.6149	0.6242	1.5430	0.3591	-2.3029
$\chi \times 1.10$	7.5487	0.7548	1.7456	0.4398	-3.2650

Notes: u is headcount unemployment share shown in percent. g is percentage points per year. CE gains are steady-state (BGP-only) consumption equivalents for each permanent policy. Parameters (Ψ_p, μ) are held at their baseline calibrated values to isolate pure primitive changes. Numerical solves use continuation and tight tolerances; no complex parts remain after real-cleaning.

Bargaining power α. Higher α raises the reservation-wage pass-through into w_p, reduces vacancy creation, and increases u. R&D policies buy larger CE gains when labour frictions are tighter.

Matching (η, κ). Easier matching (higher κ or lower η) lowers u with minimal impact on g; CE gains from targeted R&D shrink modestly because the displacement margin weakens. **Frisch elasticity χ.** Changes in labour-supply curvature move L_p and L_r and thus wages; u and g adjust, but the ranking of policies (subsidy > credit > profit-tax cut) is preserved.

The exercises above perturb primitives holding the baseline calibration fixed. We next conduct a targeted robustness check for the Frisch elasticity, re-calibrating the model at each value of χ to keep the same steady-state targets.

2.C.3 Frisch elasticity robustness

The baseline calibration sets the Frisch elasticity to $\chi = 0.5$, following Chetty et al. (2011). Recent evidence based on a large meta-analysis suggests that, after accounting for publication and identification biases, intensive-margin Frisch elasticities above about 0.4 are difficult to justify and typical values are closer to 0.2 (Elminejad et al., 2023). Motivated by this, we re-solve the model for $\chi \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$ and, for each χ, re-calibrate the remaining parameters to match the baseline steady-state targets for u, g, L_r, and w_r/w_p. We then recompute steady-state consumption-equivalent (CE) welfare effects for the three permanent policy reforms.

Table 2.C.2: Sensitivity to the Frisch elasticity: consumption-equivalent welfare effects of policy reforms (recalibrated targets)

Frisch elasticity χ	CE gain: Δs (%)	CE gain: $\Delta \tau_r$ (%)	CE gain: $\Delta \tau$ (%)
0.5	2.334	0.569	-3.693
0.4	3.314	0.782	-4.217
0.3	4.511	1.014	-4.510
0.2	6.681	1.378	-4.835
0.1	11.928	2.021	-5.194

Notes: For each value of χ, the model is re-calibrated to match the baseline targets for (i) steady-state unemployment u, (ii) trend TFP growth g, (iii) the R&D labour share L_r, and (iv) the skilled-to-production wage premium w_r/w_p. Consumption-equivalent (CE) gains are reported in percent. Policy reforms are: $\Delta s : 0.10 \rightarrow 0.20$, $\Delta \tau_r : 0.06 \rightarrow 0.12$, and $\Delta \tau : 0.33 \rightarrow 0.30$.

Table 2.C.2 shows that the qualitative ranking of policies is unchanged across the empirically relevant range of χ: increasing targeted R&D support raises welfare, while a broad corporate tax cut lowers welfare. Lower χ tends to magnify CE effects in our calibration, but the signs and policy ranking remain unchanged.

2.C.4 Numerical Details

We solve each perturbed BGP with a continuation scheme (5 steps) from the baseline solution and strip tiny imaginary parts when below 10^{-10}; feasibility checks enforce $u \in (0, 1 - \lambda)$ and $x \in (0, 1)$.

Numerical checks.

- **Interior solutions.** Verify $\alpha\gamma < 1$ and $x \in (0,1)$ across all experiments (report $\max_t x_t$).
- **Convergence.** For transition paths, report maximum residuals and variable changes at solution (e.g., $< 10^{-8}$).
- **Policy timing.** Confirm pre-announcement at $t = 0$ and implementation at $t = 1$ in the PF solver (documented shock path).

Chapter 3

The Consequences of Skill Obsolescence in the Face of Technological Change

3.1 Introduction

Technological progress has had a significant impact on the labour market, where substantial shifts have occurred over the last decades. Rapid technological advancements, particularly in the fields of automation, artificial intelligence, and digitisation, have redefined the nature of work and reshaped occupational structures. This evolving labour market is characterised by a growing divergence between occupations. Some occupations are witnessing substantial growth while others, especially those vulnerable to automation or structural economic changes, are experiencing decline or stagnation.

The issue, however, extends beyond occupations to the skills required for these jobs. Technological advancements have increased demand for certain skills while rendering others obsolete, a phenomenon known as "skill obsolescence." Although research on job polarization sheds light on the structure of occupational employment and income inequality, these studies often overlook changes in skill demands within occupations. Understanding within-occupational transformations is crucial for observing the labour market outcomes of those negatively impacted by these changes.

Workers experiencing skill obsolescence tend to face worse labour market outcomes (De Grip and Van Loo, 2002). Previous research mainly associated skill obsolescence with the decline of human capital resulting from extended periods of unemployment or occupational switches upon displacement, documenting considerable and enduring adverse effects. This approach, however, does not account for potential exposure to obsolescence *within* current occupations due to evolving skill requirements.

To address this gap, I focus on the changing structure of skill demands within occupations, acknowledging significant heterogeneity among workers in terms of their skill sets by considering individual skills as multidimensional. This approach implies that workers exposed to obsolescence experience varied consequences. Although current literature often treats skills as one-dimensional, recent research underscores the multidimensional nature of skills (Guvenen et al., 2020; Lise and Postel-Vinay, 2020).

This study follows this multidimensional view, using Armed Services Vocational Aptitude Battery (ASVAB) scores from the National Longitudinal Survey of Youth 1979 (NLSY79) to determine workers' skill endowments. Unlike previous studies, I utilise these varied traits and abilities to define workers' levels of exposure to changing skill demands within occupations.

The contribution of this paper is to move from purely occupation-level measures of technological exposure to a worker-level measure of exposure to skill obsolescence that combines (i) heterogeneous baseline skill endowments and (ii) within-occupation changes in skill demand. This shift matters for two reasons. First, workers in the same occupation can face systematically different obsolescence risk depending on their skill profiles, so occupation averages can conceal meaningful within-occupation heterogeneity. Second, focusing on within-occupation demand changes allows me to distinguish whether adjustment occurs predominantly *within* occupations (changing task/skill requirements in place) or *between* occupations (mobility and reallocation).

Empirically, I link this worker-level exposure measure to a coherent set of outcomes such as wages, occupational switching, and non-employment spells so that the paper documents not only exposure gradients in wage levels but also dynamic patterns of adaptation. Against this backdrop, this paper examines the impact of skill obsolescence on labour market outcomes. In doing so, I consider within-occupational changes in skill demands based on the dataset by Atalay et al. (2020) and combine it with the worker-level panel of the NLSY79.

This study focuses on the period 1978–2000 for three related reasons. First, it covers a canonical episode of labour-market restructuring associated with computerisation and routine-biased technological change, with the main changes concentrated in the 1980s and 1990s. Second, it is the window in which the two core data sources used in this chapter align most naturally. NLSY79 respondents are observed as they enter and progress through the labour market, and the occupation-level skill-demand measures are available at an annual frequency over the same decades. Third, studying 1978–2000 provides a historically clean laboratory to analyse within-occupation changes in skill demands and the associated adjustment of workers through wages, mobility, and non-employment spells. The aim is not to extrapolate mechanically to today's AI-era labour market, but to quantify a closely related mechanism, i.e., skill obsolescence and task reallocation, during a well-documented period of technological change.

By considering within-occupational changes in skill demands and the multidimensionality of individual skills, I aim to provide a better understanding of the dynamics at play and offer insights into potential policy responses to mitigate the adverse effects of skill obsolescence.

3.2 Literature Review

The impact of technological change on labour markets has been a topic of extensive research, revealing significant shifts in employment patterns, skill demands, and individual career trajectories. One strand of literature has examined how technological change has reshaped the occupational structures and labour market, leading to a phenomenon known as job polarisation. Autor et al. (2003) were among the first to document this trend, noting that middle-skill jobs, often involving routine tasks, are increasingly being automated, while high-skill cognitive jobs and low-skill manual jobs remain relatively unaffected.

This bifurcation is evident across various advanced economies, contributing to the growing disparity in income and employment opportunities (Goos et al., 2009). Further studies have supported these findings, highlighting the differential impact of technological change across job categories. Autor and Dorn (2013) illustrated that automation has disproportionately affected routine manual and cognitive jobs, leading to employment growth at the high and low ends of the skill spectrum. This polarisation exacerbates income inequality as middle-wage occupations decline, forcing displaced workers to transition into lower-wage positions or face unemployment (Acemoglu and Autor, 2011).

Technological advancements, however, are not only eliminating jobs but also altering the demand for different skills in the labour market. Bresnahan et al. (2002) discuss how the rise of information technology has increased the demand for cognitive and interpersonal skills while reducing the necessity for routine manual skills. As technology automates repetitive and predictable tasks, the labour market increasingly values skills associated with problem-solving, critical thinking, and social interaction. Deming (2017) highlights the rising importance of social skills, suggesting that jobs requiring a combination of cognitive and social skills have experienced the most significant growth.

Recent reviews on artificial intelligence and robotization stress that the labour-market effects of new technologies are mixed and heterogeneous. Vivarelli and Arenas Díaz (2025) underline that observed outcomes depend on the balance between displacement effects and compensation mechanisms associated with innovation. Consistent with this, Guarascio et al. (2025) find in a meta-analysis that average employment and wage effects of industrial robots are close to zero, but with larger negative effects concentrated in specific settings (e.g. manufacturing and middle-skilled work). These findings suggest that focusing only on aggregate employment and wage trends may conceal important within-occupation adjustments in tasks and skill requirements, motivating the analysis of within-occupation skill change and obsolescence.

To unpack where these adjustments occur, a related strand of the literature examines whether changing task structures and skill demands are driven primarily by shifts across occupations or by transformations within occupations (Deming and Kahn, 2018; Atalay et al., 2020; Consoli et al., 2023). Constructing a dataset from newspaper job ads, Atalay et al. (2020), for instance, show that almost 88% of overall task change in the US labour market occurred within rather than between occupations. Moreover, using data from the DOT and O*NET, Consoli et al. (2023) find that around one-third of the decline in routine tasks is attributable to within-occupation change.

Whether resulting from changes between or within occupations, the shifts in the types of skills demanded in the labour market can lead workers to face the risk of skill obsolescence, making their skill sets less relevant to the market. Workers can be exposed to obsolescence if they work in occupations with declining demand or in occupations where their skills decrease in demand. The former relates to between-occupational changes, while the latter focuses on within-occupational changes.

The studies regarding between-occupational changes differ in terms of their perception of how obsolescence occurs. Numerous studies emphasise that skills are usually occupation- or industry-specific, and an involuntary separation from them will leave skills unused, resulting in large earning losses upon reemployment (Ljungqvist and

Sargent, 1998, 2008; Kambourov and Manovskii, 2009; Fujita, 2018; Laureys, 2021). Therefore, people forced out of declining occupations or industries lose their skills due to long unemployment spells or occupational switches. In his study on displaced workers, Neal (1995) finds evidence for the industry-specificity of skills where people switching industries suffer greater losses upon displacement. Kambourov and Manovskii (2009) emphasises that skills are often specific to particular occupations and shows that workers face worse outcomes once they switch occupations as they lose their tenure.

The occupational or industrial specificity of human capital is, however, challenged by authors who assert that skills are task-specific (Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010). Workers accumulate different skills in their occupations and can transfer some of them to new ones depending on how close the occupations are in terms of skill requirements. Robinson (2018) discuss that not only distance but also the direction of the switch matters; individuals shifting to a skill vector lower than in their previous occupations experience worse outcomes.

The studies on task-specific human capital acknowledge that individual skills are multidimensional, suggesting that workers' skills do not become obsolete altogether when they have to change their occupation or industry. However, workers' skill sets in these studies are presumed to be the same as their present occupation. Therefore, all workers in an occupation are considered to have the same skill profiles. To overcome this, recent literature on multidimensional skills makes use of various test scores of individuals to construct their skill vectors (Speer, 2017; Guvenen et al., 2020; Lise and Postel-Vinay, 2020).

Lise and Postel-Vinay (2020), for instance, uses ASVAB scores to obtain individual skills and construct a three-dimensional skill vector where the skills are cognitive, manual and interpersonal. In a similar manner, Guvenen et al. (2020) define the vector composed of math, verbal and social skill scores for each individual. In these studies, skills become obsolete as a result of a mismatch between workers' skills and occupations' requirements. This paper also follows this strand of literature in constructing the skill sets of workers. However, I differ from them in terms of the root of obsolescence. Unlike these studies, I emphasise the changing nature of occupations in terms of skill demands is the main reason for obsolescence and workers are exposed to obsolescence when their skills are losing value in their occupations.

Although still scant, there are some similar attempts focusing on exposure to obsolescence in the face of within occupational changes. Using data from online vacancies, Deming and Noray (2020) highlight that workers in rapidly changing fields, like STEM, face a higher risk of skill obsolescence. Moreover, Braxton and Taska (2023) used skill requirements from online job postings between 2007–2017 and Displaced Worker Supplement (DWS) to study the impact of exposure to technological change in explaining the substantial and persistent earning losses upon displacement. They measure the exposure as the change in computer or software requirements in each occupation. Following a similar idea, I measure obsolescence as the change in requirements of cognitive, manual and interpersonal skills in each occupation. However, using the multidimensional skill structure of individuals, I also let the levels of exposure vary among the individuals.

This study then contributes to the literature by focusing on skill obsolescence due to within-occupational changes in skill demands and their impact on labour market outcomes. In particular, I consider individual skills as multidimensional, recognising the significant heterogeneity among workers in their skill sets. As a novelty of this paper, I define different levels of exposure to skill obsolescence, acknowledging that workers exposed to obsolescence do not experience the same consequences.

3.3 Overall Trends in Occupational Employment and Skill Demands

The transformation of the labour force during the 20th century was remarkable. During this period, certain occupations experienced a significant decline in their employment share, while others saw a substantial increase. These changes in the occupational employment structure are mainly explained by the job polarisation phenomenon, in which the employment share increases in high- and low-skilled occupations and decreases in middle-skilled occupations. Figure 3.1 shows simple evidence of this pattern by presenting the change in employment shares in 8 occupational categories in the US between 1980 and 2000. I group occupations according to those in Acemoglu and Autor (2011) and Bárány and Siegel (2018), in which service occupations represent low-skilled occupations, production, operator, clerical, and sales occupations represent middle-skilled occupations, and managerial, professional, and technical occupations represent high-skilled occupations. I focus on 1980–2000 here because the underlying Census-based employment shares are observed at decadal frequency and this window provides a standard and transparent comparison.[1]

According to Figure 3.1, almost all so-called middle-skilled occupations shrank over the two decades, whereas the low-skilled and high-skilled occupations grew in terms of their shares in total employment. This shift in employment distribution is not only a result of technological progress and globalisation but also signals a significant change in the skill sets demanded by the job market. Along with the evolution of the employment structure, the types of skills that support it are also evolving.

The reduction of roles in sectors that require middle-skilled, manual-intensive labour corresponds with a broader transformation in the prioritisation of skills. The decline in the need for manual skills in job advertisements during this time is not an iso-

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[1] This descriptive window is chosen for comparability with decadal Census tabulations. The main person-level analysis in subsequent sections uses the NLSY79 panel over 1978–2000, reflecting the earliest year in which the worker histories and occupation-level demand measures can be consistently aligned.

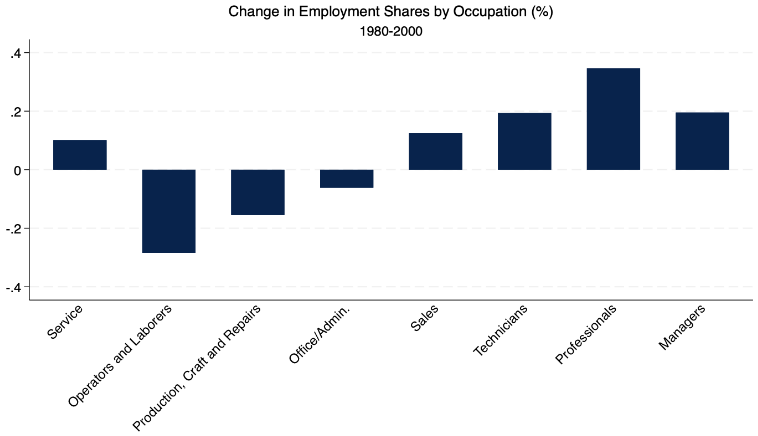


Figure 3.1: Percent Change in Employment Shares by Occupations

Notes: Changes across broad occupation groups, 1980–2000. See text for group definitions.

lated phenomenon; it is closely associated with the growing emphasis on cognitive and interpersonal skills. Figure 3.2 illustrates these significant shifts by showing the demand for cognitive, manual, and interpersonal skills across decades. Up until the 1980s, there was still a strong demand for manual skills, exceeding that of cognitive and interpersonal skills. Nevertheless, the proportion of job postings requiring manual skills has steadily decreased over the years, while the importance of cognitive and interpersonal skills has risen.

The increasing demand for cognitive and interpersonal abilities, along with the reduction in the requirement for manual skills in the workforce, reflects changes in the competencies valued by the economy. However, this overall trend in skill demands does not tell much about how occupations themselves have evolved in terms of the skills they require. In fact, there is a significant variation in the demand changes for different skill types among professions. This is only apparent when these demands are broken down by occupational categories. In this regard, Figure 3.3 provides a clearer view of changes in skill demands within-occupation.

The most notable pattern here is that, although all occupations seem to become much more reliant on cognitive and interpersonal skills, the size of the change in the demand is striking for the occupations with declining employment shares observed in Figure 3.1. These occupations are undergoing substantial transformations in their

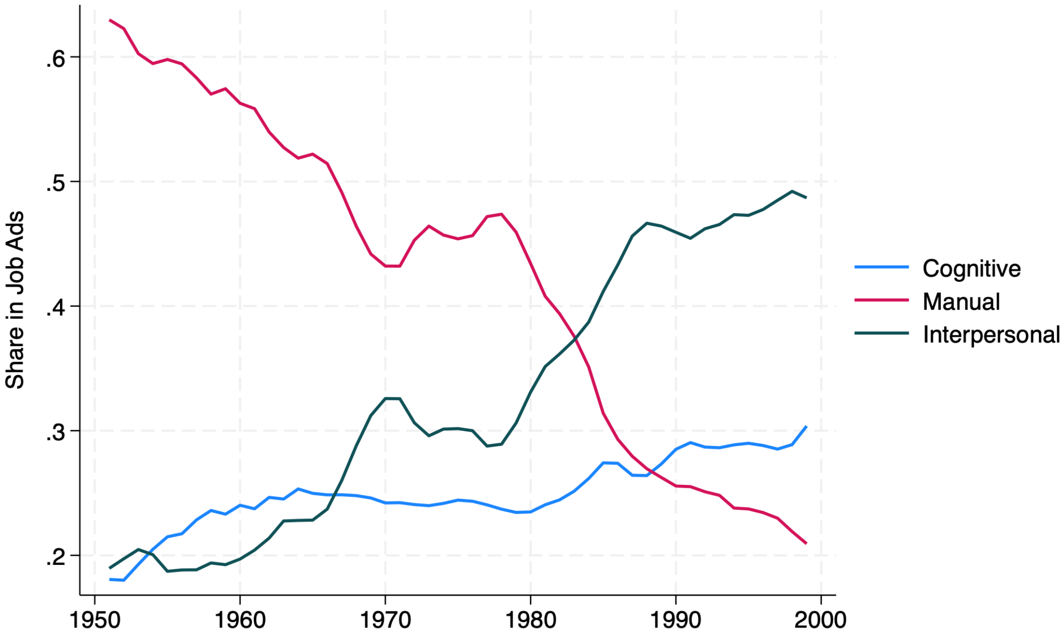
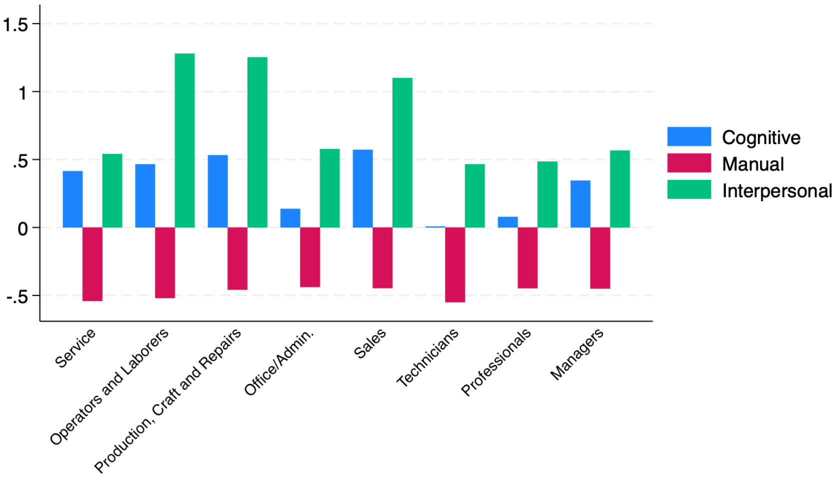


Figure 3.2: Skills Demanded in the US Labour Market



Note: The data needed to build this figure is taken from Atalay et.al(2020).

Figure 3.3: Percent Change in Skill Demands by Occupation, 1979-1999

skill requirements. Nevertheless, the extent of this shift varies markedly across job titles. For instance, while both administrative support and operator categories show a reduction in manual skill demands, the increase in cognitive skill demand is moderate for administrative roles but much more substantial for operators. This suggests that as employment dynamics shift, the skill sets required for remaining roles within these occupations are also evolving, with some jobs facing more pronounced changes

Table 3.1: Changes in Employment Shares and Skill Demands by Occupation (1980-2000)

Rank	**Occupation**	**Chg. Emp. Share**	**Chg. Cognitive Req.**	**Chg. Manual Req.**	**Chg. Interpersonal Req.**
Panel A. Occupations with the highest increase in employment shares					
1	Customer service reps, investigators and adjusters (ex., insurance)	4.702	0.083	-0.134	0.051
2	Computer systems analysts and computer scientists	4.486	0.053	-0.134	0.081
3	Dental laboratory and medical appliance technicians	4.250	0.227	-0.054	-0.173
4	Supervisors of motor vehicle transportation	3.973	0.083	-0.364	0.281
5	Management support occupations	3.831	0.002	-0.134	0.132
6	Legal assistants, paralegals, legal support, etc	3.797	0.120	-0.107	-0.013
7	Welfare service workers	3.267	0.063	-0.181	0.118
8	Special education teachers	3.145	0.280	-0.126	-0.154
9	Recreation workers	3.082	0.025	-0.283	0.258
10	Repairers of data processing equipment	3.035	0.501	-0.339	-0.161
Panel B. Occupations with the highest decline in employment shares					
1	Technicians, n.e.c.	-0.991	-0.048	0.005	0.043
2	Other metal and plastic workers	-0.942	0.879	-0.648	-0.231
3	Helpers, constructions	-0.879	-0.041	0.106	-0.066
4	Shoemaking machine operators	-0.879	0.097	-0.336	0.239
5	Other science technicians	-0.847	0.646	-0.634	-0.013
6	Statistical clerks	-0.824	-0.423	-0.358	0.782
7	Typists	-0.784	-0.030	-0.268	0.298
8	Grinding, abrading, buffing, and polishing workers	-0.725	-0.057	0.207	-0.150
9	Misc textile machine operators	-0.716	-0.035	-0.488	0.523
10	Repairers of industrial electrical equipment	-0.711	0.418	-0.279	-0.139

Notes: Absolute changes in occupation employment shares from 1980 to 2000. Columns for skill-demand changes are computed within occupation for three skill groups (1978–2000).

than others.

It is also important to clarify that in predominantly white-collar occupations (e.g., managerial/administrative categories), the manual component of vacancy text is typically small relative to the cognitive and interpersonal components. Therefore, declines in this manual component should not be interpreted as implying that manual tasks were central in these jobs; rather, they reflect a further reduction in the already limited emphasis on manual requirements in postings. Appendix 3.A provides illustrative examples of the manual keywords most frequently appearing in selected 3-digit managerial/administrative occupations in the early period and how their frequency changes over time.

To delve deeper into the occupational changes, I broke down the occupations at the finest level possible. By doing so, I showed how individual occupations, which experience the most significant increase/decrease, change in terms of their skill demands. In this regard, Table 3.1 demonstrates the occupations with the highest increase and decrease in their employment shares as well as the net change in employers' demand for cognitive, manual and interpersonal skills in these occupations between 1980 and

2000. Panel A shows the top ten occupations with the largest increase in employment shares, where the shares more than doubled in 2000 compared to 1980. On the contrary, panel B presents the ten occupations that experienced the most significant decline in employment shares, which were almost halved compared to 1980. Occupational changes in skill demands are evident in the second to fourth columns. Changes in skill demands are expressed in terms of the change in shares of each skill between 1980 and 2000.

Occupations in Panel A are almost uniform in experiencing an increase in cognitive skill requirements and a decline in manual skill requirements. The change in interpersonal skill demands, however, is relatively more heterogeneous across occupations. For the occupations that experience the highest drop in employment shares, there is a significant heterogeneity for all skill types regarding demand changes. The shifts in skill demands seem highly occupation-specific. This non-uniform pattern can be observed even among jobs under the same broad category. For instance, seven of the ten occupations in Panel B are operators and labourers. However, the change in skill requirements is highly diverse among them. For “Technicians”, the demand for interpersonal and manual skills increased. At the same time, the cognitive requirements decreased over two decades. In the case of “Other Metal and Plastic Workers” and “Repairers of industrial electrical equipment”, however, the picture is the direct opposite; the cognitive skill requirements rose while the demand for other skills declined.

The evidence presented throughout this section highlights a significant transformation in the job market and skill requirements during the latter half of the 20th century, especially from 1980 to 2000. The noticeable job polarisation, marked by the growth of high- and low-skilled occupations at the expense of middle-skilled roles, reflects broader economic and technological shifts that have fundamentally altered the structure of employment. This transformation is not only about the redistribution of job shares but also signifies a pivotal shift in the skill sets valued within the labour market. The observed within-occupation changes in skill demands reveal the complexity of this change, highlighting the varying impacts across occupational categories.

3.4 Data and Methodology

This study is based on two datasets. First of all, it utilises longitudinal data from NLSY79. The NLSY79 is an extensive survey of American residents aged 14-22 in 1979. NLSY79 provides a weekly longitudinal work record of each NLSY79 respondent. It contains information on respondents' current and previous jobs, earnings, and characteristics such as age, sex, and race. Thus, the use of NLSY79 is instrumental in tracking down the labour histories of workers over the years.

The unit of analysis in this chapter is the person–month. NLSY79 provides weekly work-history records and I aggregate these to a monthly panel by assigning each week to its calendar month and constructing monthly outcomes from the within-month information (described step-by-step in Appendix 3.B). Worker skill proxies (ASVAB and psychometric measures) are observed once around 1980 and are treated as time-invariant individual characteristics. Occupational skill demands from Atalay et al. (2020) are observed at the occupation–year level. In the empirical construction, I summarize each occupation's evolution using the long change in these measures between 1978 and 2000 to classify occupations into exposure categories. As a result, exposure is constant for a given occupation and can change over time for a worker only when the worker changes occupation.

The NLSY79 includes ASVAB scores, administered to most respondents in 1980. I use these scores (together with the Rotter and Rosenberg measures) to construct baseline proxies for multidimensional abilities and non-cognitive traits measured early in life. These baseline proxies are interpreted as initial endowments that shape subsequent human-capital accumulation and occupational sorting. Because they are observed only once, they do not capture later re-skilling or on-the-job learning; I discuss this limitation explicitly below.

Given the continuously changing skill demands within occupations, I also consult Atalay et al. (2020)'s dataset, which provides a valuable tool for observing the skills employers demand in the US labour market between 1940 and 2000. This data set is constructed by extracting the text content from almost 7.8 million job advertisements in 3 major US metropolitan newspapers: the Boston Globe, the New York Times, and the Wall Street Journal.

The authors associate the words in the job requirements with their corresponding tasks. In addition, using machine-learning techniques, they assign appropriate Standard Occupational Classification (SOC) codes to job titles that they can directly observe in the job ads. They map words and phrases to commonly employed measures of skill content, such as DOT and O*NET, as well as to the job task classification framework utilised in previous research, such as Autor et al. (2003), Spitz-Oener (2006) and Deming and Kahn (2018).

By linking these datasets, I track workers from their first job and observe shifts in demand for different skills within their occupations. To determine the multidimensional skill vectors of individuals, I follow Guvenen et al. (2020) and Lise and Postel-Vinay (2020), who define three-dimensional skill vectors (cognitive, manual, and interpersonal) using ASVAB scores, the Rotter Locus of Control score, and the Rosenberg Self-Esteem scores. However, I do not perform a principal component analysis to extract the skill scores. Instead, I follow Speer (2017) and simply take the mean scores of the related components.

In particular, I used the mean scores from the “Arithmetic” and “Mathematical Knowledge” components to define a worker's cognitive skill score. I calculate the manual score as the mean of the ”Mechanical Comprehension” and ”Auto and Shop Information” components. Finally, I averaged the Rotter and Rosenberg self-esteem scores to define the interpersonal scores. I then normalise the scores to make them comparable. I then construct the same skill categories from Atalay et al. (2020)'s data in order to match them with the worker skill data. To do so, I choose skills most relevant to each dimension based on their descriptions in O*NET. As in Speer

(2017), I take the average of these skill measures to determine the measure of the related category.

This construction uses equal weights within each skill block. The advantage is transparency and comparability with prior NLSY79-based work and a clean mapping into the three occupation-level dimensions. A limitation is that equal weights abstract from within-dimension heterogeneity across subtests and may introduce measurement error in the worker skill proxies.

These indices should be understood as baseline ability proxies rather than complete measures of realised, job-specific skills at each point in time. Individuals with the same baseline scores may accumulate different skills through schooling, training, and experience. Consequently, the exposure measures constructed below capture how occupational demand shifts interact with baseline endowments, and they should not be interpreted as measuring skill depreciation or re-skilling directly.

Table 3.2: Keywords to identify different skill types

	Keywords
Cognitive	Research, Analyse, Decision, Solving, Math, Statistic, Thinking
Manual	Repair, Operating, Maintenance, Controlling Machine, Handling Objects
Interpersonal	Communication, Teamwork, Collaboration, Negotiation, Presentation

Specifically, I utilise a set of keywords for each skill type to determine whether a vacancy specifies that skill type. Following Hershbein and Kahn (2018), I choose all ads that has keywords “Research, Analyze, Decision, Solving, Math, Statistic, or Thinking” in their O*NET descriptions to identify cognitive skill demands. Moreover, in line with Deming and Kahn (2018), I use keywords “Communication, Teamwork, Collaboration, Negotiation, or Presentation” to determine interpersonal skills. Finally, I take all ads that contain “Repair, Operating, Maintenance, Controlling Machine, Handling Objects” to construct manual skill requirements. Then, I calculate the change in skill demands within each occupation based on these narrowly defined skill categories between 1978 and 2000. The Table 3.2 presents the selection of keywords to identify different skill types.

To define different types of exposure to skill obsolescence, I use both individual skill scores and changes in occupational skill requirements. By doing so, I first identify the primary skills of workers (the skill in which their score is the highest among the three skill groups). Then, I check whether the primary skill of a worker experiences a decline in demand in the occupation she is working in, while the demand for other skills she possesses increases. I call this exposure to "primary skill obsolescence". It is also possible that in some occupations, more than one skill group is decreasing in demand. If the demand for a primary skill decreases alongside another skill or people who work in an occupation where at least two skill groups decrease in demand, it is considered "high exposure" to obsolescence. I consider the rest to have little or no exposure.

I define a decline in demand for a skill as a negative change, both in relative and absolute terms. Using the change in demand shares directly reflects shifts in the occupation's skill composition. If a skill's share is declining, it indicates that, within the occupation's overall skill structure, that skill is playing a progressively more minor role. I believe that relative measures are more sensitive to early signals of change. This early warning can be valuable in understanding transitions and prompting timely interventions, such as retraining or occupational moves. However, using shares alone might overestimate the exposure groups as the demand for the skill in question can also be stable or even slightly increasing in absolute terms. To account for that, I also check whether the demand is genuinely declining using absolute changes. Thus, to signal the obsolescence, a change in skill demands should show a decline in both relative and absolute values.

In constructing the panel, I dropped all the observations for which the occupation information was missing. I also exclude people for whom the skill scores cannot be constructed due to missing data. To avert the influence of outliers and misreporting, I remove observations with less than one year of education. Following Deming (2017), I exclude real hourly wage values that fall below 3 or exceed 200$. I also dropped all the individuals who left the survey. In addition, to obviate inconsistencies in occupational coding throughout the survey years in NLSY79, I used crosswalks from Autor and Dorn (2013) and removed all observations that do not match. As NLSY is criticised for oversampling the ethnic minorities, I keep only the cross-sectional white sample of NLSY79, following Lise and Postel-Vinay (2020) and De la Roca et al. (2023). After aggregating at the monthly level, the panel has 4230 individuals and 717,224 person-month observations.

3.4.1 Descriptive Statistics

To better understand the characteristics of workers across different levels of exposure to skill obsolescence, Table 3.3 summarises key demographic, skill, and labour-market variables for individuals classified as No Exposure, Primary Skill Obsolescence, and High Exposure. These descriptive statistics offer insights into the heterogeneity of workers' profiles and their alignment with exposure to skill obsolescence.

Table 3.3: Summary Statistics

	No-Exposure	Primary	High
Age	29.29	30.08	27.82
Education	14.41	12.88	13.47
Female	0.56	0.23	0.52
Hourly Wage	9.04	9.04	7.75
Tenure (Year)	4.30	4.81	3.83
Years of Experience	9.09	10.16	7.98
Cognitive Score	0.67	0.55	0.61
Manual Score	0.59	0.70	0.59
Interpersonal Score	0.44	0.43	0.44
Share of Cognitive Req.	0.36	0.33	0.30
Share of Manual Req.	0.15	0.19	0.22
Share of Interpersonal Req.	0.49	0.47	0.48
Observations	396314	108121	217674

Notes: Unit: person-month. "Primary exposure" means the worker's highest skill faces a within-occupation demand decline; "High exposure" means at least two skills decline.

Workers with no exposure tend to have higher average education levels, 14 years, compared to those subject to primary skill obsolescence (12.8 years) and high exposure (13.4 years) groups. The exposure groups, however, differ considerably in gender composition. The group of workers with little or no exposure has a higher percentage of women (56%). In contrast, the group with Primary Exposure exhibits a significant gender disparity, with only 23% of workers being female. Moreover, workers suffering from high exposure are relatively younger than others, with an average age of around 28 years.

In terms of skill endowments, the skill profiles of individuals differ markedly across exposure groups. Workers in the No Exposure group score the highest in cognitive skills (0.67), while those in the Primary Exposure group score the lowest (0.55). Conversely, manual skill scores are highest for workers whose primary skill is subject to obsolescence (0.70), reflecting the manual-intensive nature of their occupations. Finally, people with high exposure have relatively lower hourly wages on average ($7.75) and tend to have lower tenure (3.8 years) compared to the other groups.

I also present how workers in the dataset are distributed across occupations based on the exposure type. Figure 3.4 shows this distribution for broad occupation groups, which I used in the previous section. It is clear that highly exposed individuals are concentrated in occupations for which the skill demand changes are sharper, such as Operators and Labourers and Production occupations (see Figure 3.3 above). Not surprisingly, these are also the occupations where employment share has decreased over the decades (see Figure 3.1). However, it is also apparent that there is significant heterogeneity at the finer occupational levels in terms of workers' exposure, as no occupational group is associated solely with a single exposure type. Further details on the distribution of workers across occupations and occupation coverage of the dataset are provided in Appendix 3.A.

3.5 Results

In this section, I analyse how exposure to skill obsolescence affects key labour market outcomes, including wages, employment duration, and occupational mobility. To do so, I estimate the fixed-effect regressions of the following form:

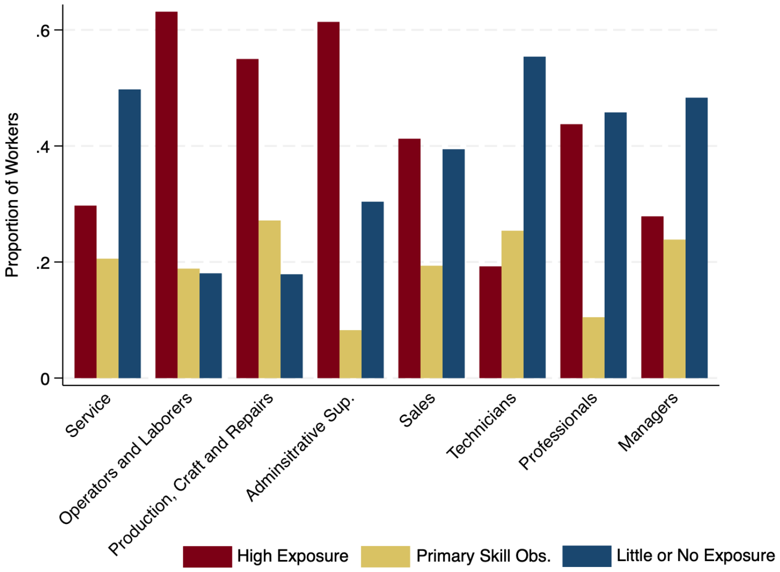


Figure 3.4: Occupational Distribution of Workers by Exposure Type

Notes: NLSY79 person-month distribution across exposure categories (None/Primary/High); exposure defined as in Table 3.3.

$$Y_{i,t} = \alpha_i + \beta_1 Primary_{i,t} + \beta_2 High_{i,t} + \Gamma \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{3.1}$$

where $Y_{i,t}$ is the outcome variable, such as real wages, weeks of non-employment or occupation switch indicator, $Primary_{i,t}$ and $High_{i,t}$ stand for exposure to primary skill obsolescence and high degrees of exposure, respectively. $\mathbf{X}_{i,t}$ is the vector of time-varying controls, which includes age, age squared, tenure, work experience, experience squared and years of completed education. Finally, in specifications with worker fixed effects, α_i is a vector of individual-specific fixed effects that captures time-invariant differences among workers. Depending on the specification, I include date (month–year) fixed effects and time-varying occupation and/or industry fixed effects to control for any business cycle and occupation-specific factors. Observations are in person-months, and I cluster standard errors at the individual level.

I begin by examining how exposure to skill obsolescence is related to workers' real wages. One of the main objectives of this study is to figure out whether labour market outcomes vary depending on the level of exposure. As the type of exposure is linked to both heterogeneous skill profiles of workers and the skill demands of their respective occupations, I aim to investigate whether possessing different skill bundles matters once workers are subject to some degree of skill obsolescence. In this respect, Table 3.4 presents the results of the estimation of equation 3.1 using the logarithm of real hourly wages as the dependent variable.

I classify each worker-month into one of three mutually exclusive exposure states: no exposure, primary exposure, or high exposure. Accordingly, I include two indicator variables, $Primary_{it}$ and $High_{it}$, with no exposure as the omitted category. Because these indicators are mutually exclusive, the fixed-effects coefficients are interpreted as within-individual differences in wages associated with being in the corresponding exposure state relative to no exposure: β_1 compares primary exposure to no exposure and β_2 compares high exposure to no exposure. Identification comes from individuals who switch exposure states over time (typically via occupational moves), but the coefficients should be interpreted as state-dependent wage differences rather than as “effects of a specific transition.”

Exposure is defined from a worker’s current occupation combined with occupation-level task trends. Because workers can respond to obsolescence risk by switching occupations, current exposure is potentially endogenous. In particular, exposure may affect switching, and switching mechanically changes exposure status. Therefore, regressions of outcomes on contemporaneous exposure (Table 3.4) are interpreted as descriptive associations across exposure states rather than causal effects of exogenous exposure shocks. The subsequent exercises explicitly model switching and use lagged exposure to better separate exposure from contemporaneous adaptation (Tables 3.5-3.6).

The results in Table 3.4 have different implications. First of all, I observe that high exposure to obsolescence negatively affects wages in all of the specifications, even after adding the fixed effects (time, individual, occupation, and industry) as well as additional controls such as age, regional dummies, regional unemployment rate, change in employment shares, and experience squared. For workers experiencing

Table 3.4: Exposure to Skill Obsolescence and Wages

	(1)	(2)	(3)	(4)
High	-0.021***	-0.021***	-0.027***	-0.021***
	(0.008)	(0.008)	(0.009)	(0.006)
Primary	0.024*	0.022*	-0.009	-0.017**
	(0.013)	(0.013)	(0.012)	(0.009)
Experience (Year)	0.033***	0.037***	0.033***	0.039***
	(0.002)	(0.002)	(0.002)	(0.002)
Tenure (Year)	0.026***	0.028***	0.031***	0.019***
	(0.003)	(0.003)	(0.002)	(0.002)
Enrolled	-0.264***	-0.247***	-0.189***	-0.193***
	(0.010)	(0.010)	(0.009)	(0.008)
Education	0.048***	0.049***	0.038***	
	(0.003)	(0.003)	(0.003)	
Observations	657999	657999	657999	657999
Worker FE	No	No	No	Yes
Time FE	No	Yes	Yes	Yes
Occupation & Industry FE	No	No	Yes	Yes
Add. Controls	Yes	Yes	Yes	Yes

Notes: Dependent var.: log real hourly wage. $Primary_{it}$ and $High_{it}$ are mutually exclusive; the omitted category is no exposure. Reported coefficients are from regressions with the OLS/FE structure indicated by the column headers.

Additional controls (where used) include age and age squared, experience and experience squared, regional dummies, regional unemployment, change in employment shares, and baseline skill scores (included when not absorbed by worker fixed effects).

Standard errors (in parentheses) clustered at the individual level. $^{*}p<.10$, $^{**}p<.05$, $^{***}p<.01$.

only primary skill obsolescence, the initial positive correlation observed in columns (1) and (2) disappears once I introduce occupation fixed effects and worker fixed effects, as shown in column (4). After accounting for time-invariant worker characteristics and stable occupation-specific factors, primary skill obsolescence emerges as a negative determinant of wages. This shift suggests that the earlier positive association may have been driven by unobserved heterogeneity or by workers initially sorting into higher-paying positions before the value of their primary skill began to erode. Therefore, being exposed to obsolescence is negatively associated with wages, irrespective of its type. This result is not surprising and in line with previous studies, which assert that skill obsolescence depresses earnings (De Grip and Van Loo, 2002; Kambourov and Manovskii, 2009).

Another interesting finding is that the size of the impact varies depending on the type of exposure. After controlling for the worker fixed effects in column (4), the magnitude of reduction is greater for the highly exposed individuals. Thus, workers facing high exposure to obsolescence have relatively worse outcomes compared to those who experience only primary skill obsolescence. This result implies that the level of exposure, indeed, matters for the labour market returns.

The findings on the negative impact of exposure to obsolescence on wages can also be interpreted as the reflection of a growing mismatch between workers' skill endowments and the skill requirements of the occupations. As certain skills become obsolete within occupations over time and others gain importance, the distance between the skills workers possess and the needs of employers can extend. Regardless of the initial match quality between workers and their jobs, I consider that obsolescence creates or widens the mismatch over the years due to within-occupational changes.

This divergence can make a worker over- or under-qualified for certain skill dimensions, which, in turn, might affect workers' earnings. In fact, Guvenen et al. (2020) and Lise and Postel-Vinay (2020) show how the resulting mismatch can depress the wages of workers and affect the prospective jobs in which they might move. Guvenen et al. (2020) find out that the mismatch leads to a persistent reduction in workers' wages, and thus workers prefer to switch occupations to reduce their skill mismatch.

The latter is one of the particular interests of this study. In other words, I analyse whether exposure to any type of obsolescence is related to occupational mobility. I argue that the tendency to change occupations can depend on the extent to which a worker is subject to obsolescence in their current occupation. Because exposure erodes skills while working because of the changing skill demands of occupations, a worker can either try to stay in the present occupation and adapt to changes by leveraging their other skills, seeking additional training, or moving to related occupations where their skills are still valued.

To explore this, I estimate equation (3.1) using the occupational switch as the dependent variable. Here, I also differentiate the switches from three, two, and one-digit occupations. Using broader occupational groups to identify switches helps us remove spurious transitions resulting from miscoding or positional change in the same workplace. Therefore, I examine whether there is a relationship between the exposure measures and occupational switches using not only three-digit occupations but also switches from two and one-digit occupations. The Table 3.5 reports the findings from this estimation.

Table 3.5: Exposure to Skill Obsolescence and Occupational Mobility

	Switch (3 digit)	Switch (2 digit)	Switch(1 digit)
	(1)	(2)	(3)
Primary	-0.003^{*}	-0.001	0.002^{*}
	(0.001)	(0.001)	(0.001)
High	0.010^{***}	0.006^{***}	0.004^{***}
	(0.001)	(0.001)	(0.001)
Observations	679410	679410	679410
Worker, Time, Occ., Ind. FE	*Yes*	*Yes*	*Yes*
Controls	*Yes*	*Yes*	*Yes*

Notes: Outcome: Switch between t and t+1 at 3-, 2-, or 1-digit levels. Fixed effects and controls as in wage specs. SE (in parentheses) clustered at the individual level. $^{*}p$<.10, $^{**}p$<.05, $^{***}p$<.01.

In all of the specifications, I find evidence that workers who are highly exposed to obsolescence tend to transition more from their occupations. This is even true for more distinct changes, such as switches among narrowly defined occupational groups. The positive and significant coefficient for high exposure highlights the unsustainability of occupations where multiple skills are becoming obsolete. Workers in such situations may experience heightened job insecurity, prompting them to seek opportunities in occupations with better demand prospects for their skill sets.

Considering that obsolescence creates or widens the skill mismatch, these results support Guvenen et al. (2020)'s findings on occupational mobility. Workers with increased mismatch due to high exposure to obsolescence are likely to change their occupations in order to improve the fit between their skill endowments and the needs of the occupations. The results in Table 3.5 are also partially in line with Braxton and Taska (2023), who find that high exposure to technological change increases occupational mobility. However, they focus on mobilities following a displacement event and indicate that mobility is higher for exposed workers upon an involuntary job loss. I, however, show that workers suffering from high levels of exposure are keen to change their occupations even if they are not involuntarily displaced.

I also observe that workers facing only primary skill obsolescence are less likely to change their occupations compared to both highly exposed and non-exposed workers. I interpret this finding as an indication of risk aversion and a preference for stability among these workers. Although their primary skills are becoming obsolete, they might benefit from having secondary and tertiary skills that are gaining importance in their occupations. Therefore, these people can be reluctant to change their occupations because such a change may reinforce skill obsolescence by also losing their occupation-specific human capital. In fact, occupational switch is usually linked to loss of occupation or industry-specific human capital, which can add to the possible negative impacts of making these transitions (Neal, 1995; Kambourov and Manovskii, 2009; Fujita, 2018).

Interestingly, I also find that workers exposed to primary skill obsolescence tend to make a substantial move into a completely different broad occupational group, as the coefficient of 1-digit switch suggests. I discuss that a larger jump to a different major occupational category may offer better alignment with the secondary or tertiary skills of these workers. In fact, if a worker's primary skill is becoming obsolete, making small, lateral moves within the same broad field may not help much if all closely related occupations also rely heavily on that diminishing skill. As a result, these workers might not find it beneficial to engage in frequent, small adjustments at the 3-digit level. However, occupational switching is only one adjustment margin. Workers can also reallocate across industries while remaining in broadly similar roles. Appendix 3.C reports analogous regressions using industry switching with particularly robust evidence for high exposure.

The consequences of this occupational mobility can vary. On the one hand, occupational mobility might improve the fitness between individual skill sets and occupational requirements. This enhanced matching is generally reflected in increased wages (Topel and Ward, 1992; Groes et al., 2015; Bachmann et al., 2020). On the other hand, the loss of specific human capital may result in a decrease in wages (Gathmann and Schönberg, 2010). Therefore, I question the results of occupational switching in the face of skill obsolescence and whether these consequences differ depending on the exposure. To study this, I re-estimate the wage equation by adding occupational switch indicators and their interactions with the exposure types. It is important to note that I consider whether a worker was exposed to any type of obsolescence in her previous occupation. Therefore, variables High and Primary in Table 3.6 indicate the lagged value of respective categories.

The findings indicate that both exposure to skill obsolescence and occupational switching are individually associated with lower wages. The wage penalty from occupational change can be attributed to losing specific human capital or can be a sign of increased mismatch upon altering the occupation. Even though workers are not suffering from any sort of obsolescence in their current occupations, switching occupations is likely to cause some skills to get lost if the destination occupation is different from the present one in terms of skill needs (Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010; Robinson, 2018). Thus, occupational mobility can

Table 3.6: Exposure to Skill Obsolescence, Occupational Mobility and Wages

	(1)	(2)	(3)
High	-0.020***	-0.019***	-0.019***
	(0.006)	(0.006)	(0.006)
Primary	-0.019**	-0.018**	-0.018**
	(0.009)	(0.009)	(0.009)
Occ. Switch (3digit)	-0.031***		
	(0.003)		
High x Occ. Switch (3digit)	0.014**		
	(0.006)		
Primary x Occ. Switch (3digit)	0.025***		
	(0.008)		
Occ. Switch (2digit)		-0.038***	
		(0.004)	
High x Occ. Switch (2digit)		0.011	
		(0.007)	
Primary x Occ. Switch (2digit)		0.030***	
		(0.009)	
Occ. Switch (1digit)			-0.053***
			(0.005)
High x Occ. Switch (1digit)			0.011
			(0.008)
Primary x Occ. Switch (1digit)			0.039***
			(0.010)
Observations	654777	654777	654777
Controls	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Occupation & Industry FE	Yes	Yes	Yes

Notes: Dep. var.: log real hourly wage. Fixed effects and controls as in wage specs. Switch indicators at 3-/2-/1-digit; exposure measured in prior occupation. SE (in parentheses) clustered at the individual level. $^{*}p<.10$, $^{**}p<.05$, $^{***}p<.01$.

lead to a reduction in wage premia irrespective of the exposure level.

However, the interaction terms with occupational switching tell a more interesting story. While switching occupations generally comes with an initial wage penalty, the positive and significant interaction coefficients for workers previously exposed to skill obsolescence suggest that occupational mobility can partially mitigate these losses. In particular, the results show that for individuals who faced primary skill obsolescence, switching occupations at any level of disaggregation (3-digit, 2-digit, or even 1-digit) tends to yield a positive and significant offset to the wage penalty. This pattern implies that making a new occupational match can help obsolescent workers recover from some of the earnings losses associated with their outdated primary skill.

For those with high exposure, the beneficial offset from switching is strongest at the finer occupational level (3-digit), but not as clearly evident at broader occupational aggregations (1- or 2-digit). This difference may reflect that high-exposure workers benefit most from lateral moves within related occupations, where they can transfer some of their non-obsolete skills, while primary skill obsolete workers need larger occupational leaps to find a better fit.

I have already shown that workers who are highly exposed to skill obsolescence are more proactive in seeking new roles by switching occupations. They may do so by moving to occupations where their remaining relevant skills are more valued or where they can more quickly adapt and acquire new skills. These workers might make more strategic occupational moves, targeting sectors or roles that are less affected by obsolescence, which can mitigate some of the wage penalties associated with switching. Similarly, even though workers suffering from primary skill obsolescence are reluctant to change their occupations, they experience a similar outcome once they do so.

Workers with low or no exposure, on the other hand, might not face the same immediate pressure to switch occupations. When they do switch, it might be for reasons other than skill obsolescence, such as personal preference, career advancement, or other factors. Without the pressing need to adapt to rapidly changing skill demands, these workers might not choose new occupations as strategically, leading to a higher wage penalty.

These results, however, are against Robinson (2018) who asserts that workers with voluntary occupational movements barely suffer from skill obsolescence and the associated wage declines upon switching, as these changes are generally towards similar occupations. I argue that workers may still be subject to obsolescence and related wage reduction in their new occupations, even if it is a similar one, if the demands for their skills are changing in a negative direction. In other words, if workers are switching from an occupation where they are facing little or no exposure to an occupation in which they suffer some degree of obsolescence might bear the negative consequences of this mobility even if the destination occupation is similar in terms of skill requirements.

Table 3.7: Exposure to Skill Obsolescence and Non-Employment Spells

	(1)	(2)	(3)	(4)
Primary	-0.002	-0.005	-0.004	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
High	0.011^{***}	0.014^{***}	0.013^{***}	0.015^{***}
	(0.002)	(0.002)	(0.002)	(0.003)
Observations	679410	679410	679410	679410
Worker FE	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes
Occupation & Industry FE	No	No	No	Yes

Notes: Dep. var.: Weeks w/o Work. FE and controls as in wage specs. SE (in parentheses) clustered at the individual level. $^{*}p<.10$, $^{**}p<.05$, $^{***}p<.01$.

The results presented in Table 3.6 reveal the wage cost of occupational change. However, the costs may not solely be about the earnings when these transitions are not immediate. In fact, exposure to obsolescence might also affect the duration of finding another job upon leaving the current one. To examine more closely and uncover what happens after leaving an occupation in the face of skill obsolescence, I analyse whether exposure to obsolescence is associated with the time spent without work after leaving an occupation, either voluntarily or involuntarily. Table 3.7 provides the results of this exercise, where the dependent variable is weeks spent without work.

The findings show no significant association between the measure of primary skill obsolescence and prolonged non-employed spells. As discussed earlier, individuals whose primary skill is becoming obsolete are reluctant to change their occupation, which might reflect their efforts to adapt to the changes in skill demands by reskilling or upskilling within their current occupation. This adaptability may allow them to stay relevant in their current jobs or find new employment opportunities without a significant gap. However, the positive and significant coefficient of "$High$" implies that people who suffer from high exposure spend more time out of employment. This result is not surprising considering that not only primary but also secondary skills erode for these workers, which may restrict the jobs available for them in the labour market, thus increasing the duration of their unemployment spell.

The results presented throughout this section used obsolescence categories based on the skill declines both in relative and absolute terms, without imposing a threshold. However, considering that small decreases might not reflect a genuine drop in skill demand and might over-estimate the impact of obsolescence, I run the same regressions using various thresholds, i.e. 10, 15 and 20%, for decreases in skill demands such that beyond the threshold a worker is no longer a candidate for any of the exposure categories. I present in the appendix that the findings are robust even when employing the thresholds.

3.5.1 External validity and limitations

This chapter documents how labour-market outcomes vary with exposure to within-occupation skill obsolescence as measured by the interaction of workers' baseline skill profiles and long-run changes in occupational skill demands. Several limitations are important for interpreting the scope of these findings.

Target population and external validity. The NLSY79 is a cohort study: it follows individuals born 1957–1964 (aged 14–22 in 1979) as they progress through the labour market. Accordingly, the estimates in this chapter are most naturally interpreted as describing patterns for this cohort over the 1980–2000 period, rather than representing the entire U.S. working population at each point in time. In addition, the baseline analysis in this chapter restricts attention to the white civilian cross-section. This restriction improves comparability with parts of the related NLSY79-based literature and reduces heterogeneity in wage-setting processes within this cohort, but it clearly limits generalisation to other demographic groups. To address this directly, Appendix 3.C re-estimates the main specifications on the full civilian NLSY79 sample. The results are qualitatively and quantitatively similar, indicating that the key patterns are not driven by the sample restriction.

Internal validity and interpretation. As discussed in Section 3.5, exposure is constructed from the worker's current occupation and is therefore not plausibly exogenous when occupational mobility is an adjustment margin. Accordingly, contemporaneous exposure-outcome regressions are interpreted as descriptive associations rather than causal effects. For this reason, the chapter places greater emphasis on specifications that model mobility explicitly and/or use lagged exposure (Tables 3.5-3.6), which are closer to tracing dynamic adjustment patterns conditional on observed switching.

Measurement and data coverage. Both worker skills and occupational demands are measured with error. Worker skill measures rely on ASVAB and psychometric instruments administered early in life and are treated as time-invariant proxies; they do not capture later re-skilling or on-the-job learning. Occupational skill demands are constructed from vacancy text using keyword-based measures and are summarised using long-run changes between 1978 and 2000. While the requirement that declines be negative in both relative and absolute measures helps avoid classifying stable/increasing components as "declining," the vacancy-based measures may still reflect changes in posting practices and coverage. Appendix 3.B provides detailed variable construction steps and illustrative examples.

Relevance beyond the 1980–2000 period. The 1980–2000 period captures a canonical episode of computerisation and task reallocation. Institutional features and technologies have changed since then, and the estimates should not be mechanically extrapolated to today's AI environment or to other countries with different labour-market institutions. The contribution of this chapter is therefore best viewed as providing an empirical benchmark on how outcomes varied with exposure to occupational task change during a major historical technological transition, rather than as a direct forecast for current or future technological shocks.

3.6 Conclusion

Technological change has profound impacts on labour markets. The transformations that occurred between occupations in terms of employment shares indicated a significant polarisation of jobs towards the higher and lower ends of the skill distribution. Technological progress, however, has not only shifted the occupational structures but also redefined the skills required within these occupations. In each occupation, some skills are becoming more important while others are declining, rendering them obsolete. This study explores substantial impacts of technological progress on labour market outcomes focusing on skill obsolescence within occupations. By examining the changes in skill demands and their effects on workers, I provide new insights into the dynamics of skill obsolescence and its implications for employment and wages.

This research highlights the importance of focusing on within-occupational changes in skill demands. This approach reveals that workers experience skill obsolescence in varied ways, depending on their individual skill profiles and the evolving demands of their jobs. Unlike traditional views that consider skills as one-dimensional, this study emphasises the multidimensional nature of skills and how this leads to heterogeneity in exposure to obsolescence.

The results presented in this paper demonstrate that exposure to skill obsolescence significantly affects labour market outcomes. Workers experiencing high levels of exposure to skill obsolescence face more severe adverse effects, including reduced earnings and prolonged unemployment. This study also shows that workers exposed to high levels of skill obsolescence are more likely to switch occupations. This increased mobility reflects the unsustainability of remaining in occupations where multiple skills are becoming obsolete. In contrast, workers whose primary skill is becoming obsolete but who possess secondary and tertiary skills that are gaining importance are more likely to remain in their current occupations, likely seeking to adapt to changing demands through reskilling or upskilling.

This paper also documents that there is a wage cost of occupational switching, regardless of being exposed to obsolescence or not in the present occupation. However, this cost is slightly mitigated for workers exposed to some degree of obsolescence, possibly indicating the strategic moves by these workers towards occupations where their skills are still valued and they are better fit to the requirements. These findings are consistent across different specifications, confirming the critical role of skill obsolescence in shaping labour market trajectories.

The implications of this research are significant for policymakers and educators. Addressing skill obsolescence requires targeted interventions that support continuous learning and skill development. Policies promoting reskilling and upskilling within occupations can help workers adapt to evolving requirements and mitigate the adverse impacts of skill obsolescence. Furthermore, educational systems need to adapt to prepare individuals with a wide range of skills that can withstand technological advancements, placing importance on cognitive, manual, and interpersonal abilities.

Appendices to Chapter 3

3.A Additional Descriptives

Table 3.A.1: Skill Evolution for HR Managers: 1980–2000

Requirement	**1980**	**1990**	**2000**
Cognitive Requirements			
Analyzing Data or Information	0.061	0.071	0.057
Making Decisions and Solving Problems	0.022	0.039	0.049
Thinking Creatively	0.050	0.091	0.037
Mathematics (Skill)	0.154	0.178	0.252
Critical Thinking	0.028	0.049	0.037
Complex Problem Solving	0.026	0.046	0.069
Judgment and Decision Making	0.021	0.016	0.020
Mathematics (Knowledge)	0.154	0.178	0.252
Interpersonal Requirements			
Comm. with Supervisors/Peers/Subordinates	0.278	0.329	0.220
Comm. with Persons Outside Organization	0.179	0.283	0.220
Establishing/Maintaining Interpersonal Rel.	0.094	0.219	0.236
Negotiation	0.054	0.093	0.057
Social Perceptiveness	0.000	0.000	0.000
Manual Requirements			
Handling and Moving Objects	0.001	0.000	0.004
Controlling Machines and Processes	0.101	0.075	0.045
Operating Vehicles/Devices/Equipment	0.048	0.036	0.012
Repairing Mechanical Equipment	0.063	0.058	0.008
Repairing Electronic Equipment	0.060	0.058	0.008
Equipment Maintenance	0.027	0.027	0.008
Repairing	0.028	0.044	0.008

Notes: Units are expressed as mentions per 1,000 job ad words.
Data is taken from Atalay et al. (2020)

Table 3.A.2: Skill Evolution for Records Clerks: 1980–2000

Requirement	**1980**	**1990**	**2000**
Cognitive Requirements			
Analyzing Data or Information	0.019	0.057	0.091
Making Decisions and Solving Problems	0.003	0.014	0.000
Thinking Creatively	0.011	0.005	0.000
Mathematics (Skill)	0.072	0.154	0.185
Critical Thinking	0.005	0.000	0.000
Complex Problem Solving	0.003	0.005	0.033
Judgment and Decision Making	0.014	0.000	0.017
Mathematics (Knowledge)	0.072	0.154	0.185
Interpersonal Requirements			
Comm. with Supervisors/Peers/Subordinates	0.084	0.137	0.129
Comm. with Persons Outside Organization	0.090	0.164	0.079
Establishing/Maintaining Interpersonal Rel.	0.014	0.050	0.108
Negotiation	0.002	0.014	0.085
Social Perceptiveness	0.000	0.000	0.000
Manual Requirements			
Handling and Moving Objects	0.002	0.000	0.045
Controlling Machines and Processes	0.043	0.105	0.073
Operating Vehicles/Devices/Equipment	0.032	0.047	0.056
Repairing Mechanical Equipment	0.020	0.047	0.073
Repairing Electronic Equipment	0.022	0.061	0.056
Equipment Maintenance	0.011	0.044	0.000
Repairing	0.002	0.000	0.000

Notes: Units are expressed as mentions per 1,000 job ad words.
Data is taken from Atalay et al. (2020)

Table 3.A.3: Occupational Composition: Estimation Sample (Pooled) vs. Age-Matched Census Benchmarks

Major Occupation Group	**Sample (pooled)**	**1980**	**1990**	**2000**
Office/Admin.	18.5%	17.4%	16.5%	16.0%
Service	17.6%	13.3%	13.7%	14.8%
Operators and Laborers	16.5%	18.4%	15.1%	13.1%
Managers	14.1%	10.5%	12.5%	12.6%
Professionals	11.4%	12.3%	13.9%	16.5%
Production/Craft/Repairs	8.8%	13.0%	11.2%	11.0%
Sales	8.5%	9.8%	11.6%	11.1%
Technicians	3.8%	3.1%	3.8%	3.7%
Farming/Fishery/Forestry	0.6%	2.3%	1.6%	1.3%

Notes: Sample (pooled) reports the distribution of employed person-months in the estimation sample pooled over 1978–2000. Census benchmarks are computed from IPUMS Census 1980/1990/2000 using person weights and restricting to civilian employed individuals in cohort-consistent age ranges (16–23 in 1980, 26–33 in 1990, 36–43 in 2000). Occupation codes are harmonised to a common 3-digit Census scheme using Autor and Dorn (2013) and then aggregated into the major occupation groups shown.

Table 3.A.3 compares the occupational composition of the estimation sample to cohort-consistent national benchmarks from the 1980, 1990, and 2000 Censuses. Overall, the sample distribution across major occupation groups is broadly similar to the age-matched Census benchmarks, suggesting that the estimation sample is not concentrated in a small set of occupational categories. Some differences remain. For example, the sample has a higher share in service and office/administrative occupations and a lower share in production/craft and farming—consistent with the NLSY79 cohort design and the sample restrictions used in the analysis. Differences may also reflect the white-only restriction in the estimation sample. This comparison is intended as a descriptive check on occupational composition rather than a claim of full national representativeness.

Table 3.A.4: Top 20 occupations by person-months in the estimation sample

Occupation	Person-months	Share
Managers and administrators, n.e.c.	74,478	0.104
Salespersons, n.e.c.	32,689	0.046
Secretaries and stenographers	28,389	0.040
Laborers, freight, stock, and material handlers, n.e.c.	22,583	0.031
Truck, delivery, and tractor drivers	21,589	0.030
Cashiers	15,807	0.022
Managers and spec. in marketing, ad., and public rel.	15,719	0.022
Machine operators, n.e.c.	15,605	0.022
Waiter/waitress	15,394	0.021
Administrative support jobs, n.e.c.	14,576	0.020
Bookkeepers and accounting and auditing clerks	13,470	0.019
Health and nursing aides	12,953	0.018
Miscellaneous food preparation and service workers	12,324	0.017
Child care workers	12,218	0.017
Production supervisors or foremen	11,935	0.017
Accountants and auditors	11,914	0.017
Primary school teachers	11,550	0.016
Registered nurses	11,261	0.016
Cooks, variously defined	11,072	0.015
Carpenters	10,185	0.014

Notes: Top 20 occupations by employed person-months in the estimation sample (unit of analysis). Occupation codes are 3-digit Census 1970 codes crosswalked to a common 3-digit Census coding scheme using the Autor and Dorn (2013) crosswalk (see text). Occupations are ordered by the number of person-months observed in the estimation sample. The share column reports the proportion of all person-months in the estimation sample accounted for by each occupation.

3.B Construction of Exposure Status

This appendix illustrates how baseline worker skills from NLSY79 are combined with occupation-level task-demand trends to assign monthly exposure status in the person–month panel.

Step 1: Baseline worker skill vector (time-invariant). Consider worker i. Using ASVAB and psychometric measures observed around 1980, I construct normalized baseline skill proxies for cognitive (C_i), manual (M_i), and interpersonal (S_i) abilities. Suppose that for this worker:

$$(C_i, M_i, S_i) = (0.2,\ 1.1,\ -0.1),$$

so the worker's *primary* skill is manual (the highest of the three).

Step 2: Occupation task-demand trends (long change 1978–2000). For each occupation o, I use the task measures from Atalay et al. to compute how the occupation's cognitive, manual, and interpersonal task shares change over the long period 1978–2000.[2] Let $\Delta^{78\to 00}C_o$, $\Delta^{78\to 00}M_o$, and $\Delta^{78\to 00}S_o$ denote these long changes in the three task shares.

Table 3.B.1 provides an illustrative example for two occupations.

Table 3.B.1: Illustrative example of occupation-level task trends and exposure assignment (1978–2000)

	Relative change (share)			Absolute change		
Occupation o	$\Delta s_C^{78\to 00}$	$\Delta s_M^{78\to 00}$	$\Delta s_S^{78\to 00}$	$\Delta a_C^{78\to 00}$	$\Delta a_M^{78\to 00}$	$\Delta a_S^{78\to 00}$
$o = 781$	+0.06	-0.08	+0.02	+12	-15	+5
$o = 245$	+0.04	+0.01	-0.05	+8	+1	-9

---

[2] In the empirical construction I require declines to be negative in both relative (shares) and absolute measures; the example focuses on changes in task shares for expositional clarity.

Step 3: Exposure classification. Exposure is defined by combining the worker's primary skill dimension with the sign of the occupation-level task-demand changes. In the example:

- If worker i (manual-primary) works in occupation 781, the long change in manual demand is negative while the other dimensions rise, so the worker is classified as *primary exposed.*
- If the same worker works in occupation 245, manual demand is not declining, so the worker is classified as *not exposed* on the manual dimension.

If an occupation exhibits declines in at least two task dimensions over 1978–2000, workers in that occupation are classified as *high exposed* according to the definition in the main text.

Step 4: Mapping exposure to the person–month panel. The analysis dataset is organized as person–months. Each person–month observation is assigned the exposure status implied by the worker's baseline skill vector and the occupation-level trend classification for the worker's current occupation. [3]

For example, if worker i works in occupation 781 from January 1993 through June 1993 and then switches to occupation 245 in July 1993, exposure is constant from January–June and changes in July due to the occupation switch.

Table 3.B.2: Mapping exposure to monthly observations (illustrative)

Month	Occupation	Year	Exposure status
1993m1–1993m6	781	1993	Primary exposure
1993m7–1993m12	245	1993	Not exposed

---

[3] Because occupation task trends are constructed as long changes, the exposure classification for a given occupation is time-invariant; monthly exposure can therefore change only when a worker changes occupation.

3.C Robustness Checks

3.C.1 Alternative sample: Full civilian NLSY79

Table 3.C.1: Exposure to Skill Obsolescence and Wages

	(1)	(2)	(3)	(4)
High	-0.027***	-0.027***	-0.045***	-0.020***
	(0.005)	(0.005)	(0.005)	(0.004)
Primary	-0.006	-0.006	-0.014*	-0.011**
	(0.008)	(0.008)	(0.008)	(0.006)
Age	0.053***	0.091***	0.065***	0.065***
	(0.004)	(0.005)	(0.004)	(0.005)
Experience (Year)	0.030***	0.044***	0.038***	0.062***
	(0.002)	(0.002)	(0.002)	(0.003)
Tenure (Year)	0.020***	0.020***	0.018***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Enrolled	-0.191***	-0.189***	-0.151***	-0.154***
	(0.006)	(0.007)	(0.006)	(0.005)
Education	0.045***	0.045***	0.035***	
	(0.002)	(0.002)	(0.002)	
Observations	1433427	1433427	1433427	1433402
Worker FE	No	No	No	Yes
Time FE	No	Yes	Yes	Yes
Occupation & Industry FE	No	No	Yes	Yes

Notes: Dep. var.: log real hourly wage. Controls and fixed effects are the same as in the main text. Standard errors (in parentheses) clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.C.2: Exposure to Skill Obsolescence and Occupational Mobility

	Switch (3 digit)	Switch (2 digit)	Switch (1 digit)
	(1)	(2)	(3)
Primary	-0.002**	-0.003***	-0.000
	(0.001)	(0.001)	(0.001)
High	0.008***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)
Observations	1,473,962	1,473,962	1,473,962
Worker, Time, Occupation, Industry FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Outcome: switch between t and t+1 at 3-, 2-, or 1-digit levels. Controls and fixed effects are the same as in the main text. Standard errors (in parentheses) clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.C.3: Exposure to Skill Obsolescence, Occupational Mobility and Wages

	(1)	(2)	(3)
High	-0.020***	-0.020***	-0.019***
	(0.004)	(0.004)	(0.004)
Primary	-0.012**	-0.012**	-0.012**
	(0.006)	(0.006)	(0.006)
Occ. Switch (3digit)	-0.034***		
	(0.003)		
High x Occ. Switch (3digit)	0.017***		
	(0.004)		
Primary x Occ. Switch (3digit)	0.010**		
	(0.005)		
Occ. Switch (2digit)		-0.041***	
		(0.003)	
High x Occ. Switch (2digit)		0.017***	
		(0.004)	
Primary x Occ. Switch (2digit)		0.012**	
		(0.005)	
Occ. Switch (1digit)			-0.051***
			(0.003)
High x Occ. Switch (1digit)			0.016***
			(0.005)
Primary x Occ. Switch (1digit)			0.016***
			(0.006)
Observations	1433426	1424983	1433426
Worker FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes

Notes: Dep. var.: log real hourly wage. Exposure is measured in prior occupation; switch indicators at 3-/2-/1-digit. Controls and fixed effects are the same as in the main text. Standard errors (in parentheses) clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.C.4: Exposure to Skill Obsolescence and Non-Employment Spells

	(1)	(2)	(3)	(4)
Primary	-0.001	-0.003	-0.003	0.002
	(0.002)	(0.003)	(0.003)	(0.003)
High	0.010***	0.008***	0.008***	0.009***
	(0.001)	(0.002)	(0.002)	(0.002)
Observations	1469041	1469041	1469041	1469041
Controls	Yes	Yes	Yes	Yes
Worker FE	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes
Occupation & Industry FE	No	No	No	Yes

Notes: Dep. var.: weeks without work. Controls and fixed effects are the same as in the main text. Standard errors (in parentheses) clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.C.2 Alternative exposure definitions: Thresholds for demand decline

Table 3.C.5: Exposure to Skill Obsolescence and Wages - Demand Decline $\geq 10\%$

	(1)	(2)	(3)	(4)
Primary	0.018	-0.004	-0.006	-0.018**
	(0.012)	(0.009)	(0.009)	(0.009)
High	-0.022***	-0.020***	-0.019***	-0.019***
	(0.008)	(0.006)	(0.006)	(0.006)
Observations	657995	657995	657995	657995
Worker FE	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes
Occupation FE	No	No	No	Yes

Notes: Dep. var.: log real hourly wage. Exposure re-defined using a $\geq 10\%$ demand-decline threshold. Controls and fixed effects are the same as in the main text. Standard errors (in parentheses) clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.C.6: Exposure to Skill Obsolescence and Occupational Mobility - Demand Decline $\geq 10\%$

	Switch (3 digit)	Switch (2 digit)	Switch(1 digit)
	(1)	(2)	(3)
Primary	-0.002^{*}	-0.001	0.002^{*}
	(0.001)	(0.001)	(0.001)
High	0.010^{***}	0.006^{***}	0.005^{***}
	(0.001)	(0.001)	(0.001)
Observations	679299	679299	679299
Worker, Time, Occupation, Industry FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Outcome: switch between t and t+1 at 3-, 2-, or 1-digit levels. Exposure re-defined using a $\geq 10\%$ demand-decline threshold. Controls and fixed effects are the same as in the main text. Standard errors (in parentheses) clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.C.7: Exposure to Skill Obsolescence and Wages - Demand Decline $\geq 10\%$

	(1)	(2)	(3)
Lag High	-0.018***	-0.018***	-0.017***
	(0.006)	(0.006)	(0.006)
Lag Primary	-0.020**	-0.020**	-0.019**
	(0.009)	(0.008)	(0.008)
Occ. Switch (3digit)	-0.029***		
	(0.003)		
High x Occ. Switch (3digit)	0.010		
	(0.007)		
Primary x Occ. Switch (3digit)	0.027***		
	(0.008)		
Occ. Switch (2digit)		-0.037***	
		(0.004)	
High x Occ. Switch (2digit)		0.008	
		(0.007)	
Primary x Occ. Switch (2digit)		0.032***	
		(0.009)	
Occ. Switch (1digit)			-0.053***
			(0.005)
High x Occ. Switch (1digit)			0.009
			(0.008)
Primary x Occ. Switch (1digit)			0.041***
			(0.010)
Observations	654773	654773	654773
Worker FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes

Notes: Dep. var.: log real hourly wage. Exposure re-defined using a $\geq 10\%$ demand-decline threshold; exposure measured in prior occupation when interacted with switching. Controls and fixed effects are the same as in the main text. Standard errors (in parentheses) clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.C.8: Exposure to Skill Obsolescence and Non-Employment Spells - Demand Decline $\geq 10\%$

	(1)	(2)
Primary	-0.000	0.003
	(0.003)	(0.003)
High	0.012***	0.017***
	(0.002)	(0.003)
Observations	657995	657995
Worker, Time, Occupation, Industry FE	No	Yes
Additional Controls	Yes	Yes

Notes: Dep. var.: weeks without work. Exposure re-defined using a $\geq 10\%$ demand-decline threshold. Controls and fixed effects are the same as in the main text. Standard errors (in parentheses) clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.C.3 Industry switching

Table 3.C.9: Exposure to Skill Obsolescence and Industry Switching

	Switch (3-digit ind.)	Switch (2-digit ind.)	Switch (1-digit ind.)
	(1)	(2)	(3)
Primary	0.002*	0.003***	0.002**
	(0.001)	(0.001)	(0.001)
High	0.003***	0.001**	0.002***
	(0.001)	(0.001)	(0.001)
Observations	679714	679714	679714
Worker FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Outcome is an industry-switch indicator between t and t+1 using 3-/2-/1-digit aggregations of the 1970 Census industry classification (IND1970). Controls and fixed effects are the same as in the main text. Standard errors clustered at the individual level. $^{*}p<.10$, $^{**}p<.05$, $^{***}p<.01$.

Chapter 4

Skill Obsolescence and the Consequences of Job Loss

4.1 Introduction

Involuntary job displacement resulting from mass layoffs or plant closures carries substantial economic and social costs. Those who have been displaced often face considerable and long-lasting declines in earnings, extended spells of unemployment, and shifts into less favourable job positions (Jacobson et al., 1993; Couch and Placzek, 2010; Farber, 2017). A vast literature documents these "scars" and links them to the partial loss of industry- and occupation-specific human capital (Neal, 1995; Kambourov and Manovskii, 2009). More recent task-based perspectives emphasise that skills are embodied in tasks rather than being fixed to occupations, so post-displacement outcomes depend on whether workers can transition into occupations that utilise similar task bundles (Robinson, 2018).

The technological advancements in recent decades, however, bring a new dimension to the subject matter. It has altered skill demands within occupations in uneven ways, eroding the value of some skills in some occupations but not others. These within-occupation shifts expose workers to skill obsolescence in their current job.

When the skills required in a job diverge from a worker's strengths, displacement can be especially costly. Hence, displacement outcomes may depend on the extent and *type* of exposure to within-occupation obsolescence.

Individuals also differ in their skill endowments. I study how within-occupation obsolescence interacts with workers' *own* skills to shape post-displacement trajectories. Exposure arises from this interaction: individuals differ in their skills, and occupations differ in how their skill requirements evolve. I distinguish three exposure types: (i) *primary-skill exposure*, where the worker's strongest skill dimension becomes less valued in the pre-displacement occupation; (ii) *high exposure*, characterised by a decline in various skill dimensions; and (iii) workers who are deemed *non-exposed.* More information about the construction and criteria can be found in Section 4.3.

Empirically, I combine the NLSY79 panel with occupation–year task measures from vacancy data to track both workers' skills (as measured by the Armed Services Vocational Aptitude Battery (ASVAB) tests) and occupations' task demands over time. Identification relies on an event-study difference-in-differences design with staggered displacement timing, following Callaway and Sant'Anna (2021), which estimates average treatment effects by exposure group. For outcomes only defined when working (e.g., match quality and landing distances), estimates are ATT among the employed.

I find four results. First, displacement causes significant and persistent losses in earnings and employment, with the extent varying based on workers' exposure to within-occupation obsolescence. Second, occupation switching rises sharply at the time of displacement, which then varies based on exposure: workers with high exposure adapt quickly, whereas non-exposed workers keep switching occupations for several years. Third, among the employed, *mismatch to own skills*—one minus the cosine similarity between an individual's ASVAB profile and the current occupation's skill vector—*declines* for primary- and high-exposed workers, but is close to zero for non-exposed workers. Fourth, conditional on re-employment, the *distance from the pre-displacement occupation* increases for all groups (most notably for high-exposure groups), indicating that re-employment often requires moving to different skill bundles.

This paper, then, has three main contributions: (i) It introduces a worker-level measure of exposure to *within-occupation* skill obsolescence by interacting individual skill endowments (ASVAB) with occupation–year shifts in task demand. (ii) It documents sizable *heterogeneity* in displacement effects by exposure type. (iii) It provides new *landing-outcome* evidence: among the employed, exposed workers move farther in skill space yet into better-matched jobs.

The remainder of the paper is organised as follows. Section 4.2 reviews related literature. Section 4.3 describes data, measurement, and the empirical strategy. Section 4.4 presents the main results and mechanism evidence. Section 4.5 concludes the research.

4.2 Literature Review

The costs and economic challenges faced by workers who lose their jobs involuntarily, such as due to mass layoffs or plant closures, have been of particular interest. Numerous studies have scrutinised the causes and consequences of job displacements. In these empirical studies, there is almost a consensus that displacements lead to lasting adverse labour market outcomes. Among the various labour market consequences, particular attention has been paid to estimating the earnings losses associated with these involuntary job separations. Although the magnitude of the impacts varies between studies depending on the dataset and the method used in the analysis, displacement is shown to cause permanent income losses (Ruhm, 1991; Jacobson et al., 1993; Kletzer and Fairlie, 2003; Couch and Placzek, 2010; Hijzen et al., 2010).

In their seminal paper, Jacobson et al. (1993) examined the earnings costs of displacement for high-tenure workers using administrative data from Pennsylvania for the years 1974-1987. They discovered that these workers experienced average annual losses of 25 percent over the long term upon displacement. Couch and Placzek (2010) extended these findings, showing that such scarring effects persist over many years and are not fully explained by business cycle conditions. Even after controlling for macroeconomic shocks, the post-displacement earnings of displaced workers lag behind those of similar, non-displaced workers.

Studies on the labour market impacts of displacement also point out that displacement often leads to prolonged periods of unemployment, which in turn exacerbates earnings losses. Chan and Stevens (2001), for instance, investigates the employment probabilities of older age workers following involuntary job loss and finds that displacement has significant and persistent negative effects on re-employment probabilities compared to those of similar non-displaced workers. This, in turn, results in significant earnings losses for the elderly and increases their likelihood of retirement (Chan and Stevens, 2004). Similarly, Farber (2017) demonstrates that displaced workers spend, on average, 25% more time unemployed than similar non-displaced workers. Full-time job losers experienced an average earnings reduction of 34.6%, with most losses attributable to non-employment and part-time re-employment.

The persistence and significance of these costs have spurred further investigation into the mechanisms driving such outcomes, as well as heterogeneity among workers experiencing these results. One strand of literature emphasises skill obsolescence due to sectoral or occupational mobility following displacement as the main source of such adverse and lasting outcomes (Neal, 1995; Kambourov and Manovskii, 2009; Huckfeldt, 2022). The main idea in this strand of literature is that job displacement tends to incur higher costs for individual workers because such specific skills cannot be transferred across different jobs and will be lost. Neal (1995), for instance, demonstrates that workers who switch industries following a job loss suffer larger wage losses compared to those who stay. Kambourov and Manovskii (2009) argue, however, that skills are occupation-specific, and their results show that displaced workers who switch occupations face a significantly larger drop in weekly earnings compared to those who are re-employed in their pre-displacement occupations.

However, occupations are generally characterised by various tasks, and skills are likely to be task-specific rather than being industry- or occupation-specific (Gathmann and Schönberg, 2010). This implies that workers have a portfolio of skills rather than just a single specific skill. Thus, the degree of the earning losses following displacement might not be directly associated with all occupation switches. In fact, based on a similar idea, Poletaev and Robinson (2008) examines the wage losses of displaced workers by employing Displaced Worker Surveys (DWS) samples between 1984 and 2000 and finds that the magnitude of losses depends on switching skill portfolios rather than changing occupation or industry. Robinson (2018) confirms this result and shows that earning losses of displaced workers depend not only on the proximity of occupations in terms of skill portfolios but also on the direction in which workers who switch to lower portfolios face worse outcomes.

Based on this task-based framework, recent studies have discovered further heterogeneity in the post-displacement outcomes of displaced workers. Macaluso (2023), for example, examines the distance between skill profiles of workers' last occupation and other jobs in a local labour market lead to different results after displacement[1]. She finds that workers with a high degree of dissimilarity experience worse outcomes. Using an administrative dataset from Germany and constructing different types of skill mismatch, Neffke et al. (2024) present that the degree of earning losses upon displacement differ substantially depending on the type of mismatch.

Recently, studies using a task-based approach emphasise the role of technological change in leading to skill obsolescence and earning losses upon job loss. Technological change, for instance, accelerates the erosion of existing skill sets by introducing new task requirements. In this regard, Blien et al. (2021) demonstrate that individuals working in occupations where tasks are routine-intensive suffer greater and lasting losses, primarily due to prolonged non-employment. They argue that these workers are forced to switch to occupations with different skill profiles as technological change erodes their routine-specific skills. Similarly, Braxton and Taska (2023)

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[1] Macaluso (2023) calls this "local skill remoteness" and anlayzes the outcomes of displaced workers who are above and below the median remoteness at the time of displacement.

find that workers displaced from occupations exposed to technological advancements experience disproportionately larger earnings losses due to the misalignment between their skills and emerging job demands. Nearly 45% of post-displacement earnings losses stem from this dynamic, as workers unable to meet these demands are forced into lower-paying occupations.

This paper also follows the concept of technology-led skill obsolescence and its role in driving post-displacement outcomes. As in the task-based framework, I acknowledge the multidimensional structure of skills. However, the departure of this paper from the current literature is that it does not assume that workers of the same occupation have the same skill profiles. Instead, follow Lise and Postel-Vinay (2020) and Guvenen et al. (2020), who construct individual skill endowments using ASVAB scores. Moreover, I focus on within-occupational changes in skill demands, as in Braxton and Taska (2023), but my definition of exposure to skill obsolescence differs from theirs. I define different types of exposure based on the skill endowments of workers and the changes in skill demands in their occupations. In doing so, I examine how the exposure to skill obsolescence affects the outcomes of displaced workers and investigate whether the consequences vary across workers with different types of exposure.

4.3 Data and Methodology

4.3.1 Data

The main dataset used in this study is NLSY79, which is a nationally representative sample of 12,686 individuals who were between the ages of 14 and 22 in the year 1979. It provides a weekly longitudinal work record of each respondent. The data includes details about the respondents' current and past employment, income levels, and demographic information such as age, gender, and ethnicity. Consequently, NLSY79 is pivotal for monitoring workers' employment histories over time and identifying their job changes, along with the reasons for these job separations, if present. Thus, it allows for the construction of the actual labour market experience of workers.

The NLSY offers several notable advantages in studying job displacements compared to more frequently used datasets, such as the Displaced Worker Surveys (DWSs) and the Panel Study of Income Dynamics (PSID). Compared to DWSs, the NLSY enables the analysis of both short- and long-term consequences of job displacement due to its longitudinal design. Moreover, it allows for a shorter recall period for documenting job losses, as interviews are conducted annually (or biennially after 1994), in contrast to the longer three- to five-year retrospectives typically employed in DWSs.

The NLSY79 also allows to retain information regarding workers' skills via ASVAB scores, which most respondents took in 1980. More specifically, the ASVAB evaluates knowledge and skills in various areas, including arithmetic reasoning, paragraph comprehension, mathematical knowledge, auto and shop information, and mechanical comprehension. Following previous research, I utilise these scores to assess the skill levels possessed by workers. In the context of this paper, it offers a significant advantage over both DWS and PSID (or even administrative and matched employer-employee datasets).

As this research emphasises changing skill demands within occupations, I complement the NLSY79 with a recent dataset provided by Atalay et al. (2020), which maps employers' skill requirements across U.S. job advertisements from 1940–2000. This dataset is created by gathering text from nearly 7.8 million job advertisements published in three major U.S. metropolitan newspapers: The Boston Globe, The New York Times, and The Wall Street Journal. The authors associate the words used in job requirements with their corresponding tasks. Additionally, they utilise machine learning methods to assign appropriate Standard Occupational Classification (SOC) codes to job titles, which are directly extracted from the job advertisements. They translate words and phrases into widely adopted measures of skill content, such as DOT and O*NET, as well as the job task classification framework employed in previous studies, including Autor et al. (2003), Spitz-Oener (2006), and Deming and Kahn (2018).

4.3.2 Sample Construction

Constructing the final panel using these datasets requires several steps. First, I need to identify multidimensional skill profiles of workers. To do so, I follow Lise and Postel-Vinay (2020) and define a three-dimensional skill vector as cognitive, manual, and interpersonal, using ASVAB scores, the Rotter Locus of Control score, and the Rosenberg Self-Esteem scores. However, rather than conducting a principal component analysis (PCA) to derive the skill scores, I adopt the methodology from Speer (2017) and calculate the mean scores of the associated components.

Specifically, I calculated each worker's cognitive skill score by averaging the scores from the "Arithmetic" and "Mathematical Knowledge" components. To determine the manual skill score, I took the mean of the "Mechanical Comprehension" and "Auto and Shop Information" components. For interpersonal scores, I averaged the Rotter and Rosenberg self-esteem scores. I then normalised these scores to ensure they are comparable. Next, I replicated the skill categories from Atalay et al. (2020) 's dataset to align them with the worker skill data. This involved selecting the most relevant skills for each dimension based on their descriptions in the O*NET database. Following the approach of Speer (2017), I averaged these skill measures to define the corresponding category measures. In particular, I use specific keywords for each skill category to determine whether a job posting requires a particular type of skill. The list of chosen keywords used to classify various skill categories is provided in the Appendix.

To categorise different levels of exposure to skill obsolescence, I consider both individual skill scores and the shifts in skill requirements within occupations. First, I identify workers whose strongest skill (the one with the highest score among the three skill categories) is experiencing a reduced demand in their current occupation, while the demand for their other skills is rising. I refer to this situation as exposure to "primary skill obsolescence." Individuals are classified as "highly exposed" to obsolescence if their primary skill's demand decreases alongside an increase in another skill, or if they are employed in occupations where the demand for at least two skill groups is declining. All other individuals are deemed to have little or no exposure to skill obsolescence.

I define a decrease in the demand for a skill as a negative change in its share. Analysing changes in demand shares directly highlights alterations in the skill composition of an occupation. When a skill's share is diminishing, it signifies that the skill is becoming less prominent within the overall skill framework of that occupation. I believe that relative measures are more responsive to early indicators of change. These early warnings are useful for understanding transitions and enabling timely actions, such as retraining or shifting to different occupations.

However, I employ a further restriction on my exposure measures. By construction, a worker may switch between exposure categories when they change occupations. This introduces further heterogeneity within individuals, which complicates the interpretation of results across different subgroups. Such issues are often dealt with by fixing the value at the time of displacement. In the context of this study, this approach is also problematic, as I aim to compare the labour market trajectories of displaced workers with those of non-displaced workers for each subgroup. Fixing the exposure level at the time of displacement would leave the exposure status of the never-displaced sample indeterminate. To overcome this problem, I fixed the exposure status for each individual depending on the fraction of time spent under the risk of obsolescence for both the displaced and non-displaced samples.

The procedure I follow for defining exposure categories, however, slightly differs between displaced and non-displaced workers. For the displaced sample, I use only the pre-treatment period, as the exposure status itself may be affected by displacement. To assign the exposure status to displaced workers, I first calculate the rate of time spent in any of the exposure groups during the pre-displacement years. If an individual spent more than 75% of their pre-displacement period at the risk of exposure, I compare the time spent under different types of exposure. I assign the high exposure status if the rate of time spent in occupations where workers face high exposure is higher. Similarly, I set the status of individuals exposed to primary skill obsolescence if they spent more time in occupations in which they are exposed to primary skill obsolescence. In the case of non-displaced workers, I use their whole labour market history and assign them to the proper categories using the same logic.

Although the choice of the threshold is somewhat arbitrary, it enables to focus on workers who spent a meaningful amount of time under one of the exposure categories. I believe that this also prevents from assigning workers to an exposure group, even though they work in occupations where they are subject to obsolescence for only a short period and then switch to occupations without the risk of exposure. However, I also employ different thresholds to show the robustness of the results.[2]

To define displacement, I follow the previous literature and consider displaced workers as those who lose their jobs due to plant closures and layoffs and exclude quits/temporary endings. In cases where individuals face displacement more than once, I only count the first displacement for these workers, as potential future displacements may be a cost associated with the initial displacement (Kletzer and Fairlie, 2003).

Unlike Chapter 3, which follows parts of the NLSY79 task-based literature by focusing on the white civilian cross-section for comparability in wage-level analyses, this chapter uses the full civilian NLSY79 sample (excluding the military oversample). The reason is that displacement events are relatively infrequent and restricting to whites would substantially reduce the number of treated observations and limit heterogeneity analysis. Importantly, the core Chapter 3 patterns are qualitatively similar in robustness checks on the full civilian sample (Appendix 3.C), so the difference in samples reflects a power/coverage trade-off rather than a change in the underlying empirical approach.

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[2] The minimum threshold I used is 50%, which means that a worker must spend at least half of their pre-displacement period under exposure.

Table 4.1: Summary statistics by displacement status (person-year means)

	Displaced	Non-displaced
Age (years)	27.53	27.36
Female	0.45	0.55
Highest grade achieved	12.94	13.32
Hourly wage (2000 USD)	7.21	7.74
Tenure (years)	3.16	4.23
Experience (years)	1.55	1.47
Weeks without work	17.36	18.37
Non-White	0.47	0.43
Cognitive score	0.50	0.53
Manual score	0.51	0.52
Interpersonal score	0.43	0.44
Individuals (N)	4385	7483
Person-years (T)	87,614	134,950

Notes: Person-year means; wages in **2000 USD** (CPI-U). “Weeks without work” count all non-employment weeks (unemployment or out of the labour force).

In constructing the panel, I used weekly employment records of workers. I restrict the analysis to the period 1978–2000 to align the NLSY79 person-years with the vacancy-based skill measures. Then I aggregated at the yearly level [3]. I excluded all individuals who left the survey, as well as the military supplementary sample, since it was not followed up on after 1984. I also removed observations if the occupation information was missing. Moreover, I omit workers for whom skill scores cannot be generated due to incomplete data.

Following Deming (2017), I winsorise real hourly wages that fall below 3$ or exceed 200$. All monetary variables are expressed in 2000 dollars using the CPI-U (BLS, annual average). In addition, to ensure consistent occupational coding throughout the survey years in NLSY79, I utilised crosswalks from Autor and Dorn (2013) and removed all observations that did not match. After aggregating at the yearly level, the panel has 11,868 individuals and 222,564 person-year observations.

The Table 4.1 presents the summary statistics for displaced and non-displaced sam-

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[3] The NLSY79 underwent a change in methodology after 1994, and the survey began to be conducted biennially. Using weekly records makes it possible to extract the information for the missing years.

ples from the dataset. Comparing the sample of displaced workers to that of non-displaced workers, both samples have an average age of approximately 27 years, as well as 13 years of education on average. Yet, displaced workers earn slightly less than non-displaced workers per hour, and they appear to have relatively shorther tenure. However, they have a lower jobless spell, averaging around 17 weeks, compared to 18 weeks for non-displaced workers. It is essential to note that 'weeks without work' is a broad measure that encompasses unemployment and time out of the labour force. Pooling all person-years, non-displaced workers include students and caregivers who never experience displacement but spend time out of work, whereas displaced workers are selected to be attached prior to the event. The event-study estimates isolate the causal increase in non-employment after displacement.

Table 4.2: Exposure categories and displacement counts

	Primary	High	Non-exposed
Individuals (N)	1,013	2,301	8,554
Person-years (T)	20,121	43,961	158,482
Displaced (N)	407	1,333	2,645
Displacement rate (%)	40.2	57.9	30.9

Notes: Counts based on the final analytic sample.

I also present the distribution of individuals categorised by exposure groups, as well as their rate of displacement in the data, in Table 4.2. Among the total of 11,868 individuals, 2,301 persons are experiencing high exposure, and 1,013 are facing only primary skill obsolescence, while the remaining 8,554 workers have no exposure to skill obsolescence. The displacement rate is highest among high-exposure individuals, at nearly 58%, and lowest for non-exposed individuals, at nearly 31%.

4.3.3 Empirical Strategy

Empirical research on the consequences of worker displacement has often relied on difference-in-differences (DiD) methods to estimate the causal impact of job loss on future earnings, employment prospects, and broader welfare outcomes. Early influential work, such as Jacobson et al. (1993), employed fixed effects regressions that compared displaced workers to a group of observably similar but non-displaced individuals. This empirical framework evolved into the widely adopted dynamic two-way fixed effects (TWFE) model, which adds both individual and time fixed effects to help control for unobserved heterogeneity across individuals and macroeconomic shocks across periods. However, when treatment time is staggered, that is, when different individuals lose their jobs at different points in time, the results obtained by the traditional TWFE approach can be biased (Goodman-Bacon, 2021; Borusyak et al., 2024).

Because displacement occurs in different calendar years across workers, I use a staggered event-study design that aligns individuals by their own displacement year and compares their outcomes to those of appropriate control workers observed at the same calendar time (never-displaced and/or not-yet-displaced, depending on the estimand). Recent methodological advances propose refined estimators that address these pitfalls more effectively, particularly by accommodating heterogeneous and dynamic treatment effects (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Borusyak et al., 2024). In this study, I adopt the method proposed by Callaway and Sant'Anna (2021), which estimates *group-time average treatment effects* (ATT(g,t)) for each cohort of displacement g and each time period t. This approach is particularly relevant for displacement research, as each cohort g can represent the year in which workers first lose their jobs. The method also allows for an event-study analysis, with which I can observe the labour market trajectories of workers over periods since the displacement.

Let g_i denote the calendar year of worker i's first displacement, t the calendar year, and event time $e = t - g_i$. I estimate staggered difference-in-differences using the

Callaway and Sant'Anna (2021) estimator, which forms group–time effects $\text{ATT}(g,t)$ for each cohort g and aggregates them to event time via

$$\text{ATT}_e^w = \sum_g w_g \, \text{ATT}\big(g,\, g+e\big),$$

where w_g are cohort weights. Standard errors are clustered at the individual level. I set the event window to $e \in [-3, 8]$. For display purposes, I omit the $e = 0$ marker while retaining it in the estimation.

All specifications include a vector of pre-treatment covariates X_i comprising sex, race, education, age, age squared, and the three individual skill endowments (cognitive, manual, interpersonal) constructed from ASVAB/psychometric scores.[4] Identification relies on conditional parallel trends: absent displacement, the average path of outcomes for treated cohorts would have followed that of the comparison group, conditional on X_i. I estimate the model via doubly robust IPW regression adjustment with clustering at the individual level.

I align comparison groups with each estimand. For outcomes anchored at the worker's own pre-displacement job such as *distance to the pre-displacement occupation*, I use *not-yet-treated* controls, since the outcome is defined relative to each worker's $e = -1$ occupation. For *mismatch to own skills* (one minus the cosine between the worker's skill vector and the time-t occupation vector), the main specification uses *never-treated* controls. (I show robustness with not-yet-treated in Appendix 4.B.5.)

Occupation–time skill vectors are normalised to unit length. For the mismatch, I use the *time-varying* occupation map. For distance, I use a *static base-decade* map, measuring both the $e = -1$ occupation and the time-t occupation in the same base decade to isolate reallocation from within-occupation drift. Landing outcomes are observed only when working; estimates are therefore *ATT among the employed.*

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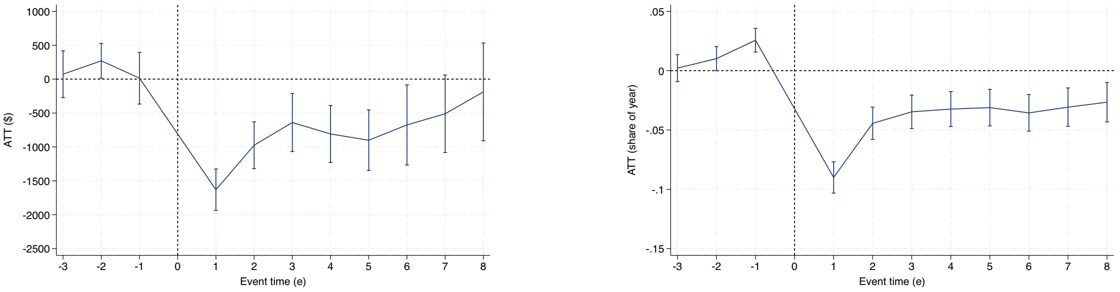
[4] I fix X_i at baseline (pre-displacement) and do not update it post-treatment.

4.4 Empirical Findings

In this section, I examine the impact of displacement on annual earnings, wages, and employment, and how these effects vary with exposure to within-occupation skill obsolescence. I estimate dynamic treatment effects using the event-time framework described in Section 4.3 and report ATTs by exposure type.

I begin by presenting how displacement affects annual earnings and employment spells in the full sample. Panel a of Figure 4.1 demonstrates that displaced workers experience a sizable drop (more than 1500$) in their annual earnings in the first year following the displacement, compared to the non-displaced individuals. The effect of displacement persists for at least 7 years following the event, while displaced people recover some of the loss over time. This result aligns with most earlier findings in the displacement literature, which indicate that displacement leads to permanent income losses (Jacobson et al., 1993; Couch and Placzek, 2010).



(a) Annual Earnings

(b) Fraction of Weeks Worked

Figure 4.1: Effect of Displacement on Earnings and Weeks Worked

Event-study ATTs for all person-years. Control group: never-treated. Event window $[-3, 8]$; $e = 0$ indicated by the vertical line but omitted in plotting the coefficient. Standard errors clustered at the individual level; 95% CIs shown. Monetary units are 2000 USD (CPI-U).

I also document that displacement not only affects earnings but also influences employment stability. Panel b of the Figure 4.1 indicates that the fraction of weeks worked in a year drops by nearly 10% in the first year following the displacement, and the impact is scarring in the long term. Despite a small recovery from the second year onwards, displaced workers work around 2 weeks (4%) less than non-displaced workers in the long term. However, I argue that displacement does not affect workers equally, and being subject to skill obsolescence is an important driver of the observed losses.

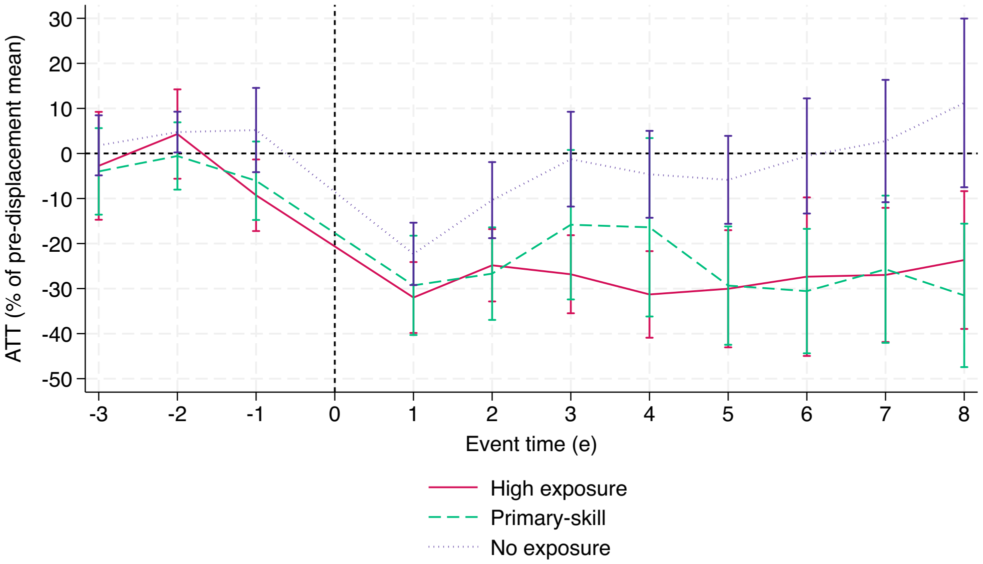


Figure 4.2: Annual earnings relative to pre-displacement. 95% CIs shown.

Event-study ATTs by exposure. Outcome: annual earnings normalised to the pre-displacement mean (2000 USD). Control group: never-treated. Event window $[-3, 8]$; $e = 0$ omitted from the display; vertical line at $e = 0$. Clustered s.e. (id); 95% CIs.

Considering the type of exposure to skill obsolescence, Figure 4.2 documents the heterogeneity in experiencing the impact of being displaced on the earnings of workers. Workers without exposure lose around 20% of their pre-displacement earnings, while those with any type of exposure lose around 30% in the first year after displacement. However, non-exposed individuals recover in approximately 3 years following the event, whereas workers with some type of exposure have continuously lower earnings even after 8 years. For the exposed individuals, the decline in earnings is slightly larger for the high-exposure group in the first 5 years following the displacement. However, workers with primary skill obsolescence experience a higher loss in the long run, which accounts for around 30% of their earnings before displacement.

There might be various mechanisms driving the observed differences between exposure groups. One crucial channel can be the ability to transfer skills to new roles. In the case of high exposure, workers face the risk that multiple skills erode, leaving

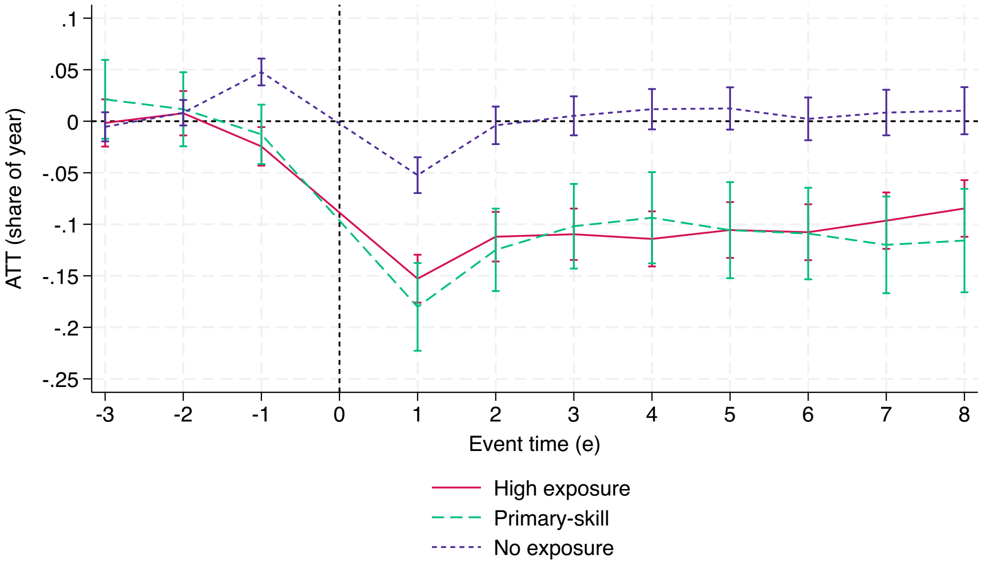


Figure 4.3: Fraction of Weeks Worked by Exposure

Event-study ATTs by exposure. Outcome: fraction of weeks worked in the year (all person-years). Control group: never-treated. Event window $[-3, 8]$; $e = 0$ omitted from the display; vertical line at $e = 0$. Clustered s.e. (id); 95% CIs.

workers with a small set of skills that can still be valued in the labour market. This, in turn, can make them more vulnerable in the labour market and depress their earnings by substantially restricting the opportunities to find a good match.

The process of finding an occupation where workers' skills are still valued might result in considerable time out of employment following a displacement. Figure 4.3 demonstrates the impact of displacement on non-employment spells across different subgroups. In Figure 4.1, I show that displacement causes a persistent increase in the time spent out of work. However, I observe a substantial difference between exposed and non-exposed individuals in terms of their employment continuity.

Being exposed to any type of skill obsolescence has a strong negative impact on the number of weeks worked. Displaced workers with any type of exposure face prolonged non-employment spells compared to their non-displaced counterparts. Both groups share a very similar trajectory, where displacement leads to a sharp increase in the number of weeks without a job, reaching as many as 10 weeks in the first year, but then slowly declining afterwards. However, these workers experience consistent periods of joblessness, averaging around one month, even after eight years following displacement.

For displaced workers without facing exposure, displacement leads to an increase in jobless weeks in the first year, but this initial surge does not appear to be long-lasting. In fact, the effect of displacement on employment fades away quickly starting from the second year, and I do not observe a difference between the spells of non-employment between displaced and non-displaced workers. This result suggests that being exposed to skill obsolescence prior to displacement has a significant impact on the post-displacement outcomes of workers. For individuals with obsolete skills, re-employment gets harder upon displacement, even in the long term, whereas workers without exposure do not suffer from prolonged non-employment spells.

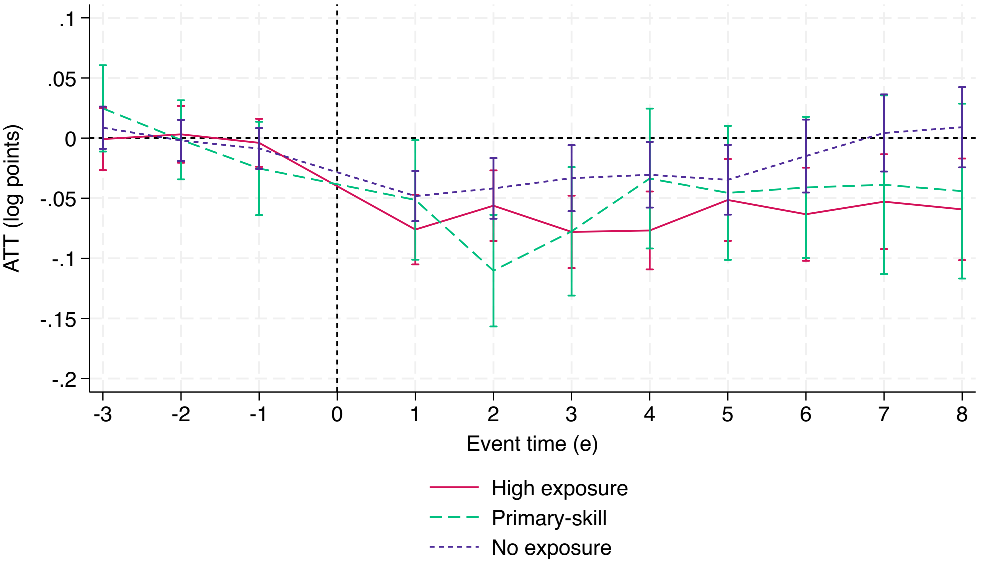


Figure 4.4: Effect of Displacement on Wages by Exposure Type

Event-study ATTs in log hourly wages *among the employed*. Control group: never-treated. Event window $[-3, 8]$; $e = 0$ omitted from the display; vertical line at $e = 0$. Clustered s.e. (id); 95% CIs. Coefficients reflect the intensive margin conditional on re-employment.

With the extensive margin in hand (Figure 4.3), Figure 4.4 evaluates the intensive margin—how log hourly wages evolve for employed workers across exposure groups. Individuals exposed to the obsolescence of their primary skill face a sharp decrease in their wages in the first two years after being displaced. The wage losses are highest in the second year, where the decline is around 10-15%. However, the losses are partly recovered in the following years, and the estimates become statistically insignificant after the 5th year. Although I cannot infer that workers suffering from primary skill obsolescence are able to fully recover, the wage effect appears more temporary (or at least less clearly persistent) compared to the "high exposure" group, which continues to exhibit a significant wage loss later in the post-displacement period.

Workers without facing any exposure, on the other hand, have a different trajectory. Wage losses reach approximately 5% on average in the first year of displacement, but recovery begins immediately thereafter. Although it takes around 6 years, it appears that non-exposed individuals can return to their pre-displacement levels in the long term, unlike those with some type of exposure. The difference between the trajectories of the various subgroups implies that not only is it important to be exposed to obsolescence or not, but also the type of exposure matters for the outcome.

4.4.1 Decomposition of Earning Losses

Having documented the earnings losses of displaced workers across different subgroups, I turn to the primary drivers of observed declines in earnings. I decompose annual earnings into an extensive and two intensive margins:

$$\text{Earnings}_{it} = \underbrace{\text{WeeksWorked}_{it}}_{\text{extensive}} \times \underbrace{\text{Hours/working-week}_{it}}_{\text{intensive}} \times \underbrace{\text{HourlyWage}_{it}}_{\text{intensive}}. \tag{4.1}$$

I estimate separate event-study ATTs by exposure for each component (weeks worked for all person-years, hours worked per working week, and wages among the employed) and report effects as percentage changes relative to the pre-displacement mean for that exposure group. Log-wage coefficients are converted to percent via the standard log-to-percent mapping. By a first-order log-linearisation of (4.1), the component series approximately sum to the earnings effect; in practice, they track it closely.[5]

For all three components (and earnings for reference), I use the same covariate set X_i described above, cluster standard errors at the individual level, set the event window to $e \in [-3, 8]$, and omit $e = 0$ from the display. The control group is the *non-displaced* workers. Hours per working week are computed from the weekly work records and are restricted to employed person–years; wage effects are therefore *intensive-margin* effects conditional on re-employment.

Figure 4.5 reports the component ATTs as percentages of the pre-displacement mean. For both exposure types, the extensive margin (weeks worked) accounts for the bulk of earnings losses, with a smaller contribution from wages and little to no role for weekly hours. In the case of high exposure (Figure 4.5a), nearly 15% of the losses are due to jobless spells and on average, 5% of the losses result from the wage declines, while working hours do not contribute at all.

Figure 4.5b shows a similar dynamics for the case of primary skill obsolescence, where increased time out of employment causes the main drop in earnings, reaching more than 20% in the first year and 15% in the long term. However, unlike the highly exposed workers, the wage impact in the earnings decline deepens in the second year, reaching almost 10% of the total loss before gradually fading away after the third year.

The dynamics, however, are different in the case of no exposure. Although the jobless period dominates the losses in the first year, the main driver of the losses in the subsequent year is the wages. As in the case of exposed individuals, none of the earnings losses in any period result from working hours. This implies that displacement did not result in a significant reduction in weekly working hours upon re-employment, indicating no clear transition from full-time to part-time jobs.

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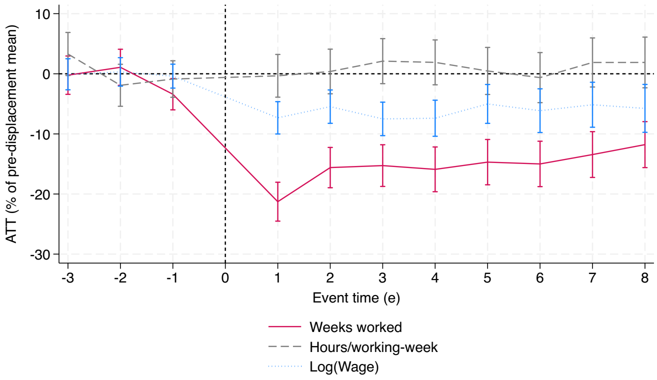
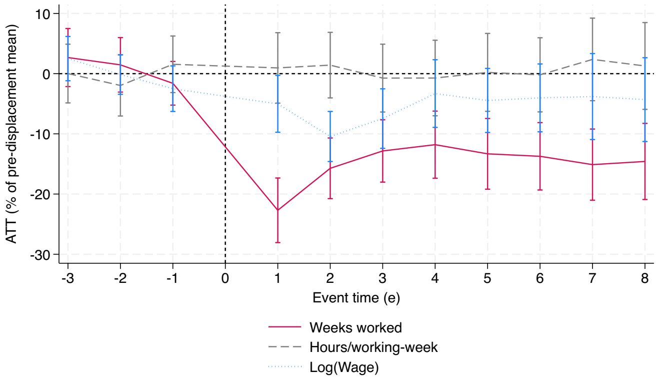
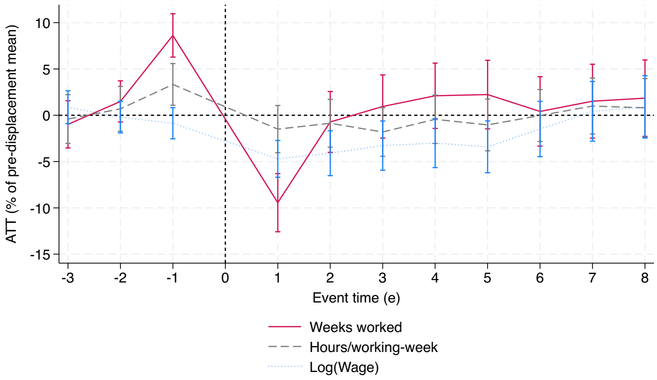
[5] Appendix 4.A details the transformations, baseline definition, delta-method standard errors, and provides an overlay showing the sum of components against the earnings series.



(a) High Exposure



(b) Primary Skill



(c) No Exposure

Figure 4.5: Earnings Decomposition

Components of earnings losses as % of the pre-displacement mean. Weeks worked: all person-years. Hours/working-week and wages: *among the employed*. Effects are estimated ATTs, converted to percentage changes (see text). Control group: never-treated. Event window $[-3, 8]$; $e = 0$ omitted; vertical line at $e = 0$. Clustered s.e. (id); 95% CIs.

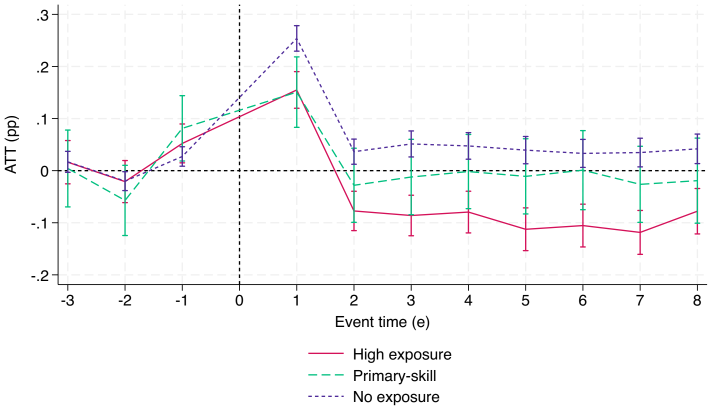
4.4.2 Mechanism: Occupation Switching

The preceding results point to persistent extensive-margin scarring. I next investigate whether displaced workers respond by changing occupations, and how this response varies with the type of skill obsolescence. Figure 4.6 plots event-time ATTs for the *flow* of switching across 3-digit occupations (Panel a) and 1-digit occupations (Panel b), defined as a change between $t-1$ and t among workers employed in both years.

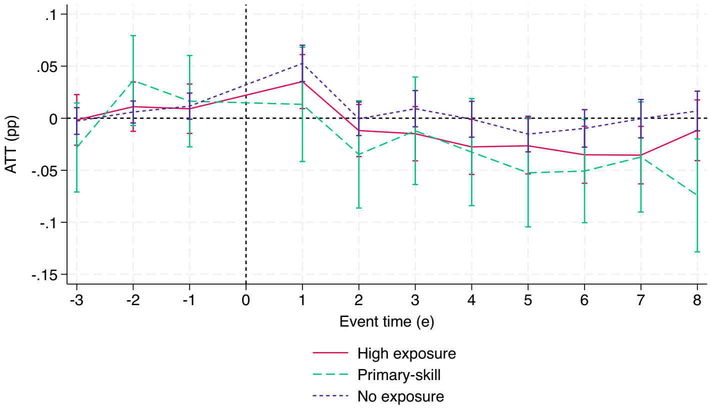
When I consider switching from 3-digit occupations, there is a sharp spike for all groups at displacement ($e = 0$), indicating an immediate rise in the hazard of moving to a new occupation. Starting around $e \geq 2$, patterns diverge by exposure. For the *high-exposure* group, estimates are below zero and statistically significant, implying that, conditional on being employed in consecutive years, high-exposure workers are *less* likely to keep switching than their counterfactual peers. This is consistent with tighter post-reemployment matches or constrained option sets when multiple skills become obsolete.

For workers with *primary-skill* obsolescence, the initial spike fades quickly (after $e \approx$ 1–2), and subsequent estimates are near zero; I do not detect persistent differences relative to controls. By contrast, the *no-exposure* group exhibits a positive impact at $e = 0$ followed by *persistently positive* ATTs, indicating continued occupation changes for several years, consistent with broader portability of skills that facilitates ongoing reallocation. Results using switching defined at the 2-digit occupation level are similar (Appendix Figure 4.B.2): displacement triggers an immediate rise in switching for all groups, while post-reemployment switching remains more persistent for non-exposed workers.

At the 1-digit (major) level, however, the persistence largely disappears. I do not observe any significant pattern of occupational change at the major level for any of the groups, and the effect mainly concentrates at $e = 0$. This indicates that mobility occurs primarily *within* major occupation groups rather than across them. No-



(a) Detailed occupation (3-digit)



(b) Major occupation (1-digit)

Figure 4.6: Occupation Switching (flow) by Exposure.

Note: Switching is a change between $t-1$ and t among workers employed in both years (units: p.p.). Vertical line at $e = 0$; 95% CIs shown.

exposure workers recover earnings faster and (at 1-digit) do not keep making large career changes; exposed workers show large initial career moves but little continued major-group churn consistent with prolonged extensive-margin losses rather than ongoing major re-sorting.

Next, I ask where the occupation switchers move. To understand *where* they land in the skill space I study two complementary outcomes among the employed: (i) a *match-quality* measure—the cosine mismatch between a worker's ASVAB vector and the *current* occupation's skill demands (using the *time-varying* occupation-skill map)—and (ii) a *reallocation-distance* measure—the cosine distance between the current occupation and the worker's own pre-displacement (event-time $e = -1$) occupation, with both occupations measured in the *base-decade* skill map. The first captures whether re-employment restores alignment with workers' underlying skills; the second captures how far they must move away from the job that was lost.

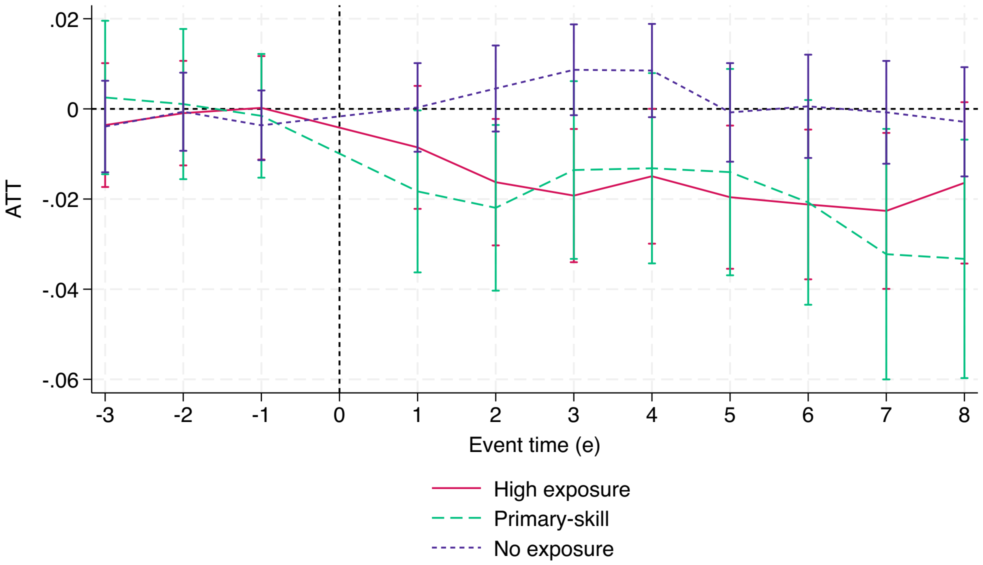


Figure 4.7: Mismatch to own skills after displacement (by exposure)

Outcome: $1 - \cos(\text{ASVAB},\ \text{occ}_t)$ using the time-varying occupation-skill map; ATT among the employed; control group = never-treated. Vertical line at $e = 0$; $e = 0$ not displayed; 95% CIs.

Figure 4.7 plots event-time ATTs for mismatch to own skills.[6] Mismatch falls after displacement for *primary-skill* exposures and modestly for *high* exposures, while it

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[6] Outcome observed only when employed; coefficients are ATT among the employed.

remains close to zero for *non-exposed* workers. In Figure 4.6 I saw a sharp increase in switching at $e = 0$ for all groups, followed by divergence: for *high exposure* the switching tendency drops below controls for $e \geq 2$, for *primary* it returns to near zero, and for *non-exposed* it remains persistently positive. Taken together, these patterns suggest that exposed workers do not continue to move across occupations; instead, conditional on re-employment, they transition into jobs that are *better aligned* with their endowments—consistent with within-occupation skill shifts having made the pre-displacement job a poorer fit.

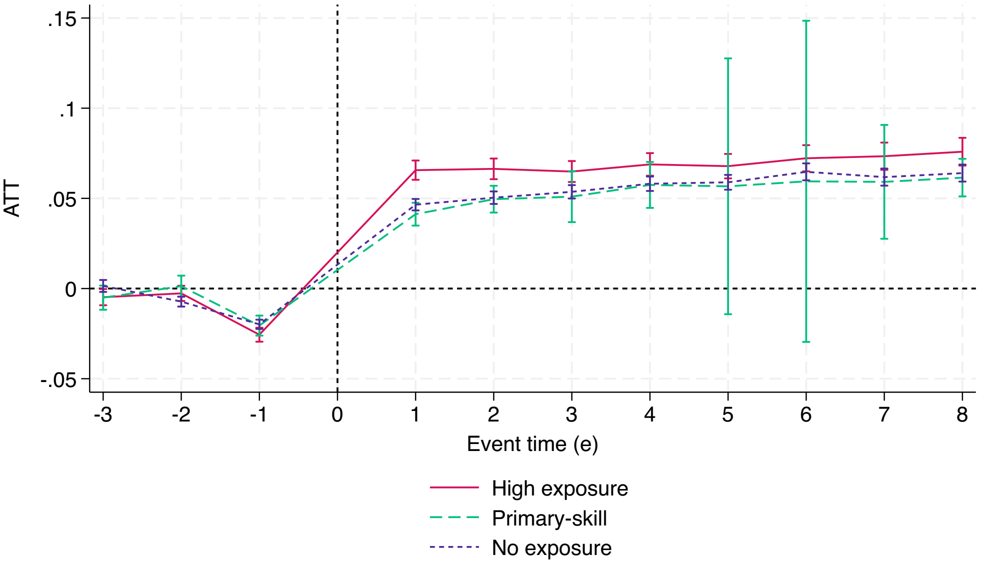


Figure 4.8: Distance to pre-displacement occupation (by exposure)

Outcome: $1 - \cos(\text{occ}_t,\ \text{occ}_{e=-1})$ measured in the base decade; ATT among the employed; control group = not-yet-treated. Vertical line at $e = 0$; $e = 0$ not displayed; 95% CIs.

Figure 4.8 examines *distance to the pre-displacement occupation.* ATTs are positive for all exposure types, implying that re-employed displaced workers move to occupations *farther* away from their own pre-displacement job in skill space, with the increase largest for *high exposure.* Together with the mismatch result, this implies that exposed workers typically make *larger* moves in terms of task content but end up in *better-matched* jobs; non-exposed workers also change occupations, yet on average without worsening (or improving) their match.

These landing patterns help explain the larger earnings losses and longer jobless spells for exposed workers: prior to displacement, within-occupation obsolescence raises mismatch; after displacement, restoring a good match often requires moving *farther* in skill space to occupations where their skills are still valued, which lengthens the time to re-employment. An additional margin of adjustment is industry/-sector reallocation. While the present chapter focuses on occupational mobility and task-space reallocation, documenting the industry destinations of displaced workers by exposure type is a natural extension that I leave for future work.

4.5 Conclusion

This paper set out to understand how within-occupation changes in task content—our notion of skill obsolescence—shape the consequences of involuntary job loss. I brought individual skill heterogeneity to the centre of the analysis by combining the NLSY79 with workers' ASVAB-based skill endowments and a vacancy-based occupation–task map. Using an event-study DiD design with staggered timing, I contrasted displaced workers across three exposure types: primary-skill exposure (where the worker's strongest dimension becomes less valued in the pre-displacement job), high exposure (declines across multiple dimensions), and non-exposed.

Four results emerge from the findings of this paper. First, displacement causes significant and persistent losses in annual earnings and employment, but the magnitude depends on the level of exposure. Non-exposed workers recover much of their earnings within a few years while exposed workers do not fully recover even eight years after the event. Second, a decomposition shows that most of the earnings decline operates through the extensive margin (fewer weeks worked) while weekly hours contribute little and wage effects are secondary and often transitory.

Third, switching behaviour rises remarkably at displacement for everyone, but post-event trajectories differ. High-exposure workers are less likely to keep changing occupations once re-employed, while primary-exposure workers revert to near-control switching rates. On the contrary, non-exposed workers continue to reallocate for several years—primarily within major occupation groups. This continued switching among non-exposed workers need not reflect instability; it may capture career progression, promotions, or other beneficial reallocation. Fourth, landing outcomes among the employed reveal a consistent pattern in which mismatch to own skills declines for exposed workers (and remains flat for non-exposed), while the distance to the pre-displacement occupation rises for all groups, most notably for those with high exposure. These results imply that exposed workers typically make larger movements in task space to restore a better match to their endowments. However, this search process is costly, prolonging non-employment spells and depressing earnings for a longer period.

These findings refine the view that skills are task specific and losses stem mainly from changes in the task content of occupations. When task content within occupations drifts away from workers' strengths, the pre-displacement job becomes a poor fit before the separation. After displacement, restoring fit requires crossing bigger task distances. The heterogeneity I document, especially the persistent shortfall on the extensive margin for exposed workers, helps explain why some workers recover quickly while others experience lasting scarring.

A natural interpretation is that exposed workers would benefit from targeted upskilling or retraining aligned with their baseline endowments, but the NLSY79 does not directly measure re-skilling or training intensity during the spell. Therefore, the results should be read as indicating where the scarring is largest (extensive margin) and where re-employment requires larger moves in task space. Evaluating specific training policies would require data on actual training participation and content.

With that caveat in mind, the results suggest that early warning and targeting may matter. Identifying workers in occupations where their primary skill is eroding could help prioritise them for preemptive support. If aligned with individual endowments (rather than generic occupation averages), re-skilling and job-search assistance may shorten search and reduce mismatch. Likewise, guidance toward task-adjacent occupations—those close in task space but with more stable demand for the worker's strengths—may reduce the "distance to land." Because the main losses operate through time out of work, activation policies (job-finding assistance, mobility support, temporary wage insurance) are likely to be particularly relevant for exposed workers.

There are some limitations of this paper. The occupation–task measures, while rich, are measured with error and anchored to specific decades. Thus, alternative maps or post-2000 skill data could sharpen inference. Mismatch and distance are observed only when employed, so those estimates are conditional by construction. My exposure classification relies on pre-period shares and thresholds; different cutoffs yield similar patterns but are not innocuous. Finally, while the design addresses staggered timing and heterogeneity, residual selection into displacement or re-employment could remain.

The paper admits several natural extensions. Linking to newer skill requirement datasets (e.g., post-2000) would test whether the same mechanisms operate in more recent waves of technological change. Moreover, exploring local labour-market remoteness and vacancy flows could connect the individual-level exposures to geographic opportunity sets. Finally, modelling the joint dynamics of task drift, training, and search would help quantify which policy lever—training intensity, search guidance, or income support—most effectively mitigates the long-run scars for the exposed.

In sum, job displacement can be detrimental, yet the extent of the impact depends on whether the job that was lost had already moved away from the worker's strengths. When within-occupation task change erodes those strengths, workers face longer periods of non-employment and must travel farther in task space to find a good match. However, conditional on landing, they do find better-aligned jobs. Recognising and acting on that interaction between task changes and individual endowments is key to alleviating future shocks.

Appendices to Chapter 4

4.A Decomposition Details

Annual earnings satisfy

$$\text{Earnings}_{it} = \text{WeeksWorked}_{it} \times \text{Hours/working-week}_{it} \times \text{HourlyWage}_{it}. \tag{4.2}$$

For each exposure group I estimate event-time ATTs for (i) weeks worked (all person-years), (ii) hours per working week (among the employed), and (iii) log hourly wages (among the employed) using the Callaway and Sant'Anna (2021) estimator with the same covariates and clustering as in the main text.

I express all effects as percentage changes relative to the group-specific pre-displacement baseline. Let $\overline{Y}_{e<0}$ denote the mean at $e = -1$; if $e = -1$ is unavailable I use the average over $e \in [-3, -1]$. Then for level outcomes $Y \in \{\text{weeks, hours/working-week, earnings}\}$:

$$\Delta\%Y_e \;=\; 100 \times \frac{\widehat{\text{ATT}}_e(Y)}{\overline{Y}_{e<0}}. \tag{4.3}$$

For log wages I use the exact log-to-percent mapping and delta-method standard errors:

$$\Delta\%\text{Wage}_e = 100\big(\exp(\widehat{\beta}_e^{\text{log wage}}) - 1\big), \tag{4.4}$$

$$\text{se}\big[\Delta\%\text{Wage}_e\big] = 100\,\exp(\widehat{\beta}_e^{\text{log wage}}) \cdot \text{se}(\widehat{\beta}_e^{\text{log wage}}). \tag{4.5}$$

By first-order log-linearization,

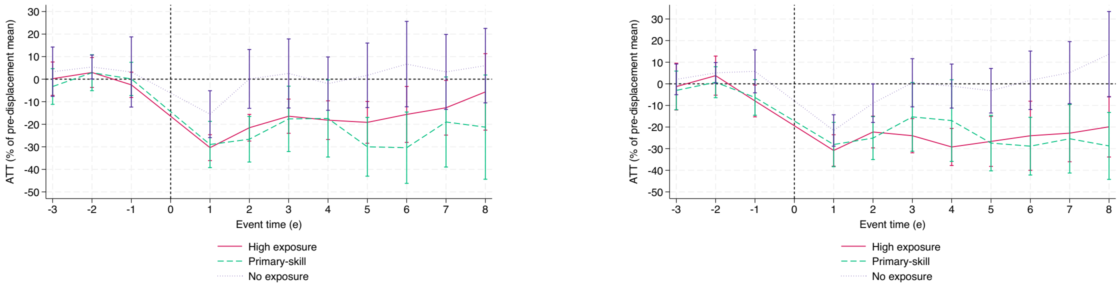
$$\Delta\%\text{Earnings}_e \;\approx\; \Delta\%\text{Weeks}_e + \Delta\%\text{Hours}_e + \Delta\%\text{Wage}_e, \tag{4.6}$$

so the sum of component series closely approximates the earnings series.

4.B Robustness Checks

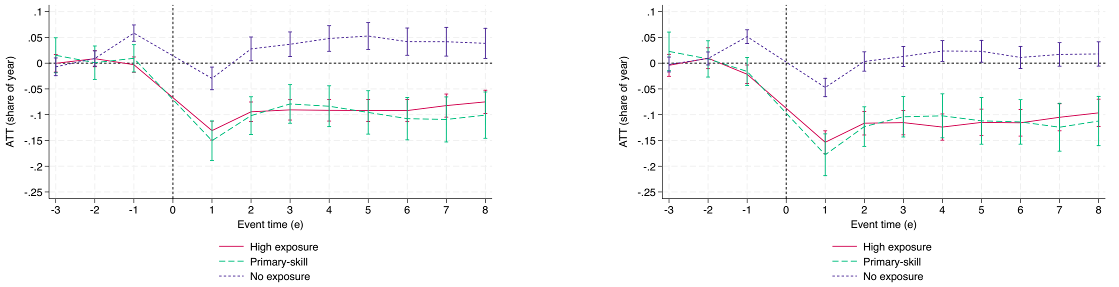
4.B.1 Alternative Thresholds

In the main text, I explained that workers is regarded as exposed to skill obsolescence if they spend at least 75% of their pre-displacement period at the risk of exposure. Below, I replicate the analysis using different thresholds to show that the results are not driven by the choice of the threshold.



(a) Annual Earnings by Exposure: Threshold= 50%

(b) Annual Earnings by Exposure: Threshold= 67%



(c) Fraction of Weeks Worked by Exposure: Threshold 50%

(d) Fraction of Weeks Worked by Exposure: Threshold 67%

Figure 4.B.1: Effect of Displacement on Earnings and Weeks Worked by Exposure

Event-study ATTs for all person-years. Control group: never-treated. Event window $[-3, 8]$; $e = 0$ indicated by the vertical line but omitted in plotting the coefficient. Standard errors clustered at the individual level; 95% CIs shown. Monetary units are 2000 USD (CPI-U).

4.B.2 Occupations Switching at 2-digit Level

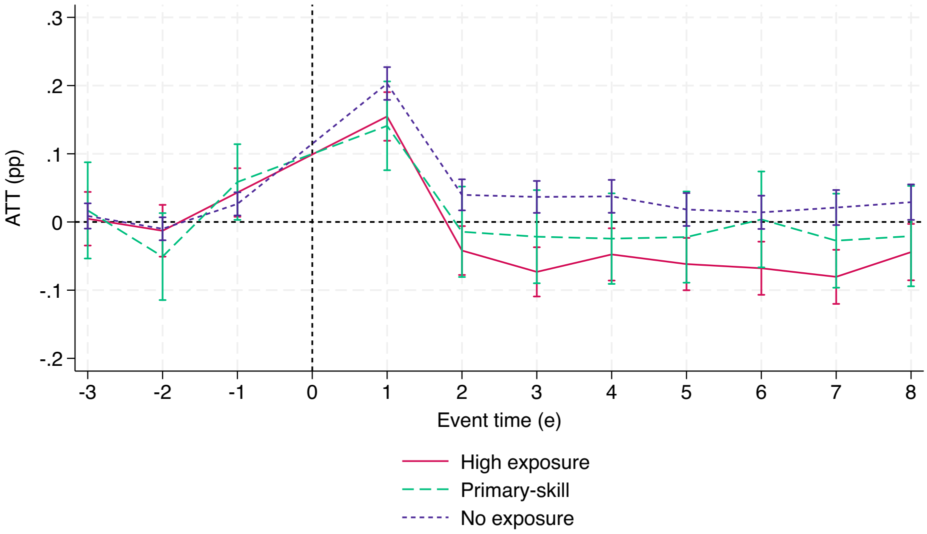


Figure 4.B.2: Occupation Switching (2-digit) by Exposure

Note: Switching is a change between $t-1$ and t among workers employed in both years (units: p.p.). Vertical line at $e = 0$; 95% CIs shown.

4.B.3 Balanced–Employment Window

Outcomes such as distance to the pre–displacement occupation are observed only when employed. A common concern is that post-treatment estimates might be driven by selective re-employment (e.g., only those who find "easier" moves show up). To examine this, I repeat the distance to pre-displacement analysis in section 4.4.2 restricting the treated to those who are observed employed at least once pre- and once post-displacement in the event window.

I construct a *balanced–employment* indicator equal to one if an eventually treated worker is employed in at least one pre period ($e \in [-3, -1]$) and at least one post period (I use $e \in [1, 3]$ for balance). I then re-run the event study for the cosine *distance to the pre-displacement occupation* using the same specification as in the main text (ATT among the employed, *not-yet-treated* controls, $e \in [-3, 8]$, doubly robust IPW–RA).

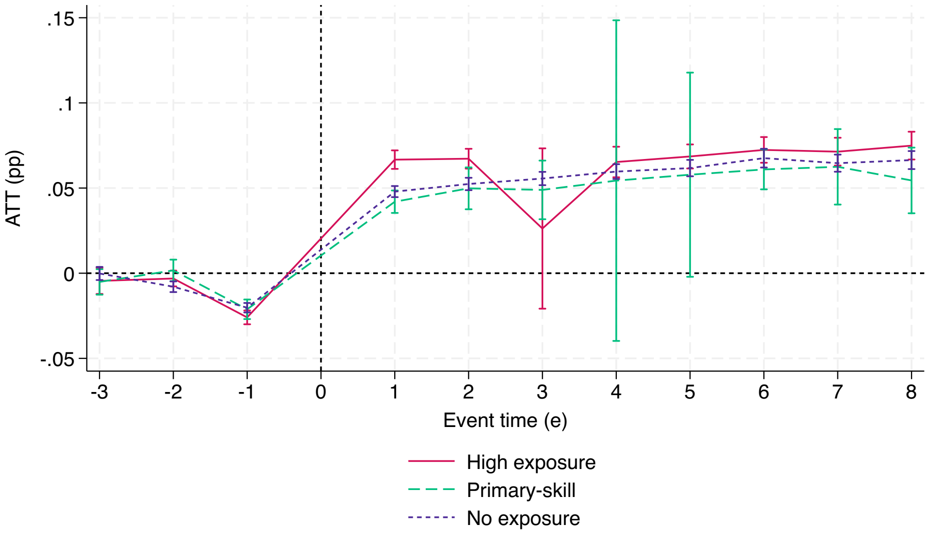


Figure 4.B.3: Distance to pre-displacement occupation, balanced–employment window.

Notes: ATT among the employed; control group = not-yet-treated; event window $e \in [-3, 8]$; $e = 0$ omitted from display; 95% CIs.

Restricting to a balanced-employment window (employed at least once pre- and once post-displacement) yields similar dynamics: no pre-trends; positive post-displacement increases in distance for all exposure groups; and a stable ordering with the high-exposure group moving farthest in task space. This indicates that these findings are not an artifact of selection into employment.

4.B.4 Discrete Landing Outcomes: Top–K Neighbors, Return to Base, Top–Percentile

The continuous distance measure summarizes reallocation in task space, but readers may wonder where displaced workers actually land. I complement distance with discrete indicators that are easy to interpret and that are less sensitive to scale: (i) whether the current occupation is among the *Top–K* closest neighbors of the worker's pre-displacement occupation; (ii) whether the worker *returns* to the exact pre-displacement 3–digit occupation; and (iii) whether the current occupation lies in the *top 10th percentile* of closest neighbors (a scale–free analog to Top–K).

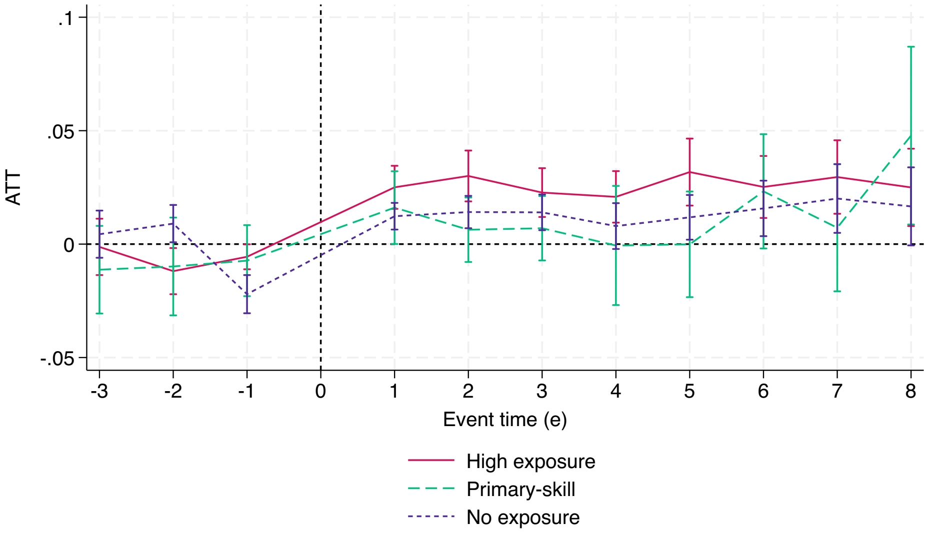


Figure 4.B.4: Landing in Top–K neighbors of the pre-displacement occupation.

Notes: $K = 5$; exact return excluded; ATT among the employed; control group = not-yet-treated; event window $e \in [-3, 8]$; $e = 0$ omitted; 95% CIs.

Using the static task map, I precompute, for each base occupation, cosine similarities to all other occupations within the same decade and rank them. I then define: $nearK = 1$ if the current occupation is among the K closest (excluding the exact return), $return = 1$ if current 3–digit code equals the base, and $near10pct = 1$ if the current occupation is in the top decile of the similarity distribution (excluding exact return). As in the main text, I estimate *ATT among the employed* with *not-yet-treated* controls and $e \in [-3, 8]$.[7]

These discrete landing outcomes are the "categorical" counterpart to the continuous distance measure. The three facts line up across designs: (i) exposed workers move *farther* in task space and are *less likely* to land in nearby neighbors or to return; (ii) non–exposed workers move *closer* and are more likely to land near their pre-displacement job; (iii) the *ordering across exposure groups* matches the main distance results.

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[7] I set $K = 5$ in the main figure but different values of K does not change the results.

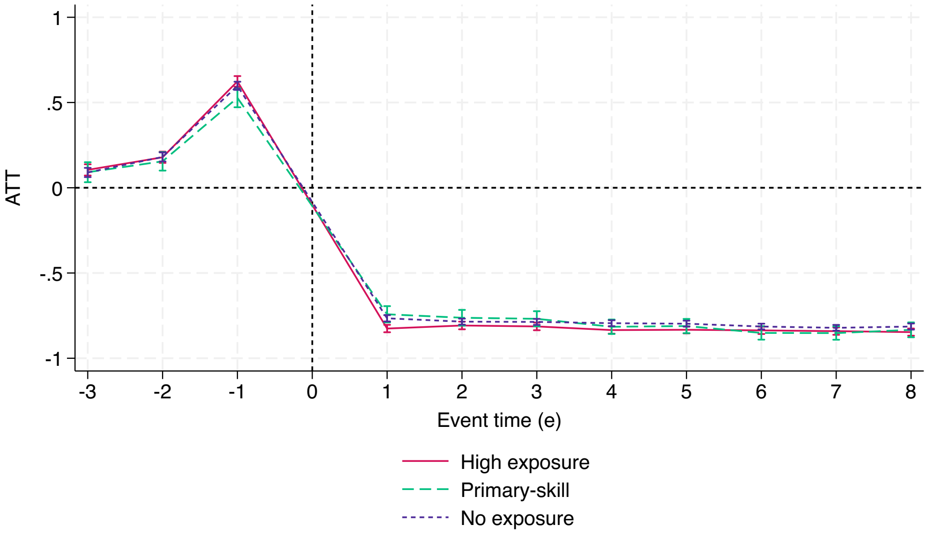

Figure 4.B.5: Return to the exact pre-displacement occupation (3–digit).

Notes: Binary outcome; ATT among the employed; control group = not-yet-treated; event window $e \in [-3, 8]$; $e = 0$ omitted; 95% CIs.

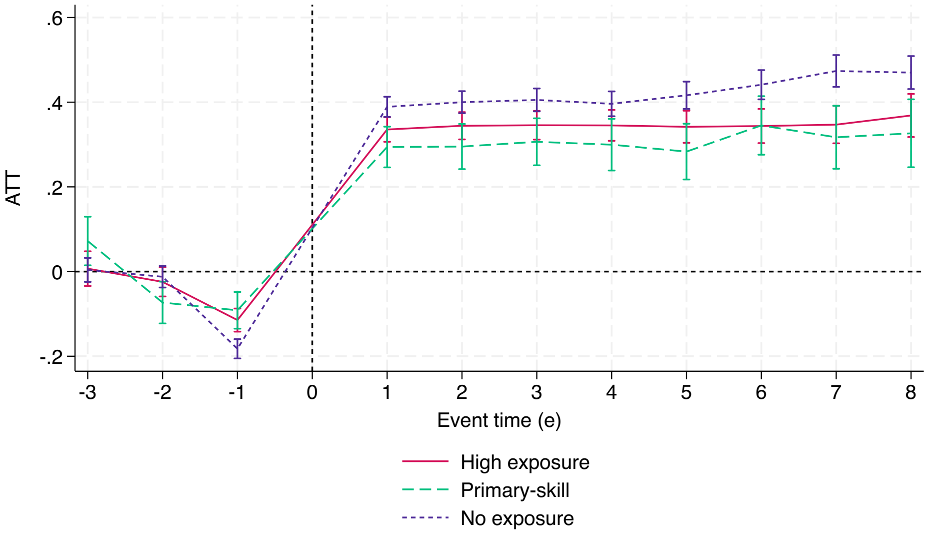

Figure 4.B.6: Landing in top–10% neighbors of the pre-displacement occupation.

Notes: Exact return excluded; ATT among the employed; control group = not-yet-treated; event window $e \in [-3, 8]$; $e = 0$ omitted; 95% CIs.

4.B.5 Mismatch to Own Skills after Displacement

In Section 4.4.2, I examined how workers' mismatch to their own skills progress following a displacement. In the main text, the analysis uses never-treated as control group. To show the robustness of the results, I repeat the same exercise using not-yet-treated controls. The Figure 4.B.7 presents the result of this estimation.

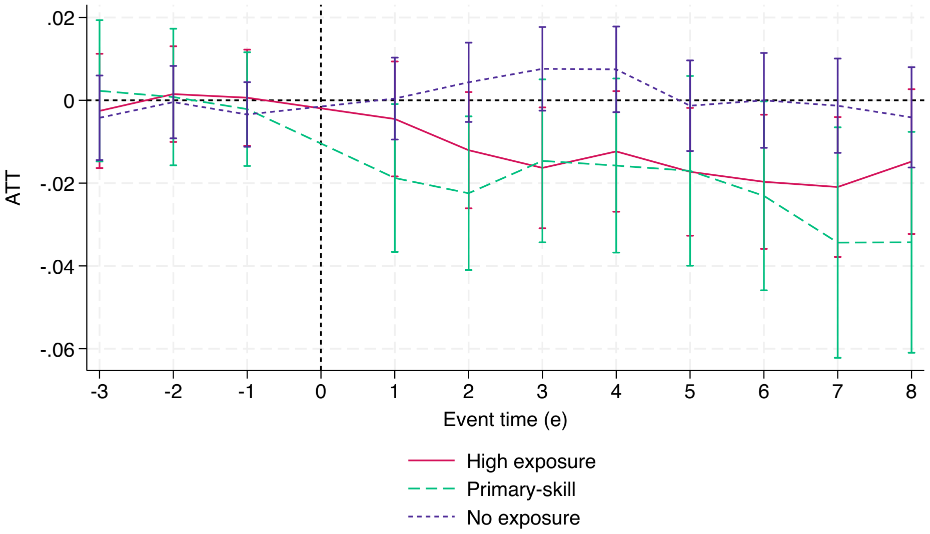

Figure 4.B.7: Mismatch to own skills after displacement (by exposure)

Note: ATT among employed; control-group: not-yet-treated;event window $e \in [-3, 8]$; $e = 0$ omitted; 95% CIs.

Chapter 5

Conclusion

This thesis investigates how technological change reshapes growth and labour-market outcomes. The three essays integrate macro and micro perspectives. In a Schumpeterian economy with search frictions, policies that lower the effective cost of R&D increase innovation and long-run growth but also accelerate creative destruction and separations. Who bears those separations, and for how long, depends on workers' skill portfolios and their alignment with evolving task demands.

Counterfactual experiments show that (i) doubling direct R&D wage subsidies generates sizable gains in growth and welfare alongside higher unemployment, (ii) doubling incremental R&D tax credits produces smaller aggregate gains but superior fiscal cost-effectiveness, and (iii) broad corporate-profit tax cuts erode implicit support for R&D, reduce innovation, and lower welfare despite modest reductions in unemployment.

At the worker level, vacancy-text measures combined with multidimensional skills show that higher exposure to within-occupation skill obsolescence predicts lower earnings, longer non-employment, and greater occupational change. After displacement, losses are concentrated in weeks worked and persist far longer for highly exposed workers, who remain below baseline many years after displacement.

The results speak to the mix of innovation policy instruments. A combination of targeted R&D subsidies and broad, rules-based tax credits is appropriate. The ideal balance depends on policy objectives and fiscal constraints. When growth is the priority and additionality is high, tilting the mix toward targeted subsidies is justified. When fiscal cost-effectiveness is binding, leaning toward rules-based R&D tax credits is preferable. In either case, pairing innovation support with adjustment policies targeted by exposure helps offset the induced increase in separations and mitigate longer non-employment spells among the exposed.

This dissertation has limitations. The baseline model abstracts from matching frictions for skilled R&D labour and from endogenous entry costs for new research lines. Both features could dampen short-run responsiveness to policy and shift relative cost-effectiveness. The framework can also be extended to include firm heterogeneity and worker heterogeneity. Introducing firm heterogeneity would allow the model to capture selection and reallocation, such as differential innovation responses across more and less productive (or more and less R&D-intensive) firms, and assess how policy benefits and costs are distributed across firms. Introducing worker heterogeneity—e.g., two types with different exposure to skill obsolescence and separation risk—would make the distribution of impacts across people explicit, enabling group-specific reporting of unemployment, earnings, and welfare, and the evaluation of targeted adjustment tools.

On the empirical side, validating the exposure measure across countries and cohorts, linking administrative earnings data to richer skill assessments, and exploiting policy variation in the generosity and design of R&D instruments would sharpen identification, illuminate intensive versus extensive margins, and strengthen external validity.

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