Doctoral School of Social Sciences
University of Trento
Doctoral Programme in Sociology and Social Research
XXXIII Cycle

Essays on Technology, Institutions, and Workers

Ph.D. Candidate: Saverio Minardi
Supervisor: Professor Paolo Barbieri

Committee members:

Professor Michael Gebel
Professor Stefani Scherer
Professor Michael Shalev
Professor Heike Solga

May 2022

Index

Chapter III

Chapter IV

List of Figures

List of Tables

Introduction

Historically, technological advancements have been considered one of the key, if not the primary, drivers of social transformation. Social scientists have traditionally interpreted improvements in the technological capacities of machinery to be the fundamental sources of socio-economic changes in occupational and class structures, social mobility, earnings inequalities, and the organisation and content of work. Indeed, since the dawn of industrialisation, each technical leap has resulted in societal changes, which are now referred to as "*industrial revolutions*." First, the introduction of spinning machines and the use of steam power; second, the internal combustion engine and the diffusion of electricity, and finally, the digitalisation of work which followed the introduction of computers.

One of the most prominent examples of technology centred explanations of social change is the long tradition of studies on the impact of industrialization on the structure, processes, and consequences of social stratification (Treiman, 1970). The concept of industrialisation at the core of this field of research was – either implicitly or explicitly – intrinsically related to the state of technological development[1]. As a result, the rising levels of skills and responsibility of the workforce, the shift of employment outside of agriculture, and the growing proportion of professional, technological and managerial employment observed during the first half of the twentieth century were almost exclusively explained through the mechanisation of labour.

The advent and spread of computerised equipment in production processes – either information and communication technologies or computer-based industry automation – led to a revival of technology centred explanations of socio-economic phenomena. Indeed, since the early 80s', computers have been considered the primary drivers of several developments observed in the US economy: the polarisation of wage and occupational structures, the rising college wage premium, and the growing complexity and abstraction of tasks performed in most occupations.

Eventually, the attempt to explain these societal transformations through technological change culminated in the development of the theory of Skilled Biased

[1] An example is Davis's (1955: 255) definition – adopted by Treiman (1970) – of industrialisation as "the use of mechanical contrivances and inanimate energy (fossil fuels and water power) to replace or augment human power in the extraction, processing, and distribution of natural resources or products derived therefrom", or Treiman's specification that "for our purposes we prefer to stick to the definition of industrialisation as the mechanisation of production" (1970, 210).

Technological Change, later refined into Routine Biased Technological Change and its underlying task-based approach (Autor, Levy, and Murnane, 2003; Autor, 2013).

The bulk of the task-based approach is the division between what tasks – i.e., units of work activity that produce output, either goods or services – machines can perform more effectively than humans. It suggests that computers are better at executing routine tasks and at complementing abstract and skilled ones. From this premise, almost any transformation in US labour markets since the 1980s was explained in terms of what human activity technology could or could not substitute or complement.

Eventually, the tasks-based framework became the most prominent approach to the relation between technology and labour markets, to the point where the task content of occupations has become a synonym of automation, and the decline in the employment levels and average earnings of occupations characterised by more routine tasks has been taken as solid evidence of the impact of technological change.

Several commentators have now suggested that we are on the brink of a new technological revolution driven by recent transformations in digital technologies and artificial intelligence, which will, once again, either eliminate human labour or drastically transform it. The relationship between production technologies and labour markets has thus regained crucial relevance.

As in the past, many investigators have ringed the bell of technological unemployment. For instance, by estimating the susceptibility to artificial intelligence and computerisation of occupations, Frey and Osbourne (2013) find that 47 per cent of total US employment is at high risk of automation – i.e., jobs that could be automated relatively soon, perhaps over the next decade or two. Other more recent and conservative studies (Arntz, Gregory and Zierahn, 2016) estimate that 9 to 10% of present occupations will be eliminated, while almost a third would experience substantial transformation.

Once again, expectations are based on the observation of what technologies can and cannot do. Thus, in line with the basic assumptions of a task-based approach, commentators define the technical capabilities of specific machinery in terms of what tasks it can perform more efficiently than humans and, from this premises, advance predictions on the future of work. However, by focusing on the technical characteristics of the technology itself, these approaches often underplay the relevance of social factors. Indeed, if the impact of new production technologies on the organization of labour were exclusively determined by technical factors, social forces would have very few options to influence the use and effect of new technologies.

As a result, a theoretical approach that almost exclusively stresses the technical capacity of machinery is bound to understate or even dismiss the complexity and importance of the social contexts in which technology is embedded, eventually promoting a somewhat deterministic understanding of the relationship between technology and social change. Nevertheless, technological change does not occur in a vacuum, but it is embedded in historically defined systems of norms and rules that eventually influence how actors adopt the available tools.

Moreover, the recent debate, steaming from a predominantly economic literature, often sought to explain almost any unsettled labour and economic issues in advanced countries – such as the growth of the wage-skill premium, the middle-class squeeze, unemployment, and the upgrading and polarisation of occupational structures – through technological change (Bogliaccino, 2014; Fernández-Macías, 2012). These theories constituted the foundation of an understanding of recent social transformations that heavily discounted the importance of many other critical elements, most notably, national institutional arrangements.

The result has been a theoretical perspective that stresses the primacy and ineluctability of technological change. Such an approach has important implications not only for social theory and social research but also for how policymakers deal with the current and future processes of automation. If such an overarching and comprehensive pattern of social transformation was generated almost exclusively by technical advancement, it would be a strong proof of the primacy of technology – and thus the triviality of social regulations – in socio-economic developments. The result would be very gloomy expectations regarding the potential to redirect the consequences of technological change towards socially desirable outcomes.

On the other hand, a growing body of socio-economic research has put this perspective into question (Gallie, 1978; DiPrete and McManus, 1996 Fernández-Macías, 2012; Oesch, 2012; 2015; Fleming, 2019; Krista and Edler, 2021). By observing societal patterns of occupational change and earnings distribution across equally developed countries, scholars recognised substantial heterogeneity in their evolutions, suggesting that technology was only a part of the story. If technology was operating primarily through its substitution and complementarity to tasks performed by workers, it should have produced similar outcomes in countries at similar stages of technological development. However, this is not the case; striking differences exist in occupational structures, earnings distributions, employment levels, and work content between advanced political economies.

The present work is an attempt to contribute to this body of research by investigating the relationship between computer-based technologies, institutions, and labour market outcomes in regard to three of the most relevant issues in the relationship between technology and work: *occupational and class structures*, *earnings distribution*, and the *content and quality of work*. The main objective is to highlight the complexity of these relationships by observing how specific computer-based technologies are related to labour market outcomes in different institutional contexts.

By dealing with computer-based technologies, the chapters of this thesis focus on a slightly earlier wave of technological change commonly referred to as the third industrial revolution or the age of computers (Frey, 2019), which began to impact western labour markets in the second half of the twentieth century. Therefore, it does not deal directly with the current process of automation prompted by the diffusion of artificial intelligence and smart machines.

Despite the fact that all the chapters of this thesis focus on broadly defined computer technologies, in each chapter, these are operationalized in different ways depending on the objectives, the pre-existing literature on the specific topic, and data availability. Nevertheless, the aim of the various parts of this dissertation is not to precisely investigate how a specific tool impacts labour market outcomes, but rather, to investigate the complex relationships between technological factors and institutional arrangements.

This work does not aim to advance predictions or build expectations on the effects of current technological breakthroughs. Such an attempt would be a rather ambitious task as we are still in the midst of this transition, and the impact of new technologies on labour markets has not yet been realised. Instead, the underlying objective is to stress the continued relevance of institutional factors despite the disruptive potential of technology.

Albeit these insights are highlighted and analysed in the context of computer technologies, they are nevertheless valuable for understanding how the current wave of automation – often referred to as industry 4.0 – will shape the future of work.

Indeed, a technology centred and often deterministic explanation of social phenomena is not a new perspective in the social sciences, and it still guides much of the current debate on the transition to the fourth industrial revolution. Eventually, the overall objective of this thesis is to criticize this widespread approach by stressing – both theoretically and empirically – how the process of technological change over the last thirty years is associated with diverse labour market outcomes across different institutional contexts. Although this broad objective guides all the sections, each chapter brings a contribution of its own.

Chapter 1 reviews the main theories on the relationship between technological change and labour market outcomes developed in the last decades, stressing the potential biases of technological change and its relation to labour market inequalities. It further advances a theoretical approach of the embeddedness of technological change in institutional systems. It builds on the vast neo-institutionalist literature to highlight the importance of the incentives and constraints generated by national institutional arrangements in shaping the best production and employment strategies adopted by employers when adapting to new technological innovations. Finally, it reviews the existing literature on the moderating role of specific institutional domains on the relationship between technological change and different labour market outcomes.

Chapter 2 investigates the heterogenous relation between industrial automation and occupational and class structures across Nordic, Continental, and Southern European institutional regimes. On a descriptive level, it first documents that occupational and class structures in western European countries have not shown a common polarising trend as suggested by the theory of Routine Biased Technological change, highlighting a shift toward less manual to more cognitive tasks stressing the difference from the US experience. Second, it highlights the diverse relationships between industrial automation and occupational structures between Nordic, Continental, and Southern European countries, suggesting that robotics is associated with a clear process of upgrading of occupational structures only in Nordic European countries and moderately so in Continental ones, and to a process of downgrading in Southern European ones. It further shows that institutions play a role in defining the winners and losers of automation, particularly regarding unemployment risks. Only low and mid-skilled male individuals in Southern European countries appear to suffer from technological unemployment. Finally, it stresses the importance of national skill regimes and labour market dualization in moderating the relationship between technology and occupational outcomes, highlighting the importance of training participation and reskilling of workers for harvesting the benefits of new technologies.

Chapter 3 focuses on ICT technologies, unionisation, and their relationships to the earnings of different social classes in the US from the early 1980s to our day. As mentioned above, the emphasis on technology as the key driver of most societal transformation has downplayed the importance of institutional factors per-se. This rhetoric has been particularly relevant in the US, where institutions have traditionally been considered less relevant in regulating labour markets. Since earnings declines were most relevant for occupations characterised by more *routine tasks,* technological change was considered the

leading cause of this development. However, the spread of computerisation since the 1980s was accompanied by a drastic decline in unions' power and the demise of wage-setting institutions. Tasks performed on the job are closely related to socio-economic characteristics such as the degree of monitorability, the specificity of skills, and, most importantly, social class. In turn, the economic returns to a social class result from workplace dynamics and several contextual factors, including the power of unions. By looking at the industry-level evolutions of technological investments, unionisation, and earnings of different social classes, the chapter shows that de-unionisation was the most relevant factor behind the earnings stagnation of manual workers throughout this period, while information and communication technologies played a minor role.

Chapter 4 investigates, in a comparative way, what is probably the oldest and most controversial topic in the study of technological change: its relationship to skill levels, tasks discretion, and the quality of work. Since the seminal work of Georges Friedman (1946) and Harry Braverman (1974), a long debate has emerged regarding the upskilling or deskilling nature of technological change in capitalist societies, and eventually, its relation to the quality of work. Several authors suggested that technology has always been an instrument in the hands of the capitalists to increase control over labour processes. Others believed that automation relieved workers from mundane tasks and increased the demand for abstract cognitive ones. By disentangling two dimensions of skills at work – tasks and tasks discretion – the chapter investigates the relationship between computers, skills, and job satisfaction in Germany and the UK. Results suggest that computers complement the performance of less routine and more cognitive tasks and how this is conducive to higher levels of discretion and job quality in both countries. However, once accounting for the type of work performed by computer users, it highlights a substantive difference in the management strategies in the two countries. Computers appear negatively associated with discretion and satisfaction in the UK but not in Germany. The chapter argues that these differences indicate the relevance of the two institutional arrangements – *Liberal vs Coordinated Market Economies* – in shaping management's use of technologies.

Chapters two and four are interested in estimating contextual differences in the relationship between a specific indicator of technology in production processes and labour market outcomes in terms of employment composition and job characteristics, respectively. These chapters are therefore interested in the moderating effect of contextual characteristics. They, therefore, focus on the overall institutional configuration and the support that institutions bring to specific firms' strategies across countries when adapting to new technologies.

Chapter three takes a somewhat different objective and looks at a single country case, investigating whether industry level and technological change have diversely influenced the earnings trajectories of different social classes. The primary interest is therefore to investigate the relationship between the two variables and the earnings of each social class. Moreover, following recent literature on class-biased technological change, the chapter explores whether de-unionization mediates or moderates the effect of technological change on the earnings of different classes.

The last chapter summarises the main findings and puts together the insights from the other chapters. It further discusses the main issues and expectations concerning the most recent wave of technological development and how insights from this thesis – mainly the importance of institutional arrangements – are relevant in building expectations regarding the future of work.

Chapter I

Technology Embedded:

The Relationship Between Production Technologies, Labour Markets, and The Moderating Role of Institutional Arrangements

Abstract

This chapter reviews the main theories connecting technological change to transformations in labour markets and in the nature of employment. Precisely, it reviews how existing approaches have connected technological change to four broad issues: employment levels, occupational and class structures, earnings inequalities, and labour content. It argues that existing theories have excessively focused on the technical capabilities of machines, often disregarding important social and contextual factors. Consequently, the rest of the chapter builds on the neo-institutionalist literature to stress the embeddedness of processes of technological change in national institutional arrangements. Finally, it reviews existing literature on the moderation of four specific institutional domains in the relationship between technology and labour markets: wage-setting institutions, the welfare state, the educational and vocational training system, and industrial and employment relationships.

In his first novels, the famous science fiction writer Kurt Vonnegut (1952) depicted a future society radically altered by extreme automation processes. He narrated a dystopian future where technology had substituted almost every human activity, with two notable exceptions: managers and engineers.

The fictional world portrayed by Vonnegut is noteworthy not only for its striking similarity to contemporary prediction of technological change but also as an exemplary case of public suspicion towards the adoption of new technologies in the production process.

Indeed, anxiety about technological unemployment is not a new phenomenon and can be traced back to the dawn of the first industrial revolution and the Luddite movement (Braverman, 1974; Hobsbawn, 1952). Public concern over the possibility of a jobless future and mounting inequalities have accompanied every wave of innovation, and recent advances in robotics and artificial intelligence have not proven an exception (Akst, 2013; Mokyr et al., 2015; Pew Research Center, 2017).

However, despite two centuries of technological progress, the number of people in work – the employment to population ratio – has continuously grown, tempering the scarecrow of technological redundancy (Autor, 2015). On the other hand, technologies have profoundly transformed the distribution and quality of jobs. First, in the transition from an agrarian to an industrial economy. Second, in the shift to a post-industrial society (Frey, 2019).

Indeed, most socio-economic literature has suggested that work will be slowly transformed rather than fully eliminated. According to these perspectives, the real change entails the task content, the distribution, and the remuneration of jobs (Goos, Manning and Salomons, 2014; Fernández-Macías, 2012; Acemoglu and Autor, 2011; Goldin and Katz, 2007; Autor, Levy and Murnane, 2003). The reason is that, while replacing certain occupations, technology will produce aggregate effects on employment which are expected to offset negative sectoral impacts through rising labour productivity and aggregate demand (Autor and Salomons, 2018). The results will be a decline in jobs in specific sectors and occupations but compensated through rising demand in others and changes in the content and remuneration of jobs affected.

The last decades have witnessed the emergence of several theoretical approaches that try to define how new technologies produce these transformations by highlighting the potential "biases" of technological change – i.e., which factors of production or group of workers are substituted or complemented by a specific technology. By reviewing these

theories, we can expect recent technologies to impact several aspects of labour by directly affecting productivity, opportunities, and returns for specific subgroups of individuals defined by at least three dimensions: *education, tasks,* and *class*.

However, one crucial problem with the majority of this literature is that it conceives the relation between technological change and inequalities as a process separated from the broader national context in which it takes place. As a result, technology is conceived by definition as biased in favour of a specific group based on its technical characteristics.

In line with recent sociological literature (Gallie, 1978; DiPrete and McManus, 1996; Oesch and Menés, 2011; Fernández-Macías, 2012; Oesch, 2012; Fleming, 2019), here I suggest that technological change is embedded in historically defined institutional systems, and therefore the understanding of its outcomes needs to be comprehended through a sociological perspective on technological adoption. By building on the neo-institutionalist literature, this chapter advances a theoretical understanding of the embeddedness of technological change in national institutional arrangements.

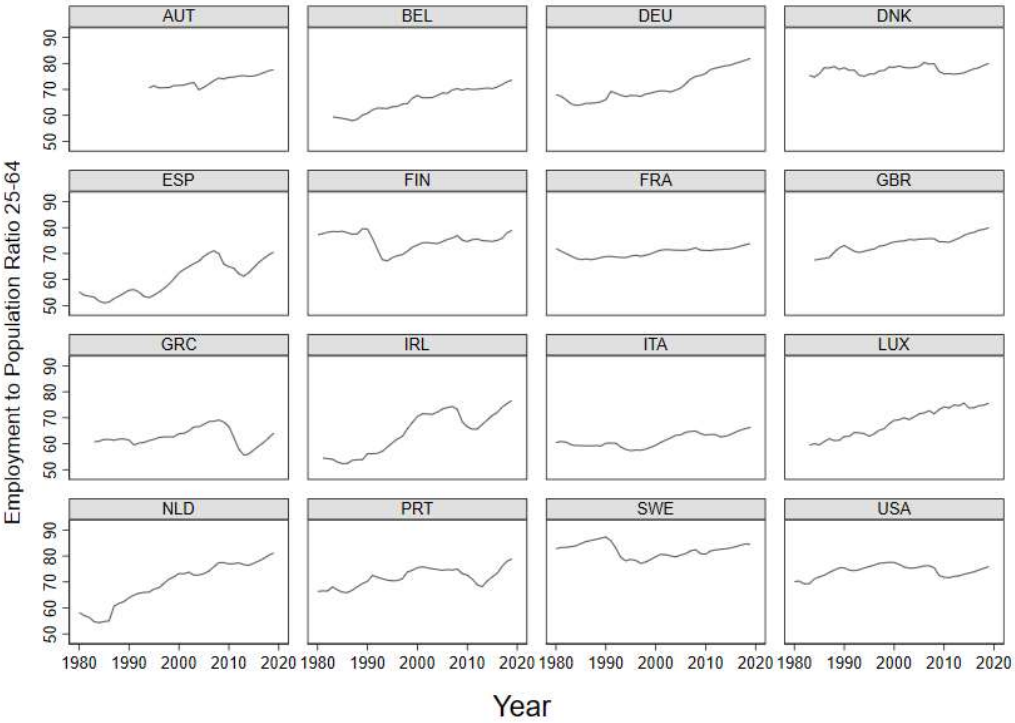
The first section will review the main existing theories directly linking technological change and labour market outcomes. This part will first include the debate on technology and unemployment and then review theories sustaining different biases of technological change: skill-biased, routine-biased, and class-biased. The second section will combine literature on technological change with neo-institutionalist literature to examine the role of different institutional realms in shaping national responses to new technological opportunities.

How does technology shape labour markets? Theories on the relationship between technological change and work

Mass unemployment or creative destruction?

When it comes to technological change, the most common public concerns are mainly tied to the fear of mass unemployment. The standard narrative suggests that, since labour-replacing technology can perform specific tasks better and at lower prices than humans, workers will be forced to specialise in a shrinking set of duties and eventually be expelled from the labour force generating "*technological unemployment*."

Figure 1.1: Trends in employment to population ratio (25-64) in EU-15 and US from 1980 to 2019



Source: OECD statistics

As straightforward as it seems, there are several shortcomings to this understanding. In fact, despite four decades of relentless technological progress and automation, the employment-to-population ratios of western advanced political economies have generally grown (Figure 1.1), and the only substantial declines are related to financial crises and economic downturns.

Socio-economic theory and research have investigated the reasons and mechanisms why technological change did not result in mass unemployment. The first crucial insight from this large body of research is a more precise definition of the nature of technology itself and its relation to human labour.

Indeed, production technologies can be broadly classified, on an ideal-typical level, along two dimensions: *labour-replacing* and *labour-enabling*. The former fully substitutes for tasks performed by workers, while the latter expands labour productivity, potentially increasing employment and wages. Therefore, the relation between technological change and unemployment is firstly related to the extent to which new technologies are more or less labour-replacing. Since no technology is neither fully labour-replacing nor labour-

enabling, each wave of automation has some potential to increase the demand for human labour (Acemoglu and Restrepo, 2018; Autor and Salomons, 2018).

Even strongly labour-replacing technologies, which primarily substitute workers in specific tasks, may give rise to mechanisms of market compensation that eventually offset the initial labour-saving effect (Autor, 2015). Socio-economic theory has proposed several ways through which labour-replacing technologies may replace labour in certain tasks without necessarily inducing higher unemployment at the aggregate level (Barbieri et al., 2019).

First, the growing productivity determined by introducing new technologies can reduce production costs and consequently market prices. If the price elasticity of the goods produced by the automated activities is high enough, the decrease in prices can foster product demand and new hiring of workers in non-automated tasks. In fact, most jobs are characterised by a wide range of duties; as machines become more and more capable of performing specific tasks, demand for workers to do the non-automated tasks around them will increase, potentially compensating for the original displacing effect (Acemoglu and Restrepo, 2019; Autor, 2015; Kremer, 1993).

Second, unemployment could be contained through lower labour costs induced by automation. If institutions allow it, the labour displacement effect reduces labour costs by increasing the labour supply. If the price elasticity of demand for non-automatable goods and services is high enough, employment in these sectors may increase. In other words, automation induces a shift in employment from the "technologically leading" sectors to the "technologically lagging" ones, where the costs of labour will decline (Baumol, 1967); these activities usually include interpersonal and social services, which are neither strongly complemented nor substituted by technologies (Autor and Dorn, 2013).

Third, from a Keynesian perspective, unemployment could be contained through increases in product demand generated by growing incomes. In many cases, workers can reap part of the benefits of increased productivity, as a result, the deployment of new labour-replacing technologies may contribute to a rise in earnings and consumption. According to well-known Keynesian mechanisms, this growth in earnings can eventually result in more product demand and employment, compensating for the original dislocation of labour.

Moreover, new production technologies may result in entirely new industries and occupations. In his classical work, Schumpeter (1912) suggested that technological change is the real driver of economic and structural change. In other words, it is technological development that promotes the birth and death of firms, markets, industries, and jobs. The

introduction of new technology may, on the one hand, rule the death of specific occupations or even entire sectors; at the same time, it can fuel the birth of new unpredictable products and markets. For instance, a recent Accenture study highlighted how firms that employ artificial intelligence in their manufacturing process create entirely new job categories (Accenture PLC, 2017). These jobs include "trainers" (those who instruct AI systems), "explainers" (those who relay and explain AI system output to customers), and "sustainers" (to monitor the performance of AI systems). Similarly, computer-based technologies rendered many old occupations completely obsolete, such as file clerks or manufacturing assemblers, but generated entirely new jobs, such as hardware manufacturers, software and app developers, computer scientists, programmers, analysts and cyber security specialists.

Finally, people may work less but more productively. The labour-enabling aspect of technology can make workers more productive and increase wages; if individuals can adjust working hours, the labour supply may fall together with labour demand.

Besides higher levels of unemployment, a second issue is a possible growth in unemployment for specific subgroups of workers due to a mismatch between technology and skills – that is, between the requirements of new technologies and the workforce's skills and abilities. This is particularly relevant for low- and mid-skilled workers, whose jobs are most susceptible to automation and who lack the general skills to transition to new occupational domains (Solga, 2002; Gebel and Giesecke, 2011). Albeit overall employment may remain unchanged or rise, specific groups of workers may struggle to adapt their skill levels and competencies to fast-changing labour markets and experience higher unemployment risk, leading to growing inequalities in occupational opportunities.

As stressed below, institutions play a crucial role in this process (Baranowska and Gebel, 2010). First, they influence the creation and destruction of old and new jobs by regulating labour costs, labour supply, and demand. Second, institutions influence the inequalities of opportunities between different types of workers through education, training, and public employment. Thus, even if labour replacing technologies could reduce demand for labour, there are several ways through which automation may not result in overall technological unemployment.

Employment outcomes will eventually be determined by factors other than the technology itself. As argued in the rest of the chapter, if any new job – and what kind of job – will be created in response to automation also depends on national institutions and policies.

Skill, tasks and class: how does technology shape occupational structures, skills and earnings inequalities?

Other than the number of jobs, changes in the diffusion and capabilities of production technologies alter the type and quality of occupations available, eventually leading to transformation in employment structures, income distribution, and work content. Indeed, if automation does not result in mass unemployment, it is very likely that it will radically transform the nature of labour. Therefore, as old jobs disappear and new ones are generated, we cannot avoid asking what kind of job will be created and who will gain or lose from these transformations.

Most of the existing literature on technological change in the last thirty years has focused on these questions. Several theories have emerged trying to explain how technology is related to labour markets and what jobs – and types of workers – have been mostly affected by it.

The primary objective of most of these theories has been the effort to explain overall transformations in labour markets in the last decades. These include growing college premiums, job and wage polarisation, increasing capital returns, and the middle-class squeeze. Technology has been addressed as the single – or most relevant – factor driving these transformations.

Several theories on technological change and labour market outcomes have emerged in explaining these macro-patterns and connecting technological change to various socio-economic phenomena. The rationale behind the most influential of these theories has usually been the assumption that computerized equipment is biased in favour of one specific group of workers or production factor. Thus, in most of these approaches, technology is assumed to be *factor-augmenting* – and in some cases also *factor-replacing* – and thus complement specific production factors, either capital or one type of labour. Three main potential biases have emerged from the literature: *skill*, *tasks* (or occupation), and *class* (or capital).

Starting from these premises, such theories generated several expectations regarding the relationship between technological change and labour market transformation on a number of crucial outcomes. However, the core of the debate has revolved around four issues: *the level of employment*, *the distribution of jobs*, the *distribution of earnings*, and the *content of work*.

Furthermore, skill-, task-, and class-biased theories of technological change have produced expectations about the relationship between technology and social stratification, suggesting that technological change has increased disparities along these three

dimensions. Clearly, the aforementioned dimensions of the biased technological change are not exhaustive of the potential inequalities lines harshened by technological advancements, but they have been recognised as the main features directly affected. Nevertheless, technology is likely to influence inequalities based on many other socio-demographic characteristics, such as age, gender and race. Indeed, individuals defined by these characteristics are unevenly distributed across the starting dimensions and are therefore likely to be differently impacted by technology.

The following sections introduce the three main theories of biased technological change, reviewing their expectations regarding several aspects of labour markets, inequalities, and work.

Skill Biased Technological Change

One of the earliest and most influential theories connecting technological development to transformation in labour markets is *Skill-Biased Technological Change* (SBTC). The primary insight of this approach is that technological change in the last decades has been mainly complementary to high-skilled workers. Technologies of the last thirty years are therefore conceptualised as labour enhancing with a bias in favour of highly skilled cognitive labour. In fact, the model mainly referred to computers and information and communication technologies characteristic of the third industrial revolution. According to SBTC, the process of technological change has produced an upgrading of the employment structure in every western capitalist political economy and increased returns from skills, sharpening inequalities based on educational level (Acemoglu and Autor, 2011; Card and Lamieux, 2001; Katz and Murphy, 1992; Tinbergen, 1975; Welch, 1973).

The starting point of this literature has been the observation of rising college premiums – relative wages of college to high school graduates – despite the continuous and significant increase in the supply of highly educated workers in the US. The phenomenon was at odds with the traditional economic theory, which predicted declining returns in response to growing supply. The unprecedented process of educational expansion should have instead resulted in declining college premium, but throughout the 80s and 90s, empirical research observed the exact opposite (Acemoglu and Autor, 2011).

This trend could only be explained by a massive increase in the demand for college graduates. Technology was thus identified as the main factor leading this growth in high skilled labour demand. The fundamental assumption was that of the skill bias of technological change, which means that improvements in technology strongly increase the

productivity of highly educated cognitive workers, making it convenient for firms to hire them.

SBTC, therefore, predicted growing income inequalities based on educational levels. On the other hand, little space is given to potential unemployment outcomes since technology is almost exclusively conceived as labour enhancing rather than labour replacing.

SBTC also had significant implications for the relationship between computers and employment structures. Given that technologies make high-skilled labour comparatively more productive, employers should favour production strategies that make higher use of highly skilled occupations. Since skills are close correlates of many other occupational characteristics such as earnings, prestige, and job quality, technological expansion should have resulted in an upgrade of employment structures.

While the SBTC model performed quite well in explaining some transformations, it could not fully account for many other patterns (Acemoglu and Autor 2011).

It does not explain why certain groups – specifically low educated male workers – have experienced real earnings declines. It cannot account for the process of wage and occupational polarisation, which has taken place in the US in the last twenty years, and differentials in earnings inequality in different parts of the skill distribution across decades. Furthermore, solely focusing on the complementarity between technology and skills does not directly address how new technology may substitute certain workers. Finally, it did not account for why the distribution of skill groups across occupations has shifted in the last thirty years, with a growing share of middle-skilled workers employed in traditionally low-skilled occupations. A new model and approach were developed to overcome these limits, which quickly gained an almost hegemonic position in the debate: *Routine Biased Technological Change* (RBTC) (Autor et al., 2003).

Routine Biased Technological Change

In response to the limits of SBTC, a second perspective developed from empirical observation of transformations in the employment structures of the US in the last thirty years. Looking at the change in the share of workers employed in different occupations, scholars noted that the share of employment in mid-level occupations had been declining and employment in high- and low-level ones increasing. Simultaneously, earnings at the middle of the earnings distribution were declining, while those at the top experienced a rapid increase and those at the very bottom underwent some moderate increase as well. The

two developments, which were mainly relevant in the US, had been described as occupational polarisation and earnings polarisation and were at odds with the idea of SBTC.

Starting from the definition of the technical capabilities of computer technologies, scholars developed a framework to connect computers to these labour market transformations based on the type of *task* that machines are capable of performing better and at lower prices than human workers. Tasks are defined as a unit of work activity that produces output, either goods or services. Autor, Levy and Murnane (2003) suggested that for any computer-based machine to accomplish a task independently, a programmer must first thoroughly understand the steps required to perform it. It follows that technology is a good substitute for explicit and codifiable operations, which the literature has defined as "*routine tasks*" (Acemoglu and Autor, 2011; Autor et al., 2003).

On the other hand, there are several tasks for which computer capacity has – for now – been limited. These are tasks requiring manual and intellectual flexibility, judgement and common sense, as well as high-level reasoning. The distribution of these tasks across occupations is by no means related to their skill content. Jobs that require high levels of training, such as performing statistical and mathematic procedures or archival research, can be easily replaced by software. Other jobs, which involve problem-solving, flexibility or social interaction, such as janitorial work or elderly care, are still far from being replaced.

More precisely, Autor, Levy and Murnane (2003) grouped occupations into four categories defined by their manual to interactive/analytic content and degree of routinisation. The results are four groups: routine cognitive, non-routine cognitive and interactive, routine manual, and non-routine manual. RBTC theory further suggested that occupations that are intensive in routine tasks are mainly concentrated in the middle of the occupational structure. The consequence is that middle-class workers employed in routine tasks intensive occupations are at higher risk of substitutions, while their outcome in terms of occupational mobility is uncertain since both high- and low-income occupations can grow. In this way, RBTC accounted for the observed processes of occupational polarization and the hollowing out of the middle-class. Regarding unemployment risks, RBTC suggests an uneven impact of technology based on occupations and reflected in social-class, where middle- and lower-class workers experience the most severe consequences.

Does RBTC also lead to wage polarisation? If demand for different occupations has changed, one would expect a similar transformation for wages – thus rising relative wages for high- and low-skilled non-routine intensive occupations. However, to establish this connection, it is important to consider three other forces: complementarity, demand elasticity, and labour supply (Autor, 2015).

First, computer technology strongly decreases the costs and increases the scope of information analysis available to workers. In this way, they substantially decrease the time necessary to retrieve and analyse information and increase the time spent interpreting it. This capacity complements abstract-intensive tasks typical of managerial and technical occupations at the top of the earnings distribution.

If demand for these occupations is inelastic, these gains in productivity may contain wage gains. However, demand for these professions has continuously risen in the last decades. The combination of complementarity between technology and abstract tasks, the elasticity of demand for abstract tasks intensive occupations, and inelastic labour supply over the short/ medium term led to wage benefits for abstract task intensive occupations. These same conditions are not in place for non-routine manual tasks, which do not experience significant gains in productivity and wages.

Consequently, while technology may induce employment polarisation in terms of the number of jobs, it does not necessarily do so in terms of wages. Therefore, income inequalities are likely to reinforce educational differences, with the highest educated workers gaining the most from technological change and others losing in terms of income or unemployment risk.

The theory of RBTC has important implications also for how technologies transform the content of work. The distinction is made clear by the original work of Autor, Levy and Murnane (2003), who, on a technical level, distinguish between an *extensive margin* and an *intensive margin.* The former refers to cross-occupation employment changes, the latter to changes in the task content within occupations. From the RBTC perspective, computers are expected to increase tasks abstraction and complexity required by specific occupations (Spitz-Oener, 2006).

This may be true even for highly routine intensive occupations, generally substituted by computerized equipment. For instance, computers may, on the one hand, reduce the demand for clerks or assemblers who perform highly routine tasks, but, at the same time, they could transform the type of tasks performed in these occupations. Indeed, since the 1980s, occupations such as secretaries and clerks have experienced profound changes in their duties, tasks, and responsibilities. For example, the *Occupation Outlook Handbook* in 1976 described the job of secretaries as mainly oriented towards typing, taking shorthand, and dealing with callers. In contrast, the 2000 edition of the *Handbook* suggested that "office automation and organizational restructuring have led secretaries to assume a wide range of new responsibilities once reserved for managerial and professional staff" (Levy and Murnane, 2003).

RBTC is a comprehensive theory that concerns all the crucial aspects of the relationship between technology and labour. First, regarding the level of employment, it suggests that computers replace routine intensive occupations and complement abstract ones. In this way, it suggests that technological change results in a polarization of the occupational structures by raising the demand for non-routine tasks at the top and bottom of the occupational hierarchy. It further stresses that computers raise returns for highly-skilled occupations characterized by more cognitive abstract and interpersonal tasks. It finally advances claims about work content, suggesting that computers have rendered labour more cognitive and abstract, eventually increasing skill requirements.

For this reason, the tasks-based approach promoted by the theory of RBTC has gained large consensus in the debate, and it has been applied well beyond the consideration of early computerized equipment. A prominent example is Fray and Osborne's (2017) analysis of the susceptibility of occupations to automation from artificial intelligence.

Nevertheless, the idea that the routine task intensity of occupations is the most important factor connecting computer-based technologies to wage and employment growth is not uncontested and critiques have emerged both on an empirical and theoretical ground. The most widespread criticism of the original argument of RBTC relates to its empirical validity outside the US. Indeed, the employment polarization pattern observed in the US is not detectable in other countries which undergone similar processes of technological change during the same period, in fact, most European countries experienced processes of occupational upgrading, putting the consistency of RBTC into question (e.g., Fernández-Macías and Hurley, 2017).

Other authors have doubted the explanatory power of RBTC even within the US. Examining the distribution of real wage growth between 1980 and 2005 for routine and non-routine occupations, Caines et al. (2017) highlight that both groups have a significant share of low- and high-pay growth occupations. This observation raises doubts on the extent to which routine task-intensive occupations are completely segmented from the rest of the economy, or whether some routine and non-routine jobs are subject to the same aggregate dynamics determining wages and employment.

Finally, RBTC's theoretical foundations have been questioned for the underestimation of all factors connected to human action and social connections that characterize the production process. According to several critical assessments, the production process in an organization is characterized by social relations embedded in the hierarchical division of labour. According to this perspective, task differences between occupations also reflect the hierarchical division of labour within the workplace and not only the technical division of

duties (e.g., Cetrulo et al., 2020). This implies that change in employment demand and earnings could be related to mechanisms of command and control over the labour force and not exclusively dynamics of task replacement and complementarity.

Class Biased Technological Change

The third set of approaches emphasises capital ownership and complementarity between technological change and capital rather than labour (Acemoglu, 2002a; Guy and Skott, 2013; Kristal, 2013). This understanding builds on two very different traditions. On the one hand, it is rooted in the Marxist argument that class conflict shapes the use of technology in the workplace and that technological change and automation are introduced in order to deskill and fragment labour, eventually reducing labour autonomy, skills, and costs (Friedmann, 1946; Braverman, 1974; Guy and Skott, 2008; Kristal, 2019). On the other, it belongs to a more traditional economic perspective and suggests that improvements in computer technologies have been primarily complementary to capital rather than labour, increasing return for employers more than workers (Acemoglu, 2002a, 2003; Bentolila and Saint-Paul, 2003).

Both understandings are grounded on a conception of social class based on workplace ownership relations[2]. In the last decades, they have gained popularity due to the observation that the labour's share of national income has declined while capitalists' profit share has risen. The main rationale is that technology can affect the distribution of functional income through its influence on capital productivity and parties' bargaining power – i.e., employers and employees (Acemoglu, 2002a, 2003; Guy and Skott, 2008, 2013; Kristal, 2013, 2019).

[2] Social classes defined in relation to capital ownership can be conceived as composed of proprietors, managers, workers, and independent producers (Dahrendorf, 1959; Eichhorst and Marx, 2011; Wright, 1979). Proprietors own the means of production and have control over workers' activities. Managers do not own the means of production but still control the activities of workers. Workers do not own nor control the means of production and therefore have no power over the activities of other workers, their labour is under the direction of employers and managers. Independent producers control the means of production but have no power over the activity of other workers.
This understanding of social classes must be conceptually and empirically distinguished from that of occupational classes (Wodtke, 2017). Occupational classes categorize workers in groups defined by functional, technical, contractually, and skill related characteristics of their job. Ownership and authority divisions are expressed in these classes but other jobs characteristics are equally – and in some cases more – relevant (Erikson and Goldthorpe, 1992; Featherman and Hauser, 1978; Weeden and Grusky, 2005).
Both conceptualizations are relevant but must be distinct since they generate technology related inequalities through different mechanisms. Occupational classes are informative of hierarchy in skills and task within workers and are therefore informative on the distribution of gains and losses related to SBTC or RBTC. Social classes reflect the direct ownership of technology and therefore inequalities related to direct capital returns and differences in the distribution of power.

In both cases, the results expected from technological change are class related income inequalities. Theories pointing in this direction can therefore be classified into two broad groups. A former focus on the complementarity between different forms of capital and is labelled as *factor-biased technological change* (FBTC). A latter, which stresses the impact of technology on the distribution of power between classes, *class (power)-biased technological change* (CBTC) (Kristal, 2013).

FBTC, similarly to SBTC and RBTC, assumes that new technologies are not factor-neutral. This explanation is based on two hypotheses. First, computer technologies increase the productivity of machines and equipment more than that of labour. Consequently, technological change increases capital income more than labour income. Second, this complementarity has led employers to decrease their demand for labour. In other words, thanks to new software and inventions, machines and other equipment have become much more productive than workers, decreasing workers' employment and income (Acemoglu 2002a, 2003; Bentolilla and Saint-Paul 2003; Blanchard 1997; Karabarbounis and Neiman, 2014; Oberfield and Raval 2014).

The second approach stressing the class bias of technological change emphasises the power relations at the workplace that derive from capital ownership. Class relations are defined as conflictual, and groups are associated with antagonistic interests. This approach suggests that the degree of income inequality is primarily a function of power distribution between classes and that both parties use their power resources to bargain a more significant share of national income. Rather than factor productivity, the core of the argument is shifted to classes' positional power in the labour process. Specifically, CBTC suggests that computer technology, far from being class neutral, possesses specific characteristics which favour capitalists and high-skilled workers over manual low-skilled employees (Kristal, 2013; Skott, 2010; Spencer, 2016).

How can technological change reduce workers' power? First, by replacing tasks performed by blue-collar workers and manufacturing jobs, which are typically among the most unionised categories (Milkman, 1995). A second mechanism suggests that technology increases management control, increasing, on the one hand, their capacity to bring on anti-union tactics (Bronfenbrenner, 2009) and, on the other, their ability to extract value from workers. Starting from the empirical observation that technology has led to an increase in work effort, this literature suggests that changes in technology have increased management capacity to monitor work, therefore increasing productivity at equal costs (Green, 2004; Green and McIntosh, 2001; Guy and Skott, 2008).

Third, recent technology has promoted skill-polarisation, upskilling high-skilled workers and deskilling production workers, thus undermining establishment workers' solidarity and reducing the likelihood of collective action (Burris, 1998; Vallas and Beck, 1996).

Similarly, Nelson (2001) hypothesises that what he defines as post-industrial innovation expands elites' power by modifying access to two primary resources: capital and organisational access. On the one hand, technologies are expensive and require capital for acquiring and updating them. Second, the adoption of technologies requires organisational access to deploy them. In both respects, capital owners are advantaged over labour and can therefore deploy them to exert stronger control and extract higher value.

Moreover, class-based approaches have advanced several claims regarding the relationship between technological change and the content of work. Starting with Georges Friedmann (1946) and Harry Braverman (1974), a long tradition of theoretical and empirical studies has argued that automating the labour process is a way of transferring control, discretion, and autonomy from the shop floor to management. In this perspective, automation facilitates the application of scientific management and thus management's ability to ensure that labour-power is used efficiently.

In this perspective, technology is an instrument to perpetrate capitalists' interest in regard to the reduction of costs and control over the labour process. They observed that the mechanization of production resulted in the division of complex tasks into routinised and straightforward steps to be performed by cheap and unskilled labour. Furthermore, they argued that technology is an instrument in the hands of capital owners and managers to increasingly monitor workers and gain knowledge about the production process, reducing workers to mere executors with little autonomy and discretion. Eventually, the deskilling thesis suggested that technological innovation would reduce intellectual skills and discretion deployed by workers.

Braverman's considerations were mainly based on the effect of industrial automation and numerically controlled machines. He argued that, through automation, craft skills were stripped down to their simplest form, consisting of a sequence of simple repetitive acts, resulting in the deskilling of work and an overall immiseration of labour.

Albeit these works were mainly focused on an earlier wave of technological development, a vast body of research has extended the same arguments to more recent computerized equipment (Zuboff 1988; Brown et al. 2010; Mazmanian et al. 2013; Elliot and Long 2016; Mennon et al. 2020;). This literature suggested that computer technologies had enabled abstract-tasks to be turned into routines that may need some level of education

but are nevertheless stripped of knowledge-based creativity and freedom of judgment, producing a new form of *digital Taylorism* (Brown et al. 2010). In this perspective, computers complement the performance of more abstract-tasks associated with higher skill levels; however, they simultaneously work as efficient instruments to routinise and monitor precisely these types of tasks.

An example of this process is the introduction of computerized information systems in wall street. On the one hand, computers increased demand for brokers who perform a vast range of analytical and interpersonal tasks but, at the same time, allowed upper management to monitor the performance of brokers by controlling how and when they used their firm's expert system and software programs and provide more complex and comprehensive work procedures (Garson, 1989).

The idea that technologies are instruments to deskill and disempower workers has received substantial critics, especially in its application to computer-based technologies. As other theories which attempted to postulate general trends and conclusions about the impact of technology, class-based theories of technological change have been criticized for their inability to account for contextual differences in the adoption of technology (Gallie, 1978; Kelley, 1990).

Empirically, the early approaches to CBTC were criticized and partly dismissed by the observation that skill requirements in most occupations – both in terms of credentials and observed skills – were increasing during the second half of the twentieth century. Moreover, quantitative analyses of the labour force composition across western countries found substantial upgrading due to an expansion of more skilled occupations rather than low-skilled jobs (Spenner, 1983; Zuboff, 1982; Gallie et al., 2003; Spitz-Oener, 2006). These kinds of observations suggested that technology was not an instrument to deskill workers and remove control from the labour process but rather increase skill demand and job complexity (Smith & Thompson, 1998).

Similarly, a vast set of organizational case studies during the early phases of computerazion suggested that many organizations promoted processes of decentralization of decision making and authority after the implementation of computerized systems (George and King, 1991). All of these evidences put the deskilling hypothesis at the basis of the class-bias approach into question, as they showed that, in many cases, the adoption of computer technologies improved working conditions and skill requirements.

Putting technology into context: the role of institutions

The previous sections have highlighted several mechanisms through which technological change may alter the distribution of jobs, the content of labour, and the allocation of earnings. Each perspective stresses the complementarity of a specific technology with different production factors or labour characteristics. Its relationship to the (re)organization of labour is inferred from the technical characteristics of the technology itself – which factor it complements, which kind of labour it replaces, what range of tasks it is capable of performing. However, any technology can be deployed in more than one way, and, when adjusting their employment, organisational, and production strategies to new technological frontiers, employers face more than one option.

When the moving assembly line was first introduced at the beginning of the 20th century, several commentators were quick to point out the immiserating and de-skilling effect that this new technology had on manual workers. For the following decades, this idea was rarely challenged, culminating in the classical work of Harry Braverman (1974), which argued that technology was an effective means to remove skills, control, autonomy and competencies from workers.

However, in the 1990s, this idea was confronted by the seminal work of Womack et al. (1990). In *the Machine That Changed the World*, the authors observed that the very same technology which in the US was connected to worsening working conditions and de-skilling was actually increasing skills requirements in Japanese establishments. Indeed, the book documented that the workers in Toyota factories underwent substantial re-training in a vast set of competencies, including quality control and statistical analysis. Furthermore, their research underlined that Japanese workers were endowed with a vast set of responsibilities regarding the management of the line (Bailey and Leonardi, 2015).

The diverse employment and production strategies associated with the same technology highlight important implications for understanding the relationship between technological change and labour markets. It documents that the impact of new technologies on the organization of work, far from being a deterministic process, results from the interaction between the technology adopted and the existing employment and production strategies.

The theories of technological change discussed above are important and useful tools as they clarify and summarize the possible paths through which a specific technology can influence numerous aspects of the employment relationship. However, they often consider technologies as inherently favourable only to a specific set of production and employment

strategies, such as using a more skilled workforce, the centralization of information, or the disempowerment of workers. In this way, they do not take into account that social actors – mainly employers – are embedded in broader social contexts, and, when adapting their behaviour to the organizational requirements of the most efficient technology available, they must also keep into consideration other contextual incentives and constraints.

In this way, they promote a quite deterministic understanding of technological change – i.e., "the familiar idea that regardless of its political preferences, any society that wants to produce industrial goods must adopt certain structures of organization, patterns of authority, and ways of doing business" (Sabel, 1982 pg:4).

The issue is that technology is not the only factor that shapes firms' strategy, and the transformations resulting from the adoption of new powerful production technologies are bounded by the broader context in which firms operate.

Indeed, a vast set of socio-economic theories, usually labelled neo-institutionalism, has highlighted that social actors adjust their behaviour in response to a vast set of incentives and constraints defined by historically rooted norms and rules which they follow for normative, cognitive, or material reasons – i.e. institutions (March and Holsen, 1984; North, 1990; Streeck, 1992; Hall and Taylor, 1996; Soskice, 1999; Hall and Soskice, 2001; Gallie, 2007; Gallie, 2011; Oesch and Menés, 2011).

As a result, actors operating in different institutional contexts are unlikely to undertake the same strategies in response to technological change; instead, technological advancements will result in diverse labour market outcomes across existing institutional arrangements.

The neo-institutionalist approach inspired the development of several mid-range theories that investigated the differences in institutional configurations across advanced national capitalist economies and how these configurations influence the behaviour of actors (Streeck, 1991; Steinmo et al., 1992; Hall and Soskice, 2001). Several insights from this growing body of research are crucial for understanding how different countries adapt to technological change.

The theory of "Varieties of Capitalism" (VoC) (Hall and Soskice 2001), sometimes labelled as production regimes theory, is one of the most prominent and influential of these approaches. VoC is a firm-centred perspective that considers companies the most crucial actors and the primary agents of adjustment in the political economy. The main objective of VoC is to provide an institutional explanation for cross-national variations in the micro-behaviour of firms and, consequently, of firms' response to technological change.

VoC claims that firms are relational actors who seek to maximize their core competencies. In order to do so, they must establish internal and external relationships and coordinate effectively with a wide range of actors[3]. The strategy that firms adopt to coordinate their endeavour is defined by the institutional configuration of the political economy in which they operate.

Based on the type of production strategy supported by a national institutional framework, the authors differentiate between two main production regimes: liberal market economies (LMEs) and coordinated market economies (CMEs).

In LMEs, usually exemplified by Anglo-Saxon countries, firms primarily coordinate their activities through hierarchies and market mechanisms. Here institutions foster the formation of short-term and antagonistic relationships between actors. As a result, firms mainly rely on a labour force endowed with general skills, limited knowledge of production processes at the firm-level, little participation rights and discretion. Overall, institutions in LMEs support the adoption of production strategies that prioritize product standardization, economies of scale, and lower costs and prices

On the other hand, in CMEs, typified by the German case, firms mainly rely on non-market forms of interaction. More coordinated institutions – such as centralized systems of collective bargaining, work-councils, and well established vocational and training systems – allow for the adoption of long-term production strategies that support the development of a more skilled workforce endowed with specialized skills. Workers are encouraged to acquire firm-level knowledge of organization, processes, and products. In turn, higher and more specialized skills influence the quality of workplace interactions and the degree of job control, involvement at work, and job security of employees. In contrast to LMEs, coordinated economies focus on what Streeck (1992) characterized as *diversified quality production*.

The crucial point of VoC is that firms benefit from adopting production strategies supported by their institutional configurations since it allows them to exploit their core competencies. Indeed, at the core of the theory of VoC is the notion of institutional comparative advantage, according to which "the institutional framework of the political economy provides firms with advantages for engaging in specific types of activities there" (Hall and Soskice 2001: 32).

[3] VoC considers five spheres in which employers must develop relationships to resolve coordination problems. These five spheres correspond to different institutional domains which frequently appear in the literature on comparative political economy, each of which raises specific dynamics for the moderation of the impact of technological change. The five spheres are industrial relations, vocational training and education; corporate governance, inter-firm relations, and employees' relationships.

Thus, given the availability of new production technologies, firms should respond by altering their practices along the management style supported by the existing institutional framework since deviation can be detrimental to their interests. As a result, at least some of the adjustment processes following the deployment of new production technologies will be geared at recreating the production techniques promoted by the existing institutional context.

Unlike prior theories of variation in capitalist societies, production regimes theorists regarded employer strategies as the primary driver of institutional evolution. On the other hand, earlier approaches tried to account for differences in institutional structures via the lens of a "*power resources*" paradigm, stressing the relative organizational capabilities of employers and labour and how this was mediated through the state (Korpi 1978, 1983; Shalev and Korpi, 1980; Shalev, 1983; Gallie, 2007).

Much of the theoretical and empirical work associated with this approach has concentrated on the relevance of employment policies and welfare states. Based on country differences in these two domains, scholars building on a power resources approach assume a more varied grouping of nations than VoC. The most popular distinction of this kind is that between welfare state regimes proposed by Esping-Andersen (1990), which differentiates between social-democratic, liberal, and corporatist welfare states.

Similarly, Gallie (2007) distinguishes between inclusive, dual, and liberal employment regimes[4]. The three employment regimes differ in terms of the extent to which organized labour is involved in decision-making, the principles that underpin employment policy, the role given to the public sector, the importance of quality of working life programs, the institutional support for the combination of paid work and family, and the level of welfare protection provided to the unemployed.

Thus, the employment regimes approach is particularly relevant since, by focusing on the degree of inclusiveness of different regimes, it allows for a deeper consideration of the crucial role of welfare state institutions and life-long training programs, both of which play a vital role in moderating the impact of technological change.

Indeed, the role of the state as a service provider and employment creator has been recognized as a crucial factor in channelling the impact of automation on occupational structures and employment levels (Oesch, 2015). Most non-automatable occupations

[4] In this way the employment regimes approach includes a further distinction compared to the VoC classification, dividing the CMEs into a Dualist and an Inclusive regime (Gallie, 2007), and in certain cases in a third Southern European one. Dualist employment regimes – exemplified by Germany – differ from inclusive regimes – typical of the Scandinavian countries – by providing strong rights only to the core workforce at the expense of the peripheral workforce.

involve social and interpersonal services that, depending on the nature of the welfare regime, can be provided by the state (Mandel and Shalev, 2009). This insight was first introduced by the seminal work of Esping-Andersen (1990), which suggested that welfare state systems would have had a key role in shaping labour market outcomes in the transition to post-industrial societies.

Eventually, despite differences in the theoretical foundation of their arguments, both approaches stress the relevance of institutions in shaping the range of options available to actors when adapting to technological change. Moreover, the central premise of both production and employment regimes theories is that many of the most important institutional structures – particularly the systems of labour market regulation, education and training, welfare states, and industrial relations – are dependent on the presence of regulatory regimes that are predominantly defined at the national level. The result is that the relationship between technological change and labour related outcomes will likely differ across countries, or clusters of countries, defined by similar institutional arrangements.

Clearly, these links are not exhaustive of the complex relationships between technology, inequality and institutional factors. Indeed, institutions may influence the introduction of new technology rather than simply moderating their impact. Nevertheless, computer technologies have become ubiquitous across advanced capitalist societies due to international competition and globalization. While institutions may influence the extent and timing of diffusion of a specific production technology across countries, the dominant type of technology appears to be quite consistent across countries at similar stages of development (Alesina et al., 2018). The following pages do not explore the relationship between institutions and technological diffusion but analyse how similar technologies are adopted in diverse institutional settings.

Moreover, technology may induce processes of institutional change and completely transform national arrangements. Still, institutional change is a slow process and, in most cases, strongly path-dependent. Thus, albeit the formal setting of existing institutional arrangements may undergo some modification, the underlying nature of the institutional configuration – such as the degree of coordination or inclusiveness – and differences across countries are likely to stick around for quite a long time, and they are therefore likely to continue to play a critical role in the current process of technological change.

Nevertheless, the neo-institutionalist assumption that pre-existing institutions play a constant and major role in shaping responses to exogenous factors has been partly questioned by scholars of institutional variation and change (e.g., Streeck and Thelen,

2005; Lieberman, 2002; Thelen, 1999). Critics of the stability of institutional arrangements suggest that theoretical approaches of divergence and continuous path dependence often yield a static picture. They argue that accounts of institutional stability often omit attempts to change and resist policy outcomes that reproduce existing arrangements and important internal and external pressures for the transformation of national institutional frameworks. According to some of these critics, neo-institutionalist explanations that stress consistency in institutional change do not fully account for varieties of policy responses to exogenous pressures and observed inconsistencies in policy outcomes in the last decades (Regini, 2000).

Moreover, path dependence and institutional stability have been criticised by convergency theorists. According to this approach, globalisation and international competition have been transforming national institutional arrangements of more coordinated and solidaristic political economies towards a single liberal model through deregulation processes (Baccaro and Howell, 2011, 2017). However, this perspective has been strongly criticised by both proponents of persistent diversity and proponents of a milder view of diversity in institutional change (Regini, 2000). They argue that, while proponents of convergence towards a single institutional model claim to explain universal patterns, the empirical data they give is limited to a few nations and areas of socio-economic regulation, their conclusions are often contested by observing other countries and institutional domains (Thelen, 2014; Streeck and Thelen, 2005; Hay, 2004; Regini, 2000).

On the other hand, a notable example of a critique of convergency theory that nevertheless recognises processes of institutional change is Thelen's (2012, 2014) analysis and conceptualisation of distinct varieties of liberalisation. Thelen (2012, 2014) argues that European countries have adopted several policies to increase flexibility without disrupting the underlying support they provide for specific production and employment strategies. Moreover, she argues that policies to increase flexibilisation have been path-dependent and consistent with regime varieties previously identified in the literature: fully-fledged liberalisation in liberal countries, dualisation in continental ones, and embedded flexibilisation in social democratic ones. In this perspective, all countries have confronted new economic challenges by increasing flexibility; however, each country has done it in a way that does not disrupt existing firms' strategies.

Other approaches have placed themselves in a theoretical middle by highlighting potential divergent policy responses but are not necessarily consistent with pre-existing arrangements or a common liberal trajectory. These studies have highlighted the diversity of institutional change processes even within similar institutional clusters. They argue that

it is not possible to identify common "national responses" that similarities across existing national contexts may suggest (Ferragina and Filetti, 2022; Regini, 2000).

More explicit recognition of institutional variation across time challenges the traditional neo-institutionalist notion that institutional arrangements channel the impact of exogenous forces. First, because the institutional arrangements themselves are not always stable, their moderating capacity may change over time. Second, it suggests that national institutions are not necessarily independent from exogenous economic and political forces and may therefore be influenced by them other than channelling their impact on labour and firm strategies.

However, most literature on institutional variation suggests that even when institutional change is not consistent with pre-existing institutions, it is rarely revolutionary, but mostly slow and incremental. Institutions can give principles, methods, and opportunities for actors to employ creatively as they innovate. However, they also tend to limit the range of possibilities they are inclined to select from (Hall and Gingerich, 2009; Campbell, 2004). Since political economies are complex ecologies of interacting institutions, change processes are likely to be incremental operating via small alterations of existing practices (Streeck and Thelen, 2005: Hall and Thelen, 2008). In fact, several studies have highlighted that despite distances between clusters of countries have in some cases reduced – and in other cases increased – countries continue to show persistent gaps across traditional domains, and that traditional heuristic divisions continue to be a useful concept to analyse variation across countries (Ferragina and Filatti, 2022; Holman, 2013; Ferragina and Seeleib-Kaiser, 2011, 2015; Hall and Gingerich, 2009; Castle and Obinger, 2008; Saint-Arnaud and Bernarn, 2003). The validity of institutional similarities between countries has also been reinforced by observing distinct growth regimes that largely overlap with previous welfare and VoC classification (Behringer and van Treeck, 2021*;* Hassel and Palier, 2021; Hall, 2018).

Moreover, it must be noted that theories of institutional change almost exclusively consider variation in institutional infrastructures and policies. They rarely address how these variations influence firms' employment and production strategies at the micro-level. However, firms adapt to regulatory change while being constrained by other institutional and internal restraints; as a result, the firm-level production and employment strategies are unlikely to change drastically, even when the institutional infrastructure undergoes some modifications.

Thus, the present thesis builds on the assumption that institutional change in response to exogenous forces will often be geared towards maintaining existing national comparative

institutional advantage, or at least not towards their disruption. This understanding does not neglect that political economies may undergo transformations in specific institutional areas that are not consistent with their existing framework. However, it builds on the idea that such transformations are slow and incremental and have not yet been sufficient to completely alter the overall incentives for the pursuit of specific production and employment strategies that national institutions generate. As a result, the institutional arrangements are very likely to continue to channel the way in which technological advancements are adopted and adapted by firms and workers.

A second important specification is that the relation between technology and inequality does not need to reflect overall societal patterns. In the last twenty years, socio-economic literature has tried to explain changes in national patterns of occupational change and wage inequalities through a shift in labour demand due, almost exclusively, to technological progress. Expectations, however, are not necessarily consistent with overall patterns (Bogliacino, 2014). In fact, as essential and ubiquitous as it is, technology is not the only factor shaping western labour markets. Institutions, culture and power-resources – other than moulding the impact of technology – have an impact of their own (Kristal and Cohen, 2017). Overall transformation in inequalities and employment structures results from a multitude of forces other than technological change.

Besides mapping different institutional configurations across countries, socio-economic literature has identified several sets of institutional domains that shape how technological change influences the organization of labour. These include, among the many, industrial relations and wage-setting institutions, the welfare state and the educational, vocational and training system. Starting from this literature, the rest of this chapter will analyse the possible moderating mechanism of these institutional domains on technological change's impact on employment, occupational structure, and income inequalities.

Labour costs and wage-setting institutions

A long strand of literature has emphasised the crucial role of labour costs, and thus wage-setting institutions, as determinants of labour market outcomes in political economies transitioning to post-industrial economies.

This understanding is founded on the seminal work of Baumol (1967). Baumol's theory rested on two main assumptions. First, he stressed the distinction between productive technologically advanced sectors and technologically lagging ones. He further

argued that the distinction between sectoral technological capacity is rooted in the role of labour in that sector. While in some sectors, such as manufacturing, labour is "primarily an instrument" for the attainment of the final product, in other sectors, such as personal services or entertainment, labour is "itself the end product" (Baumol, 1967 Pg. 416). This difference led to an uneven capacity for technological development and productivity growth. If, in activities such as manufacturing, it is possible to cumulative substitute labour inputs and raise labour productivity, it is almost impossible for sectors in which labour is the main – if not the only – component.

The second assumption of Baumol's theory is that wages in the two types of activities are strictly connected. Assuming a certain degree of labour mobility between sectors, it is unrealistic to expect wages in technologically advanced and highly productive industries to continue to rise while wages in the interpersonal service sectors lag behind. Instead, the two evolve together because of market mechanisms and egalitarian wage-setting institutions.

These two assumptions have important implications for the impact of labour replacing technologies on the number of jobs available. On the one hand, technological change increases productivity and wages while reducing the demand for labour in the "progressive" sector. On the other, it increases wages with no impact on productivity in the technologically lagging sector, thus increasing product prices. Therefore, if demand for these products is not highly price inelastic, labour demand in both sectors will decline.

Thus, according to this perspective and in the absence of other factors, the result of technological development in case of a close match between labour costs in technologically advanced and technologically lagging sectors is growing unemployment. The reason is that productivity increases in the former industry do not produce positive demand spillovers to compensate for the labour-saving effect of technology (Iversen and Wren, 1998).

It is important to stress that this result is strictly related to the price and income elasticity of the goods produced by the technologically lagging sector. Services like healthcare and education have proven to be strongly price inelastic and income elastic. As a result, employment in these sectors has continuously grown despite lagging productivity and rising prices. However, most non-automatable low-level occupations have very high price elasticity.

From these premises, political-economic literature has highlighted the risk of technological unemployment in contexts characterised by strongly egalitarian wage-setting institutions. Minimum wages and strongly centralised and coordinated collective bargaining systems may keep wages in low productivity sectors too high, inhibiting the

possibility of generating new jobs to compensate for losses due to technological change. The result is a trade-off between employment and equality (Iversen and Wren, 1998; Oesch and Menés, 2011).

In any case, the major losses are likely to be suffered by unskilled rather than skilled workers and labour rather than capital owners. Since technology remains, in most cases, complementary to high skilled-labour and substitutes for low-skilled one, even in contexts of strongly egalitarian wage institutions, low-skilled employees may be those experiencing higher unemployment risks.

Other than employment levels and earnings inequalities, wage-setting institutions may influence employer choices concerning their demand for different jobs and the skill and tasks requirements of occupations. For example, high minimum wages may drive companies to invest in workers' productivity and supply comparatively more highly skilled occupations by making the development of low-skilled positions less profitable. As a result, depending on the wage-setting institutions of the country, a comparable shift in labour demand due to technological development may have quite diverse impacts on occupational structures (Acemoglu, 2001).

This perspective has been recently spurred by the observation of diverse patterns of occupational change across countries defined by different institutional arrangements. For example, in Anglo-Saxon countries, characterised by very high wage flexibility, scholars observe occupational polarisation. That is the simultaneous growth of employment shares in high-level and low-level occupations and a decline in mid-level ones. In Continental and Nordic countries, we more often observe occupational upgrading (Oesch and Menés, 2011; Nellas and Olivieri, 2012; Oesch and Piccitto, 2019).

Finally, higher labour costs can incentivise employers to adapt the work content of low-skilled jobs in response to technological change by making them comparatively more productive. This can be done by extending their range of tasks and responsibilities through on-the-job and continuous training.

Eventually, egalitarian wage systems directly influence firms' strategies, which in response to changing labour supply due to technological displacement, may decide if generate or not new positions – and what kind of positions – in non-automated services based on their costs. However, employers are not the only providers of these services, and welfare states also play a crucial role.

Welfare state

In his classical work, *The Three Worlds of Welfare Capitalism,* Esping-Andersen (1990) introduced the fundamental idea that the nature of national welfare state systems would have played a vital role in the evolution of labour markets in the transition from industrial to post-industrial economies. Far from being a simple source of social protection and redistribution, welfare states are seen as key drivers in the process of social stratification.

The classic understanding of social policy suggested that the primary purpose of the welfare state is to shelter individuals from labour market-related risks and guarantee a safety net for people unfit or unable to work. However, modern welfare states go much further than that and are responsible for several aspects of the life cycle, such as optimising people's capacity for work, guaranteeing good pay and working conditions, and generating employment.

Furthermore, the welfare state mediates people's conditions for labour market exit and entrance. As a result, welfare states have a crucial role in promoting the creation of new jobs and in regulating labour supply in response to changes in employment levels. This role is highly relevant in shaping the relationship between technological change, employment structure and inequalities.

There are, in fact, at least two mechanisms through which the welfare state can influence the transformation of labour markets in response to rising automation. First, by directly affecting wages, labour supply and labour costs. For instance, by regulating unemployment benefits and retirement age. In fact, by restricting or expanding labour supply, welfare state policy can influence labour costs and thus firms' practices. These mechanisms refer to the discussion on wage-setting institutions treated above.

Second, through its overall "Keynesian" stimulus of demand and creation of new jobs. The welfare-state can become a source of absorption of new labour market entrants. As pointed out by Esping-Andersen, "Modern welfare states are no longer systems of social provision only. They have, in many nations, become virtual employment-machines, often being the only significant source of job growth." (Esping-Andersen, 1990, p. 149)

One type of occupation is particularly relevant in the relation between welfare states and technological change: interpersonal service workers (Oesch and Menés, 2011). Education and care services are little impacted by technological change, and people need to provide them in person. Different welfare states differently influence the growth rate of employment in the service sector and the nature of this employment by promoting the creation of social-services activities.

Following Esping-Andersen's classification of welfare states, these services can be provided by the state, the family or the market. Since losses in employment due to technological change are primarily compensated by new jobs in non-automatable services, these three agents are responsible for creating new jobs influencing the final impact of technology on labour markets.

Therefore, welfare states are pivotal for how countries deal with technological induced "cost disease." The results are diverging trajectories of occupational change between the three well known ideal-typical welfare state regimes: liberal, conservative, and social-democratic (Oesch, 2015). Moreover, the type of jobs and opportunities created to compensate for job losses due to automation are necessarily related to the evolution of social inequalities. According to Iversen and Wren (1998), the combination of wage-setting institutions, welfare state public spending, and automation eventually gives rise to the well-known trilemma of the service economy and diverging post-industrial trajectories of employment and inequalities across institutional regimes.

In liberal countries, where the market is the leading provider of new occupations, low-skill, low-wage jobs in personal service can proliferate simultaneously to high-level technical and managerial positions complementary to technology. This means that low-skilled and mid-skilled workers displaced from mid-level occupations are relocated to worst positions while high-skilled ones can move upward in the occupational structure. Therefore, the result is an increase in inequality based on a skill divide. Income inequalities between classes, defined in regard to their relation to capital, are also likely to exacerbate since low-income protection allows wages of low-skilled employees to decline while returns from capital increase due to improvements in productivity.

In Nordic countries, where the state hires large numbers of workers, inequalities are likely to be contained. Here "junk jobs" are not allowed to proliferate due to high labour costs, and instead, better paid social-service activities are generated by the state. In this context, low- and mid-skilled workers displaced by the automation process can be relocated to public positions, and skilled based inequalities are contained. Class inequalities are also limited since the state redistributes the gains from higher productivity through income support, social benefits and direct employment creation. Technological change results in a generalised upgrading in occupational position and income at the expense of higher public debt or taxation.

Finally, in Continental countries, where egalitarian wage-setting institutions are combined with a conservative welfare-state, neither the market nor the state generate new jobs in personal services or social-service activities. The results are higher unemployment

and inactivity for low and mid-skilled workers displaced by the automation process. Rather than income inequality, the results are inequalities of opportunities based on a skill divide, with high-skilled workers benefiting from new occupations complementary to technology and low-skilled ones that struggle to remain in the labour market. Class income inequalities are contained through minimum wages and coordinated collective agreements capable of redistributing, at least in part, the gains from growing productivity related to technological improvement – with notable differences, however, between central and southern labour markets and welfare state systems. The process of automation in a conservative kind of welfare state will, therefore, most likely strengthen labour market segmentation, increasing the divide between labour market insiders and outsiders. Here egalitarian wage policies implemented through minimum wages and collective bargaining are conducted in favour of the employed workforce, limiting the opportunity for job expansion for outsiders.

Educational and vocational training systems

A third important factor is the supply of skills available in a political economy. Firms determine their production strategies, and consequently, their demand for labour, partially based on the availability of production factors (Hall and Soskice, 2001; Oesch and Menés, 2011). It follows that demand for high-skilled rather than low-skilled labour is at least in part dependent on their supply (Goldin and Katz, 2007). Indeed, in their recent work, Bynjolfsson and McAfee (2014) suggest that the capacity to endow workers with the right set of skills is the main factor determining whether modern political economies will be capable of harvesting the benefits of recent technological change.

The supply of skills is determined, on the one hand, by the rate of participation in tertiary education and, on the other, by the nature of the vocational and training system (Allmendinger, 1989; Powell and Solga, 2010). The former aspect defines the overall number of individuals with a college degree – i.e., high-skilled labour supply. The second, the skill type and adaptability of low- and mid-educated workers. These two factors combined determine the type of skills available, which, in turn, influence the production and employment strategies pursued by individual firms.

The overall supply of skills is crucial since it influences the availability and relative cost of high rather than low-skilled labour. In contexts characterised by strong educational expansions, firms may find it more convenient to develop employment strategies and produce goods and services that predominantly use high-skilled productive workers since these are comparatively less expensive. As a result, a process of technological change in

the context of a sizeable high-skilled labour supply will more likely result in an overall occupational upgrade, with a higher share of college graduates filling better positions, possibly spilling over to low- and mid-skilled individuals. On the other hand, when firms and employers are faced with a high supply of low-skilled workers, they may find incentives to increase low-level occupations such as junk services.

Growing shares of highly educated workers may create incentives to generate new high-skilled jobs and eventually contain overall inequalities stemming from the introduction of labour replacing technologies. However, the same process can increase inequalities between high-skilled and low-skilled workers since opportunities for this latter group may reduce.

Moreover, skill-based inequalities and occupational polarization can be contained through an encompassing vocational and training system capable of endowing even less-educated workers with the right skills to cope with technological change. For instance, Maurice, Sellier and Silvestre (1986) find that the same firms hire vocationally trained workers to fill supervisory positions in Germany and college-educated ones in France. A similar difference is found by Finegold and Wagner (1998) between German and British firms.

In this regard, Estevez-abe, Iversen and Soskice (2001) distinguish between three broad types of skills defined by their degree of portability: firm-specific, industry-specific, and broad occupational and general skills. First, firm-specific skills are provided through extensive on the job training. These skills are valuable to employers but have low transportability and, unless there are substantial employment and social protection, represent a risky investment for employees. Second, industry-specific skills are provided through vocational training systems and are valuable to employers in the same industry. Finally, general skills are provided by the broader educational system and are potentially valuable to every employer and highly portable, therefore guaranteeing employability for workers.

The extent to which each country is oriented towards providing one of these skills is intrinsically related to the broader institutional system and its incentives for both workers and employers. For instance, strong social and employment protection encourages workers to invest in firm-specific skills by reducing uncertainty about their future. At the same time, coordinated wage-setting institutions promote firms' investments in training by containing the risk of poaching by other firms. Therefore, the features of the training system are closely connected to the broader institutional system.

As a result, firms operating in coordinated contexts may be driven to promote firm-level and industry-level training to endow workers with the skills and ability necessary to cope with the technologically induced restructuring process. Here, the skill-related inequalities are contained since even less skilled workers can adapt to new technologies that are typically complementary to high skilled labour.

Furthermore, a well-developed vocational training system can endow pupils who do not have good academic records with the right competencies to enter new technically intensive labour markets (Solga, 2014). Here firms can take advantage of a labour force endowed with stronger skills at the middle of the skill distribution (Heisig and Solga, 2015). Consequently, they face fewer incentives to substitute core middle-class workers but rather adapt their duties to face technological innovation.

However, a potential issue for countries characterized by stronger vocational and training systems oriented towards providing highly specific skills is that the skills given are mainly pre-determined and restricted to existing industries and occupations. As a result, skill formation systems favouring highly specialized rather than broad skills without continuous retraining opportunities impede the creation of new unprecedented occupational domains.

A second potential downside of skill systems defined by firm- and industry-specific skills is that employers and employees have a stake in supporting employment protections. The result is a potential alliance between skilled labour market insiders and their employers favouring social protections advantageous to them and detrimental for labour market outsiders with no access to firm-specific training.

Finally, the state can take charge of workers' employability by promoting active labour market policies and training programs beyond vocational schooling and despite individuals' employment conditions. Indeed, employment regimes theory has criticized the limited division of skills regimes promoted by the production regimes approach (Gallie, 2011). For instance, Edlund and Grönlund (2008) suggest that skill policy can vary in response to the degree of inclusiveness of the employment and welfare regime. Thus, inclusive regimes, differently from dualistic ones, adopt several training strategies that favour not only middle-skilled workers but also lower-skilled and the unemployed. These are usually training programs to provide considerable levels of general skills at the bottom of the skill distribution.

Therefore, state promoted active labour market policies in inclusive institutional regimes include training programs that endow unemployed individuals and low-skilled workers with the proper skills to respond and adapt to transformation spurred by current

technological change. Since, in this case, training is usually offered simultaneously to unemployment benefits, training in specific skills is less risky for both workers and employers. An exemplary case is the advanced continuous vocational education and training model of the Scandinavian countries, which does not discriminate between workers in jobs and unemployed (Damian et al., 2019). The result is contained inequalities among all the lines mentioned above. In this context, firms face few incentives to adopt low-road employment production strategies when adapting to technological change since they can rely on a highly skilled labour force with up-to-date skills at all levels of the educational distribution,

Industrial and workplace relationships

The role of industrial relations systems can be considered crucial in the mediation of technological change for reasons beyond its capacity to regulate wages and labour costs[5]. Industrial relations institutions include all the norms and rules that regulate the interaction between employers, workers, their representative organizations, and the state. On the one hand, they partially regulate the distribution of power between social partners and, therefore, unions' ability to guarantee good working conditions and redistribute gains from technological change. On the other hand, they determine how unions and workers influence firms' production strategies through participation and involvement in decision-making.

As highlighted above, theories of class-biased technological change have suggested that the introduction of new technologies reinforces the position of employers by deskilling and disempowering workers (Braverman, 1974; Kristal, 2019; Kristal and Cohen, 2017). In this perspective, technological development is conceived as necessarily embedded in an uneven distribution of power and antagonistic relationships between classes. According to this literature, technology can decrease workers power by reducing employment in historically unionized sectors, increasing polarization and conflict between workers, facilitating anti-union tactics, and improving employers' monitoring ability.

[5] The institutional spheres of wage setting institutions and industrial relations are overlapping in many respects. For the present discussion the two are discussed separately. Wage setting institutions are considered as those institutions that regulate costs and wages, and which are usually, but not exclusively, identified in the various levels of collective bargaining and national wage regulations. Industrial and workplace relationships here are more broadly referred to as the norms and rules that regulate the interaction between employers, workers, and their representative at the proximity level and how this interaction shape management choices and firm strategies in the organization of work. These usually includes issues such as employees' participation in decision making, employer-employee conflict, the degree of discretion and flexibility allowed to workers, the organization of team work, and the sharing of information. The two areas are clearly closely related; however, they are often discussed by quite different literature and engage different issues. For the sake of clarity, I decided to discuss them separately.

However, comparative political economy has recognised that the role of unions can go far beyond organisation and mobilisation (Soskice, 1990, 1999; Shalev, 1992). Union's institutional power resources can result from at least two other arrangements. First, they can stem from government-generated rights, which make the engagement of unions in politics and decision-making inevitable (Rigby and García Calavia, 2018). Second, unions can be recognised as beneficial actors – by both employers and the state – because of their role in wage determination and in-company relations. Literature has stressed that in more coordinated market economies, unions promote firms' coordinated production strategies and sustain their institutional comparative advantage (Soskice, 1999; Streeck and Recchi, 1994; Thelen, 2001).

These functions may involve different levels of labour market regulation, from national policy making to firm-level management. At the firm level, key institutions that regulate workplace interactions include coordinated decentralized bargaining rights, mandatory workers representation, co-determination, and work councils. At the national level, they entail participation in policy-making and policy implementation through corporatist arrangements, recognition of collective bargaining rights, and extension clauses.

If institutions of this kind are in place, changes in the balance of power due to technological change may be contained since unions can count on historically established rights over the management of employment relations at the national, local, sectoral, or establishment level. The class bias of technological change can thus be contained by the presence of strong unions or institutional frameworks that support the regulatory positions of the social partners.

Moreover, industrial relations arrangements may elicit the pursuit of different production and employment strategies due to the support they provide to employers to adopt more or less coordinated activities. In this perspective, typically advanced by promoters of production regimes theories, industrial relations are not necessarily an arena of confrontation between social parties.

As stressed by the original theory of VoC, firms face several crucial coordination problems vis-vis their own employees. In this regard, companies' fundamental challenge is ensuring that employees have the necessary competencies and work effectively with other workers and management to achieve the firm's goals. In establishing these relationships, employers face several adverse selection problems, moral hazard and information-sharing. Indeed, workers possess essential and specialized information about the firm's operations that can be of value to management. They, therefore, have the ability to either share or

withhold this information. The kind of relationships that companies form to tackle these challenges shape their own competencies and the nature of an economy's production regimes.

Employers have more than one way to deal with such issues. The first is to centralize power and decision-making, increase monitoring, and reduce the information available to workers. The second is to elicit employees' participation in decision-making by taking advantage of their knowledge of production processes. Technological change has traditionally played a critical role in explaining divergent monitoring choices, and a long debate in organizational studies has contended whether computerized types of equipment were instruments to either centralize or de-centralize information and decision-making (George and King, 1991).

Given the strong right to participation guaranteed to workers in CMEs, employers face more substantial incentives to develop production strategies that rely on a highly skilled labour force that is given significant work autonomy and is encouraged to share its knowledge to improve product lines and manufacturing processes. In this context, employers develop production strategies that require the constant participation and information sharing of employees; hence they have little reasons to utilize new technology to deskill and remove discretion from workers since their participation is essential to exploit the firm's core competencies.

In LMEs, where institutional arrangements of this kind are not in place, employers and employees face more explicit risks and moral hazards. Therefore, their comparative institutional advantage is built on pursuing production strategies that closely resemble traditional Fordist modes of production. In contexts like this, employers face more significant incentives to use technologies to centralize information and increase control over work processes since it improves the exploitation of their core competencies.

Conclusions

This chapter has highlighted the potentially disruptive and transformative power of technological change in terms of overall changes in several aspects of the organization of labour, including mainly employment levels, the occupational structure, earnings, and working conditions. At the same time, it has stressed the relevance of historically defined and rooted institutional systems in moderating the revolutionary transformations that accompany the introduction of new and powerful production technologies.

Despite a long strand of sociological literature has stressed the importance of contextual factors in moderating the impact of technological change, the existing dominant theories of technological change continue to highlight the inherent bias of specific technologies in favour of specific production factors or groups of workers.

Building on a long tradition of neo-institutionalist approaches, this chapter has highlighted that the way firms adapt their activities in response to the availability of new and more efficient production technologies is influenced by the limits set by the existing institutional arrangements. These limits can be defined in terms of the institutional support for the pursuit of more or less coordinated production strategies – as suggested by production regimes theories – or by the distribution of power resources between the main actors involved – as suggested by the employment regimes approach. However, despite differences in the antecedents that define national institutional arrangements, both approaches suggest that employers' choices are bounded by the existing norms and rules set by the national institutional configuration. Therefore, firms' restructuring does not easily follow the course of action indicated by the most efficient deployment of the technology considered.

The chapter has gone through several institutional domains characteristics of modern industrialised political economies, such as wage-setting systems, the welfare state, educational and vocational training systems, and industrial relations. By defining the costs, quantity and quality of factors available, these institutions generate incentives for employers, workers, and the state to adopt specific production strategies in response to technological change.

Clearly, these dimensions are not exhaustive of the several factors which may act as "countermovement" against the transformations in place. Still, the dimensions considered have been identified in the comparative political economy literature as critical determinants of different institutional regimes, relevant in the transition to post-industrial economies and shaping firms' production strategies – and therefore workforce composition. Thus, the main conclusion is that it is a strong oversimplification to evaluate the impact of technology without considering the specific institutional context in which its introduction is embedded.

Technological change is likely to strengthen the defining characteristics of different institutional arrangements. In this way, an institutionally informed theoretical approach to technological change emerges in sharp contrast to convergency theories, which suggest that technological change, among many other exogenous forces, would produce similar working conditions and work organization across developed countries.

Throughout the chapter, one potential pitfall is that technology has been mainly treated as an exogenous factor whose development and adoption are independent of specific contexts. However, a long strand of interdisciplinary literature has highlighted how countries, industries and periods differ in their innovative performance (Acemoglu, 2002b; Hall and Soskice, 2001; Pavitt, 1984). Historically, these differences have involved how much a country innovates and what it innovates in (Casper and Van Waarden, 2005). However, the flexibility of recent production technologies has rendered them quite pervasive across every context. Information and communication technologies, artificial intelligence and robotics can be easily adapted to various production strategies, and countries have seemed to differ in the magnitude or speed of technological adoption rather than in the type of technologies adopted (Comin and Hobijn, 2004).

The introduction of new technologies has become inevitable and ubiquitous across every context. Highly competitive markets and internationalised economies force firms everywhere to take up the most productive machinery and software available. Still, the process of employment restructuring induced by the simultaneous employment replacing and productivity-enhancing effect of new technologies can be channelled by the nature of the institutional system in which it takes place. Therefore, we can expect several potential inequality outcomes related to technological change and defined by features of the institutional context.

The differences between institutional regimes are strengthened by the existence of *institutional complementarities*. Two institutional domains are sad to be complementary if one institution's presence (or efficiency) improves the other's returns (or efficiency). Nations with some sort of coordination in one sector of the economy should develop complementary practices in other areas. Consequently, different types of institutional practices should not be spread throughout nations at random. Instead, when employers in different nations adapt to technological change, it is reasonable to expect some clustering along the characteristics that separate existing institutional regimes.

The final impact of technological change is influenced by the combination of all of these factors. Eventually, what the future of work will look like is a matter beyond technological change. It will depend on the interaction between innovation and historically established features of the institutional systems in which it is introduced. While it is difficult to make a precise prediction, looking at the institutional domain reviewed in this chapter, it seems quite clear that technology-related socio-economic transformations will differ across historically defined institutional arrangements, suggesting that the possible

results in terms of inequalities, employment, occupational structures, and work quality are far from univocal.

Chapter II

Robots, Tasks, and Class:

Labour-replacing Technologies and Changes in Occupational and Class Structures Across Institutional Regimes*

Abstract

This chapter examines the impact of labour-replacing technologies in Western European countries from 1997 to 2017. More precisely, it investigates the relationship between the introduction of industrial robots and changes in unemployment risks, workforce composition, and occupational stratification across countries belonging to three institutional arrangements: Nordic, Continental, and Southern European. Results reveal that the relationship between industrial automation and changes in employment and class structures is highly embedded in national institutional configurations. Overall, findings suggest that industrial automation is associated with different outcomes across Europe with overall upgrading of employment structures in the Nordic and, to a lesser extent, in the Continental arrangement but with a downgrading of the employment structures, accompanied by higher unemployment risk for less-educated male workers, in the Southern European arrangement.

* This chapter is the result of a joint work with Paolo Barbieri and Giorgio Cutuli from the University of Trento

Among the many changes brought by technological change, the transformation of occupational and class structures has always received primary interest in socio-economic research. As a result, scholars have documented massive processes of occupational polarisation or upgrading in almost every advanced economy in the past thirty years. Technological change has been recognised as the most important factor behind these long-term developments due to computers' ability to substitute for routine-tasks concentrated at the middle and bottom levels of the occupational structure (Autor et al., 2003; Goos et al., 2009; Haslberger, 2021; Milanovic, 2016; Oesch & Menés, 2011).

The fact that automating technologies of the last decades are good substitutes for routine-tasks typical of mid and low-level occupations makes these modifications plausibly non-neutral from a social stratification standpoint. Relatedly, notwithstanding the feeble empirical support in countries other than the US (Brandolini et al., 2018; Dallinger, 2013: Oesch and Piccitto, 2019), the idea of a "*hollowing out of the middle classes*" has gained popularity in the literature (Pressman, 2007, 2009; Scott & Pressman, 2011; OECD,2017).

However, as argued in the previous chapter, one of the problems with a task-based perspective is that it conceives the relation between technological change, labour market and social stratification dynamics as being strongly *deterministic* and mainly defined by the technical capabilities of machinery. Nevertheless, automation processes do not occur in a vacuum; instead, they are embedded in historically defined national *institutional arrangements*. As a result, technology may have very different consequences across countries, depending on the features of the institutional context.

While several contributions have traced back the patterns of occupational change displayed in distinct Western countries to factors other than technical innovation (Fernández-Macías & Hurley, 2017; Hasleberg, 2021; Oesch & Ménes, 2011), the diverse relationship between a direct measure of technological adoption and labour market outcomes across different contexts has so far been tested mainly in the domain of earnings inequalities (Kristal, 2013; Kristal & Cohen, 2015; Kristal & Edler, 2020; Parolin, 2021).

The focus of this chapter lies on the existence of a context-specific relation between the adoption of industrial robotics, employment composition and class structure across Western European countries from 1997 to 2017.

The chapter adopts a theory-driven, cluster-based comparative perspective to highlight the importance of cross-country institutional differences in moderating the consequences of robotisation. It builds on the classification of institutional clusters in Europe suggested by Boeri (2011) and supported by a vast theoretical and empirical literature that distinguishes between a Nordic, Continental, Southern, and Anglo-Saxon

regimes[6] (Edlund & Grönlund, 2008; Gallie, 2011; Häusermann & Schwander, 2012; Iversen & Stephens, 2008; Muffels & Luijx, 2008; Schwander & Häusermann, 2013).

Moreover, in line with the literature on the institutional embeddedness of the labour markets (Barbieri, 2009; Boeri et al., 2012; Davis & North, 1971; Eichhorst & Marx, 2010; Maurice et al., 1986; Nee & Swedberg, 2005), and more specifically on the interplay of educational and labour market factors in shaping employment outcomes (Breen, 2005; Brzinsky-Fay, 2017; Scherer, 2005; Wolbers, 2007), it considers three national institutional features that strongly vary across the three analysed clusters to be particularly relevant for the dynamics under scrutiny: the degree *labour market dualisation*[7], the average levels of education supported by the *educational systems*, and the degree of skill specificity encouraged by the national *system of skill formation*. Considering these dimensions yield a typology of ideal-typical "institutional arrangements" that will shape the impact of technological innovation and robotics diffusion on occupational and class structures.

Eventually, the chapter has multiple objectives. The first one is to highlight the diverse relationship between industrial automation and overall changes in employment structures across western European countries. Second, to investigate how this relationship diversely affects individuals based on their education and gender across contexts. Finally, to investigate to what extent differences in skill provision and training systems relate to the observed institutional heterogeneity in the relationship between automation and occupational outcomes – i.e., whether the effects of automation on specific groups of workers are less detrimental in contexts characterised by more training participation.

In order to address the first objective, the chapter adopts longitudinal data for 49 NUTS1 regions from 10 European countries clustered across institutional regimes and observed for 21 years. To investigate the second and third objectives, the analysis is based on a pseudo-panel built on region, gender, and educational level observed for 21 years and clustered across institutional regimes.

It contributes to the existing literature on automation and occupational change in three ways:

---

[6] Given the specific interest in industrial automation in the form of industrial robots, this relationship is not explicitly investigated in the Liberal settlement—Ireland and the UK, the fourth ideal-type. In fact, these countries have experienced a very limited growth in industrial automation throughout the observed period (see figure A2. 2 appendix). Eastern European countries were also excluded for data limitation. Data on regional industrial composition at early periods were not available for the majority of these countries, moreover occupational coding in the micro data is often much more aggregated at levels not comparable to other countries.

[7] In the following, labour market 'dualization' and 'segmentation' are used as synonyms. Segmentation here does not refer to Segmentation theory à la Piore (1978) – thus Demand side originated – but as the term is used in the literature on labour market deregulation at the margins or dual-EPL reforms or two-tier labour markets or segmented/dualized labour markets (Bentolila et al. 2020).

First, by taking a comparable indicator of automation – industrial robots – findings suggest that far from being a deterministic process, the relation between automation and the employment and class structure is moderated by the specific institutional context in which technology is introduced. *Second*, results highlight the potential role of technological change as a source of context-specific social stratification, leading to different modifications of the employment and mobility opportunities for individuals characterised by different educational levels and gender across institutional regimes.

Finally, the results stress the importance of the skills formation institutions in moderating the impact of automation on employment structures and inequalities. In regional contexts characterised by extensive training provisions (even for the low-skilled), labour-replacing technologies appear to have far more positive outcomes and go hand in hand with less inequality between educational groups.

The relationship between automation and occupational and class structures

The relation between industrialisation and changing class structures in Western societies has long been a central topic of classical research on social stratification (Golden, 1957; Soares, 1966; Treiman, 1970; Erikson et al., 1979). According to the so-called liberal theory of industrialisation, processes of automation have deeply transformed the occupational and class distribution of Western political economies by decreasing the proportion of people engaged in agriculture, shifting the occupational distribution from the production of goods to the provision of services, and generating entirely new occupations (Bell, 1973; Treiman, 1970). Similarly, early economic research indicates that the process of technological change that began in the 1970s has been largely "skill-biased", thereby increasing the opportunity and demand for highly skilled workers and eventually leading to an upgrading of the employment structure (Autor et al., 1998; de Vries et al., 2020; Goldin & Katz, 2007).

Despite important differences, both liberal theory and skill-biased technological change (SBTC) theory predict that a burst of new technology will cause an increase in the demand for highly skilled workers and should – in turn – lead to an overall upgrading of the occupational structure by shifting employment from low-level, routine-intensive occupations to high-level, knowledge-intensive ones.

These expectations have not gone unchallenged, with socio-economic research having been quick to point out that several Western economies have experienced an increase in

the proportion of workers employed not only at the top but also at the bottom level of their occupational structures (Autor & Dorn, 2013; Goos et al., 2014). As a result, the theory of Routine-Biased Technological Change (RBTC) has become prominent in studying the relationship between technological change and occupational change. RBTC argues that technologies that have been introduced in recent decades have served as good substitutes for explicit and codifiable "*routine-task*" operations (Autor et al., 2003) and that several tasks exist that require manual and intellectual skills, in addition to high-level reasoning, and for which technological substitution has been limited.

RBTC theory further suggests that routine tasks are mainly concentrated in mid-level occupations, such as production workers and clerks. Autor et al. (2003) group occupations into different categories defined by their content and their degree of routinisation: non-routine cognitive analytical content, non-routine cognitive interactive content, routine cognitive content, routine manual content, and non-routine manual content. By reducing the demand for routine-intensive occupations at the middle level of the employment structure and creating incentives for the growing demand for non-routine occupations at the top and/or bottom level, automation fosters dynamics of occupational polarisation.

In the same vein, Breen (1997) stressed that changes in technology and new work organisation and monitoring methods worsen the situation of those occupations in mid-low class positions, unable to hedge themselves from new market and technological risks. Therefore, intermediary jobs, routine non-manual employees, lower-grade technicians, and supervisors of manual workers are especially affected by these new processes. In contrast, higher white-collar and service class workers will maintain their peculiar "service relationship" within the firm, thus sheltering their positions and gaining from technological and organisational change.

While RBTC offers important insight into understanding the relationship between technological change and employment composition, less attention has been paid to its implications for socio-economic inequalities. In Western European countries, routine-intensive occupations have traditionally been unevenly distributed among workers of different genders and educational backgrounds. It follows that robotics acts as a stratifier as it implies a non-neutral distribution of changing employment opportunities, unemployment risks, and wage consequences for distinct social groups. The distribution of tasks among the workforce closely reflects occupational stratification (Erikson et al., 1979; Rose & Harrison, 2007), with manual tasks – both routine and non-routine – predominantly performed by the working classes and with abstract cognitive tasks concentrated in the highest ISCO categories and ESeC classes (Figures A2.1 and A2.3, Appendix II).

Technology into context: the moderating role of national institutional arrangements

Several contributions in the socio-economic literature have revealed that patterns of occupational change can differ across countries despite similar evolutions of technological endowments (Fernández-macías, 2012; Fernández-Macías & Hurley, 2017; Oesch, 2015; Oesch & Menés, 2011; Oesch & Piccitto, 2019). Furthermore, a long-standing tradition of neo-institutionalist research, from the political economy of capitalism (Goldthorpe, 1984) to production and employment regimes theories (Gallie, 2007; Hall & Soskice, 2001; Mandel & Shalev, 2009), has suggested how national institutional arrangements orient the consequences of economic transformations both at macro and micro level. It follows that technological innovation too will result in different labour market and stratification outcomes once its impact is moderated by the specific institutional arrangements.

Moreover, a long tradition of comparative socio-economic literature has highlighted the existence of broad clusters of European countries characterised by similar institutional configurations (e.g., Boeri, 2011). Following this literature, this chapter focuses on three well-distinguished institutional regimes: Nordic, Continental, and Southern European. Albeit many differences exist, this section suggests that there are three main institutionally defined characteristics that play a crucial role in defining the heterogenous relationship between automation and changes in employment and class structures: the degree of labour market dualisation, the average levels of education promoted by the educational system, and the degree of skill specificity supported by the national skill formation and training systems.

The process of "two-tiered" labour market flexibilisation implemented in Europe prompted a process of normative dualisation (Emmenegger et al., 2012; Palier & Thelen, 2010; Bentolila et al., 2020) between a protected core workforce and a peripheral, less-skilled, less-trained, and less-paid workforce (Barbieri & Cutuli, 2018; Cutuli & Guetto, 2013), endowed with reduced social and labour rights (Brülle et al. 2019; Passaretta and Wolbers, 2016; Gebel, 2010; Polavieja, 2003; Esping-Andersen and Regini, 2000). Although partial and targeted deregulation represented a generalised trend of labour market flexibilisation in Europe, several contributions have underlined the existence of a cross country heterogeneity in the strictness of labour market dualisation (OECD, 2014), which increasingly worsens moving southwards: Southern European countries show the most severe patterns of insider-outsider dynamics (Barbieri et al., 2015; Barbieri & Cutuli, 2016;

Häusermann & Schwander, 2012; Eichhorst, Marx and Wehener, 2017; Bentolila et al. 2020).

On the demand side, in response to technical changes, the more segmented and less inclusive labour markets represent an incentive for firms to take up low-road competition strategies, thus spurring employment volatility and increasing employment in lower-level positions, following a strategy of labour-cost competition based on a selected core workforce of skilled insider workers and a buffer of low-qualified secondary labour market workers.

Side by labour market dualisation, the characteristics of the educational and training system strongly differ across European clusters of countries and can be expected to influence, both from a demand and a supply side, the impact of automation on occupational and class structures. Firms adapt their production and employment policies to the available quality and quantity of input factors (Hall & Soskice, 2001; Murphy & Oesch, 2018).

At least two dimensions can describe the national supply of skills: on the one hand, the average skill levels and the overall supply of highly educated workers. On the other, the type of skills and the degree of specificity of the skill supply.

The supply of a highly educated workforce influences the availability and relative cost of highly qualified labour (McCollum & Findlay, 2015; Korpi & Tåhlin, 2009). Employers who face a highly skilled labour force are incentivised to increase their demand for high-level occupations. As a result, a process of technological change in the context of a highly qualified and trained labour supply can lead to a high-road employment- and production strategy and an overall occupational upgrading. Moreover, workers equipped with suitable educational levels and qualifications can more easily shift to new occupations emerging from the process of technological change (Fillmore & Hall, 2021), thus sheltering themselves from new technologically-driven market risks thanks to the transferability of their skills and their aptitude to be retrained. The opposite holds for low skilled, less trainable workers.

However, the supply of human capital in a specific labour market is not solely represented by average levels of formal educational competencies. The comparative socio-economic literature stresses the importance of the type and specificity of skills in shaping employers' production strategies and patterns of inequality (Estevez-Abe, Iversen & Soskice, 2001; Gallie, 2007; Hall & Soskice, 2001; Heisig & Solga; 2015; Powell and Solga, 2010), thereby highlighting the relevance of national vocational and training systems and leading to the definition of distinctive skill regimes characterised by the different emphasis on initial vocational training and continuous training.

The degree of skill specificity has important implications for what type of non-manual occupations prosper in response to industrial automation. On the one hand, the vocational orientation of a skill regime can facilitate the transition from routine-manual occupation to cognitive ones through dual school-work systems capable of responding to employers' demands. However, on the other hand, the skills provided are largely pre-determined during secondary education and are mainly confined to existing industries and occupations. As a result, the emergence of new occupational domains is hampered by skill formation systems that promote the development of more specialised rather than broad skills without proper retraining opportunities.

As suggested by Becker (1962), workers with training specific to an industry, occupation, or firm are less likely to leave that industry, occupation, or firm. As a result, workers' industrial, occupational, and firm mobility is restricted, inhibiting the development of new knowledge-intensive occupations in nations with an initial vocational training system geared toward developing more specialised – and hence less transferable – abilities.

Different supply of general and specific skills between vocational and non-vocational systems may not be the only reasons for diverse relationships between technological change and occupational structures. In fact, as shown by Heisig and Solga (2015), the country differences in mean numeracy and literacy skills among intermediate-educated workers are quite small. Other than differences in the type of skills available, the creation of new knowledge-intensive occupations in continental countries characterized by strong VET systems may be partly inhibited due to the close connections between formation systems and the labour market, which often result in high levels of credentialism and occupational closure, thus reinforcing the reproduction of existing occupational domains.

Finally, the degree of skills transferability can be fostered by well-developed systems of continuous training. Participation in training can endow workers with good general skills at all points of the educational distribution and facilitate the transition to fast-growing occupational domains. Thus, occupational upgrading will be more likely in contexts where workers can quickly adapt to new opportunities prompted by technological innovation. High investments in training policies also appear decisive in mitigating skill-based and class inequalities, especially since they allow skill obsolescence to be limited for workers whose formal education is pre-determined and essentially unchangeable. Thus, adult learning and continuous training emerge as crucial policy instruments for poorly educated and unskilled manual workers, whose jobs are most likely to be replaced by automation (Mahnkopf, 1992; Solga, 2008).

Following Davis and North (1971), institutional arrangements (or configurations) indicate the specific institutional mix resulting from the interaction of different institutions and thus favouring – or not – a series of socio-economic outcomes. From the combination of their distinctive systems of skill formation – defined by the overall supply of highly skilled workers, the average degree of skills specificity, and the availability of training programs – and degrees of labour market dualisation, it is possible to distinguish between three institutional configurations relevant for the dynamics under scrutiny: Nordic, Continental, and Southern European countries (Boeri, 2011; Edlund & Grönlund, 2008; Gallie, 2011; Iversen & Stephens, 2008).

In the Nordic arrangement, the highest supply of tertiary-educated workers is combined with high levels of both *occupation-specific and general skills*. Moreover, the availability of well-developed training programs delivers good levels of general and transferable skills for workers at all levels of the educational distribution. Combining these factors provides a valuable stock of human capital to be valorised by firms to develop high-value-added productions strategies based on knowledge- and skill-intensive occupations. At the same time, the limited labour market dualism increases firms' opportunity cost of resorting to a low-skilled peripheral labour force. Here automation is most likely to result in a shift in employment from lower-level occupations to higher-level ones, thus generating occupational upgrade. Moreover, a low supply of less-skilled workers and inclusive training programs shelter low-educated workers from rising unemployment risk.

Similarly, Continental arrangements are defined by relatively high average educational credentials among employees; however, their vocational and training systems are more oriented towards providing industry-specific skills – through a dual-educational system and strong apprenticeship programs – but only moderate levels of general skills, especially for mid- and low-educated workers. Thus, while a relatively large supply of highly skilled workers allows for a shift to higher-level occupations, this is less so than in the Nordic context, where high levels of occupation-specific skills and general competencies are available across the entire workforce. Moreover, the limited supply of low-skilled workers, the presence of a robust vocational and training system, relatively more diffused training programmes, and a less pronounced caesura between primary and secondary labour market segments (at least in comparison with the Southern European cluster) is a safeguard against technological unemployment.

In Southern European arrangements, the combination of a high supply of low-skilled workers[8] and close to the lowest level of combined school and work-based programmes in

[8] See Figure A2.5 appendix.

vocational education (OECD 2020) in a context of highly dualised labour markets with few investments in training or activation policies, puts firms in a situation in which they face few options but to adopt low-road, low-cost, labour-intensive production strategies. Such production strategies foster employment growth at the bottom level of the occupational and class structure and often in the secondary labour market segment. In this situation, automation and technological change lead to increased risk of unemployment for workers provided with low and obsolescent skills and inhibit status upgrading for most groups since skill distribution discourages the development of new, high-level occupations.

Other than the overall distribution of jobs, automation may diversely affect the occupational opportunities of individuals based on socio-economic characteristics. Industrial automation in particular replaces middle and low skilled occupations while generating incentives for the development of more high-skilled ones. As a result, highly educated individuals are more likely to reap the benefits of new growing cognitive occupations. Differences between educational levels are also likely to be moderated by the specific institutional contexts. In countries characterized by more training opportunities and more inclusive labour markets, differentials between levels of education are likely contained. Since we are looking at industrial automation – i.e., automation of manual jobs in manufacturing industries – gender is also likely to be an important dimension of stratification. Blue-collar jobs are in fact historically male-dominated, while many new emerging occupations in the service sectors are female-dominated. As a result, employment opportunities for less educated males are more at risk compared to women. Once again, in contexts characterized by less segmented labour markets and more training opportunities, gender differences can be contained.

Research hypothesis

In light of the previous discussion, it is possible to summarise the key research expectations about the relationship between industrial automation, occupational structures, and social stratification dynamics.

Technological change alters occupational structures by modifying the demand for different types of tasks. However, as decades of literature have signalled, occupational and class structures are associated (Erikson et al., 2012; Ganzeboom & Treiman, 2003; Oesch, 2003; Rose & Harrison, 2007; Weeden & Grusky, 2005; Williams & Bol, 2018). Obviously, occupations and social classes cannot be considered perfectly collinear, and classes may be more heterogeneous than are closed occupational groups. Nevertheless, we

can expect technological changes to be associated with transformations in demand for different tasks and, consequently, with occupational and class structures (*Hypothesis 1*).

That said, economic structures and transformations do not come about in a vacuum: the characteristics of national institutional arrangements moderate the consequences of the spread of technological innovation. Therefore, we can expect automation to generate heterogeneous transformations depending on well-established institutional configurations. Based on the previous discussion, it is possible to expect an overall upgrading of employment and class structure in the Nordic arrangement, a moderate upgrading in the Continental arrangement, and a downgrading in the Southern European arrangement (Hypothesis 2). Given that robots are expected to alter employment and class structure by replacing routine manual tasks intensive occupations, we can expect variation in employment and class structures to take place through a decline in occupation characterized by more routine manual tasks in all contexts and an increase in non-routine cognitive ones in Nordic and Continental countries but not necessarily in Southern European ones (*Hypothesis 3*).

Moreover, automatable tasks are unequally distributed across workers at different levels of education and gender. Thus, we can expect automation to diversely impact employment and occupational opportunity between educational and gender groups across institutional contexts. In contexts characterised by more inclusive labour markets, well developed training systems and overall occupational upgrading, automation is more likely to equally benefit all groups of workers; in contexts defined by some level of dualisation and stronger vocational and training systems, technology-driven occupational change is more likely to benefit secondary and tertiary educated workers, since they are endowed with the proper skills to transition to new occupational domains, without however worsening the position of lower educated ones, since contextual characteristics inhibit the creation of lower level jobs. Finally, in contexts characterised by strongly dualized labour markets, low levels of training, and overall automation related downgrading of occupational structures, no group of workers is likely to benefit from automation since no higher-level positions are generated, and less skilled male workers are more likely to be pushed out of the labour market since they are overrepresented in occupations highly exposed to automation without access to proper retraining opportunities (Hypothesis 4).

Finally, since the type and level of skills are closely connected to the nature of the training system, we can expect the participation in training to enhance workers' likelihood – especially less-skilled workers – of transitioning to better, higher-level positions and

reduce their risk of unemployment, thus limiting technologically induced educational inequalities and partly explaining contextual differences (Hypothesis 5).

Data, methods, and variables

Microdata came from the EU-LFS from 1997 to 2017.[9] Task indices were created using O*Net 3.0, and information on the adoption of robots was taken from the International Federation of Robotics. Analyses are based on a regional-level approach, connecting indicators of robots' exposure at the regional level to regional and individual indicators of employment, occupational level, class composition, and performed tasks. Regions – rather than countries – are taken as the main units of analysis since subnational areas are not equally exposed to automation due to regional sectoral specialisation and industrial and economic development. Similarly, regions within countries differ in their training policies and levels of participation in training. Thus, a regional approach allows to better control for these sub-national heterogeneities (Barbieri et al., 2019).

The analysis was structured on two levels. First, on the regional level, the units of analysis are 49 nuts-1 European regions from 10 European countries observed over 21 years, these regions are subsequently grouped into three clusters.[10] Indicators of regional employment, class structure, and task composition are connected to an indicator of regional robotics exposure.

Second, to investigate diverse effects across gender- and educational groups, individuals from the EU-LFS are aggregated into pseudo-individuals defined by three time-invariant characteristics (region of residence, three ISCED educational levels, and gender). Time-varying averages of the variables of interest are computed (Biegert, 2017), and the group values of each unit are followed over time while treating them as conventional panel observations. In so doing, it was possible to connect longitudinal variation in the response variables for each (regional, gender, and educational) group to the variation of the specific regional level of robotics exposure. Analyses are restricted to the unemployed and employed aged 25 to 60.

Group-level fixed-effects models are applied to exploit the longitudinal dimension of the data to connect the regional indicator of robotics exposure to changes in regional

[9] Germany entered the analysis beginning in 2002 since EU-LFS microdata do not include information on region of residence before this year. Region DE50 is merged to region DE90 and region FI20 to FI10 due to small sample size. For Denmark and Finland NUTS1 correspond to the whole country.

[10] Countries included in the analysis were Italy, Portugal, and Spain (Southern European arrangement); Germany, Belgium, France, and Austria (Continental arrangement); and Sweden, Finland, and Denmark (Nordic arrangement).

occupational composition and pseudo-individual outcomes. In this way, it was possible to control for time-constant unobserved heterogeneity at regional and pseudo-individual levels, respectively.

For the regional-level analysis (Equation 1), three sets of variables (Y_{rt}) are separately regressed on the regional indicator of robotics exposure (Rbt_{rt}) for region r at time t in country cluster c.

$$[1] \qquad Y_{rt} = \sum_{C=1}^{3} \beta_c Rbt_{rt} * Cluster_r^c + \sum_{C=1}^{3} \theta_c X_{rt} * Cluster_r^c + \varphi_t + u_r + \varepsilon_{rt}$$

The first dependent variable refers to the impact on unemployment- and employment structures, the second to the regional class composition, and the third to the task composition of the labour force (see next section for variable descriptions). All models included regional fixed effects (u_r) which control for between region time constant heterogeneity, year fixed-effects (φ_t) to control for common exogenous shocks across regions and a vector of time-varying regional features (X_{rt}) as well as the corresponding vector of coefficients (θ_c), which included the *youth unemployment rate* to control for the time-varying economic conjunctures; the regional share of university graduates over the active population to control for the period- and regional-specific rise in average educational attainment. The rationale for including educational expansion was that it is considered one of the key determinants of occupational upgrading and technological adoption itself. In fact, automation could be confounded by the increase in a more educated workforce and changes in the relative prices of skilled and unskilled labour, which simultaneously increases employment in higher level occupations. Nevertheless, by applying fixed-effects models, we exploit within region variation in the supply of highly educated workers and not between cluster differences in the overall levels of skill supply, which are of primary interest in the heterogeneous effect of robotics across countries. Moreover, educational expansion is also interacted with dummies for country clusters, thus mainly capturing variation in within region educational expansion for regions belonging to the same cluster rather than between clusters. Finally, ε_{rt} represents the region-year specific error term.

To investigate the heterogeneous relation across institutional contexts, each regional variable is interacted with three dummies ($Cluster_r^c$) that indicated the institutional arrangement each region belonged: Nordic, Continental, and Southern European.

For pseudo-individual level analysis, in order to identify the "winners" and "losers" of employment restructuring spurred by automation in terms of education and gender, the models regressed two separate dependent variables (Y_{irt}), the unemployment rate and the

ISEI level of pseudo-individuals, on the regional indicator of robotics exposure (Rbt_{rt}) for pseudo-individual i in region r and cluster c at time t, as shown in Equation 2.

$$[2] \qquad Y_{irt} = \sum_{C=1}^{3}\sum_{E=1}^{3}\sum_{G=1}^{2}\beta_{CEG}\, Rbt_{rt} * Clust_{ir}^{C} * Edu_{ir}^{E} * Gen_{ir}^{G} + \sum_{C=1}^{3}\sum_{E=1}^{3}\sum_{G=1}^{2}\theta_{CEG}\, X_{rt} * Clust_{ir}^{C} * Edu_{ir}^{E} * Gen_{ir}^{G} + \varphi_t + u_{ir} + \varepsilon_{irt}$$

Since pseudo-individuals were generated by intersecting region, education, and gender, pseudo-individuals fixed effects (u_{ir}), for pseudo individual *i* in region *r,* control for time-constant unobserved heterogeneity between these characteristics. Additionally, all the controls specified for the regional model are included. As in Equation 1, in order to investigate the heterogeneous effect of robotics across institutional clusters and groups, each regional variable was interacted with dummies for the three clusters ($Clust_{ir}^{C}$), dummies for the three educational levels (Edu_{i}^{E}), and dummies for the sex of the pseudo-individuals (Gen_{i}^{G}).

Finally, the last set of analyses considered how training exposure moderated the impact of automation on individuals' unemployment risk and ISEI level. For each pseudo-individual, we considered the period average share of the active population between 25 and 60 years who had undergone training in the four weeks preceding the interview ($Train_i$). The variable represents the average of the yearly percentages of individuals in the labour market who have done some sort of taught learning activities, for each gender and education group, over the full 1997-2017 period. Therefore, the variable captures the time-constant and region-specific propensity of individuals in the specific group to undergo training and can be taken as an indicator of contextual between-region differences in training participation for each gender-educational group.

By interacting this measure with the indicator of automation and with dummies for individual characteristics (Equation 3), it was possible to detect the heterogeneous impact of robotics for similar groups of workers in regional contexts characterised by different levels of training. In all the analyses, standard errors were clustered at the regional level.

$$[3] \qquad Y_{irt} = \sum_{E=1}^{3}\sum_{G=1}^{2}\beta_{EG}\, Rbt_{rt} * Train_{ir} * Edu_{ir}^{E} * Gen_{ir}^{G} + \sum_{E=1}^{3}\sum_{G=1}^{2}\theta_{EG}\, X_{rt} * Train_{ir} * Edu_{ir}^{E} * Gen_{ir}^{G} + \varphi_t + u_{ir} + \varepsilon_{irt}$$

A potential problem with this approach is that technology adoption might be endogenous to the specific institutional arrangements, as the degree of labour market flexibility or the type of skills available may generate incentives to adopt more or less

capital- rather than labour-intensive technology. However, if and while institutions may impact the degree and timing of a given technology across nations, it is reasonable to assume that the dominant kind of technology tends to be rather constant among countries at similar stages of development. For example, in terms of industrial automation, robots have emerged as the most ubiquitous technology, even in the presence of country and regional level heterogeneity in the amount of technology adopted.

From an analytical perspective, the main focus of the analysis is not to explain variation in the levels of technological change nor how this potential heterogeneity in levels accounts for distinct patterns of occupational change. Instead, the analyses aim to highlight how a given technology, when implemented, diversely affects occupational and class structures and group-specific labour market advantages across institutional contexts.

Employment and class structure

The occupational position was defined by taking the International Socio-Economic Index (ISEI) scores of each ISCO-88 3-digit occupation and by grouping them into five quintiles. The regional share of unemployed or employed in each of these five groups represented the first set of six dependent variables. Occupations were ranked such that each quintile consisted of the same occupations in each analysed country. Robotics was expected to impact occupational structures and occupational opportunities by replacing specific occupations based on their task content. The type of tasks performed in an occupation was taken as an intrinsic characteristic of the occupation *per se*, independent of the number of people employed in that occupation or the remuneration of the occupation in a specific country. By ranking occupations based on the Europe-wide ISEI-level distribution, occupational quintiles were made comparable across time and countries[11] (see appendix AII.1 for details).

Literature on occupational change and the hollowing-out of the middle classes has almost exclusively investigated changes in the nationally ranked distribution of occupations in terms of wages or income. However, this approach neglects important dimensions of employment relations, such as the degree of work-asset specificity and the ability to monitor work efforts and achievements, which are crucial to enabling a

[11] Other authors have ranked occupations based on the national skill or wage distribution (e.g., Haslberger, 2021). However, using a common ranking for all countries was more suited to this specific research question. By looking at a common occupational distribution across countries it was possible to distinguish whether the association between automation and occupational change was due to different institutional arrangements rather than different occupational distributions across countries.

sociological understanding of the ongoing transformations. Therefore, this chapter extended the analyses focusing on occupational class composition.

This chapter further investigated how automation has changed the employment composition across the analysed clusters in terms of the European Socio-economic Classification (ESeC) – a categorical classification based on occupation, employment position, and contract type (Rose & Harrison, 2007). In this way, it was possible to look at the stratificational impact of technology and provide some clarity in the long-standing debate on the "shrinking middle".

A five-category definition of the ESeC was adopted (salariat; intermediate employees; small employers and the self-employed; lower services, sales, and clerical occupations; lower technical occupations and routine occupations)[12], thus, the second set of dependent variables were defined as the regional share of workers employed in each class.

Task composition

Since the relation between automation and employment structure was expected to go hand in hand with shifts in task composition, analysis in this chapter further investigated how robotics had influenced the regional distribution of jobs as defined by their tasks content. The Occupational Information Network 3.0 (O*NET 3.0) is used as a source of information on the task content of the occupations. O*Net 3.0 data were collected in the US for approximately 1,000 occupations based on the SOC-2000 classification.[13] O*Net data contain several indicators of tasks performed in each occupation regarding the importance, level, and extent of the activity. Following Acemoglu and Autor (2011), indexes were built using the Importance Scale[14] (1 to 5) of sixteen items representing five task-content dimensions (Table A2.1, Appendix II). Items were standardised and then combined via an additive scale in five indices: non-routine manual (NRMN), routine manual (RTMN), routine cognitive (RTCOG), non-routine cognitive interpersonal (NRCIP), and non-routine cognitive analytical (NRCA).

[12] The simplified ESeC scheme was adopted, with no supervisory information since EU-LFS data do not contain this piece of information for the period under analysis.

[13] O*Net data have been frequently used in studies on countries other than the US: Arias et al. (2014), Goos et al. (2014), Hardy et al. (2016), and Lewandowski et al. (2017). Handel (2012) has demonstrated that US-based occupational surveys and non-US skill surveys produce very similar outcomes for European countries. Furthermore, Cedefop (2013) has revealed that results from O*Net and two surveys that followed the same methodology in Italy and Czechia yielded highly correlated results for task indices (corr. > 0.8), suggesting that it is methodologically valid to apply O*Net information also to Europe.

[14] O*Net items are measured using two scales: one measuring the importance of each task and the other the level. Importance and Level scales are highly correlated (0.92 in O*NET 2003 and 0.96 in O*NET 2014). Following Acemoglu and Autor (2011 the importance scale was used.

To estimate the task content of jobs in each European country and region, O*NET task indices were connected to the corresponding three-digit ISCO-88 codes and ranked in percentiles based on the distribution of occupations per task index. Each ISCO-88 three-digit occupation was assigned a number from 1 to 100 that represented its level of content in each specific task dimension.[15]

Occupational scores were then combined with individual data from the EU-LFS from 1997 to 2017. In this way, each employed individual in the EU-LFS was assigned five task scores corresponding to their ISCO-88 code of occupation. Individual values were then averaged for each region-year, producing five regional-level indices of task composition. As the values of the indices for each occupation were constant over time, variation in regional scores was given exclusively by change over time in the distribution of employment across occupations, and occupational task content was held constant at the 2003 level. Variation in regional scores was not the only source of variation as several studies have documented changes in task content within occupations (Autor et al., 2003; Spitz-Oener, 2006). Nevertheless, this variation in regional scores was the most pertinent to our research objective since we investigated changes in employment structures that were necessarily produced by shifts in employment between occupations (see Appendix II for details). The indicators only reflect the distribution of employment between occupations in terms of a task-based occupational ranking. Therefore, it is only indicative of the relative position of occupations, and it does not capture variation within occupations as well as the scale of difference between occupations, which is a crucial source of between-country differences. However, the rationale of including indicators of task variation between occupations is to investigate whether transformations in employment structures in terms of socio-economic indicators are mirrored by employment structures in terms of distribution of tasks, but not the actual change in the type and levels of tasks adopted in different contexts, neither the absolute differences, since analysis are interested in employment shifts between occupations. As a consequence, it is not possible to distinguish whether differences in the relationship of interest between countries are due to differences in the effect of technology per-se or dissimilarities in the scale of difference between jobs, or whether variation in task content takes place within rather than between occupations.

[15] The use of occupational ranking for tasks rather than the direct task values facilitates the transposition of US-based values to Europe and relaxes the assumption of a perfect correspondence in task content, since, while occupations are likely to differ in their levels of each task indicator between countries, they are more likely to rank in a similar way within countries.

Robotics

The regional variable of robotics exposure was constructed using data provided by the International Federation of Robotics (IFR). The IFR collects information on the introduction and stock of industrial robots – disaggregated by detailed application sectors – for 50 countries beginning in 1993. The adoption of robots has been arguably the most relevant source of industrial automation for the last 30 years. Robot sales have been steadily rising in recent decades, reaching almost 4 million by the end of 2017, thereby rendering robotics the most salient form of technology to replace physical activity. Furthermore, robotics is a clearly defined form of technology[16] and allows for a comparable measure of automation across countries and industries. We combined IFR data with employment counts by country, industry, and year from the EU-LFS from 1997 to measure the number of industrial robots per thousand workers.[17]

Following Acemoglu and Restrepo (2017) and Dauth et al. (2018), the measure of robotics exposure was developed for each region-year as the sum of regional industrial employment shares *(EMPLrjt0/EMPLrt0)* times the ratio of the national diffusion of robots in each industry over industrial employment *(RBTSjt/EMPjt0)*.[18] The full equation is shown in [4], where *r* represents the European regions, *t* represents each year from 1997 to 2017, *t0* represents levels from 1997, and *j* represents the reference industry.

[4] $$Regional\ Robotics\ Exposure_{r,t} = \sum_{j \in J} \frac{Empl_{rj,t0}}{Empl_{r,t0}} \times \left(\frac{Robots_{jt}}{Empl_{jt0}}\right)$$

In other words, the national share of robots per industrial branch was assigned to each region-year, based on the employment level in that regional industry during the first

[16] Robots are defined by the International Federation of Robotics as automatically controlled, multipurpose, manipulator-programmable devices rotatable around three or more axes that can be either fixed in place or mobile for use in industrial automation applications. Robots are comparable across countries; they have a clear technical definition which makes them easily comparable and allows to distinguish whether the difference in their effect is related to contextual factor rather than differences in the technologies adopted. Other technological indicators are generally based on investments in information and communication technologies making it harder to disentangle which type of technology is being observed. Robotics is therefore a useful tool to stress heterogeneous relations across contexts. Moreover, the variable has recently been used in various studies investigating the impact of automation on employment levels and mobility (Acemoglu and Autor, 2022; Dauth et al, 2017).

[17] Data on national and regional employment at the NACE 2-digit level were provided by EUROSTAT through their data extraction service.

[18] Acemoglu and Restrepo (2017: 3) define it as "*exposure to robots, a measure defined as the sum over industries of the national penetration of robots into each industry times the baseline employment share of that industry in the labor market*". The authors computed regional robotics exposure as the difference between the stock of industrial robots in each industry between 1990 and 2007. Instead, this measure is based on the stock of robots in each observed year and thus exploited all 21 time points for each region.

observed period.[19] Values for all industries were then summed for each region-year, yielding the overall regional robotics exposure.

Results

Figure 2.1 displays the variation in the share of workers employed in each of the five ISEI quintiles for each country during the period under analysis. In line with most sociological literature, these descriptive statistics do not highlight a common trend towards polarisation – i.e., the simultaneous growth in the share of employment in the lowest and highest quintiles of the occupational structure and a decline in the middle ones – but rather patterns of occupational upgrading in the majority of European countries (Hasleberg, 2021; Oesch & Menés, 2011; Oesch & Piccitto, 2019).

Figure 2.1 National trends in the share of workers aged 25 to 60 employed in five groups of occupations ranked by their ISEI score (1997–2017)

Notes: Own calculations from weighted EU-LFS data from 1997 to 2017. Variables were rescaled to have mean 0 in 1997.

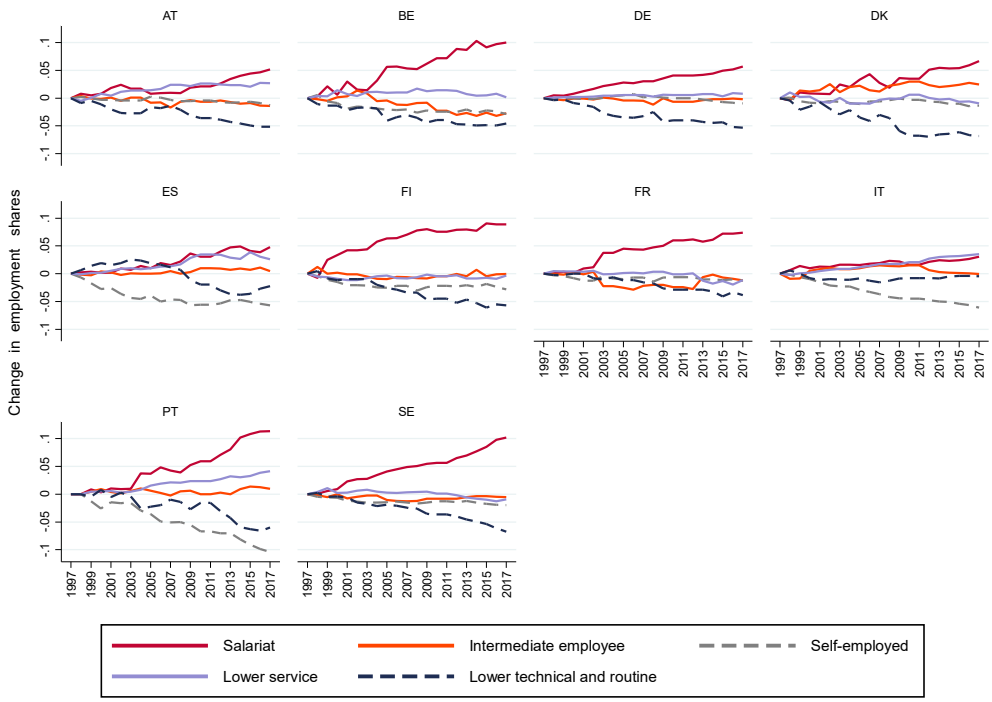
[19] This choice avoided any mechanical correlation between robotics and overall- or industry-level employment outcomes. For instance, the introduction of robots may have increased or decreased total industrial regional and national employment levels and may thus have directly affected the denominators. Taking values at the first observed period allowed us to focus on persistent differences in the regional specialisation of different industries.

The same dynamics emerge from exploring the trends in class composition (ESeC), as shown in Figure 2.2. During the analysed years, the share of the salariat grew, whereas that of lower technical and routine workers decreased in every country observed.

On the other hand, the middle classes (intermediate occupations and the self-employed) stagnated in most countries, the only exception being a steady decrease in the share of self-employed individuals in the Southern European countries. Therefore, a sociologically informed definition of socio-economic class casts some doubt on the idea of a hollowing-out of the middle-class and instead highlights a pattern of upgrading with declining shares of working classes and growing shares of upper classes.

The patterns presented in Figures 2.1 and 2.2 are also mirrored by the labour force composition in terms of performed tasks. Figure 2.3 displays national trends in the five task indices. A clear shift in task composition from manual tasks to cognitive abstract- and interpersonal tasks emerges, suggesting that changes in employment- and class structure were driven by a shift from manual occupations to cognitive, knowledge-intensive occupations.

Figure 2.2 National trends in the share of workers aged 25 to 60 employed in five ESeC classes (1997–2017)

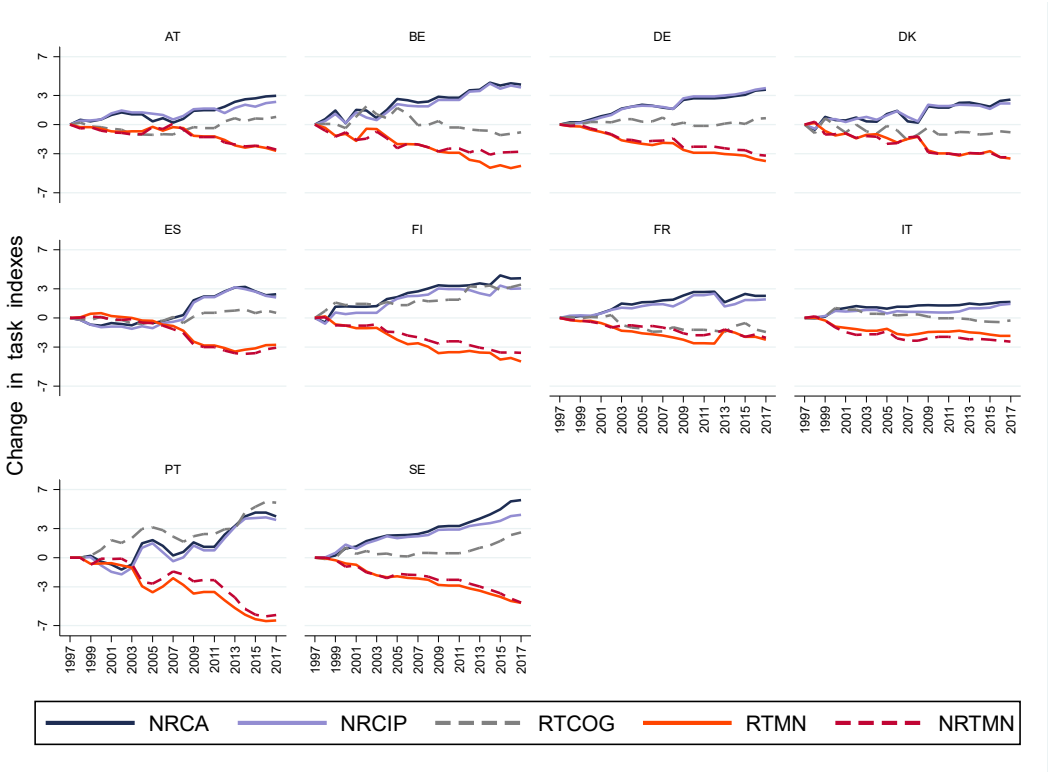


Notes: Own calculations from weighted EU-LFS data from 1997 to 2017. Variables were rescaled to have mean 0 in 1997.

Figures 2.4, 2.5, and 2.6, report the relationship between robotics and occupational structures in terms of ISEI quintiles, ESeC, and tasks, respectively. Jointly they bring support to Hypothesis 1, highlighting the existence of a relationship between automation and overall variation in employment and class structures.

Figure 2.4 reports the average marginal effects of regional robotics exposure on the regional unemployment rate and the share of workers employed in each of the five ISEI quintiles for the three institutional arrangements. Each bar represents the change in the regional share of unemployed (dark bar) or employed individuals in each quintile (lighter bars) in response to an increase of one robot per thousand workers.

Figure 2.3 National trends in average tasks performed by workers aged 25 to 60 (1997–2017)



Notes: Own calculations from weighted EU-LFS data from 1997 to 2017 and O*Net 3.0. Variables were rescaled to have mean 0 in 1997. NRCA: Non-routine cognitive analytical, NRCI: Non-routine cognitive interpersonal; RTCOG: Routine cognitive; RTMN: Routine manual; NRTMN: Non-routine manual.

Robotics does not appear to be significantly associated with the overall trends of regional unemployment in any institutional arrangement, which is a relevant outcome as it reveals that technological innovation in manufacturing sectors is far from being merely a form of substitution for labour. The relationship to unemployment without controlling for youth unemployment is further investigated in Table A2.7. Results suggest a negative association between automation and unemployment in Southern and Continental countries,

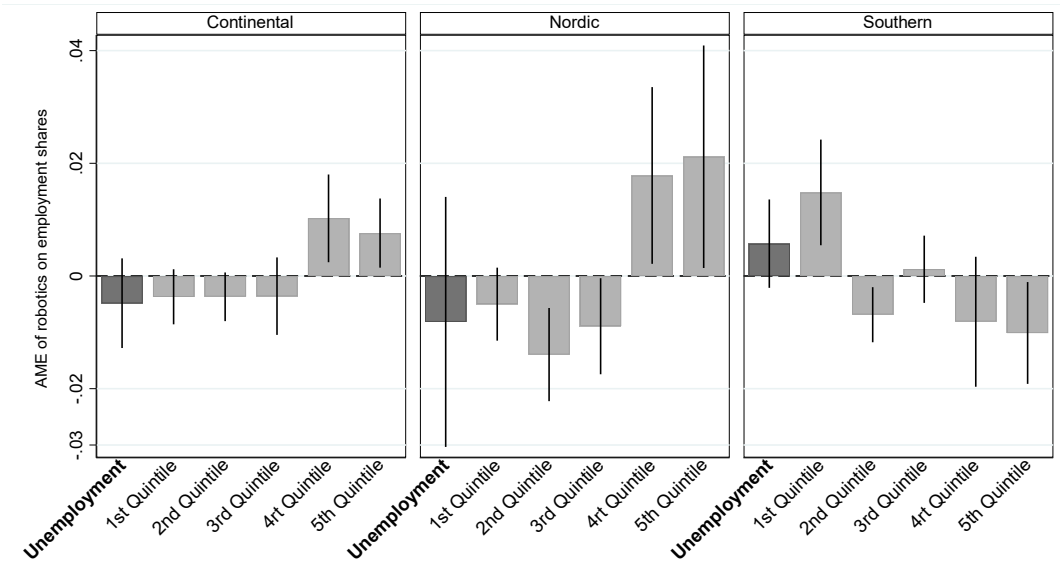
in line with the idea that automation is not exclusively an instrument to replace labour and some compensatory effects are in place. This negative association should however be taken as descriptive since it is very likely that firms invest in robots in periods of economic growth, when they are also most likely to hire new people. This negative association is therefore most likely related to economic cycles and performance associated with both investments in automating technologies and overall unemployment.

In line with expectations from Hypothesis 2, robotics appears to have a rather heterogeneous impact on the employment structures of different institutional clusters.

A clear pattern of upgrading emerges in the Nordic and Continental countries, with the upper two ISEI quintiles being the most favoured by a trend of employment growth. The opposite holds for the Southern European countries, where robotics is associated with growth in the share of workers employed in low-level occupations and with a minor – albeit statistically significant – decrease in the number of top positions.

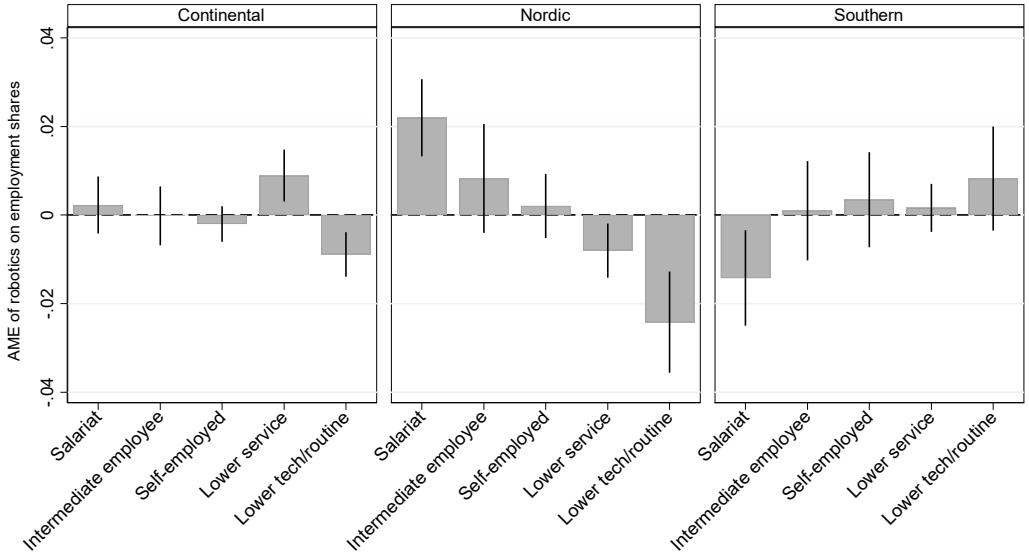
The same pattern can also be found in Figure 2.5, which shows the AME of robotics on the share of workers employed in each of the five ESeC classes. Taking the ESeC as an indicator of class structure allows us to distinguish between the technologically induced upgrading processes in the Nordic and Continental arrangements.

Figure 2.4 Average marginal effect of robotics on regional unemployment and the regional share of workers employed in five ISEI quintiles, disaggregated by country clusters



Notes: Fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate and the share of the highly educated active population interacted with country clusters. Full results in Table A2.2 in the Appendix II.

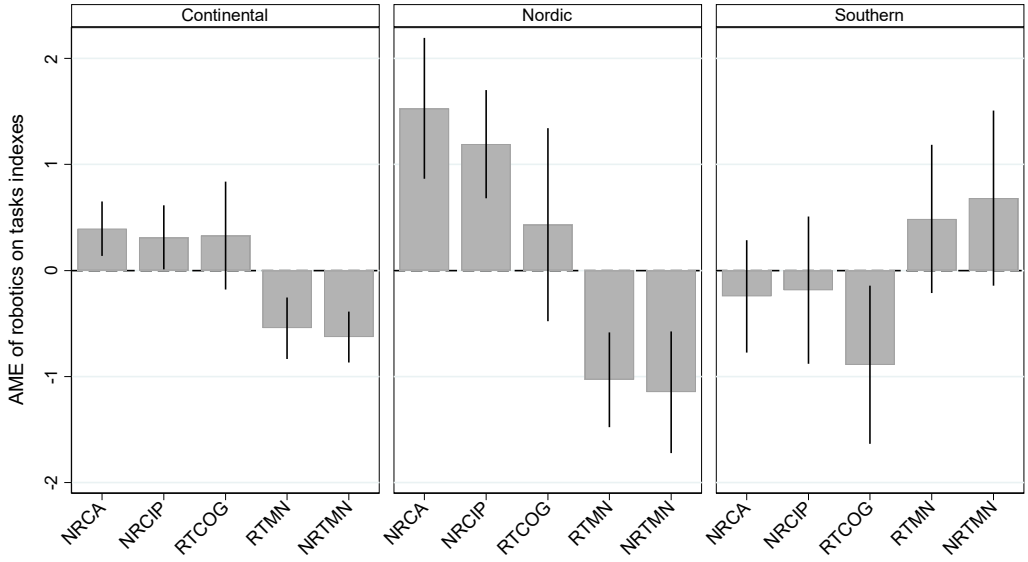
Figure 2.5 Average marginal effect of robotics on the share of workers in five ESeC classes, disaggregated by country clusters



Notes: Fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate and the share of the highly educated active population interacted with country clusters. Full results in Table A2.3 in the Appendix II.

In both groups of countries, robotics significantly reduces the share of workers who belong to lower technical and routine occupations. However, while employment growth in the Nordic arrangement occurs among the salariat, employment growth in the Continental cluster occurs mainly in lower services. While the orientation of the Continental countries towards providing industry-specific skills favours the generation of cognitive and interpersonal professional occupations, the high levels of both specific and general skills in the Nordic cluster allow for knowledge-intensive and creative occupations to proliferate in the salariat class. Moreover, the downgrading process in the Southern cluster is confirmed by examining the composition in terms of ESeC, which reveals that robotics is associated with a decrease in the share of upper classes and an increase in the lower classes. Finally, Figure 2.6 illustrates the AME of robotics on regional task composition. Again, what emerges is a striking difference between the Southern arrangement and the rest of Europe. In the Nordic and the Continental arrangements, industrial robots reduce regional employment in manual task-intensive occupations and shift employment to more cognitive and abstract occupations. The same process is not present in the Southern European arrangement, where no significant pattern emerges and – if anything – the introduction of robotics appears to reinforce employment in routine manual occupations.

Figure 2.6 Average marginal effect of robotics on the regional level of tasks indexes, disaggregated by country clusters



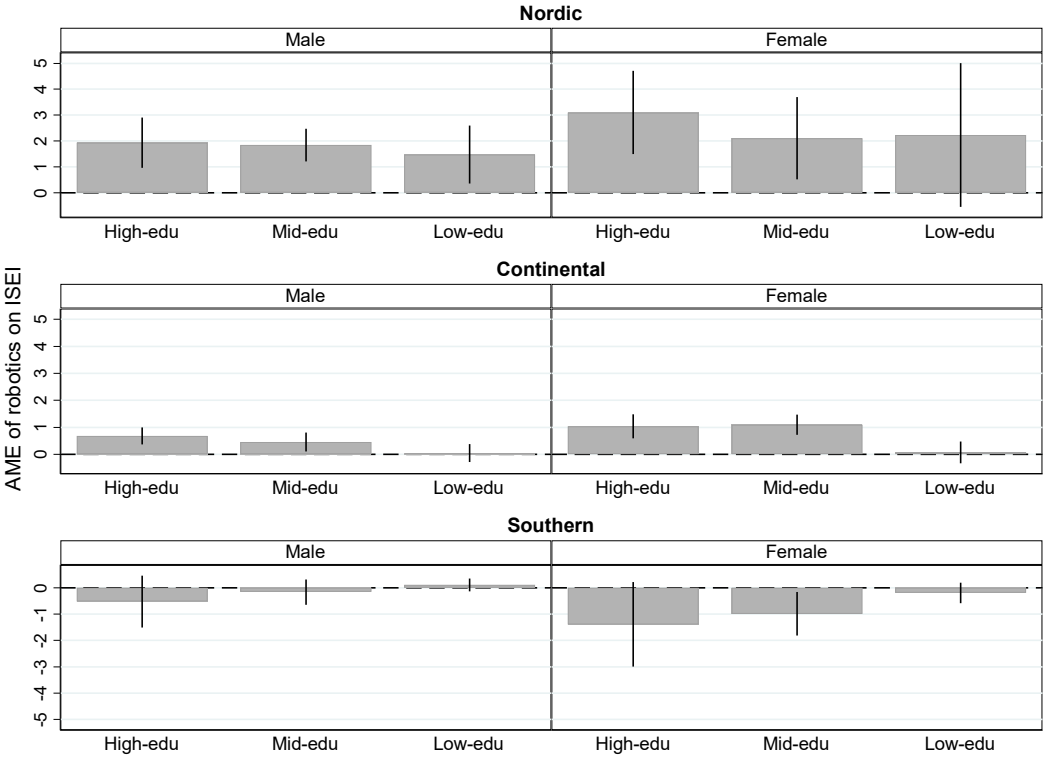
Notes: Fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate and the share of the highly educated active population interacted with country clusters. NRCA: Non-routine cognitive analytical, NRCI: Non-routine cognitive interpersonal; RTCOG: Routine cognitive; RTMN: Routine manual; NRTMN: Non-routine manual. Full results in Table A2.4 Appendix II.

Therefore, in terms of variation in the relationship between robotization and task indexes results do not fully confirm Hypothesis 3. In the Nordic and Continental clusters, robots are associated with a decline in occupations characterized by more manual tasks and less cognitive ones. However, the decline is not limited to routine-manual occupations but also to non-routine manual ones. Since the indexes capture variation in tasks between-occupations, and given that routine and non-routine manual tasks are strongly correlated, a decline in occupation intensive in routine manual tasks is necessarily reflected also in non-routine manual ones. Results are less conclusive in the case of Southern Europe, where a quite static relationship is observed. Robots do not seem associated with the expected decline in routine manual occupations. This could be due to a number of reasons related to both substantive argument and the nature of the task variables. First, while robots replace routine intensive occupations, employment may grow in other occupations characterized by similar levels of routine tasks in non-automated industries. Second, change in task content may take place within occupations rather than between them, and the indexes adopted here would not be able to capture this source of variation. Finally, the task indexes may not properly capture the relative ranking of occupations in different contexts. These limitations call for further research and new cross-national data sources on occupational task content.

Albeit the heterogeneous relationship across contexts is still very clear, without controlling for variation in educational expansion, the automation induced downgrading process is less evident in Southern Europe, where we observe little relationship in terms of ISEI and tasks and a shift from salariat and self-employment to intermediate employees and lower-service in the case of ESeC (see table A2.7 to A2.8 in the appendix). This result, however, should be taken carefully as regions that invest in robotics are more likely to simultaneously experience an increase in higher educated workers. As an increase in skilled workers is likely related to growing service employment, the relationship between automation and occupational structures may be confounded, especially in Southern Europe, where regional differentials in educational expansions are more marked.

Figures 2.7 to 2.8 investigate the presence of a heterogeneous effect of robotics on individuals at different levels of education and gender across institutional clusters (Hypothesis 4).

Figure 2.7 Average marginal effect of robotics on the ISEI score by level of education, gender, and country clusters

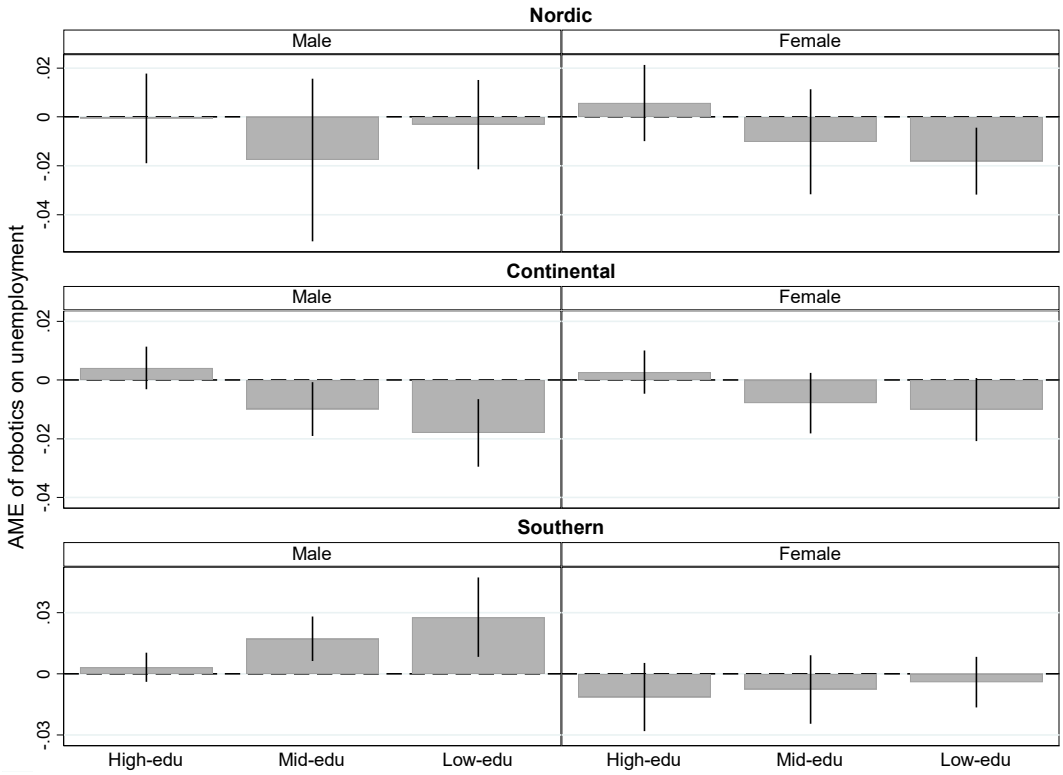


Notes: Pseudo-individual fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate and the share of the highly educated active population interacted with country clusters, education, and gender. Full results in Table A2.5 in the Appendix II.

Figure 2.7 illustrates the AME of regional robotics exposure for each of the three groups of countries on the ISEI levels of individuals defined by their level of education and gender. For the Nordic cluster, results reveal a positive effect of robotics for all individuals, regardless of their level of education or gender. However, in the Continental cluster, such advantages are confined to mid- and highly educated workers, regardless of their gender, while Southern European countries display, if any, hints of penalisation for middle and high-educated women.

Figure 2.8 displays the average marginal effect of robotics on the unemployment risk of each group by country clusters. As evident in the last section of the graph, robotics is positively associated with the unemployment rate of Southern European low- and mid-educated males.

Figure 2.8 Average marginal effect of robotics on unemployment rate by level of education, gender, and country clusters

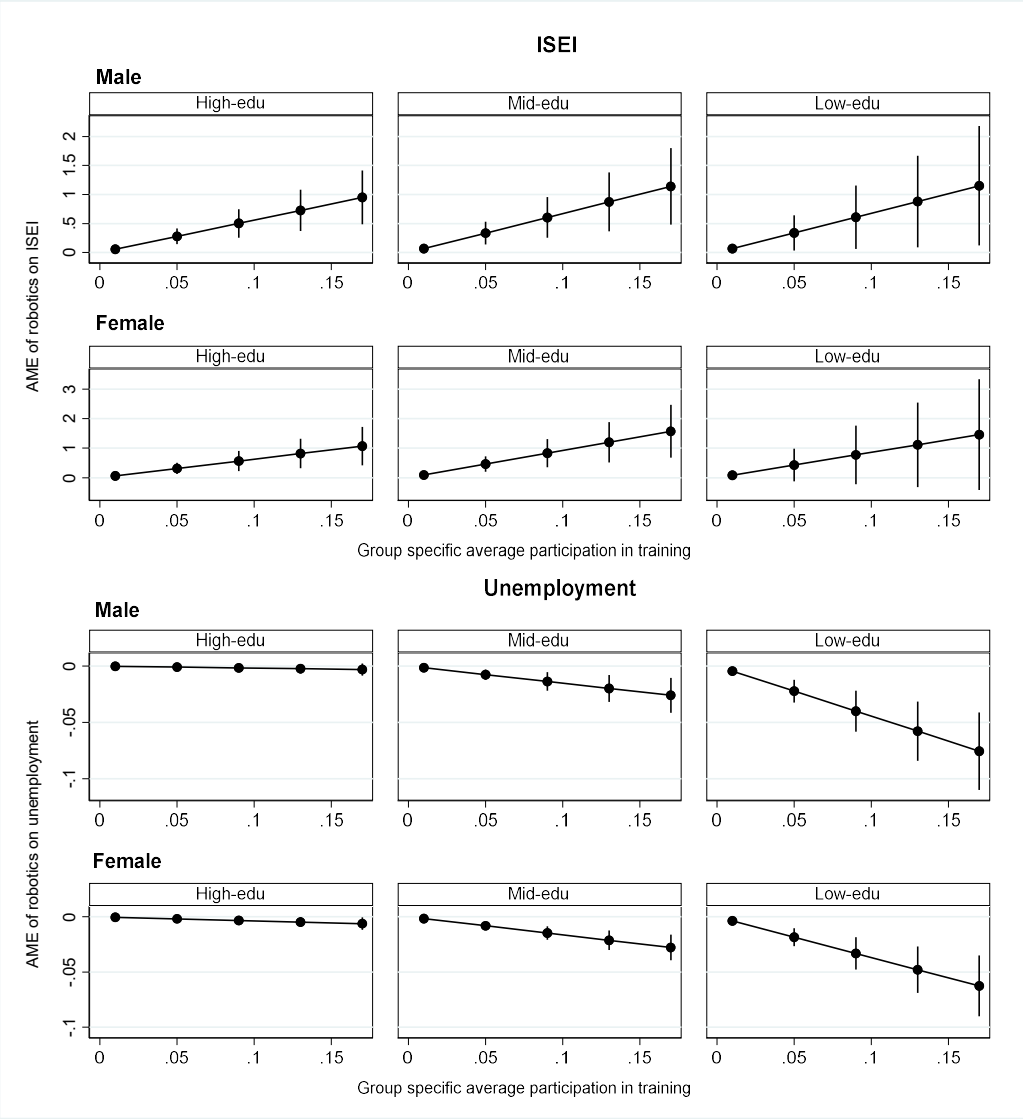


Notes: Pseudo-individual fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate and the share of the highly educated active population interacted with country clusters, education, and gender. Full results in Table A2.5 in the Appendix II.

This finding is not surprising since these men are almost exclusively employed in occupations highly vulnerable to industrial automation. At the same time, these men have

few retraining opportunities. As robots continue to take over their traditional employment domain, they are rendered unfit for the new, fast-growing technological occupations and face harsh competition in accessing the few occupations available to them.

Figure 2.9 Average marginal effect of robotics on the ISEI levels of pseudo-individuals defined by levels of education and gender at different levels of participation in training



Notes: Pseudo-individual fixed-effects models with clustered standard errors at the regional level. Controls include year fixed effects, the regional youth unemployment rate and the regional share of the highly educated active population interact with training, education, and gender. Full results in Table A2.6 in the Appendix II.

Finally, figure 2.9 investigates the importance of training participation in defining the aforementioned group differences across countries as suggested in Hypothesis 5. The upper section of Figure 2.9 reports the average marginal effect of robotics exposure on the ISEI level of each group of individuals at different levels of participation in training. The

positive effect of robotics on individual ISEI levels is substantially greater for groups of individuals who actively participated in training programs during the analysed period.

The opposite effect can be seen concerning unemployment. The lower section of Figure 2.9 displays the AME of robotics on the unemployment risk for each group at different levels of participation in training. The negative effect of robotics is much more substantial for groups of individuals who had extensively participated in training. This effect is particularly strong for low-educated individuals. The clear message from these results is that training is crucial in lowering educational inequalities spurred by automation. Even if low-educated men appear to be strongly exposed to the risk of automation, their employment- and occupational prospects appear significantly better in the presence of training provisions.

Conclusions

A vast strand of socio-economic research suggested that technological change in recent decades has transformed the employment- and class structures of Western political economies, inducing either occupational polarisation or upgrading. The primary mechanism connecting the two phenomena is articulated by the theories of skill- and routine-biased technical change, which implications provide fodder to the fear of a disappearing middle class in advanced economies.

As claimed throughout this chapter, the theory of S/RBTC is highly deterministic insofar as it stresses the technical capabilities of technologies yet disregards important contextual and institutional dynamics that can ultimately shape how actors respond to the introduction of new technologies. The present chapter underscores the relevance of contextual factors in shaping the ultimate impact of automation on employment- and class structures and the distribution of gains and losses stemming from the automation process. Among other potential relevant institutional and contextual factors, the chapter suggested that the three patterns identified in our analyses largely reflect the nature of the trade-off between the kind of labour market (de)regulatory practices and the characteristics of national educational and training systems.

Albeit this chapter has theoretically advanced the claim that differences between regimes are due to a variation in the degree of dualisation and the characteristics of the skill formation system, variation could be due to other features of the three institutional clusters. In fact, there are strong complementarities between features of the skill formation system, the level of dualisation and many other spheres of the political economy such as industrial

relations and welfare states. However, at this level of aggregation, it is difficult to pinpoint and isolate the contribution of each domain, and further research will be needed to evaluate which institutional features are most relevant for moderating the impact of technological change.

Nevertheless, results highlight the potentially disruptive and transformative power of technological change in its ability to modify national occupational structures and inequalities in class and occupational opportunities.

In terms of the overall impact of robotics on employment and class structures, three different "worlds of technological innovation" emerge, with a clear process of technologically driven upgrading, which benefits all individuals regardless of their level of education and genders, occurring solely in Nordic European countries. The opposite is true for the Southern European context, where automation induces a general downgrade of occupational structures accompanied by rising unemployment risk for the less-educated male workers. Finally, in the Continental countries, automation seems to induce a moderate upgrading process by shifting employment from manual- and lower technical occupations to lower services.

These heterogeneous relations do not mirror the common descriptive pattern of upgrading in occupational and class structures. This discrepancy suggests that technological change in the form of industrial automation should not be interpreted in itself as the only force shaping occupational change.

Eventually, the rationale of this chapter has not been to advance a strong causal claim on the effect of automation on occupational and class structures across countries but rather to highlight the heterogeneity in this relationship across clusters of countries theoretically grouped by similar institutional characteristics. This broad agenda comes with several limitations in precision, strength of causal claims, and analysis of within-cluster heterogeneity. In fact, it is not feasible to investigate separate country models given the small number of regions and short time dimension. As a result, there might be significant within-cluster variation in the relationship of interest. The extent to which heterogeneity between clusters is reflected in each single country is an interesting avenue for future research, especially in light of the debate on the continued validity of traditional institutional categories. Furthermore, it is not possible to disentangle which specific institutional area and institutional mechanisms are mostly responsible. In fact, while a cluster-based approach allows flexibility and less stringent assumption on what institutional domain is relevant for the moderation, the downside is that the exact institutional mechanisms in place cannot be identified. As stressed before, the suggested

mechanisms are only attempted, and many other institutional domains can be relevant for the moderation. An important avenue for future research is to directly investigate which institutional domains lead to this heterogeneity.

Finally, results highlight the importance of training opportunities and reveal that training is crucial in moderating the impact of automation and its consequences on social stratification. Indeed, the capacity of national and local systems to provide workers with the right set of skills is one of the main factors determining whether modern political economies can reap the benefits of the global trend of technological change. In these regards, the chapter has investigated the diverse effect of automation on the opportunities of individuals characterized by their level of education and gender, and how these differences are related to the specific institutional context. Albeit these two dimensions are crucial, they are not exhaustive of all possible stratifying characteristics (e.g., age, migration status, ethnic background). Future research should look at how automation influences individuals based on a larger set of socio-demographics and how institutional contexts increase or decrease the automation effect on these inequality lines.

.

Chapter III

Unions, Technology, Social-class, and Earnings Inequality in the US, 1984-2019

Abstract

Earnings inequalities in the US have steadily grown in the last decades, and between-class inequalities have been a central component of this process. However, while research has highlighted the strengthening relationship between occupational social classes and earnings, less attention has been paid to what factors have altered the market returns of different social classes. The present chapter investigates the contribution of two of the most widely recognized drivers of wage inequalities – de-unionization and technological change – to the growth of between-class inequalities. Using direct measures for computerization and union density at the industry level, this chapter analyses their relationship to the earnings growth of employees in different social classes from 1984 to 2019. Descriptive results underline the diverging earnings growth of manual and non-manual workers. Furthermore, minor support is found for the claim that computerization at the industry level was associated with the earnings growth of salariat and non-manual workers. In contrast, de-unionization is related to the diverging fortunes of manual and service classes in two ways. First, unionization is positively associated with the earnings of all social classes but more strongly with those of the lower classes. Second, manual workers were employed in much greater numbers in industries that experienced severe declines in union density and have thus been majorly affected by its decay. Finally, the growth in educational levels for non-manual classes emerges as a crucial determinant of their faster earnings growth. Overall, results support recent sociological literature suggesting that institutional factors, rather than technological change, are primarily responsible for rising inequalities in the US.

Starting from the 1980s, the distribution of personal earnings in the US has become substantially more unequal, breaking a general pattern of decreasing inequalities that dates back to the beginning of the twentieth century (Levy & Murnane, 1992; McCall & Percheski, 2010; Piketty & Saez, 2003). A large body of sociological research has investigated whether this take-off in earnings inequality has played out in a way that strengthens or weakens inequalities between occupations and aggregate social classes, and a long debate emerged investigating whether earnings inequalities were mainly driven by changes in class income differences, by changes between occupations within the same class, or by changes within occupations (Kim & Sakamoto, 2008; Mouw & Kalleberg, 2010; Weeden et al., 2007; Zhou & Wodtke, 2019).

Among these dimensions, social class inequalities are of paramount interest to sociological research since they combine homogeneous socio-economic groups, filled with individuals who share similar life conditions, expectations, skills, career trajectories, and earnings (Breen, 2005). As a result, an increase in economic inequality between classes would almost surely result in a more separate and hierarchical social order, possibly exacerbating the social and political implications of inequality (Edlund & Lindh, 2015; Evans, 2000; Lipset, 1960; Wilkinson & Pickett, 2011).

While existing studies on the decomposition of overall levels of inequalities have underlined the progressive consolidation of the relationship between social classes and earnings (Goedemé et al., 2020; Morgan & Tang, 2007; Weeden et al., 2007; Zhou & Wodtke, 2019), little research has been carried on the reasons and macro determinants of this process. On the other hand, several studies have explored the drivers of overall wage dispersion and the functional distribution of income (Elsby et al., 2013; Kristal, 2013; Kristal & Cohen, 2017; Lin & Tomaskovic-Devey, 2013).

Results from this body of research have generally pointed toward two main factors behind rising inequalities. A first strand of primarily economic literature has suggested that computerisation and technological change have increased the productivity and wages of more skilled workers relative to less skilled ones. On the other hand, social science research has repeatedly shown that the demise of wage-setting institutions and workers' power has inhibited wage growth for lower incomes and increased earnings dispersion (Card et al., 2017; Kristal, 2013; Kristal & Cohen, 2017; Lin & Tomaskovic-Devey, 2013; Western & Rosenfeld, 2011; Blau & Kahn, 2009). Finally, a growing body of research has highlighted the combined effect of these two factors, suggesting a moderating and mediating effect of

de-unionisation in the relationship between technological change and labour market inequalities (Acemoglu, 2001; Kristal, 2015, 2019; Parolin; 2021).

The present chapter attempts to combine these two strands of research by investigating how these crucial factors – i.e., technological change and de-unionisation – have diversely influenced the earnings growth of employees in different social classes, therefore exacerbating class inequalities in the US in the period from 1984 to 2019. However, given the extensive research on the functional distribution of income – i.e., inequalities between capital owners and workers – the present chapter focuses exclusively on social class inequalities between dependent employees, as they make up the vast majority of the working population. Furthermore, the mechanisms connecting technological change and institutional factors to inequalities between groups of workers may be substantially different from those hastening disparities between workers and capital owners.

Thus, based on industry-level data, the chapter investigates whether changes in technological endowments, institutional settings and labour force composition diversely impacted the earnings growth of different aggregate social classes defined using the EGP classification (Erikson & Goldthorpe, 1992).

In other words, the chapter investigates how existing theories of technological and institutional change can account for specific transformations in between-class inequalities. Thus, the objective is not to test the validity of different theories but rather if and how they apply to this inequality dimension. Nevertheless, the chapter adds to recent literature investigating the relevance of institutional vis-à-vis technological factors for the growth of various dimensions of inequalities in the US, and similarly suggests that institutional factors have been among the main drivers of raising inequalities.

Results highlight the diverging fortunes of services and manual workers. The formers have experienced significant wage growth in the analysed period, while the latter's earnings have stagnated or declined. Results suggest that technological change at the industry level had little relation with the earnings trajectories of all social classes. In contrast, the industrial union density positively affected all social classes' earnings, but more so those of manual classes.

Moreover, the fall in union density appears to be the most relevant factor explaining diverse earning growth between manual and non-manual workers due to the different exposure to de-unionisation between these two groups. In other words, a more significant part of skilled and non-skilled manual workers compared to salariat and routine non-manual workers were employed in industries that experienced substantial declines in union density in the period examined. Little evidence emerges of a mediating or moderating effect of de-

unionisation in the relationship between ICT investments and the earnings of each social class. Finally, results suggest that changes in each class's demographic and educational composition also played an important role.

The remainder of the chapter is structured as follows. The first section reviews the main literature connecting employees' class position to market returns and earnings. The second section highlights the importance of macro institutional factors in shaping the relationship between social class and earnings; it focuses explicitly on technological change and unionisation and how they influence workers employed through a labour contract or service relationship. Section three introduces data and methods, while section four presents the results from a panel analysis, and section five discusses the findings.

Social class and earnings

Social class, and its relation to unequal economic returns, has been one of the most relevant and useful, as well as debated and contested, concepts of social analysis (Wright, 2005). Indeed, many different theoretical definitions and operationalisation of social class exist, each rooted in different traditions. Albeit this section does not claim the superiority of one approach over another, it mainly builds on the so-called Weberian tradition primarily associated with the work of John Goldthorpe and colleagues and the development of the EGP class schema (Erikson et al., 1979; Erikson and Goldthorpe, 1992, Ch. 2; Goldthorpe, 2000; Breen, 2005). Nevertheless, most of the arguments connecting social class positions to earnings inequalities are not exclusive to any theoretical tradition of social class but are easily extendable to other approaches[20].

In Erikson and Goldthorpe (1992), social classes are understood as bundles of individuals who share common economic life chances due to their position within labour markets and work organisations. The primary underlying assumption is that social class – typically proxied by the occupation an individual belongs to – is a good indicator of access to economic resources, first of all, earnings (Goldthorpe & McKnight, 2006; Morgan & Tang, 2007). Therefore, the objective of defining a meaningful classification of social classes lies in identifying what puts individuals in a common position.

[20] Indeed, the EGP schema has often been characterized as neo-Weberian, but it appears more accurate to consider it an amalgam of mainly, but not exclusively, Weberian and Marxian principles. Indeed, Erikson and Goldthorpe (1992) stressed that "the opposition between Marxist and Weberian conceptions of class is in many respects exaggerated", they do accept that "The principles of differentiation that we adopt have been mainly derived from classic sources, in particular, from Marx and Max Weber." (p. 37)

In Goldthorpe's schema, classes depict the distinctions between proprietors vs non-proprietors and, among dependent employees, between those whose position is regulated by a "*labour contract*" and those regulated by a "*service relationship*." At the basis of the distinction between these two lies the contractual hazard employers face in solving two main problems: *work monitoring* and *asset specificity*. The former occurs when the employer cannot strictly control a worker's productivity on the job – and thus explicitly relates to the degree of job autonomy and discretion over the tasks undertaken.

Human asset specificity, instead, refers to the content of a job in terms of specific skills, qualifications, or information. These are job-related characteristics, and variations in these attributes explain the different employment relationships between workers and classes.

To boost employees' efficiency in difficult-to-monitor jobs and reduce the risk of employee turnover in asset-specific jobs, the employer must elicit commitment to the company from the employees involved. The service relation is the tool for doing this: a compensation arrangement that binds employees to the company by providing job protection and good internal career opportunities, not least in terms of earnings growth. Hence the disparities in earnings between classes. Higher earnings – the so-called "efficiency wage" (Akerlof, 1984) – are very likely to be a crucial part of employers' benefits to the upper classes[21]. On the other hand, occupations with low human asset specificity and low monitoring problems constitute the working class, controlled via labour contracts and workplace discipline.

Besides the working class and the salariat, other groups are characterised by employment relationships that take on a mixed form. These are routine non-manual workers, lower grade technicians, and skilled manual workers (Erikson and Goldthorpe 1992, p. 43). However, these mixed forms occur for different reasons in each case. For example, routine non-manual jobs like clerks, secretaries, and other routine administrative employees usually do not require asset-specificity but pose specific monitoring challenges, whereas, in the case of professional manual workers and technicians, the opposite holds.

[21] It is important to notice that the rationale highlighting a causal link between social class and earnings is similar to that suggested by Marxist approaches to social class. In the same vein as Goldthorpe, Wright (1997) recognizes that the essence of the work performed by the upper classes is such that employers are incentivized to devise methods to cultivate the loyalty and dedication of upper class workers, and salaries are an important means of achieving that goal. In addition to what is beneficial from the standpoint of the employer, Wright emphasizes the importance of the bargaining power of different classes. Because of their strategic role within the company, managers and professionals can advance claims and bargaining for a portion of the profit in the form of higher earnings. Managers can thus claim a "loyalty rent," while specialists can claim a "skill rent." These claims extend the rationale for a causal relationship between social status and earnings.

The consequent incentives and rewards position these occupations in a theoretical "middle" between the working and service classes.

In addition to monitoring difficulties and asset specificity, social classes can be tied to different socio-economic returns through different skill requirements and related productivity levels (Le Grand & Tåhlin, 2013; Tåhlin, 2007). Indeed, even if productivity is not usually considered in the main theoretical definitions of social class, employees in the service class can obtain comparatively significant gains from the productive value of their duties, highly worthen in the employer's eyes. Thus, according to this perspective, jobs in upper-class occupations have higher incomes because their experience, training, and expertise make them more profitable. This viewpoint suggests that class is a reasonable indicator of income disparity since it captures workers' talents and skills. [22]

Technology, unions, and changing economic returns to social class

As seen, social class theory connects employees' class position to earnings through mechanisms mainly related to workplace relations, such as the need to monitor or reward workers. However, other institutional and contextual factors play a crucial role in explaining wage levels and differentials.

Since social class implies that individuals' position in the labour market results in different social and economic advantages and disadvantages, transformations in labour market regulation should result in changes in economic returns from different market positions. Social class can be related to personal income through many factors that have drastically changed in the last decades, including supply and demand for various factors of production, the speed and type of technological advancements, the balance of bargaining power between social groups, and the role played by institutions.

Therefore, it is not surprising that differences in earning returns between classes have taken off since the US economy experienced significant transformations in labour market composition, technological endowments, and unions' power. Each of these factors may indeed substantially alter the market position of different groups.

This understanding reflects Breen's (1997) suggestion that an occupation, or group of occupations, may benefit from certain aspects of the service relationship not solely because

[22] In addition to ability and talents, other aspects associated with the class may explain class disparities. A correlation between class and earnings is likely to be observed because social status is linked with a particular individual or household attributes associated with earnings. Earnings would then be linked to social status through various alternative routes such as gender or race (Morgan & McKerrow, 2004). However, as Rose and Harrison (2014) argue, these alternative dimensions can also be seen as components of social class disparity, giving support to class theory.

it maximises productivity but also because the workers' bargaining power enables them to capture these aspects in the form of rent. It is plausible that transformations in the terms and conditions of employment governing many jobs over the last twenty years are attributable to the worsening of workers' bargaining position vis-a-vis employers as well as to changes in the skill requirements of these jobs and the new job monitoring opportunities associated to recent technological change. Based on these claims, the returns to a class position do not follow so quickly from a simple consideration of productivity and workplace relations. Other historical, institutional, and technical factors must be considered in justifying any specific change in class structures and social stratification.

According to a large body of research on the determinants of earnings dispersion and the fall in the labour share, technological change and the demise of unions' power and wage-setting institution can be considered the most critical factors in explaining rising inequalities in the US. As argued below, many of the arguments connecting these factors to the overall distribution of earnings are also crucial in defining economic returns to different social classes.

Technological change

The factor most often deemed responsible for the change in market returns for different occupational groups has been the process of technological change. As it took place in the last decades, technological development can be considered connected to the market position of different social classes in at least three ways. First, through its complementarity to skill levels, second through its relation to the tasks content of work, and third through its connection to workers' autonomy and power.

Following the seminal contributions by Krueger (1993), Berman et al. (1994) and Goldin & Katz (1998), the theory of *Skilled-Biased Technological Change (SBTC)* maintained the primacy of technological change in determining a generalised skill upgrading of the workforce. Under this perspective, technology was considered the main explanatory factor behind rising college wage premium, suggesting that information and communication technologies were mainly complementary to highly skilled workers, thus raising returns to skills.

After observing the polarising trend in the US earnings and occupational distribution, the theory of SBTC was revised and refined by the theory of *Routine-Biased Technological Change* (RBTC) (Autor et al., 2003). RBTC distinguishes occupations based on the content of their tasks. Accordingly, technological change is expected to substitute workers

performing routine tasks while complementing the execution of abstract cognitive and interpersonal ones, thus increasing demand, productivity, and eventually earnings for occupations characterised by more cognitive and non-routine duties.

Both SBTC and RBTC are closely related to the concept of social class. Indeed, the definition of a social class depends on the type of work and tasks that employees undertake, thus leading to different employment relationships – based on labour contract or service relationship – tailored to different kinds of work. As a result, both SBTC and RBTC would suggest a positive association between the earnings of occupational categories which perform more cognitive and less monitorable tasks, such as managers, professionals, and non-manual workers in general.

A second channel through which technological change may have contributed to diverse earnings growth between social classes is by altering the monitoring problem faced by employers, increasing managements' and employers' ability to monitor and control low-skilled workers, thus strengthening the dynamics underlying the labour contract (Guy & Skott, 2015; Skott & Guy, 2007).

Starting with the early work of Braverman (1974), socio-economic research has suggested that technologies lead to higher monitoring, lower skill requirements, and more precise tasks specification, and especially so for lower-skilled workers whose tasks do not require expert knowledge and creative thinking (Hunter & Lafkas, 2003; Menon et al., 2019). The growth in usage of information and communication technologies (ICT) since the 1970s has had the potential to reduce the autonomy and control over the work process of lower-level employees, therefore tempering their wage growth.

On the other hand, managerial activity is aimed at the efficient production of output and involves high levels of decision-making after collecting and analysing information. ICTs have drastically increased the amount of information and options available to higher-level employees. This large amount of information and possible path of action strongly aggravate the monitoring problem for higher classes (Guy & Skott, 2013). As suggested by Kristal (2020), computerisation may have strengthened the market position of some occupations due to their different access and control of information on the production processes. These include occupations involved with the management, circulation, and reorganisation of information and data, such as computer programmers, information systems specialists, and those who receive these information flows and translate, interpret, and use them to support decision-making strategies, such as managers and professionals.

Eventually, existing theories of technological change would suggest, on the one hand, a positive relationship between technological change and the earnings of higher classes

(Hypothesis 1) – due to their higher skill set, the type of tasks performed, and power relations related to the control and use of information flows – on the other, a negative relationship to those of the working classes (Hypothesis 2). More ambiguous is the relation to the earnings trajectories of those classes characterised by a mixed relationship. On the one hand, RBTC indicated that these middle-classes are the most substitutable due to their higher content of routine tasks (Autor et al., 2003), and should therefore experience declining earnings in response to technological change (Hypothesis 3a). Similarly, Breen (1997) suggested that the market positions of these classes were particularly at risk due to new detailed methods of monitoring and their vulnerability to technological change. At the same time, these are occupations characterised by considerably higher skill requirements, interpersonal tasks, and use of information (especially those constituting the non-manual workers) compared to the working classes. Therefore, they may benefit from productivity gains spurred by technological change and thus experience wage gains (Hypothesis 3b).

Unionisation

Literature on routine and skilled biased technological change has often disregarded the crucial role of labour market institutions. Nevertheless, institutions are critical determinants of earnings inequalities, and research has consistently indicated that more coordinated and inclusive institutional arrangements are generally associated with lower inequalities.

Among the most relevant institutions to be considered, when dealing with wages and earnings distribution in US labour markets, trade unions deserve a central position due to their impact on income inequality via the increase in wage levels and the related drop in wage dispersion (VanHeuvelen, 2018; Western & Rosenfeld, 2011; Acemoglu et al. 2001).

Indeed, unions are collective actors who increase labour's power resources and improve labour's bargaining position against capital owners and employers, positively affecting employees' economic returns (Jacobs & Dirlam, 2016; Kristal, 2013). Thus, the most obvious channel through which trade unions can reduce inequalities is by directly bargaining higher earnings for unionised workers (Brady et al., 2013; Card et al., 2017; Freeman, 1984; Maxwell, 2008), and particularly so for less educated and manual ones (Freeman, 1980; Kristal, 2013; Maxwell, 2008; Mishel et al., 2012; Western & Rosenfeld, 2011). For this reason, the decline in unionisation can be expected to play a crucial role in the growth of social-class inequalities.

However, bargaining for union members is only one of the potential paths through which unions affect the overall distribution of wages. As literature has shown, trade unions also positively affect the earnings of non-unionised workers and increase the overall labour share

of total income by combining collective bargaining and support for minimum wage (Grimshaw et al. 2014; Checchi, Lucifora 2002), through spill-over effects, and through threats to non-unionised firms (Denice & Rosenfeld, 2018; Freeman, 2005; Leicht, 1989).

Furthermore, recent literature has suggested that trade unions may exert a positive effect on the wages of non-unionised workers by promoting a vast set of egalitarian norms and principles prescribing fair distribution, usually reassumed under the label of a "moral economy" (VanHeuvelen, 2018; Western & Rosenfeld, 2011). Finally, the positive effect of unions may spread to other non-unionised workers through social comparison, given that higher wages bargained by unions can establish higher expectations for the whole industry in which unions operate (Alderson & Katz-Gerro, 2016; Rosenfeld, 2006).

Despite unions' potential to raise earnings for all workers, their positive effect is particularly relevant for lower-skilled and manual employees (Freeman, 1980; Kristal, 2013; Maxwell, 2008; Mishel et al., 2012; Western & Rosenfeld, 2011). Indeed, lower classes cannot bargain higher wages based on their favourable workplace position since they rely on different contract relationships and have poor individual bargaining power (Rosenfeld, 2006). As a result, unionisation and labour regulating institutions have traditionally been the primary way workers in classes regulated by a labour contract have gained part of the privileges typical of service classes. It follows that a decline in the labour movement's bargaining power primarily affects this group of workers.

As suggested by Breen (1997), part of the benefits that lower and intermediate classes enjoy have been acquired through labour mobilisation when labour-power was much more significant than now. Under this perspective, the stagnation in earnings observed for middle and lower classes since the '90s and 80s can be understood as the erosion in rent acquired in previous periods.

A second reason the decline in unionisation may have been more relevant for the earnings of lower and manual classes is their different exposure to the phenomena. Workers in lower classes and manual workers are more present in industries that experienced strong de-unionisation processes. As a result of this uneven distribution of social classes between more or less unionised industries, even a similar functional relationship between unionisation and earnings between social classes may result in more significant earning losses for lower classes.

The decline in unionisation rates observed in the US in the last decades emerges as a crucial factor behind the stagnation in working-class earnings and consequent inequalities between social classes (DiNardo et al., 1996; Mishel et al., 2012; Parolin, 2021; Rosenfeld, 2006; Western & Rosenfeld, 2011). We can therefore expect de-unionization to be more strongly associated with the earnings of lower and manual classes (Hypothesis 4).

Finally, it is crucial to recognise that the two "forces" – de-unionisation and technological change – are not simply additive factors but are likely to be interrelated. On this specific point, recent studies have stressed that technological change and unionisation are associated and that the process of (de) unionisation may act as a mediator of the direct link between technology and economic inequality (Hypothesis 5). Moreover, strong unions can moderate the impact of technological change (Hypothesis 6) either by containing its impact on the wage growth of higher classes or by limiting the increase in the deskilling and disempowerment of less-skilled workers (Acemoglu, 2001; Kristal, 2015, 2019).

Data and variables

The connection between unionisation, technological innovation and earnings change between different social classes is tested using longitudinal data on US private non-agricultural industries from 1984 to 2019. The unit of analysis is defined by the combination of 40 industries and four social classes observed for 36 years, yielding a total of 5760 industry-class-year observations clustered in 160 industry-class groups.

Information on individual earnings and socio-demographic characteristics are taken from the CPS-MORG harmonised by IPUMS (Flood et al., 2020). The sample is restricted to full-time employees (at least 30 hours per week[23]) 18 to 69 years old.

Social classes are defined using the EGP class schema adapted by Morgan (2017) to the 2010 census occupational classification[24]. Throughout the years analysed, the CPS underwent some modifications to the occupational classification, the most severe of which took place in 2002[25]. Therefore, in order to obtain a consistent classification of social classes, all occupational codes are converted into a joint 2010 definition using crosswalks provided by the US Census Bureau (Scopp, 2003) (see appendix for details on the occupational crosswalk) and then into EGP categories based on Morgan (2017).

Social classes are defined using the seven-class version of the EGP suggested by Goldthorpe (1992), which results in four categories after excluding the self-employed

[23] After 1994 the CPS has included the option "hours vary" among the possible responses to the question "hours usually worked per-week." In this chapter, individuals who reported "hours vary" after 1994 are treated as non-full-time workers and thus excluded from the sample. The inclusion of these respondents creates a significant break in time-series after 1994 and some authors (Schmitt, 2003) suggest that estimates appear to be more reliable by excluding them. However, analyses including these workers in the sample are almost identical.

[24] The EGP schema has become, in the last decades, the most prominent given its deployment in a number of different research contexts, among which social mobility, (e.g., Erikson & Goldthorpe, 1992; Hout, 1989), voting behavior (e.g., Heath et al., 1985; Manza & Brooks, 1999), health, earnings and career trajectories. The EGP schema also appears robust from a theoretical standpoint (see Goldthorpe, 2000), based on a wide range of literature from both economics and sociology (see Erikson & Goldthorpe, 2002).

[25] Other than the 2002-2003 change, occupational codes in the CPS were revised in 1992 and 2011.

(class IV) and agricultural workers (class VIIb)[26]. The resulting categories are the salariat (classes I-II), routine non-manual (classes IIIab[27]), skilled manual (classes V-VI) and unskilled manual (class VII).[28]

Industries are defined based on an approximation of the two-digit NAICS classification that matches the Bureau of Economic Analysis (BEA) data on industry investments. As occupations, industrial classification underwent some changes in the period under analysis. The present analysis starts with the harmonisation of the 1990 census industry code performed by IPUMS (IPUMS USA, 2018). It converts to the 2012 NAICS classification using the crosswalk from the US Census Bureau (2013) to match data on technological investments[29] (see appendix for more details on industry harmonisation and the complete list of industries).

The dependent variable of interest is the mean of ln weekly earning for each social class. Weekly earnings are adjusted for inflation using the CPI and set to 2000 USD. Individuals reporting less than 50 dollars per week are excluded, and top coded earnings are imputed, assuming a log-normal distribution (Schmitt, 2003). Different procedures to deal with the top coding led to the same conclusion. In particular, the primary model is tested using the median of industry-class earnings (see Table A3.2 model 2 and Table A3.4 model 14 in the appendix).

Using the MORG-CPS, a number of information on socio-demographic characteristics on each unit is computed: the share of tertiary educated, the share of females workers, the share of white non-Hispanic workers, and the average age. All industry-class-year aggregate statistics are computed using sampling weights.

The two main industry-level variables are union density and computer investments. As usually in the literature, union density is measured by the ratio of union members in each industry by the number of total wage and salary workers aged 16 and over. It is thought

[26] After the exclusion of the agricultural sector few agricultural workers—class IVc and VIIb—are still in the sample. These are combined respectively to class I-II and VIIa.

[27] In some cases, class IIIb is merged with class VII rather than a single class III (see for example Breen, 2005; Tåhlin, 2007). However, as shown by Evans (1992) class IIIb is more similar to IIIa than VII in a number of aspects of the employment relations. Furthermore, the present study is mainly interested in earnings change over time and Figure 3.1 highlights that class IIIb has experienced earnings trends quite similar to class IIIa.

[28] The analysis is restricted to four aggregate social classes instead of a more fine-graded definition due to limited yearly sample size, which would otherwise result in some empty industry-class-year cells, and to limit breaks in time series due to the changing occupational classifications.

[29] Some industries are aggregated to a two-digit NAICS due to low numerosity or ambiguity in the cross-walk. The intersection of industry class and year does not result in empty combinations, however in some cases it results in low cell numerosity which produce quite noisy time series. To deal with this issue a number of different strategies are adopted. First, models are tested excluding units made up by less than 50 and less than 100 observations (see table A3.2 models 3 and 4, and table. A3. 4 model 15 and 16 in the appendix). Second, models are tested weighting each unit of analysis by its average cell numerosity (see table A3.2 model 5 and table A3.4 model 17 in the appendix), so that small (and noisier) units contribute less to the estimation. All specification led to the same conclusions.

to capture overall sectoral unions' power rather than the representation of any specific group, thus reflecting the idea that unions exert an influence on economic conditions beyond unionised workers. As recent sociological literature on technological change and industry level inequalities, the industry's reliance on computer technologies is measured as investments in computers and software as a share of total non-residential investments using data on investments in fixed assets from the BEA (Kristal, 2013; Kristal & Cohen, 2015, 2017; Lin & Tomaskovic-Devey, 2013). Computers include investments in mainframe computers, personal computers, direct access storage devices, computer terminals, computer storage devices, integrated systems, and software. The industry-level approach and variable selection – computer investments and unionization – follow closely the recent literature on the competing effect of technological change and institutional factors on earnings inequalities. Industries are meant as a proxy of firms and investment in ICT is the best indicator available for this kind of analysis. Given that technological change may take different forms depending on the industry, this broad indicator is the best to capture technological change in different industries. Finally, the log of real industry value added from the BEA is included as a control variable to account for different economic growth rates between industries.

Methods

The method of analysis aims to examine the relationship between indicators of computerisation and union density at the industry levels and industry variations in the earnings of each social class. The main specification is a dynamic two-way fixed effect model estimated separately for each class, including industry-class fixed effects, class-year fixed effects and a lagged dependent variable among the predictors as reported in Equation [1].

$$[1] \qquad Y_{cit} = \alpha_1 Y_{cit-} + \beta_0 ICT_{it} + \beta_1 Union_{it} + \beta_n X_{cit} + a_{1ci} + a_{2ct} + \varepsilon_{cit}$$

Y_{cit} represent the earnings of social class *c* in industry *i* at time *t*, Y_{cit-1} is a one-year lag of the dependent variable, ICT_{it} and $Union_{it}$ represent respectively the intensity of investments in computer technology and unionisation at the industry level; X_{cit} is a vector of industry-class and industry-specific characteristics. Industry-class covariates include the share of tertiary-educated workers, the share of female workers, the share of white non-Hispanic workers, and the average age. The industry level control is the log of real value

added to account for different economic growth rates across industries and industry-specific economic downturns. a_{1ci} are industry-class specific intercept, which accounts for unobserved time-constant heterogeneity at the industry-class level, a_{2ct} are yearly-class intercepts which account for year-class specific economy-wide shocks.

Fixed effects estimators exploit within industry-class variation and therefore control for time-constant heterogeneity between units. In this way, it focuses on the within industry-class variation over time, and coefficients represent the average cross-industry longitudinal effect for each social class. The model further includes class-year fixed effects to account for specific time shocks and trends which affected the same classes in all industries. Finally, a lag of mean ln earnings for each social class is included among the predictors to control for potential serial correlation and for the fact that earnings are path-dependent, i.e., current earnings for each class are bargained based on the levels of the previous year earnings[30] [31]. Furthermore, autocorrelation involves evaluating time series data in the context of socioeconomic dynamics. Instead of worrying about residuals mechanically, existing literature has suggested to build specifications that describe the dynamic processes in question. The inclusion of a lagged dependent variable is often advocated because it allows to properly model time dynamics and the persistence of the effect of the independent variable in future periods. The main assumption behind the inclusion of a lagged dependent variable is the idea that changes in the independent variable are not realized exclusively immediately but distributed over time. The impact of an independent variable on earnings at time t will continue to have a geometrically declining effect in subsequent periods, while a static specification would assume that all variables have an instantaneous and only an instantaneous impact (Keele and Kelly, 2006; Beck and Katz, 2011). Moreover, past variations in earnings can be a confounder of the current relationship between the key independent variables and earnings. Previous variation in earnings may influence current earnings by setting starting bargaining levels and

[30] One of the potential disadvantages of this strategy is that the inclusion of a fixed effect term a_{1ci} and a lag value of Y $\alpha_1 Y_{cit-1}$ could result in the so-called Nickell bias. Using the standard within-group estimator for dynamic models with fixed individual effects generates estimates which are inconsistent as the number of "individuals" tends to infinity if the number of time periods is kept fixed (Nickell, 1981). However, it usually vanishes with a long time-dimension as in this case (Judson and Owen 1999).

[31] Some authors have suggested that conditioning on a lagged dependent variable may cause collider bias in the case of simultaneous presence of unobserved common causes of the independent variables and the lagged values of the independent variable, as well as unobserved persistent causes of the outcome (Morgan and Winship, 2015; Dafoe, 2018). This chapter follow previous literature on the relationship of unionisation, technology and inequalities and conditions on lagged values of the dependent variable to account for dynamic processes (e.g. Kristal, 2013; Kristal and Cohen, 2017).

expectations, but also on workers' choice to join a trade union as well as firms' choice to invest more in capital and technology rather than labour.

As mentioned above, to investigate the diverse effect of each covariate on the earnings of different social classes, the model is estimated separately for each social class, resulting in four different datasets made up of 40 industries observed for 36-time points. It must be noted that the estimation of four separate models is equivalent to estimating one fully interacted model, where each covariate is interacted with social class, and coefficients are interpretable as differences from the reference category. In order to facilitate interpretations, results are presented as separate models and the equivalent interacted model is presented in tables A3.2 to A3.5 (appendix) to test statistical difference between the reference class (the salariat) and other classes.

One potential problem in analysing cross-section time-series data is that time series are likely to be non-stationary, increasing the risk of spurious relations due to the variables trending together over time. A common way to deal with non-stationarity is to estimate models in first difference. While the first difference is a convenient technical solution, it estimates only short-term effects because it removes any long-term information. However, the presence of non-stationarity does not rule out long-term relationships, which are the main interest of the current analysis.

A second option to estimate long and short-term relationships simultaneously are single equations error correction models (ECM) as Equation 2. ECMs allow for the simultaneous estimation of short-term and long-term effects while dealing with variables non-stationarity (De Boef & Keele, 2008). An ECM, as in Equation 2, is thus estimated:

$$[2] \quad \Delta Y_{cit} = \alpha_1 Y_{cit-1} + \beta_0 \Delta ICT_{it} + \beta_1 ICT_{it-1} + \beta_2 \Delta Union_{it} + \beta_3 Union_{it-1} + \beta_{n0} \Delta X_{cit} + \beta_n X_{cit-1} + a_{1ci} + a_{2c} + \varepsilon_{cit}$$

Where ΔY_{cit} is the first difference of the mean of ln earnings for each social class, and all other covariates enter the Equation both in differences and in one period lag in levels. The ECM, as reported in Equation 2, is a reparameterisation of a panel autoregressive distributed lag model similar to the one reported in Equation 1, and coefficients in level variables are thus comparable to those estimated from Equation 1.

Finally, to investigate the potential moderating effect between the two main explanatory variables, both models are estimated, including an interaction term between the indicators of ICT investments and unionisation.

However, estimates of models one and two are not readily interpretable in regard to each factor contribution to overall national earnings trends over the period analysed for each class for two reasons. First, the models are dynamic, meaning that the effect of each covariate on Y_{cit} continues to affect later periods through its lagged values. Second, models one and two are informative only of the functional relationship between the covariates of interests and earnings of each social class and do not account for the actual exposure of workers in each class to changes in analysed factors. However, as mentioned above and shown in figures A3.2 and A3.3 (appendix), workers in different social classes were diversely distributed across industries more or less affected by technological change and de-unionisation. As a result, despite similar functional relationships, each industry level factor may have contributed differently to each social class's overall national earnings trajectory.

To better understand the actual contribution of each factor to the earnings growth of different classes in the period analysed, a series of dynamic counterfactual estimates are derived from models in Equation 1 (see appendix for technical details). The observed earnings trends for each social class are compared to what they might have been if unionisation, investments in technology, and educational levels were fixed at the 1984 levels. Forecasts for each class industry combination are then combined to the national levels by computing yearly class averages of the forecasts weighted by the class industry employment size to reflect overall national earnings trends for each class. The difference between the observed trend and the counterfactual trend can therefore be interpreted as the net impact of each factor that was realised in the observed period.

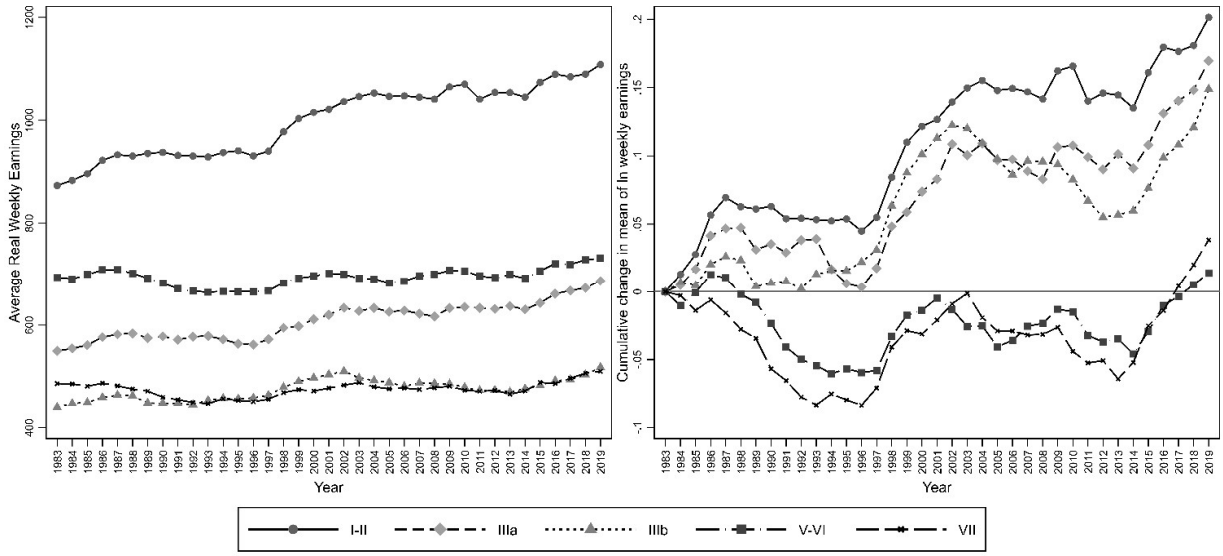
Results

Before moving to the econometric results, this section presents some descriptive analysis on the evolution of earnings of different social classes over the period under analysis. Figure 3.1 shows the evolution of weekly earnings from 1983 to 2019 for five categories of the EGP schema. The left panel shows the average real weekly earnings in 2000 USD for each social class. Besides giving a first grasp of the increase in earnings for the higher classes, the left panel of Figure 3.1 highlights the different market positions of the five social classes in terms of earnings. The Salariat class has a clear advantage that has increased throughout the period analysed, followed by skilled manual workers (class V-VI) and skilled routine non-manual workers (class IIIa); the two classes characterised by a mixed relationship. Albeit skilled manual workers received higher earnings than routine

non-manual, average earnings of the two groups have converged in the observed period. Finally, classes VII and IIIb are the less paid, with similar average earnings but very different growth rates in the period analysed.

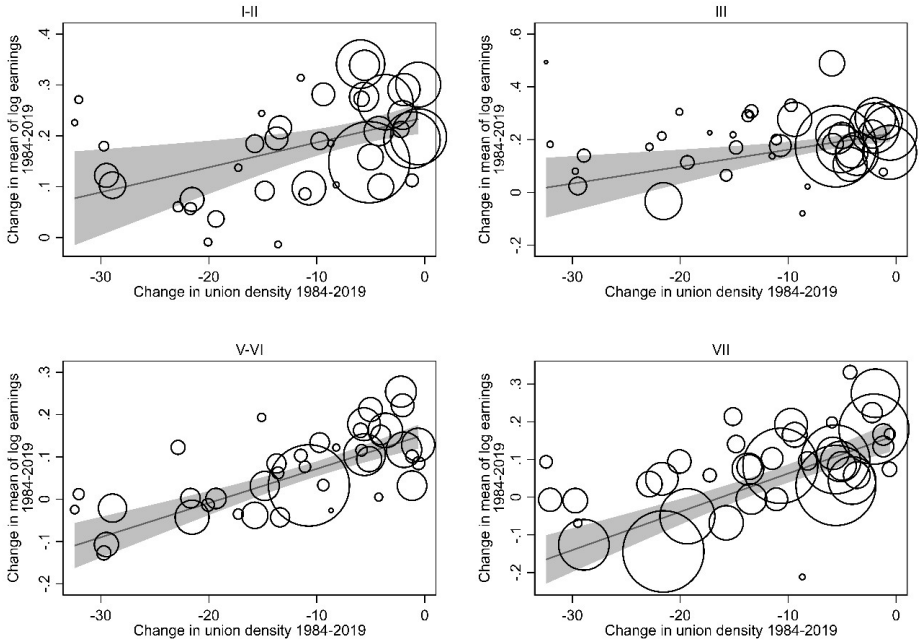
The right panel of Figure 3.1 reports the cumulative change in the mean of the natural logarithm of weekly earnings for the five classes and gives a better depiction of the diverse growths in weekly earnings for each social class and thus in the evolution of between-class inequalities. The mean earnings of classes I-II, IIIa, and IIIb – those characterised by more significant monitoring difficulties – rose on average much more than manual classes V-VI and VII. An analysis of earnings growth in terms of the EGP class schema highlights a significant pattern of decreasing returns for manual workers (Classes VI and VII) in comparison to service-sector non-manual workers (Classes IIIa and IIIb) and, most notably, the salariat class (I-II). Therefore, the critical question is which socio-economic transformations have altered the market position of different social classes driving the diverging earnings trajectories for these groups.

Figure 3.1 Mean weekly earnings by EGP classes (left panel) and cumulative change in the mean of ln weekly earnings (right panel)



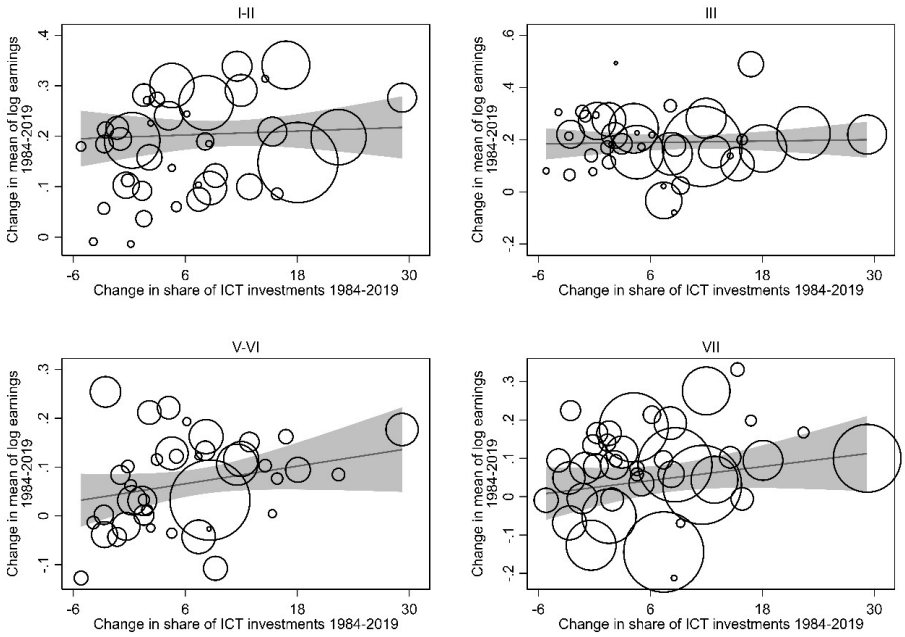
Notes: Own calculations from weighted CPS-MORG data from 1983 to 2019 The left panel reports average weekly earnings; the right panel reports change in average ln weekly earnings from 1983. Values are adjusted to 2000 US dollars using CPI. Classes are the salariat (classes I-II), higher-level routine non-manual (classes IIIa), lower-level routine non-manual (classes IIIb), skilled manual (classes V-VI) and unskilled manual (class VII).

Figure 3.2 Relationship between industry-level change in union density and social class earnings (1984-2019)



Notes: Own calculations from weighted CPS-MORG data. 1984-2019 industry-level change in union density and 1984-2019 change in industry-class mean ln of weekly earnings. Aggregate statistics are computed using sampling weights. Circle sizes indicate the 2019 industry-class employment size.

Figure 3.3 Relationship between industry-level change in ICT investments and social class earnings (1984-2019)



Notes: Own calculations from weighted CPS-MORG data and BEA data on investments in fixed assets. 1984-2019 industry-level change in ICT investments and change in industry-class ln of weekly earnings. Aggregate statistics are computed using sampling weights. Circle sizes indicate the 2019 industry-class employment size.

As mentioned above, socio-economic research has considered the decline in unions' power and increased reliance on information and communication technologies as the main factors behind the increase in earnings inequalities since the 1980s. Figures 3.2 and 3.3 give a first stylised, albeit highly informative, description of the relation between these two factors and the change in earnings for the four different social classes.

Figure 3.2 shows the relation between the change in industry level union density over 1984-2019 and the change in the mean of ln weekly earnings for each social class. Each industry-class combination was weighted by the total employment in 2019. Two facts emerge from this figure. First, earnings for all classes have grown the most in industries that experienced only limited union density decline (in many cases because they had low levels of union density to start with, see Figure A3.1 in the appendix). Second, it emerges that a larger share of workers from manual classes (V-VI and VII) are employed in industries that experienced strong processes of de-unionisation compared to service classes (this evidence emerges regardless of the time point taken into consideration for the distribution of employment, see Figure A3.2 in the appendix). Even in terms of slope, descriptively, we observe a class gradient with the relationship between change in union and earnings progressively increasing from salariat to lower manual classes[32].

Overall, Figure 3.2 brings support for Hypothesis 4, suggesting that industry-level de-unionisation has been a relevant factor for the fortunes of all social classes, but lower manual classes have been the most exposed to the phenomena.

The same figure considering investments in ICT is reported in Figure 3.3. Contrary to de-unionisation, no clear pattern emerges, highlighting little or no relation between industry reliance on new technologies and earnings of different social classes. Even in terms of slope[33], contrary to what expected from Hypotheses 1 to 3, there is less evidence of a descriptive relationship. Even though it is possible to observe a positive correlation for the lowest classes, these are smaller compared to the union's correlation and statistically non-significant.

Table 3.1 shows the results for Equation 1 estimated separately for each social class. All the social-demographic controls enter the Equation with the expected sign. Most importantly, results in Table 3.1 confirm the first conclusions drawn from descriptive

[32] Slopes and standard errors for Figure 3.2 for each class are: I-II .0048 (.0016); IIIab .0064 (.0020); V-VI .0080 (.0011); VII .0101 (.0014).
[33] Slopes and standard errors for Figure 3.3: I-II .0006 (.0015); IIIab .0004 (.0016); V-VI .0030 (.0018); VII .0030 (.0021)

Figures 3.2 and 3.3: technological change appears to have had no relation to the earnings of all social classes while unionisation is positively related to earnings of social classes and more so for manual ones. Indeed, there is a substantive relevant social class gradient[34] in the relation between unionisation and earnings, as expected from Hypothesis 4.

The same conclusions are evident from the ECMs in Table 3.2, suggesting that variables non-stationarity does not influence the results from the first specification. The lag coefficient of technological change has a close to zero and non-significant effect on the earnings of all social classes, while unionisation exhibits once again a clear social class gradient.

The ECM further allows analysing the immediate effects given by the coefficients of the first differenced variable. Unionisation has an immediate positive effect on the earnings of all social classes except the salariat, while, as expected, investments in computer technologies have an immediate positive effect on the earnings of services classes only.

Table 3.1 Results for two-way fixed-effects models for EGP classes, the dependent variable is the mean of ln weekly earnings

Class	I-II		III		V-VI		VII	
VARIABLES	Coef	se	Coef	se	Coef	se	Coef	se
ICT investments	0.0002	(0.0003)	0.0005	(0.0006)	-0.0005	(0.0006)	-0.0002	(0.0005)
Union density	0.0019***	(0.0006)	0.0034***	(0.0012)	0.0044***	(0.0008)	0.0050***	(0.0008)
Share of high-educated	0.0032***	(0.0003)	0.0046***	(0.0004)	0.0029***	(0.0006)	0.0042***	(0.0009)
Share of female	-0.0019***	(0.0005)	-0.0027***	(0.0003)	-0.0009**	(0.0004)	-0.0029***	(0.0005)
White non-Hispanic workers	0.0004	(0.0005)	0.0004	(0.0004)	0.0009**	(0.0003)	0.0012**	(0.0006)
Average age	0.0085***	(0.0017)	0.0057**	(0.0024)	0.0082***	(0.0021)	0.0019	(0.0015)
Ln of real VA	0.0048	(0.0096)	-0.0196	(0.0120)	-0.0036	(0.0130)	-0.0159	(0.0120)
Mean ln Earning t-1	0.2866***	(0.0391)	0.1770***	(0.0579)	0.2807***	(0.0441)	0.4047***	(0.0751)
Year fixed effects	Yes		Yes		Yes		Yes	
Observations	1,440		1,440		1,440		1,440	
R-squared	0.6731		0.6067		0.4521		0.5381	
Number of ids	40		40		40		40	

Cluster robust standard errors at the industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[34] A test for the statistical difference of the relationship between union density across classes suggest that the effect is statistically different between class I-II and the two manual classes V-VI and VII with a p value of respectively <0.05 and <0.01, for both the two-way fixed effect and ECM. For class IIIab, even though it is possible to substantively appreciate a gradient of the effect, it is not possible to reject the null hypothesis of zero difference with any of the other classes. However, dynamic simulations which show the overall contribution of unionization of earnings growth accounting for uncertainty of the estimates and exposure to the phenomena suggest that de-unionization had a minor impact on the earnings of this class compared to the manual ones.

Tables A3.6 and A3.7 in the appendix show the results for the two models, including an interaction term between investments in ICT and union density, to investigate possible moderating effects. Coefficients for all covariates are almost identical to the main specification, but the interaction terms are statistically non-significant and approximate zero; thus, the results do not support the idea of a moderating relationship between the two variables (Hypothesis 6).

In Tables A3.3 to A3.4 and A3.8 to A3.9, the potential mediation of de-unionization, as suggested in Hypothesis 5, is investigated by looking at the association between ICT and the earnings of each class without conditioning on union density. Without including any control, results show a small and positive effect of ICT for all social classes, suggesting that ICT may be associated with higher earnings growth but equally distributed across occupational classes. This effect slightly shrinks after controlling for union density and completely disappears once we control for class-industry educational expansion, suggesting that the positive effect of ICT on earnings could be in part mediated by increasing educational levels of the workforce. The relationship between ICT and educational expansion is particularly relevant since, according to the theory SBTC we would expect technological change to positively affect earnings by raising skill requirements, positing a possible mediation effect of educational attainment. However, the effect of ICT, even without controlling for union density or educational expansion, is quite small and equal across classes and turns zero after including other controls, thus confirming that ICT is not related to diverse earnings trajectories and bringing little support for the idea of a mediation effect of either unionization (Hypothesis 5) or educational expansion on the earnings evolutions of the four classes.

As mentioned above, the straightforward interpretation of the functional effects estimated by models 1 and 2 is not fully informative about the overall contribution of each factor due to the dynamic nature of the models and the fact that workers in different classes are not equally distributed across industries. As figures A3.2 and A3.3 in the appendix highlight, a much larger share of manual workers was employed in industries that experienced strong de-unionisation since 1984. For example, in 2019, 73.4 and 83.6 per cent of employees in salariat and non-routine manual classes were employed in industries that experienced less than a six-percentage point decline in union density against the 43.4 and 50.4 per cent of workers in skilled and non-skilled manual classes. As a result, one would expect unionisation to have had a more decisive contribution to the overall evolution in earnings of manual classes and, therefore, an essential role in explaining divergent earnings trajectories between the groups.

Figure 3.4 presents the estimated changes in the mean of ln weekly earnings for each social class for 1984-2019 over the total economy estimated from model one and holding covariates of interest to their 1984 levels (counterfactual forecasts for the whole period are presented in Figure A3.4 appendix). Forecasts are estimated for each industry-class combination and then combined to represent the entire economy by taking the yearly averages weighted by each cell employment size. The results are counterfactual estimates of each class earnings growth had industry levels covariates remained at 1984.

Table 3.2 Results for fixed-effects ECMs for EGP classes, the dependent variable is the mean of ln weekly earnings

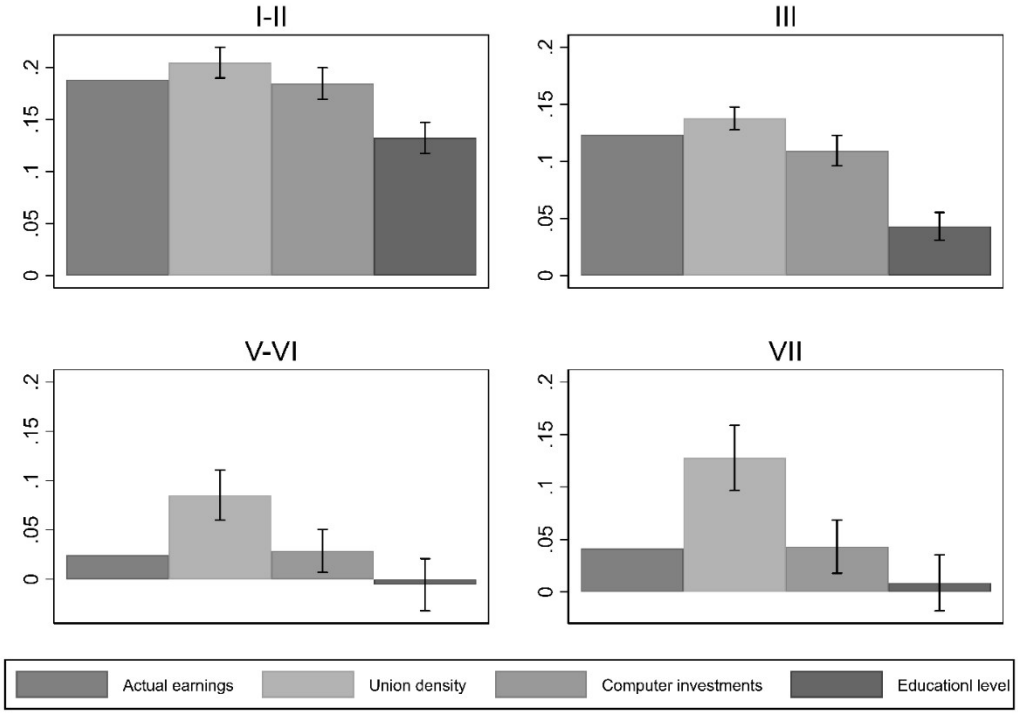
Class	I-II		III		V-VI		VII	
VARIABLES	Coef	se	Coef	se	Coef	se	Coef	se
L. ICT investments	0.0001	(0.0003)	0.0004	(0.0005)	-0.0005	(0.0006)	-0.0002	(0.0004)
Δ ICT investments	0.0017**	(0.0008)	0.0023**	(0.0009)	0.0008	(0.0011)	0.0006	(0.0013)
L. Union density	0.0018**	(0.0007)	0.0029**	(0.0012)	0.0042***	(0.0009)	0.0048***	(0.0010)
Δ Union density	0.0007	(0.0010)	0.0037***	(0.0013)	0.0038***	(0.0012)	0.0049***	(0.0011)
L. Share of high-edu	0.0026***	(0.0005)	0.0045***	(0.0009)	0.0027***	(0.0006)	0.0029***	(0.0008)
Δ Share of high-edu	0.0035***	(0.0004)	0.0045***	(0.0004)	0.0031***	(0.0006)	0.0043***	(0.0010)
L. Share of female	-0.0013**	(0.0006)	-0.0022***	(0.0005)	-0.0003	(0.0006)	-0.0031***	(0.0009)
Δ Share of female	-0.0020***	(0.0005)	-0.0028***	(0.0003)	-0.0010**	(0.0005)	-0.0027***	(0.0004)
L. Average age	0.0060***	(0.0015)	0.0057**	(0.0026)	0.0059*	(0.0034)	-0.0027	(0.0022)
Δ Average age	0.0111***	(0.0017)	0.0059**	(0.0028)	0.0100***	(0.0014)	0.0034*	(0.0017)
L. Share of white	0.0002	(0.0006)	-0.0004	(0.0005)	0.0006	(0.0005)	0.0005	(0.0005)
Δ Share of white	0.0004	(0.0004)	0.0007	(0.0005)	0.0012***	(0.0003)	0.0017**	(0.0006)
L. Log of real value added	0.0084	(0.0087)	-0.0156	(0.0123)	-0.0011	(0.0116)	-0.0105	(0.0119)
Δ Log of real value added	0.0051	(0.0233)	-0.0399*	(0.0233)	0.0060	(0.0375)	-0.0355	(0.0247)
L. Mean log earnings	-0.6658***	(0.0405)	-0.8110***	(0.0854)	-0.6899***	(0.0582)	-0.5682***	(0.0805)
Year fixed effects	Yes		Yes		Yes		Yes	
Observations	1,400		1,400		1,400		1,400	
R-squared	0.5052		0.5568		0.4587		0.4187	
Number of ids	40		40		40		40	

Cluster robust standard errors at the industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The first bar of each box represents the actual earnings growth for each social class, as reported in Figure 3.1. The other bars represent the estimated change had union density, computerisation, and share of tertiary educated remained constant. Given that the literature on social class has explicitly referred to differentials in human capital, skill requirements, and related productivity levels as key reasons for between-class inequalities (Le Grand & Tåhlin, 2013; Tåhlin, 2007), the fastest growth in educational credentials for non-manual

classes is likely to have played a significant role for their wage growth even beyond the introduction of computerized equipment. As a result, educational expansion for each class is given particular relevance as an explanatory factor.

Figure 3.4 Counterfactual estimates of 1984-2019 earnings growth for EGP classes



Notes: 1984-2019 change in observed and counterfactual dynamic estimates predicted from model 1 using bootstrapped standard errors and holding values of the dependent variables at their 1984 levels. Details of the procedure and change in forecasts for the entire period are available in the appendix to Chapter III, section "Counterfactual estimates." Classes are the salariat (classes I-II), routine non-manual (classes IIIab), skilled manual (classes V-VI) and unskilled manual (class VII).

Differences between the observed earnings change and the counterfactual estimates can thus be interpreted as the total long-term contribution of each factor to the earnings development of each class. Particular attention is paid to educational level other than industry level covariates since skills are considered among the main determinants of social-class earnings, and increases in educational returns are considered among the main driving forces of earnings inequalities.

Looking at the change in earnings related to de-unionisation, Figure 3.4 highlights that the earnings growth for classes I-II and III would have been almost identical had unionisation remained at its original levels. On the contrary, the decline in union density is the only substantively relevant factor for manual classes. Moreover, investments in

computer technologies do not emerge as a relevant factor for any of the classes analysed, contrary to the increase in tertiary-educated workers, which explains a considerable part of the earnings growth of the salariat classes and almost the entirety for routine non-manual workers.

Conclusions

The present chapter has investigated the contribution of de-unionisation and computerisation at the industry level to the evolution of earnings of different social classes in the US from 1984 to 2019. Socio-economic literature has repeatedly shown that overall earnings inequalities in this period have grown and that between-occupations inequalities have been an essential dimension of this process.

The main narrative, promoted by mainstream economic literature, suggested that technological change has been the most crucial cause of rising inequalities. Most importantly, the theory of RBTC extended this claim to explain diverse earnings growth between occupations and eventually social classes. By claiming that technological change since the 1970s was a good substitute for routine tasks and middle-class workers mainly performing these tasks, RBTC suggested that the increased reliance on computerised equipment was responsible for the observed hollowing out of the middle-classes and the so-called middle-class squeeze.

Sociological literature, however, has questioned this assumption suggesting that institutions and the bargaining power of different groups and classes matter. As a result, several empirical studies have shown that other factors, such as the fall of union density, minimum wages and financialization, have played a significant role in the growth of earnings inequalities in terms of overall dispersion of earnings or functional distribution of income, often much more than technological change.

This chapter confirms this conclusion in regards to inequalities between social classes. Indeed, tasks and occupation are a crucial dimension in the definition of social classes and play a crucial role in the definition of economic returns beyond their susceptibility or complementarity to technological change. Literature on social stratification and mobility has traditionally highlighted that the tasks performed, in terms of monitorability and asset specificity, are strictly related to workers' social class and, eventually, economic returns.

Based on the existing literature on industry-level determinants of inequalities, the present chapter has focused exclusively on the private sector. This is due to data availability

on investments and variation in the classification of public sectors across time. However, most importantly, it is because power relations, automation, and unionisation processes may follow very different dynamics in the public sector due to different economic objectives, interests, and government participation. Nevertheless, earnings evolutions in the public sector are central to understanding overall national patterns and cross-country differences. As a result, the interplay between technology, unionisation, and class-based inequalities in the public sector of the economy deserves detailed attention from future research.

Nevertheless, results for the private sector suggest that, while technological change is a relevant factor in determining the demand for specific tasks and the degree of monitorability of others, it is not the only one. On the contrary, the industry-level decline in union density appears a crucial factor behind the diverging fortunes of manual and non-manual workers.

An observation of the earnings levels and growth of four different EGP classes has highlighted that earnings are associated with social class and that this association has changed over the last decades. More precisely, earnings of the salariat and routine non-manual workers have grown while those of skilled and unskilled manual workers have either stagnated or declined.

Both descriptive statistics and econometric analysis suggested that industry-level investments in computer technologies have had a negligible impact on the earnings growth of all social classes in the period considered, casting doubts on the theories of routine and skilled biased technological change. However, it must be noted that conclusions are limited to the industry-level relation, that is, the effect of industrial computerisation on workers employed in that industry. However, technological change may have an effect beyond the industry in which it is implemented, for instance, by raising the demand for workers in specific classes. Nevertheless, both RBTC and SBTC suggest a relation between technology and earnings related to the complementarity between computers and skills. It follows that a positive association between the two should be most evident in industries that invest extensively in computer technologies.

On the other hand, union density emerged as a crucial factor behind the diverse earnings growth of the different classes in two ways. First, union density is positively associated with the earnings of all classes but more so for non-salariat ones. This finding confirms recent literature suggesting that unions increase average wages for all groups of workers through several mechanisms-such as unionisation threat, the promotion of a moral economy, and social comparison. However, that benefits are more pronounced for blue-

collar and less-skilled workers who cannot bargain higher wages based on their market position.

Second, the decline in union density had played a significant role for skilled and unskilled manual workers due to their higher exposure to the phenomena. In fact, during the period analysed, a much large share of classes V-VI and VII were employed in industries that experienced significant declines in union density compared to classes I-II and III. As a result, manual workers have been much more influenced by de-unionisation.

Interestingly, the results do not confirm the presence of a mediating or moderating role of unionisation in the relationship between technological change and the earnings of each social class in the period under consideration. This finding is not in line with a growing body of research that has stressed the two phenomena' interrelatedness. However, it must be noted that this result is confined to the observation of between-class inequalities at the industry level. On the other hand, the two macro factors may interact in their relationship to overall earnings dispersion, labour's share, or inequalities defined by cleavages other than social class. Moreover, the interrelatedness between two factors may play out at other levels of analysis, such as the national level or in the relationship between industries.

Finally, results have highlighted the importance of different skill levels between classes in terms of the share of tertiary-educated workers. Despite technological change, the average share of tertiary-educated workers emerged as a positive factor for all classes. However, the increase in educational level has been pronounced only for non-manual workers who consequently benefitted the most. This result echoes Tåhlin (2007) suggestion that occupational skill requirements may be among the strongest justifications for between social classes disparities, and the more robust increase in human capital for service classes has contributed to the divergent growth in earnings.

Chapter IV

Computers at Work in Germany and the UK

The Relationship Between Computer Use and Job Satisfaction, and the Mediating Role of Tasks and Discretion*

Abstract

This chapter investigates the relationship between computer use at work and both job tasks and task discretion, as well as the mediating role that job tasks and task discretion play in the relationship between computer use and job satisfaction. By comparing these relationships in Germany and the UK, the chapter contributes to the long-standing debate on the upskilling/deskilling nature of the use of technology and the repercussions of this use on the overall quality of work. The chapter uses data from the UK Skills Surveys and the BIBB/BAuA Employment Surveys and applies structural equation modelling (SEM). In line with the literature on routine-biased technological change (RBTC), results suggest that computers are complementary to the performance of less routine and more abstract cognitive tasks and that this relationship is conducive to a higher level of task discretion and job satisfaction in both countries. Moreover, after accounting for differences in job tasks performed, results highlight a negative direct effect of computer use on both task discretion and job satisfaction in the UK but not in Germany. Results indicate that the ultimate effect of the use of technology on both jobs and job satisfaction depends on the institutional contexts in which this technology is introduced. These contextual differences are related to the institutional arrangements and managerial practices typical of different production and skill regimes.

* This chapter is the result of a joint work with Paolo Barbieri from the University of Trento, Carla Hornberg and Heike Solga from the WZB Berlin Social Science Center

Since their early appearance in the workplace, computers have spurred a vivid debate on their consequences for work, organisational, and social processes. At the core of this debate lies the question of whether technological change leads to an upgrading of skills or a downgrading of work (Attewell, 1987; Bailey and Leonardi, 2015; Bloomfield and Coombs, 1992; Gallie, 1991). With the digital transformation of work, this question has recently regained importance, partly because the skill requirements of jobs are strongly associated with job quality and ultimately with workers' job satisfaction (Gallie, 2007) as well as with labour market inequalities (e.g., in terms of earnings) (Kristal and Edler, 2019).

Despite its relevance, answers to the question of the upskilling or deskilling nature of technology – and the related consequences of this technology for job quality – remain controversial. Scholars from a largely Marxist tradition argue that technology is an instrument used to increasingly standardise labour processes by reorganising work into a series of low-skilled tasks and that technology has therefore resulted in lower-skilled jobs with little intellectual content and autonomy (Braverman, 1974; Jenkins and Sherman,1979). Various qualitative case studies support this perspective empirically (e.g., Haakestad and Friberg, 2017). In contrast, scholars who support the upskilling thesis suggest that a technology-driven decentralisation of information (Acemoglu et al., 2007) and the complementarity of technology to non-routine cognitive tasks have increased the demand for skills and led to large human-capital endowments (Autor et al., 2003; Goldin and Katz, 1998). This upskilling perspective is supported by a series of quantitative studies that document a steady growth in abstract tasks and skilled occupations, with corresponding benefits for wages (e.g., Breemersch et al., 2017; Fonseca et al., 2018; Keister and Lewandowski, 2017).

These conflicting perspectives and findings might result from conceptual differences in the definition of skills: While upskilling proponents typically focus on the type and range of tasks performed, deskilling proponents refer to the degree of autonomy and to workers' control over the work process. Several authors therefore suggest considering both *distinct yet related* dimensions of occupational skills to derive a better understanding of the relationship (a) between technology and both upskilling and deskilling and (b) between technology and the quality of work (De Witte and Steijn, 2000; Martinaitis et al., 2020; Noon et al., 2013; Rolfe, 1986, 1990; Spenner, 1983, 1990; Vallas and Beck, 1996; Felstead et al., 2007). This conceptional differentiation is also supported by the fact that trends in job tasks and task discretion do not necessarily evolve in the same direction

(Gallie, 2012). Moreover, whether technology and the quality of work are positively or negatively related might depend on the type of job tasks and on workers' task discretion (e.g. Hardin, 1960; Parayitam et al., 2010; Shepard, 1977).

This chapter therefore addresses two research questions: First, it examines the link between computer use (i.e., the use of any computerised equipment at work) and both job tasks and task discretions and thereby reveal whether upskilling and deskilling are indeed mutually exclusive. Second, it investigates the mediating role of both job tasks and task discretion in the relationship between computer use and job satisfaction. Computer use is taken as an indicator of the use of technology because computers are the most widespread form of technology among the labour force (Autor et al., 2003; Elsayed et al., 2017; Green, 2012; Menon et al., 2019; Spitz-Oener, 2006). Moreover, computer use has been collected in a similar way in both surveys used in this chapter, and it has been extensively used in studies of this kind investigating the relationship between technology, tasks, effort, satisfaction, and various indicators of job content.

Moreover, these relationships are compared between production regimes in both Germany and the UK. This comparison challenges the deterministic notion of the upskilling and the deskilling thesis because both argue that the impact of technology is common to all institutional and organisational contexts (e.g. Bailey and Leonardi, 2015). This chapter argues that while computers are generally complementary to a specific set of tasks and substitutive to the performance of others, their impact on organisational practices – and thus the extent to which they replace certain tasks and impact the degree of workers' task discretion – is contingent on the specific institutional arrangements in which they are used (Autor et al., 2002). Germany and the UK are characterised by clearly different institutional arrangements regarding their market coordination (Estevez-Abe et al., 2001; Hall and Soskice, 2001), skill formation (Thelen, 2004), and corporate governance (Waddington, 2004). The mixture of industrial and managerial practices and cultures in these two countries might therefore influence how computers are adapted to production processes and thereby shape workers' task discretion and job tasks as well as their overall job satisfaction (Gallie, 2007, 2011; Green and McIntosh, 2001).

This chapter theoretically and empirically highlights how job tasks and task discretion are related yet distinct aspects of occupational skills and investigates their role as mediators in the relationship between technological innovation and workers' job satisfaction (i.e., workers' assessments of the quality of work). Moreover, it demonstrates the importance of national institutional contexts in moderating the impact of technology on work organisation and job satisfaction.

A brief synopsis of the upskilling/deskilling debate

In the European debate, Friedmann (1946) is one of the most influential authors to point to how technology leads to a deteriorating quality of work by negating workers' *craftsman-like* skills/tasks and removing workers' capacity to control the production process. As Gallie (2012) notes, Friedmann identifies technology as the main factor behind *Taylorising* work tasks and thereby behind eliminating the opportunity for workers to exercise discretion, autonomy, and control over their jobs. In the US debate, Leavitt and Whisler (1958) were among the first to claim that computer and information technology (ICT) leads to a centralisation of decision-making, authority, and power in the hands of high-ranking managers and employers. Similarly, Braverman (1974) argues that the automation of the labour process is a means of transferring control, discretion, and autonomy from the shop floor to management because this automation supports the application of scientific management and thus also this management's ability to ensure that labour power is successfully converted into labour.

The underlying idea of the deskilling thesis is that information is a source of power and that workers and middle management would therefore lose power if information gathered in computerised systems became accessible to top management. Supporting empirical evidence has been provided by a large body of organisational studies (e.g. Gallie et al., 2003; Menon et al., 2019). The equation between required skills and task discretion is crucial to the deskilling perspective, with discretion understood as workers' ability to choose between alternative courses of action and to exercise control over the way, order, and turnaround times in which tasks are performed. Reducing skills thus entails closer supervisory control and a loss of workers' autonomy and discretion in the workplace (Fox, 1974; Gallie et al., 2003; Jaques, 1956, 1967; Spenner, 1983, 1990).

In contrast, proponents of the upskilling thesis argue against any inherently centralising tendency of computer technology (Lindbeck and Snower, 2000; Radner,1993; Wyner and Malone, 1996). They stress that such a tendency could lead to substantial costs for management and that computers may instead promote the organisational decentralisation of power and control due to shared information or the number of management levels. Moreover, an upskilling scenario is echoed in the literature on *skill-biased technological change* (SBTC), which suggests that computer technology, education, and skills are strongly complementary and that technology thus favours returns for skilled workers and increases the demand for skills (Goldin and Katz, 1998). This position is

strengthened by a large number of empirical studies that document strong relationships between ICT use, high-skilled tasks, the demand for tertiary-educated workers, and rising college wage premiums (e.g. Bresnahan et al., 2002; Goldin and Katz, 2008).

Due to the theoretical and observed evidence of polarising trends in both earnings and occupational structures (Acemoglu, 1999), the SBTC thesis was developed into the thesis of *routine-biased technological change* (RBTC) (Acemoglu and Autor, 2011; Autor et al., 2003; Goos et al., 2009), whose key argument is that computer technology modifies the job tasks required and performed in the workplace, which are classified along two distinct dimensions: *routine* vs *non-routine* and (analytical and interpersonal) *cognitive* vs *manual* tasks.

While SBTC relates the introduction of computers to changes in earnings structures mainly through the complementarity of computers to skill levels and through returns to more highly educated workers, it makes no direct claim regarding the relationship between technology and the content of work in terms of job tasks or task discretion. In contrast, RBTC connects technology and the evolution of earnings and occupational structures through its relationship to the types of tasks performed by workers in different occupations and thus also makes an argument for the relationship between computers and job tasks. According to RBTC, technology serves as a substitute for explicit and codifiable routine-task operations – at both the low and middle level of the occupational hierarchy – and as a complement to higher-level cognitive and manual tasks, resulting in a steady growth of skilled jobs. However, the RBTC literature also signals a parallel increase in non-automatable manual tasks, thereby causing a polarisation of the occupational structure (Autor et al., 2003; Goos et al., 2009; Acemoglu & Autor, 2011).[35]

The deskilling and upskilling perspectives clearly refer to two different dimensions of occupational skills: The upskilling perspective points to the complexity and variability of job *tasks*, while the deskilling argument refers to task *discretion*. The argument that task discretion and the complexity of tasks are two fundamental yet distinct dimensions of skills follows from the work of Fox (1974), Friedmann (1961), and Spenner (1983, 1990). For

[35] The economic literature usually identifies a rise in low-skilled jobs in Europe and the US and a growth in low-skilled janitorial services, which echoes the sociological thesis of the so-called *service proletariat* (Esping-Andersen, 1993). Bernardi and Garrido (2008) have shown evidence of a U-shaped trend of polarisation for Spain; however, Fagan et al. (2005) report notable skill differences in the occupational structure of manual services between Germany and the UK, with a higher level of manual-workforce qualification in the German service sector. It follows that "non-automatable, non-routine manual/physical tasks" may differ between the two countries. Unfortunately, the data do not allow for properly distinguishing between these differences.

example, Spenner (1990, p. 402, 403) differentiates between *substantive complexity* ("the level, scope and integration of mental, manipulative and interpersonal tasks in a job") and *autonomy control* ("discretion or leeway available in a job to control the content, manner, and speed with which tasks are done"). Similarly, Rolfe (1986, 1990) distinguishes between *technical complexity* and *discretion* based on the same idea that while tasks are carried out as organisational requirements, the nature of such requirements does not dictate how tasks should be completed, but how they should be determined by the hierarchy of power within an organisation (see also Myles, 1990; Martinaitis et al.. 2020; Autor et al., 2002). The interplay between the type and complexity of job tasks and the degree of task discretion thus varies across organisations.

Following this line of reasoning, the clear distinction between these two dimensions might allow recent evidence on the evolution of skills and tasks to be reconciled without necessarily implying a unidimensional upskilling view of technological change. This view has received empirical support (e.g., Iacono and Kling, 1991; Vallas, 1993; Vallas and Beck, 1996). For example, Zuboff (1988) identified a general upskilling of production work for more abstract job tasks but a minimal expansion of autonomy.

This brief synopsis of the upskilling/deskilling debate highlights the relevance of disentangling different dimensions of occupational skill requirements in order to understand the skill-biased nature of technological innovation and its ultimate impact on job satisfaction. However, while studies have shown that job tasks and task discretion may be affected differently by technology, how the interplay between these two dimensions determines the overall effect of technology on job satisfaction remains poorly understood. Moreover, researchers in this area – using mostly single-country cases – are quick to generalise their findings and might thereby underestimate the role of the institutional context of the implementation of technology.

Embeddedness in institutional contexts

Both the upskilling and deskilling perspectives are based on a deterministic understanding of technological change and therefore assume that technology similarly impacts job tasks and task discretion across countries (with similar levels of economic development). However, cross-country studies reveal that workers in similar occupations can be exposed to different job tasks (Green, 2012; Green et al., 2003) and to very different styles of managerial supervision and control (Galliem, 2007, 2011; Lincoln and Kalleberg, 1990; Maurice et al., 1986).

Such country differences could result from the fact that capitalist economies follow different production strategies, which also results in favouring different types of employment relationships, skill-formation regimes, and skills equilibria (tasks and discretion) (Estevez-Abe et al., 2001; Gallie, 2007, 2011; Hall and Soskice,2001). In this line of reasoning, both the *Varieties of Capitalism* (VoC) approach (Hall and Soskice 2001) and approaches related to *employment regimes* theory (Gallie 2007) are prominent. This chapter builds on the VoC approach, which distinguishes between two broad types of political economies based on the degree and institutional arrangement of market coordination. *Coordinated Market Economies* (CMEs) – which are exemplified by the German case – are characterised by a set of institutions (e.g. centralised and coordinated wage bargaining, the presence of work councils, and strong vocational education and training systems) that incentivise firms to adopt employment strategies that rely on highly skilled labour endowed with extensive work autonomy, responsibilities, and the encouragement to share information (Estevez-Abe et al. 2001; Herrigel and Sabel 1999). In contrast, firms in *Liberal Market Economies* (LMEs) – which are exemplified by Anglo-Saxon countries, such as the UK – rely heavily on competitive market relationships and hierarchies to organise relationships between workers and other actors. Top managers typically have strong, unilateral control over both the firm and production processes, including substantial freedom to hire and fire in order to adapt to fast-changing employment conditions and product markets. Due to highly fluid labour markets, firms adopt employment strategies based on a workforce that is mainly endowed with general skills and low(er) company attachment. The underlying idea is that these different national institutional contexts are associated with different managerial strategies and practices of organising work at the firm level because firms have a comparative advantage if they behave according to the respective institutional rationale (Hall and Soskice 2001; Holm et al. 2010; Lopes et al. 2014, 2017).

The implementation of new technologies and the consequences of these technologies for job tasks and task discretion are hence likely to differ in these two institutional arrangements. In CMEs, in which workers' occupation- and industry-specific skills more strongly contribute to the organisation of product lines and production processes, firms should use technology more often to relieve their (comparatively well-paid and well-trained) workers from simple routine tasks and increase the use of workers' analytical, problem-solving, and non-routine manual potential, which enhances labour productivity. However, due to the prevalence of diversified quality production in Germany (Sorge and Streeck, 2018) and the more-consensus-based approach to decision-making in

CMEs (Edlund and Grönlund, 2008), technology-implementation processes are influenced by strong trade unions and high levels of employment protection, especially in manual-intensive industries (see also Baccaro et al. 2018). Routine tasks might thus be more integrated than substituted when implementing computerised work tools. Here, routine tasks also more often include tasks that require manual dexterity and occupation-specific skills than in LMEs, which are more often associated with simple tasks. In LMEs, in which firms have less access to a highly trained workforce and face higher labour turnovers, technology can be used as an instrument to more effectively increase control over work processes, to increasingly standardise tasks, and to reduce skill requirements (Dobbin and Boychuk, 1999).

Comparative case studies show very high variability in the degree of discretion that workers exert on their job – regardless of similar technological work settings – according to diverse forms of managerial control and skill regimes (Gallie, 2007; Lincoln and Kalleberg, 1990). For example, Dobbin and Boychuk (1999) report strong differences in workers' task discretion between Scandinavian (social-democratic) countries and LMEs and conclude that production regimes and managerial systems may favour skill- versus rule-governed modes of production, with contrasting consequences for job autonomy. Hence, to gain a better understanding of how production and work are restructured in response to technological innovations, the institutional context in which firms operate must be considered. This chapter compares Germany and the UK as the two ideal-typical cases of CME and LME. Due to the different types of institutional embeddedness of managerial strategies in the two countries, it might be as misleading to assume a common trend towards deskilling in terms of a generalised loss of workers' discretion as it would be to expect a common upskilling trend towards an increase in non-routine or cognitive tasks.

Before presenting comparative expectations, the next section discusses a stylised theoretical model of the mediating role that job tasks and task discretion play in the relationship between computer use and job satisfaction.

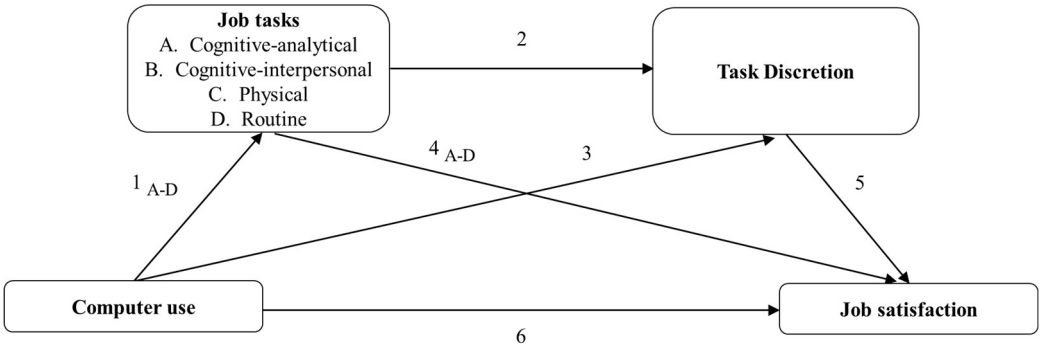
Theoretical model and expectations

Figure 4.1 presents the stylised theoretical model. The relationship between computer use and both job tasks and task discretion as two distinct yet related dimensions of skills (the first research question) is indicated by Paths 1 and 3, respectively. The mediating role of the two skills dimensions for the relationship between computer use and job satisfaction (the second research question) is indicated by the joint Paths 1–4 and 3–5, respectively.

Path 6 indicates the remaining direct influence of computer use at work on job satisfaction, independent of (i.e., after controlling for) jobs tasks and task discretion. Here, research has revealed that the use of computerised equipment in the workplace can also have a direct *alienating* effect, for example, due to technostress or computer anxiety (e.g., Ayyagari et al., 2011; Brod, 1984; Ragu-Nathan, 2008).

In the rest of this section, the theoretical expectations for the two mediations are first presented and expectations about country differences are derived. Some considerations on variations across groups of workers are then presented, focusing on occupational class position and participation in job-related training.

Figure 4.1 Stylised theoretical model of the role of tasks and task discretion on the relationship between computer use and job satisfaction



Research has consistently shown that the diversity and complexity of job tasks (Path 4) as well as the possibility of controlling the pace, timing, and methods of work (Path 5) are associated with higher levels of job satisfaction. Concerning the proposed mediation via job tasks (Paths 1–4), RBTC research argues that computers complement (analytical and interpersonal) cognitive tasks yet substitute (manual and non-manual) routine tasks. Thus, the extent of computer use should result in variations in the extent to which non-routine (cognitive and manual) job tasks are reinforced and that routine tasks should be reduced (Path 1), which should thus influence workers' job satisfaction (Path 4) (see also Taber and Alliger, 1995).

Through their complementarity to more non-routine (especially cognitive-analytical) tasks, computer technologies may eventually be conducive to higher levels of task discretion (Paths 1–2) because non-routine (especially cognitive) tasks are more difficult for employers and management to monitor, which may thus also yield higher job satisfaction (Nassab, 2008). Gallie et al. (2003, pg. 419) interpret the rise in task complexity

as being "accompanied by rising task discretion", whereas Green (2012) proposes that discretion impacts job tasks. While the lack of appropriate longitudinal data on work practices impedes the ability to empirically study the opposite directions of this relationship, in order to properly model the direct effect of computer use on task discretion (i.e., net of differences in tasks between computer users and non-users), this model builds on Gallie et al. (2003) and Green et al. (2021) and impose a direct relationship between job tasks and task discretion, as indicated by Path 2.

Moreover, while the use of computerised equipment is complementary to more abstract and less monitorable tasks, this use may simultaneously (according to the deskilling perspective) increase the possibility for management to monitor and control work by centralising information, independent of the type of job tasks. According to Bloom et al. (2014), while information technologies are associated with more workers' empowerment and autonomy, cheaper communication technologies act as a centralising force, thereby allowing a broader span of managerial control and reducing workers' discretion. This process can lead to a negative direct effect of computers on workers' task discretion, as indicated by Path 3. By influencing the extent of workers' task discretion (Path 3), the extent of computer use could generate differences in job satisfaction (Path 5). Indeed, for Scotland, Sutherland (2016) has shown that job autonomy is positively related to job satisfaction.

Based on the discussion about the differences between skill and production regimes, the introduction of computerized equipment should be embedded in different employment and production strategies in the two countries. As a result, computers should be used as instruments to centralize information and increase managerial control in the UK. Here computer users should experience less discretion in their work compared to non-users performing similar jobs and tasks. On the contrary, computers in Germany will more likely be used to foster firms coordinated strategies, thus increasing the information available and the discretionary effort in the hands of employees. Contextual characteristics are likely to influence the way in which computers are implemented by employers by raising incentives to use them to monitor employees or providing less cooperative work environments, more stringent deadlines and increased effort, and thus primarily moderate the direct effect of computers on discretion- and satisfaction.

The mediating role of job tasks and task discretion in the interplay between technology and job satisfaction might differ not only across institutional contexts but also across groups of workers (within countries). Two workers' characteristics are considered to be closely related to this interplay: *occupational class position* and *further training*. Both

social stratification and labour market research highlight the importance of the monitoring problem for justifying the favourable position of upper-service-class positions (Erikson and Goldthorpe 1992). Hence, employees in service-class positions (i.e., the salariat) might experience computer use differently than other workers because computers are considered to be largely *complementary* to the non-routine cognitive tasks typical of higher-level occupations and to simultaneously constitute a powerful instrument for controlling and monitoring the discretionary efforts of highly educated workers, whose activities are intrinsically difficult to monitor. For other workers, computer use might be less influential for task discretion because their work is characterised by a higher degree of routine (cognitive or manual) tasks, which are generally easier to monitor even without computerized equipment. Occupational class could thus be a moderator for the direct effects of computers on discretion and satisfaction. Therefore, the negative direct effect of computer use on both discretion and satisfaction should be more prominent for higher classes since computers are most effective for this kind of occupations.

Participation in job-related adult training might be another relevant moderator related not only to the direct impact of computer use on job satisfaction (Path 6) but also to the mediating role of job tasks (Paths 1–4). Adult training might increase workers' proficiency in ICT skills, which could thereby contribute to mitigating the stress-enhancing and alienating effects associated with computer use (Path 6) or to increasing requirements in problem-solving or other cognitive job tasks (Path 4) (Cedefop 2015; Desjardins and Rubenson 2013). Accordingly, a stronger direct negative effect of computer use on job satisfaction may be in place for non-trained workers and a more-positive mediating effect of jobs tasks for trained workers.

Due to the difficulty of deriving concrete expectations about country differences for these two potential moderators, the two moderation analyses are included as an explorative analytical step in this study.

Data and variables

The main data sources are the BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany and the Skills Survey (2006, 2012, 2017) for the UK. Both surveys provide comparable and high-quality information on the variables of interest (see below). Sample is restricted to employees aged 20 to 65. After dropping cases with missing information on at least one variable of interest, the final sample consists of 49,446 cases for Germany that

range from 16,040–16,778 cases per survey year. For the UK, sample sizes are considerably smaller, with 11,283 cases in total and 2,742–5,853 cases per survey year.

Data were collected using the *job requirements approach*, which is essentially an adaptation of occupational psychologists' methods in the context of socioeconomic surveys. This approach provides information on several job-related characteristics, such as the use of technology, job tasks, task discretion, and job satisfaction. Table 4.1 reports information on each selected item and its latent construct of reference.

Computer use measures the use of any computerised equipment at work. This broad indicator is also useful in accounting for workers for whom computer use may not be a central component of the job but is relevant in shaping workplace dynamics. In the UK, computer users include workers who reported that computer use is *essential*, *very important*, or *fairly important* in their job, whereas non-users are those who reported *not very important* or *not important at all*. In Germany, computer users are defined as workers who reported that they work with computers *frequently*, whereas non-users are those who do so only *sometimes* or *never*. Different specifications of the variable yield similar results.

Workers' *job satisfaction* is operationalised with an indicator consisting of three items about workers' satisfaction with both the skills content of their job (in terms of job tasks and task discretion) and their job altogether. Although the wording of these items differs slightly across the two country datasets, both are considered as belonging to the same latent construct of interest. Cronbach's alphas of 0.76 for Germany and 0.84 for the UK indicate reasonable levels of reliability. Table 4.2 shows average levels of normalised items of job satisfaction for computer users and non-users: In Germany and the UK, computer users are more likely than non-users to be satisfied with each of the three satisfaction dimensions.

To measure *job tasks* and *task discretion*, a set of items is identified from each dataset that is comparable and clearly belongs to only one of the latent constructs of interest. Using a factor analysis (FA), four factors are obtained that capture different task domains – cognitive-analytical, cognitive-interpersonal, physical, and (manual and non-manual) routine – and one indicator that captures task discretion, thereby confirming the theoretical definition of the latent-skills dimensions for both countries. Detailed factor solutions are reported in Table A4.1 in the Appendix.

To confirm the robustness of the latent constructs, a further FA is performed including additional items that are not directly comparable across datasets but that are nevertheless related to the underlying concepts. The results support the classification based on the comparable items only (see Table A4.6 in the appendix). Distributions of each item

for computer users and non-users are reported in Table 4.2. As the range of scales differs across items as well as countries (see Table 4.1), each item is normalised on a scale from 0–1 to increase comparability.

Table 4.1 List of selected items on latent constructs of interest

The UK	Germany
Job satisfaction	
Satisfaction with the opportunity to use your abilities[1]	Satisfaction with opportunities for applying skills[2]
Satisfaction with able to use your own initiative[1]	Satisfaction with type and content of work[2]
Satisfaction with this aspect of own job – the work itself[1]	Satisfaction with work on the whole[2]
Job tasks	
Cognitive-analytical	
Importance of spotting problems or faults[3]	Confronted with new tasks[4]
Importance of working out causes of problems/ faults[3]	Recognise and close your own gaps in knowledge[5]
Importance of thinking of solutions to problems[3]	Improve existing procedures or try something new[4]
	React to problems and solve them[5]
Cognitive-interpersonal	
Importance of counselling, advising or caring for customers or clients[3]	Purchasing, procuring, selling[5]
Importance of dealing with people[3]	Advertising, Marketing, Public Relations, PR[5]
importance of selling a product or service[3]	
Physical	
Importance of physical stamina[3]	Work standing up[4]
Importance of physical strength[3]	Lift and carry heavy load[4]
Routine	
How much variety in job[8]	One and the same operation is repeated in every detail[4]
How often work involves short repetitive tasks[6]	Execution of work is prescribed in every detail[4]
Task discretion	
Influence personally have on: how hard work[7]	Influence the amount of work assigned to you[4]
Influence personally have on: how to do the task[7]	Plan and schedule your own work yourself[4]
Influence personally have on: what tasks to do[7]	
How much choice over the way in which job is done[7]	Decide for yourself when to take a break[4]

Original scales: [1] 1 (*completely satisfied*) to 7 (*completely dissatisfied*); [2] 1 (*not satisfied*) to 4 (*very satisfied*); [3] 1 (*essential*) to 5 (*not at all*); [4] 1 (*never*) to 4 (*frequently*); [5] 1 (*never*) to 3 (*frequently*); [6] 1 (*never*) to 5 (*always*); [7] 1 (*A great deal*) to 4 (*none at all*); [8] 1 (*a great deal*) 5 (*none at all*). Some variables are reverse coded to facilitate interpretation.

Occupational class position is operationalised differentiating workers between the salariat group (as defined in Goldthorpe, 1992) and all other classes as the second category based on the 2008 International Standard Classification of Occupation (ISCO-08).[36] Different operationalisations yield similar results.

Adult training participation is measured as attendance at any job-related training within the two years prior to the interview for Germany. For the UK, the item is measured based on whether a worker "received instructions or training from someone that took them away from their normal job" or completed "some other work-related training" in the previous twelve months.

Workers' educational attainment is included as a control variable. Educational attainment is measured using the 1997 revision of the International Standard Classification of Education (ISCED). It distinguishes between less-educated (ISCED 0–2), intermediately educated (ISCED 3–4), and highly educated workers (ISCED 5+). Moreover, a number of control variables is considered in the robustness checks: industry captured by nine categories of the one-digit SIC92 classification for the UK and by ten categories of the NACE rev 1 classification for Germany, gender as a dummy variable, age captured by three 15-year groups (with ethnic background as a dummy variable, indicating non-white workers for the UK and migration background for Germany), and survey year (three categories). Correlation matrices and descriptive statistics for all included variables are presented in the tables from A4.7 to A4.10 in the appendix.

[36] Armed-forces occupations are excluded.

Table 4.2 Mean and standard deviation of items of interest for computer users and non-users in Germany and the UK

The UK	User Mean	SD	Non-user Mean	SD	**Germany**	User Mean	SD	Non-user Mean	SD
					Job satisfaction				
Satisfaction with					Satisfaction with				
the opportunity to use your abilities	0.76	0.19	0.70	0.22	type and content of work	0.75	0.20	0.70	0.20
being able to use your own initiative	0.77	0.18	0.73	0.21	opportunities for applying skills	0.72	0.22	0.68	0.23
this aspect of own job – the work itself	0.74	0.18	0.73	0.19	work on the whole	0.74	0.20	0.71	0.21
					Job tasks				
					Cognitive-analytical				
Importance of:									
spotting problems or faults	0.79	0.24	0.66	0.30	React to problems and solve them	0.85	0.25	0.70	0.32
working out causes of problems/ faults	0.74	0.26	0.58	0.32	Recognise and close your own gaps in knowledge	0.66	0.28	0.52	0.31
thinking of solutions to problems	0.78	0.24	0.57	0.32	Confronted with new tasks	0.77	0.25	0.62	0.31
					Improve existing procedures or try something new	0.68	0.27	0.56	0.31
					Cognitive-interpersonal				
Importance of:									
counselling […]	0.68	0.35	0.49	0.40	Purchasing, procuring, selling	0.33	0.40	0.27	0.38
dealing with people	0.91	0.18	0.78	0.28	Advertising, Marketing, Public Relations, PR	0.27	0.35	0.13	0.27
selling a product or service	0.46	0.39	0.30	0.38					
					Physical				
Importance of:									
physical stamina	0.41	0.35	0.65	0.29	Work standing up	0.60	0.38	0.89	0.25
physical strength	0.34	0.34	0.64	0.30	Lift and carry heavy load	0.30	0.36	0.61	0.38
					Routine				
How much variety in job	0.28	0.26	0.46	0.32	Execution of work is prescribed in every detail	0.51	0.35	0.56	0.37
How often work involves short repetitive tasks	0.57	0.28	0.67	0.28	One and the same operation is repeated […]	0.66	0.36	0.76	0.33
					Task Discretion				
Influence personally have on:									
how hard work	0.80	0.23	0.75	0.27	Plan and schedule your own work yourself	0.87	0.27	0.70	0.36
how to do the task	0.66	0.29	0.53	0.34	Influence the amount of work assigned to you	0.57	0.38	0.50	0.39
what tasks to do	0.75	0.26	0.64	0.32	Decide for yourself when to take a break	0.76	0.37	0.59	0.43
How much choice over the way in which job is done	0.71	0.26	0.63	0.31					
N		8,596		2,687			36,023		13,423

Notes: All variables are normalised on a scale from 0–1, with higher values indicating higher levels of the latent construct of interest. Weighted. Original scales reported in Table 4.1. *Sources:* UK Skills Survey (2006, 2012, 2017) for the UK; BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany; authors' calculation

Methods

The theoretical model is tested using structural equation modelling (SEM), as presented in Figure 4.2. Circled variables represent latent constructs. The underlying observed variables for each dataset are reported in Table 4.1. Squared variables are observed. The thick lines represent relationships that directly test hypotheses and the theoretical model reported in Figure 4.1. Models are tested for each country separately on the yearly pooled sample as no major changes in the relationships of interest are expected across analysed years.[37]

The SEM includes a correlation between the errors of the different job-task dimensions (which is theoretically supported by the fact that the different tasks required in an occupation are related), and the overall definition of a job is given by the *simultaneous* observation of all dimensions. Thus, the mediating role of each single task index on task discretion and job satisfaction is not interpreted separately since the complementarity between computers and job requirements is given by the overall task profile. To check for theoretically possible moderations by occupational class position and adult training participation, multi-group SEM models for these subgroups of workers are estimated.

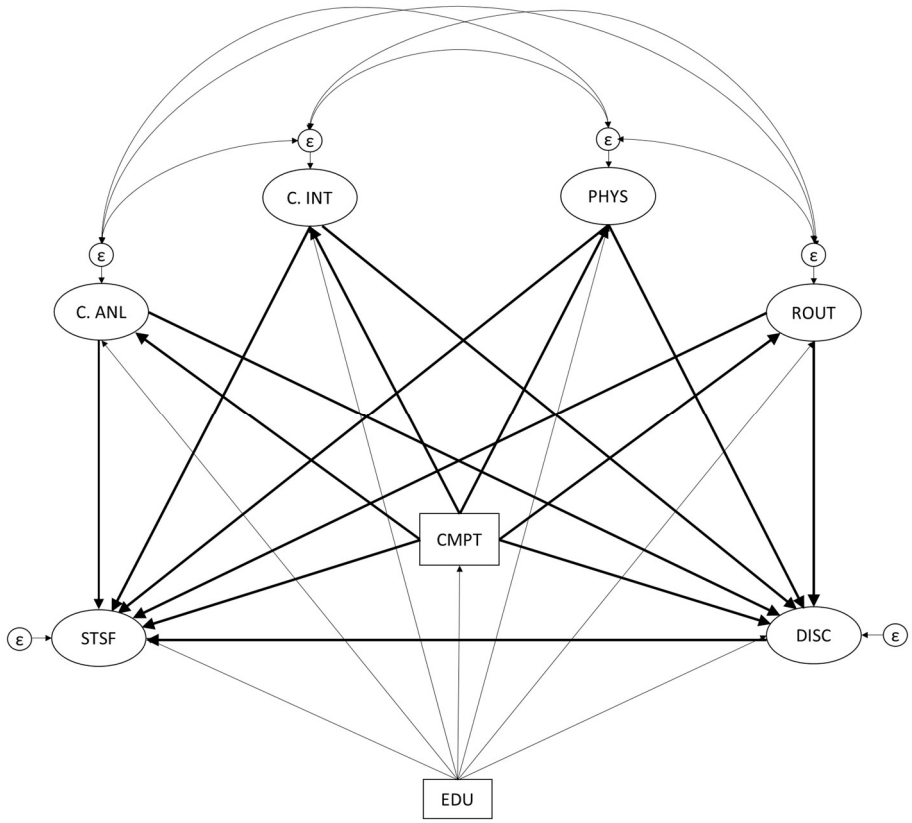
SEM has several advantages: First, it allows both measurements and structural components to be included, which is critical because job satisfaction and skill requirements at work are not directly observed but obtained through latent constructs. Second, SEM tests the theoretical model by including both structural paths and latent constructs on different data and contexts, and it compares the performances under different conditions. This advantage also relaxes the issue of different item wordings across datasets. Third, SEM enables path models of complex direct and indirect effects to be developed, thereby helping us accurately test the complex mediating processes of interest (Chin 1998).

As highlighted by Bollen and Pearl (2013), the core of the SEM analysis involves specifying a theoretical model and subsequently testing whether this model is plausible given the observed data. SEM is a confirmatory approach that relies on translating theory into a statistical model. If the theoretical model is problematic and/or if empirical instruments are not accurate, the model will not be able to reproduce the data, and estimated parameters will not be interpretable, thereby casting doubt on the strong causal assumptions of zero coefficients or zero covariances. In other words, researchers do not obtain any causal relationship from SEM, and SEM instead reflects and depends on researchers'

[37] Multiple-group SEM for each year is also tested. The Wald test could not reject the null hypothesis of equality in the parameters of interest. Furthermore, OLS regressions for each path of interest are estimated, including the survey wave as a control variable (see Tables A4.1 and A4.2 in the Appendix).

theoretical assumptions about *possible and plausible* causal connections (Bollen and Pearl 2013). In the present work, the main assumption indicates the exogeneous nature of the technological change (Path 1 in Figure 1).[38]

Figure 4.2 Empirical structural equation model



Notes: STSF = job satisfaction; C.ANL = cognitive-analytical tasks; C.INT = cognitive-interpersonal tasks; PHYS = physical tasks; ROUT = routine tasks; DISC = task discretion; CMPT = computer use at work; EDU = level of education.

Defining the theoretical foundations of an SEM model is even more relevant when disposable data on technological innovation take the form of cross-sectional surveys, as in this case, which leaves room for possible objections of endogeneity. It is, of course, possible and legitimate to argue that the changing nature of work towards more abstract and analytical cognitive content and procedures requires and/or favours the introduction of new technologies and computers in the workplace (thereby reversing Path 1 in the

[38] For a recent discussion on technology as the exogenous driver behind new forms of work and on the effects of new technologies on the future of work and skills, see: "The changing nature of work and skills in the digital age" (European Union 2019).

theoretical model). While endogeneity issues cannot be statistically excluded, a firm theory of the effects of technological innovation on production, occupational structures, social life, and organisations has been established in social sciences for decades. This study is in line with this body of research. However, a crucial limitation of SEM is its difficulty in including numerous control variables to account for potential confounding factors, which are usually considered in the analysis of the effects of computer use on skills and tasks at work (Green 2012; Green et al. 2003; Menon et al. 2019). Thus, separate OLS regressions are estimated for all paths highlighted in the SEM model, including the aforementioned controls. This robustness check confirms the results estimated via SEM (see Appendix, Tables A4.2 and A4.3).

Results

Descriptive statistics in Table 4.2 indicate that while the performance of cognitive-analytical tasks is the most pronounced (especially for computer users) in both countries, important differences exist regarding the use of the other three task subsets both within and between countries: In Germany, routine and physical tasks are relatively more frequent than cognitive-interpersonal tasks (among both computer users and non-users), which is exemplary of the technology-implementation processes in diversified quality production in German manufacturing, as discussed above. In the UK, cognitive-interpersonal tasks are more frequent than routine or physical tasks for computer users, whereas for non-users, the extent of physical tasks is the greatest among these three subsets. Differences in task use between computer users and non-users are thus generally more pronounced in the UK than in Germany.

Table 4.3 presents the results of the SEM for both the UK and Germany, decomposed into direct and total effects and the percentage of total effects accounted for by mediation. Goodness-of-fit (GoF) statistics are included at the bottom of Table 4.3 to provide information on how well the model fits the data. The comparative fit index (CFI) indicates that the model improves the fit of a baseline model that assumes no covariances between items among latent variables by 95.4 per cent in the UK and 92.8 per cent in Germany. These improvements are considerable and exceed the recommended minimum value of 0.90 for a satisfactory model fit. Moreover, regarding the root mean square error of approximation (RMSEA), which adjusts for errors for each degree of freedom used, results are indicative of a good model fit, with values equal to the recommended upper bound of 0.05. Finally, the index of the standardised root mean square residual (SRMR) is

presented. In both countries, values are below the recommended cut-off of 0.05, which again confirms that the model fits the data well in both Germany and the UK (for details on GoF, see Acock, 2013; Kyndt and Onghena, 2014).

The upper part of Table 4.3 presents estimates for Path 1 in the theoretical model and the association between computer use and the four factors/dimensions of job tasks. In both Germany and the UK, computer use is clearly associated with higher levels of (analytical and interpersonal) cognitive tasks and lower levels of routine and physical tasks. These effects are highly significant. One country difference emerges: The negative association between computer use and routine tasks appears larger in the UK than in Germany. Part of this difference may originate from the measurement of routine tasks performed in the two surveys. Fernandez-Macias and Hurley (2016) criticise the concept of routine tasks proposed by the economic literature for its imprecise definition and introduce a further distinction between *routine tasks* (in terms of the level of cognitive or manual simplicity/sophistication) and *repetitive tasks* (in a temporal sense). In this respect, Frey and Osborne (2017) identify finger- and manual dexterity characterised by the repetitive performance of hand- and finger accuracy as a potential bottleneck for automation. These tasks are thus *repetitive* but *not routine*. Data do not allow for operationalising this distinction; thus, the measure of routine tasks is likely conservative. Similarly, the somewhat larger association with physical tasks in Germany is likely driven by substitutions of routine- rather than non-routine physical tasks.

In fact, results for the relationship between computer use and tasks indexes including detailed controls (Tables A4.11 and A4. 12) generally confirm what observe in the SEM model, with the exception that the association between computer use and routine tasks turns positive in Germany after controlling for occupation categories, suggesting that the negative association from the main model is driven by differences in task composition between occupations characterized by different levels of computer use. These results should be taken cautiously since the task profile of jobs is given by the combination of all the tasks indexes, and the overall effect of computers on the task profile should be inferred by the combined relationship to all dimensions. In fact, part of the degree of routine tasks performed by a specific worker could be captured by the manual or cognitive component. Moreover, as mentioned above, part of this difference may originate from the measurement of routine tasks performed in the two surveys and the fact that the routine indicator in Germany is more likely to capture both repetitive and routine tasks. Since repetitive tasks (rather than routine tasks) are associated with high levels of manual dexterity and skilled manual-intensive jobs, these are also more likely to be complemented than replaced,

especially in the German context characterized by well-educated and skilled workers in manual-intensive occupations. Finally, it could also be that routine tasks in Germany are reduced by shifting employment between occupations rather than transforming the task requirements within jobs.

The middle of Table 4.3 reports estimates for the association between computer use and task discretion and integrates mediation via job tasks. Beginning with the direct effect of computer use on task discretion (i.e., net of computer-task complementarities and while capturing Path 3 in the theoretical scheme), important country differences can be observed: Computer use is associated with lower levels of task discretion in the UK (-.034) but with higher levels in Germany (.085) [39]. The same results emerge after including detailed controls for workforce composition (see Appendix, Tables A4.2 and A4.3). Both effects are relatively small yet statistically significant. The total effect of computer use on task discretion (including both Paths 2 and 3) is positive and statistically significant in both countries, but larger in Germany. In the UK, 118 per cent of the total effect is explained by mediation via job tasks (Path 2), which links the observed differences in task discretion between computer users and non-users to different tasks performed.

In Germany, this mediation accounts for 80 per cent of the total effect, and estimates for the different task dimensions reveal that cognitive tasks are associated with higher levels of discretion, whereas routine and physical tasks are associated with lower levels. Effects are significant in both countries but considerably larger in Germany, except – again – for routine tasks (see discussion above). In sum, the differences between the direct and total effects of computer use on task discretion reveal the importance of tasks as composite indicators of types of occupations and jobs that explain most variation between workers. The country differences found are indicative of the dissimilar production strategies that underlie these associations.

[39] Unfortunately, it is not straightforward to give a clear substantive interpretation of effect sizes, since we use standardize scores of latent indexes built using different items with different scaling and response options in the two countries. We therefore refrain from giving an actual interpretation of the effect size and mainly focus on their direction. However, just to have a grasp of the main relationship we can compare them to some more intuitive variables in the regression model in tables A4.2 and A4.3. For instance, the difference in discretion between low and high educated in the UK is 0.12 standard deviations while the difference between a manager and a worker employed in an elementary occupation is -0.93. In the case of job satisfaction these differences; are respectively -0.22 and -0.69. Thus, the total effect of computer use on discretion in the UK is larger and comparable to that of having a tertiary degree, while the direct effect is approximatively a fourth of that. In Germany the difference in discretion between low and high educated is 0.30. standard deviations while the difference between a manager and a worker employed in an elementary occupation is -0.89. In terms of job satisfaction these are respectively -0.20 and -0.61. In Germany the total effect of computer use on discretion is 0.42 standard deviations and the direct effect is 0.085.

Table 4.3 Direct and total effects of computer use on job tasks, task discretion, and job satisfaction in the UK and Germany

	The UK		Germany	
	Direct effect	Total effect	Direct effect	Total effect
Path 1: Relationship between computer use and job tasks				
DV: Cognitive-analytical (A)				
Computer use	0. 447***	n.i.p.	0.352***	n.i.p.
	(0.020)		(0.007)	
DV: Cognitive-interpersonal (B)				
Computer use	0.471***	n.i.p.	0.113***	n.i.p.
	(0.020)		(0.006)	
DV: Physical (C)				
Computer use	-0.529***	n.i.p.	-0.696***	n.i.p.
	(0.020)		(0.010)	
DV: Routine (D)				
Computer use	-0.213***	n.i.p.	-0.057***	n.i.p.
	(0.013)		(0.008)	
Paths 2 and 3: Relationship between computer use and task discretion (incl. mediation via tasks)				
DV: Task discretion				
Computer use	-0.034*	0.187***	0.085***	0.427***
	(0.015)	(0.015)	(0.012)	(0.009)
Cognitive-analytical	0.087***	n.i.p.	0.418***	n.i.p.
	(0.008)		(0.013)	
Cognitive-interpersonal	0.067***	n.i.p.	0.258***	n.i.p.
	(0.011)		(0.018)	
Physical	-0.022**	n.i.p.	-0.215***	n.i.p.
	(0.008)		(0.009)	
Routine	-0.653***	n.i.p.	-0.276***	n.i.p.
	(0.030)		(0.012)	
Paths 4, 5, 6: Relationship between computer use and job satisfaction (incl. mediation via tasks and discretion)				
DV: Job satisfaction				
Computer use	-0.122***	0.176***	-0.021	0.190***
	(0.022)	(0.022)	(0.013)	(0.009)
Cognitive-analytical	0.053***	0.094***	0.185***	0.290***
	(0.011)	(0.012)	(0.013)	(0.012)
Cognitive-interpersonal	0.027	0.059**	0.011	0.076***
	(0.016)	(0.017)	(0.017)	(0.017)
Physical	0.009	-0.001	-0.032**	-0.086***
	(0.012)	(0.013)	(0.010)	(0.010)
Routine	-0.828***	-1.144***	-0.259***	-0.328***
	(0.046)	(0.046)	(0.013)	(0.013)
Task discretion	0.483***	n.i.p.	0.251***	n.i.p.
	(0.025)		(0.012)	
Goodness-of-fit statistics				
CFI	0.954		0.928	
RMSEA	0.051		0.047	
SRMR	0.038		0.035	

Notes: DV = dependent variable; n.i.p. = no indirect path included. All continuous variables are z-standardised (mean = 0, standard deviation = 1). Controlled for educational attainment. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: UK Skills Survey (2006, 2012, 2017) for the UK and BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany; authors' calculations.

The bottom part of Table 4.3 reports results on the mediating role of job tasks and task discretion in the relationship between computer use and job satisfaction. The direct effect of computer use on job satisfaction – that is, independent of job tasks and task discretion (referring to Path 6 in Figure 1) – is negative in both countries (-0.117 in the UK and -0.021 in Germany) and could be generated by technostress or anxiety. These direct effects are larger and statistically significant only in the UK. Once the role of job tasks and task discretion has been accounted for (via Paths 1–4, 3–5, and 1–2–5, respectively), the total effect of computer use on job satisfaction becomes positive and statistically significant in both the UK and Germany (0.184 and 0.190, respectively). Mediation via the indirect paths of job tasks and task discretion accounts for 164 per cent of the total effect in the UK and 111 per cent in Germany. These results reveal the explanatory relevance that the associations between computer use, job tasks, and task discretion have for job satisfaction.[40]

Overall, the results confirm the theoretical expectation that complex job profiles and the possibility of controlling work processes should be positively associated with job satisfaction in both countries (see direct and total effects of job tasks and task discretion), thereby linking differences in task composition and task discretion between computer users and non-users to workers' job satisfaction. Country differences between Germany and the UK reflect the different skill- and production regimes, as discussed in the theoretical section above. In the UK, mediation via job tasks – and particularly via routine tasks[41] – is much more pronounced than in Germany, which accounts for a substantial part of the total effects of computer use on both task discretion and job satisfaction. Differences in the levels of task discretion and job satisfaction by computer use that remain net of the indirect paths via job tasks are indicative of prevalent managerial practices of implementing and using computer technologies as a means of centralising decision-making and increasing control over work processes. In Germany, on the other hand, total effects of computer use on job satisfaction are more-strongly determined by decentralising modes of production that encourage the discretionary effort of workers both directly via computer use and indirectly via job tasks.

As discussed in the theoretical section, there could be relevant differences in the relationships of interest across groups of workers, especially across types of occupations

[40] As a robustness check, OLS regressions are estimated including controls for demographic, occupational, and industrial characteristics. The total effect of computer use on the degree of job satisfaction was found to decrease in the UK and to no longer be significant, while the negative direct effect remained significant (see Appendix, Table A4.2). In Germany, the already small negative direct effect approximated zero and became non-significant (see Appendix, Table A4.3).

[41] Routine tasks in the UK have by far the largest direct and total effect on job satisfaction; however, the negative direct effect of computer use is robust after excluding the routine-task indicator from the SEM model.

and participation to training. Thus, multi-group comparisons of SEM between salariat workers and members of other occupational classes in tested. Detailed results are presented in Table A4.4 (Appendix). In the UK, the observed *direct* effects of computer use on both task discretion and job satisfaction remain negative across all occupational classes but statistically significant only for non-salariat workers. Nevertheless, the positive *total* effects of computer use on both task discretion and job satisfaction are more pronounced for non-salariat- than for salariat workers. As expected, these positive associations are determined by mediation via job tasks, with computer-task complementarities being most relevant to non-salariat worker groups.

For Germany, the alienating effect of computer use on job satisfaction is more pronounced among salariat- than non-salariat workers, which also results in a smaller total effect that is still positive and statistically significant. In contrast, the positive *direct* effect of computer use on task discretion is larger among salariat workers. However, the positive *total* effect of computer use on task discretion is larger for other occupational classes – most likely due to a stronger mediation via job tasks – and further reflects the large positive total effect on job satisfaction.

Second, participation in adult training is expected to intervene in the interplay between job tasks, task discretion, and job satisfaction. Results for this group-comparison SEM model are presented in Table A4.5 (Appendix). In both countries, the main group difference is observable for the direct negative effect of computer use on job satisfaction. In accordance with the theoretical considerations, an alienating effect of computer use is larger and statistically more relevant among non-trained than trained workers in both countries. Differences are somewhat more pronounced in Germany; however, little empirical support emerges for the expectation that the mediating effect of job tasks should be more positive for trained workers. These results should be considered explorative because tests for group invariances of the parameters could not reject the null hypothesis of equality between occupational classes and between training groups. Moreover, as only observed level differences but not differences in the direction of effects, these findings imply that the theoretical model of the relationship between technology and job satisfaction applies to different groups of workers, though to differing extents.

Conclusions

By comparatively analysing Germany and the UK, two exemplary types of different production regimes, and management practices, this chapter contributes both theoretically and empirically to the ongoing upskilling/deskilling debate by examining how computer use is associated with tasks performed and task discretion as two distinct dimensions of occupational skills. Moreover, the chapter contributes to a better understanding of whether job tasks and task discretion mediate the relationship between technological innovation and job satisfaction.

Results stress that in both countries, computers are complementary to less routine and more abstract tasks while reducing physical and repetitive tasks and that this relationship is conducive to higher average levels of task discretion and workers' job satisfaction. This finding is in line with the RBTC thesis that technology complements highly skilled jobs and substitutes more routine ones. After accounting for the association between computer use and the types of tasks performed, the direct effect of computer use on task discretion and workers' job satisfaction proved to be exemplary of the two different institutional regimes: Results imply that technology in the UK (a liberal market economy in which firms have strong incentives to pursue production and employment strategies based on a flexible labour force with little attachment to the firm) serves as an instrument for further centralising decision-making and increasing control over the labour process. This is not the case in Germany.

Scholars have argued that the German political economy has undergone processes of institutional change, which have made its institutional arrangement more similar to that of an LME (Sorge and Streeck, 2018; Streek, 2009; Hassel, 2014). This kind of research has highlighted processes of bargaining decentralisation, labour market dualisation, and de-unionisation, which might have disrupted the coordinating capacity of the German economy. While these processes are undeniable, it is important to stress that much evidence shows that they have been gradual, and strong differences still exist between the two models in the areas of welfare states, dualisation, inclusiveness, and firms' strategies (e.g., Ferragina and Filatti, 2022; Ferragina and Seeleib-Kaiser, 2011, 2013; Holman, 2013). Moreover, while some institutions may change others remain the same, generating constraints for employers to completely alter their firm-level management strategies. As stressed by Sorge and Streeck (2018), institutional support and firms' strategies can often be uncoupled. As a result, British and German firms are likely to continue to show relevant

differences in the way in which they integrate technologies in their production processes. However, the underlying reasons for these differences are the subject of ongoing debate.

More generally, results indicate that technology is not an entirely exogeneous variable that affects the outcomes of implementation – in terms of job tasks, job discretion, and workers' satisfaction with their working conditions – in a deterministic and unilateral way. The study thereby contributes to the upskilling/deskilling debate by demonstrating the different yet related issues of the complexity of the tasks performed and the degrees of work discretion. Moreover, results stress that the relationship between computer-task complementarities and firms' organisational structures and practices – and perhaps also job discretion and satisfaction – is contingent on the institutional context in which technology is introduced.

Clearly distinguishing between different skill dimensions is relevant to better understanding the link between technology and the overall quality of work – as demonstrated in this study – not only theoretically, but also policy-wise. Policy interventions that aim to increase job satisfaction should focus on strategies that encourage the use of computerised equipment by means of decentralising information and decision-making at the shop-floor level, thereby empowering workers and lower-level managers not only in collaborative work environments and production systems, as in Germany, but also in shareholder-oriented production models, as in the UK. One important instrument in this regard might be *targeted* training measures for increasing workers' proficiency in ICT use and complex task domains. Such training could equip the labour force with relevant skills and strengthen workers' capacity to exercise control over their work process and conditions while enabling executives to maximise labour productivity and the competitiveness of firms.

Although the theoretical expectations are corroborated by empirical evidence, conclusions are not without limitations, which are mainly related to the nature of the available data. Despite the vivid debate on technological change and the task content of jobs in the last decade, micro-level longitudinal and cross-country comparable data are still lacking. It is therefore difficult to advance strong causal claims via an empirical analysis of cross-sectional data. The *causal* paths are hence mainly driven by theoretical considerations, however solidly embedded they may be in decades of literature. Consequently, one of the main issues that future research will have to tackle (using appropriate data) is that the relationship between computers and any potential outcome (e.g., wages, discretion, or satisfaction) could be the result of occupational (or institutional) characteristics that simultaneously determine the use of technology and the content of the

work. Existing research has dealt with this issue by building an occupational-level pseudo panel (Green 2012). While this approach is certainly informative, it only accounts for within-occupational differences between computer users and non-users and/or for variation in time within aggregate constructs. The advantage of this approach is that including continuous measures of job tasks performed enables us to account for differences in job tasks and task discretion between computer users and non-users, even *between* occupational categories.

Moreover, findings for Germany suggest that future research and survey operationalisation should better differentiate repetitive tasks in terms of frequency from routine tasks in terms of simplicity/sophistication. Not only are the two kinds of routine tasks distinct in terms of content, but they also – at least theoretically – have different implications for the risk of being automated as well as for monitoring capacities.

Conclusions

Final thoughts and some insights for the future of work

Technological change has historically played a central role in explaining socio-economic transformations, and social scientists have developed several theoretical approaches to understand the relationship between production technologies and the organisation of labour. However, as stressed in the chapters of this thesis, many of these positions are based on technology cantered perspectives that stress machinery's technical capabilities while underplaying the capacity of social contexts and social actors to channel and redirect the consequences of automation.

While it is undoubtedly true that the bulk of the relationship between technology and labour can be inferred from the technical capabilities of specific machinery, this understanding is oversimplistic and often discounts the centrality of many contextual and institutional factors. For instance, spreadsheet applications are designed to perform calculations, therefore driving a common use of this technology. It would be unreasonable for a company to use computers to deal with creative and unpredictable tasks while delegating calculations and repetitive duties to humans. Each component has a specific comparative advantage in performing a specific set of tasks. Indeed, the fourth chapter of this thesis has highlighted that computers complement the performance of abstract tasks in two very different institutional arrangements: Germany and the UK.

However, this is only one part of the story. Many aspects of the employment relationship and firm demand for different occupations result from complex institutional factors that shape firms' employment and production strategies. As spreadsheets replace the duties of many white-collar workers, what new tasks and occupations will emerge in response to the productivity gains they produce depends on many contextual factors.

The chapters that make up this dissertation have tried to stress and support the idea that technological change is not a relentless process and its consequences are bounded by institutional and cultural components, which, in many cases, are defined at the national level. The present thesis addressed the crucial relevance of national institutional arrangement vis-à-vis technical progress in three different areas of labour organisation: the occupational and class structure, the distribution of earnings, and the content and quality of work.

The main research question that guided all the chapters of this thesis has been whether technological change has comparable impacts on different aspects of work in diverse institutional contexts across western advanced political economies. A second implicit research question has been which institutional configurations have been most conducive to developing desirable social outcomes in response to automation and technological developments. Meaning in which contexts technological change has been associated with the expansion of more high-skilled and more rewarded occupations, the development of more fulfilling and satisfactory occupations, and the containment of social inequalities.

Indeed, the most prominent socio-economic theories on the relationship between technology and labour market outcomes usually stress the inherent bias of computer technologies in favour of one group or another. The first chapter of this thesis has reviewed three different theoretical approaches which suggest that technological change is likely to influence occupational and class structures, earnings distribution, employment levels and the content and quality of work by affecting workers divided along three major cleavages: *skill levels, tasks performed, and social class*. These cleavages are promoted respectively by the theories of *skill- routine-, and class-biased technological change*.

These demarcation lines are not mutually exclusive and winners according to one perspective, are likely to be winners also for the others. However, each approach stresses a different mechanism connecting computer technology to labour market outcomes and to the definition of winners and losers in the process of technological development. SBTC stresses that technology complements skills, thus favouring highly skilled workers but without any losses for other groups. RBTC stresses the complementarity between technology and abstract tasks and the substitutability of routine tasks, thus suggesting that technology favours workers in occupations characterised by more abstract and less routine tasks. Finally, CBTC highlights the impact of technology on the power distribution between classes and management's monitoring capacity, thus suggesting that technology will benefit employers and higher management at the expense of lower-level workers. Each theory advances well-documented facts and compelling links to digital technology, and the relation between technological change and labour market outcomes is most likely the result of a combination of these dynamics.

While all of these approaches offer important insights into how computer technologies have influenced the demand for different occupations, the distribution of earnings and the quality of work, they are mainly built on what computers can and cannot do and often underplay the importance of other social factors. However, societal forces can influence many aspects of the restructuring process spurred by new technologies. The second section

of the first chapter of this thesis has built on the neo-institutionalist literature on comparative models of capitalism to stress the idea that national institutional arrangements create several incentives and constraints for actors in a political economy to adopt different employment and production strategies. These incentives and constraints are also relevant in actors' choices when adapting to new technological possibilities.

The subsequent chapters, especially chapters two and four, have built on this insight and have expanded and investigated the heterogeneous relationship that the same technology can have to labour market outcomes in different institutional contexts.

Chapter two has focused on the relationship between industrial automation and occupational structures, one of the main concerns of the recent literature on technological change. Descriptive results have not confirmed a generalised process of occupational polarisation across European countries. By connecting an indicator of industrial automation –robot exposure – at the regional level to occupational and class structure indicators, it has highlighted that automation is associated with an upgrading process in Nordic European countries and less so in Continental ones, but to occupational downgrade in Southern European ones. Cluster differences also emerge in the association between robotics and occupational opportunities for individuals at different levels of education and gender, and continuous training appears as an important tool to contain technology-related inequalities. Indeed, groups of workers that more intensively participated in training in the observed period emerge as less likely to experience occupational downgrading or unemployment in response to industrial automation, and this is particularly evident for less-educated workers.

Chapter three has focused on the US experience and has investigated whether technological change or the demise of trade unions have been relevant factors for the growth of between-class inequalities. The determinants of the growing levels of earnings inequalities in the US have been a central research topic in the last decades. An extensive economic literature has suggested that technological change is the main driver of such process, while broader socio-economic research has pointed towards the demise of wage-setting institutions or the interaction of both technology and institutions. Results from the chapter highlight that the major earnings losses for lower classes have occurred in industries that experienced strong de-unionisation rather than growing investments in information and communication technologies. Moreover, results suggest that lower-class workers were mainly employed in industries affected by major de-unionisation processes, suggesting that de-unionisation has been a major driver for the growing inequalities between manual and non-manual workers. Overall results cast doubts on the technocentric

explanation of growing inequalities in the US, suggesting that institutional factors play a decisive role.

Chapter four has investigated the relationship between computer technologies and work content in terms of tasks performed, discretion over tasks, and job satisfaction in Germany and the UK. Results confirm that computers complement the performance of more abstract and less routine tasks and that this complementarity is conducive to higher levels of task discretion and job satisfaction in both countries. However, significant cross-country differences emerge after accounting for differences in the type of tasks performed between computer users and non-users. Computer use is negatively associated with tasks discretion and job satisfaction in the UK but not in Germany. The chapter argues that these differences exemplify the employment and production strategies supported by the institutional arrangements of the two countries: liberal vs coordinated market economies.

Overall, results from the chapters of this thesis add to a growing body of sociological evidence which stresses the embeddedness of computer technologies in institutional and social contexts.

Each chapter dealt with a different aspect of the relationship between technology and labour market outcomes and thus dealt with different strands of literature. Albeit the underlying technology is always computer-based, depending on the chapter, technological adoption is operationalized in different ways according to existing research on the specific issue and substantive interests.

Nevertheless, albeit most of these results are based on computer technologies, they offer essential insights on the more general ability of societal actors to deal with current and future processes of technological change. Moreover, these insights have become even more relevant in the last decade since renewed concerns about the future of work have emerged due to the development of new labour replacing technologies that, according to many, will dwarf previous waves of technological change. As a result, many scholars and observers have raised the question: *is this time different?*

Many agree that the current wave of innovation has drastically raised the automative capacity of computer-based technologies. Several commentators have brought to the public attention the power and wonder of recent technological advancements mainly spurred by developments in artificial intelligence and fast-growing computer capacity. Indeed, machines are now capable of performing tasks beyond most science-fiction scenarios.

In their seminal work, the *New Division of Labour,* Levy and Murnane (2005) suggested that computers had a comparative advantage over humans in performing routine tasks, meaning those tasks that are easily programmable into computer code. However,

after recent advancements in artificial intelligence, routine tasks are not the only ones at risk of automation. For example, Martin Ford (2015) argues that computers may now perform all "*predictable*" tasks. This means that any job that a person could learn by studying a detailed record of something someone else has done in the past or repeating the tasks that someone has already completed has a good chance of being replaced by an algorithm.

Google's self-driving vehicles are one of the most famous examples of non-routine activities that are increasingly automated. In 2004, Levy and Murnane brought attention to the challenges of reproducing human vision in the chapter "*Why People Still Matter*," claiming that driving in traffic is insusceptible to automation since it involves many unprogrammable tasks usually, defined by Polanyi's paradox. However, in December 2018, Waymo, a Google spinoff, launched the world's first completely self-driving taxi service in Chandler, Arizona.

Despite speculative predictions, the automative capacity and overall impact on the work of artificial intelligence and other recent advancements continue to be hazardous as most of these technologies are not yet widespread across labour markets. A notable exception is Frey and Osbourne's (2013) estimation that 47% of US occupations are at high risk of automation. Albeit founded on a task approach, their result was based on the assumption that whole occupations rather than single tasks will be automated. However, by considering the heterogeneity of workers' tasks within occupations, Arntz, Gregory, and Zierahn (2016) reach much more conservative conclusions and suggest that only 9% of jobs across OECD countries are fully automatable.

It remains to be seen how technological advancement in the twenty-first century will affect labour market outcomes. Throughout history, technical advancements have dramatically altered the makeup of work, shifting it from agriculture and artisan shops to manufacturing and clerking, and finally to service and managerial jobs. However, the fear of technological unemployment has turned out to be overstated.

Beyond replacement and unemployment, many commentators suggest that technological change will once again lead to growing earning inequalities between the top and bottom earners and between employers and employees, suggesting that future technologies will continue to favour specific groups over others. Growing technological capacity is likely to further exacerbate the divide between winners and losers – those that can keep up with technological change and those who cannot. Indeed, Frey and Osborne (2013) have further shown that wage levels and education are negatively associated with automation risk. The same conclusion was shared by the study of Artz et al. (2016), which

suggested that even though automation and digitalisation of work are unlikely to destroy a large number of jobs, low skilled workers are likely to be the most affected as the automability of their jobs is the highest.

In these regards, recent empirical findings are quite concerning. Beaudry et al. (2013) report a drop in skill demand over the last decade, despite an increase in the supply of employees with higher education. They indicate that high-skilled people have migrated down the occupational ladder, taking up tasks previously held by low-skilled workers, pushing low-skilled individuals farther down the occupational ladder and, in some cases, out of the labour force.

Future research must carefully address what occupations are more or less susceptible to current processes of automation but, most importantly, which are not and are likely to rise in the near future. However, as this thesis has outlined, research and forecasts on the future of work must take the role of institutions more seriously. While accelerating information technology is nearly sure to impact the future economy and job market, it will remain deeply intertwined with other powerful forces. If artificial intelligence poses many challenges to employment, equality, and the quality of work, earlier waves of automation have taught us that social actors and policy may help redirect these transitions towards more socially desirable outcomes

In this regard, this thesis has stressed that more coordinated and inclusive institutions are likely to lead to better occupational prospects and less pronounced inequalities by generating incentives and constraints for firms to take up employment and production strategies that make use of more skilled and more qualified labour force, endowed with a higher level of discretion and responsibilities while reducing demand for low skilled low-level occupations.

Many institutional domains play a crucial role, but the most recognised and quoted institutional and policy area undoubtedly concerns the provision of skills (Brynjolfsson and McAfee, 2014). Indeed, as technology progresses and more jobs become vulnerable to automation, the traditional response has been to provide employees with additional education and training so that they can transition into other, higher-skilled, professions. Because all studies agree that the positions most at danger of automation are low-skilled and low-paid, we can be confident that additional education and training will be the major remedy for most impacted employees. Of course, skills provision is not limited to higher educational attainment but must involve continuous and life-long training directed at developing adaptable skills throughout the life course. Training and education will be further helpful to contain inequalities between workers at different skill levels and propel

the deployment of production and employment strategies that use knowledge-intensive occupations.

A second critical institutional domain is that of wage-setting institutions and industrial relations. More inclusive and redistributive institutions are likely to contain inequalities both between workers and between employers and employees. As chapter three of this thesis has highlighted, trade unions are a key factor driving a fairer distribution of societal gains. Similarly, other studies have highlighted that inclusive and coordinated collective bargaining systems can contain the adverse effects of technological change. Moreover, higher labour costs can inhibit the creation of low-skilled jobs since these may result less profitable and thus favour the expansion of more productive knowledge-intensive occupations. This may come at the expense of higher unemployment risk for less-skilled workers underlying the need for extensive retraining and educational support.

Finally, workplace arrangements that encourage employee participation and decision-making can foster an inclusive and participatory work environment and thus encourage the enhancement of workers' skills and competencies, eventually promoting the development of more fulfilling and satisfactory jobs in response to technological change. Moreover, workers' participation in firm-level decision making can facilitate the transition to a digitalised workplace by keeping into account workers' needs while at the same time exploiting their knowledge of production processes.

Eventually, it is hard to predict how current technological development will influence labour organisation, the demand for new occupations, employment levels, and any other aspect of the employment relationship. However, technological change will continue to be embedded in social contexts and historically defined norms and rules. As a result, technology should not be considered a technical, relentless, and unstoppable process that will eventually eliminate labour but rather a social process that social actors can control and regulate.

References

Accenture PLC. 2017. "How Companies Are Reimagining Business Processes With IT." https:// sloanreview.mit .edu/ article/ will- ai- create- as-many- jobs- as-it eliminates/.

Acemoglu, D. (1999). Changes in Unemployment and Wage Inequality. *American Economic Review, 89*(5), 1259-1278

Acemoglu, D. (2001). Good Jobs versus Bad Jobs. *Journal of Labor Economics, 19*, 1–21.

Acemoglu, D. (2002a). Directed Technical Change. *Review of Economic Studies*, *69*, 781–809.

Acemoglu, D. (2002b). Technical Change, Inequality, and the Labor Market. *Journal of Economic Literature*, *40*(1), 7-72.

Acemoglu, D. (2003). Labor- and Capital-Augmenting Technical Change. *Journal of European Economic Association*, *1,* 1–37.

Acemoglu D., Aghion P., Violante G. (2001) Deunionization, technical change and inequality, Carnegie-Rochester Conference Series on Public Policy 55 (2001) 229-264

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In O. Ashenfelter & D. Card (Eds.), *Handbook of Labor Economics*, (1st ed, 4th volume, 12th CHP 12, pp. 1043-1171) Elsevier.

Acemoglu, D. and Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review*, *108*(6), pp. 1488–1542.

Acemoglu, D. and Restrepo, P. (2019). Automation and new tasks: how technology displaces and reinstates labor. *J Econ Perspect*, *33*(2), pp. 3–30.

Acemoglu, D., and Restrepo, P. (2017). Robots and Jobs: Evidence from US Labor Markets. *NBER Working Paper No. 23285*.

Acemoglu, D., Aghion, P., Lelarge, C., van Reenen, J., and Zilibotti, F. (2007). Technology, Information, and the Decentralization of the Firm. *The Quarterly Journal of Economics 122*(4), 1759–1799.

Acock, A. C. (2013). *Discovering structural equation modelling using Stata*. College Station: Stata Press.

Akerlof, G. A. (1984). Gift exchange and efficiency-wage theory: Four views. *The American Economic Review*, *74*(2), 79–83.

Akst, D. (2013). What Can We Learn from Past Anxiety over Automation? *The Wilson Quarterly, 37*(3), pp.65-77

Alderson, A. S. and Katz-Gerro, T. (2016). Compared to whom? Inequality, social

comparison, and happiness in the United States. *Social Forces, 95*(1), 25–54.

Alesina, A., Battisti, M., and Zeira, J. (2018). Technology and labor regulations: theory and evidence. *Journal of Economic Growth*, *23*(1), 41-78.

Allmendinger, J. (1989). Educational systems and labor market outcomes. *European sociological review*, *5*(3), 231-250.

Arias, O. S., Sánchez-Páramo, C., Dávalos, M. E., Santos, I., Tiongson, E. R., Gruen, C., de Andrade Falcão, N., Saiovici, G., and Cancho, C. A. (2014). *Back to work: growing with jobs in Europe and Central Asia*. Europe and Central Asia Reports, Washington, DC: World Bank.

Arntz, M., Gregory, T. and Zierahn U. (2016). "*The Risk of Automation for Jobs in OECD Countries.*" OECD Social, Employment, and Migration Paper no. 189, Org. Econ. Cooperation and Development, Paris.

Attewell, P. (1987). The deskilling controversy. *Work and Occupations, 14*(3), 323–346.

Autor, D. H. (2013). The Task Approach' to Labor Markets. *Journal of Labour Market Research 46* (3): 185-9

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation, *Journal of Economic Perspectives*, *29*(3), pp. 3–30.

Autor, D. H. and Dorn, D. (2013) The growth of low-skill service jobs and the polarization of the US Labor Market. *American Economic Review*, *103*(5), pp. 1553–1597.

Autor, D. H. and Salomons, A. (2018). Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share. *Brookings Papers on Economic Activity Conference Draft*.

Autor, D. H., Katz, L. F., and Krueger, A. B. (1998). Computing inequality: have computers changed the labor market? *The Quarterly Journal of Economics*, *113*(4), 1169–1213.

Autor, D. H., Levy, F. and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics, 118*(4), pp. 1553–1597.

Autor, D. H., Levy, F: and Murnane, R. J. (2002). Upstairs, downstairs: computers and skills on two floors of a large bank. *ILR Review, 55*(3), 432–447.

Ayyagari, R., Grover, V., and Purvis, R. (2011). Technostress: technological antecedents and implications. *MIS Quarterly, 35*(4), 831–858.

Baccaro, L., Doellgast, V., Edwards, T., and Whitford, J. (2018). Diversified Quality Production 2.0. *Socio-Economic Review, 16*(3), 613-635.

Baccaro, L., & Howell, C. (2011). A common neoliberal trajectory: The transformation of industrial relations in advanced capitalism. Politics & Society, 39(4), 521-563.

Baccaro, L and Howell, C (2017) Trajectories of Neoliberal Transformation. Cambridge: Cambridge University Press.

Bailey, D. E. and Leonardi, P. M. (2015). Explaining Technology Choices in the Workplace: Proposing an Occupational Perspective. In D. E. Bailey and P. M. Leonardi (Eds.), *Technology Choices: Why Occupations Differ in Their Embrace of New Technology* (pp. 19–42). MIT press.

Barbieri, P. (2009). Flexible employment and inequality in Europe. *European Sociological Review*, *25*(6), 621-628.

Barbieri, L., Piva, M., Mussida, C. and Vivarelli, M. (2019). Testing the employment impact of automation, robots and AI: a survey and some methodological issues. *IZA Discussion Paper No. 12612*. Bonn: Institute for Labor Economics.

Barbieri, P., and Cutuli, G. (2016). Employment protection legislation, labour market dualism, and inequality in Europe. *European Sociological Review, 32*(4), 501–516.

Barbieri, P., Cutuli, G., Guetto, R., and Scherer, S. (2019). Part-time employment as a way to increase women's employment:(Where) does it work? *International Journal of Comparative Sociology*, *60*(4), 249–268.

Baranowska, A., and Gebel, M. (2010). The determinants of youth temporary employment in the enlarged Europe: Do labour market institutions matter?. *European Societies*, *12*(3), 367-390.

Baumol, W. J. (1967). Macroeconomics of unbalanced growth: anatomy of an urban crisis. *American Economic Review, 57*(3), pp. 415–426.

Behringer and van Treeck (2021). Varieties of capitalism and growth regimes: the role of income distribution, Socio-Economic Review

Bentolila, S. and Saint-Paul, G. (2003). Explaining Movements in the Labor Share. *Contributions to Macroeconomics, 3*(1), 1-33.

Bentolila, S., Dolado, J. J., and Jimeno, J. F. (2020). Dual Labor Markets Revisited. In *Oxford Research Encyclopedia of Economics and Finance*.

Berman, E., Bound, J., Griliches, Z., (1994). Changes in the demand for skilled labor within U.S. manufacturing industries: evidence from the Annual Survey of Manufacturing, Quarterly Journal of Economics, 109, 367-397.

Berman, E., Bound, J., and Stephen, M. (1998). Implications of skill-biased technological change. *The Quarterly Journal of Economics, 113*(4): 1245–1279.

Bernardi, F., and Garrido, L. (2008). Is there a new service proletariat? Post-

industrial employment growth and social inequality in Spain. *European Sociological Review, 24*(3), 299–313.

Biegert, T. (2017). Labor market institutions, the insider/outsider divide and social inequalities in employment in affluent countries. *Socio-Economic Review*, *17*(2), 255-281.

Blanchard, O. (1997). The Medium Run. *Brookings papers on economic activity*, *1997*(2), 89-158.

Blau, F.D. and Kahn, L. (1996) International differences in male wage inequality: Institutions versus market forces, Journal of Political Economy 104, 791-837

Blauner, R. (1964). *Alienation and Freedom.* Chicago: University of Chicago Press.

Bloom, N., Garicano, L., Sadun, R. and van Reenen, J.. (2014). The distinct effects of information technology and communication technology on firm organization. *Management Science 60*(12), 2859–2885.

Bloomfield B. P. and Coombs, R. (1992). Information technology, control and power. *Journal of Management Studies, 29*(4), 459.

Boeri, T. (2011). Institutional reforms and dualism in european labor markets. In *Handbook of Labor Economics* (Vol. 4, Issue PART B). Elsevier Inc.

Boeri, T., Conde-Ruiz, J. I., and Galasso, V. (2012). The political economy of flexicurity. *Journal of the European Economic Association*, *10*(4), 684–715.

Bogliacino, F. (2014). A critical review of the technology-inequality debate. *Suma de Negocios*. Elsevier, *5*(12), pp. 124–135.

Bollen, K.A. and Pearl, J. (2013). Eight myths about causality and structural equation models. In St. L. Morgan (Eds.), *Handbook of causal analysis for social research* (pp. 301–328). Dordrecht: Springer.

Bosch, G. (1992). *Retraining--not redundancy: innovative approaches to industrial restructuring in Germany and France*. International Institute for labour studies.

Boyd, R. and Holton, R. J. (2018). Technology, innovation, employment and power: Does robotics and artificial intelligence really mean social transformation? *Journal of Sociology*, *54*(3), pp. 331–345.

Brady, D., Baker, R. S., and Finnigan, R. (2013). When unionization disappears: State-level unionization and working poverty in the United States. *American Sociological Review*, *78*(5), 872–896.

Brandolini, A., Gambacorta, R., and Rosolia, A. (2018). Inequality amid income stagnation: Italy over the last quarter of a century. *Bank of Italy Occasional Paper*, *442*.

Braverman, H. (1974). *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century*. New York: Monthly Review Press.

Breemersch, K., Jože, D.P. and Konings, J. (2017). *Labour market polarization in advanced countries.* OECD Social, Employment and Migration working papers 197. Paris: OECD Publishing.

Breen, R. (1997). Risk, Recommodification and Stratification. *Sociology*, *31*(3), 473–489.

Breen, R. (2005). Foundations of a neo-Weberian class analysis. *Approaches to Class Analysis*, 31–50.

Bresnahan, T. F., Brynjolfsson, E. and Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor. *The Quarterly Journal of Economics 117*(1), 339–376.

Brod, C. (1984). *Technostress: The human cost of the computer revolution*. Reading, MA: Addison-Wesley.

Bronfenbrenner, K. (2009) *No Holds Barred: The Intensification of Employer Opposition to Organizing*. *Economic Policy Institute*. Washington, DC: Economic Policy Institute, Briefing Paper 235.

Brown, P., Lauder, H. and Ashton, D. (2010). *The Global Auction: The Broken Promises of Education, Jobs, and Incomes*. Oxford: Oxford University Press.

Brunello, G., and Wruuck, P. (2019). *Skill shortages and skill mismatch in Europe: A review of the literature*. EIB Working Papers, No. 2019/05, European Investment Bank (EIB), Luxembourg,

Brynjolfsson, E. and McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton and Company.

Brzinsky-Fay, C. (2017). The interplay of educational and labour market institutions and links to relative youth unemployment. *Journal of European Social Policy*, *27*(4), 346-359.

Burris, B. H. (1998). Computerization of the Workplace. *Annual Review of Sociology*, *24*, pp. 141–57.

Busemeyer, M. R. (2009). Asset specificity, institutional complementarities and the variety of skill regimes in coordinated market economies. *Socio-Economic Review 7*(3), 375–406.

Caines, C., Hoffmann, F., & Kambourov, G. (2017). Complex-task biased technological change and the labor market. *Review of Economic Dynamics*, *25*, 298-319.

Campbell, J. L. (2004). Institutional change and globalisation. Princeton University Press.

Card, D. and Lamieux, T. (2001) 'Can falling supply explain the rising return to college for younger men? A cohort-based analysis', *Quarterly Journal of Economics*, *116*, pp. 705–706.

Card, D., Lemieux, T., and Riddell, W. C. (2017). Unions and wage inequality. In *What Do Unions Do?* (pp. 114–159). Routledge.

Casper, S. and Van Waarden, F. (2005). *Innovation and Institutions: a Multidisciplinary Review of the Study of Innovation Systems*. Northampton: Edward Elgar.

Castles, F. G., and Obinger, H. (2008). Worlds, families, regimes: Country clusters in European and OECD area public policy. West European Politics, 31(1-2), 321-344.

Cedefop. (2013). *Quantifying skill needs in Europe occupational skills profiles: methodology and application.* Cedefor Research Paper No. 30. Luxembourg: Publications Office.

Cedefop. (2015). *Job-related adult learning and continuing vocational training in Europe.* Cedefop research paper No 48. Luxembourg: Publications Office.

Cetrulo, A., Guarascio, D., and Virgillito, M. E. (2020). Anatomy of the Italian occupational structure: concentrated power and distributed knowledge. *Industrial and Corporate Change*, *29*(6), 1345-1379.

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly 22*(1), vii-xvi.

Comin, D. and Hobijn, B. (2004). Cross-country technology adoption : making the theories face the facts. *Journal of Monetary Economics*, *51*(51), pp. 39–83.

Cowen, T. (2011). *The Great Stagnation*. New York: Penguin.

Cutuli, G., and Guetto, R. (2013). Fixed-term contracts, economic conjuncture, and training opportunities: A comparative analysis across european labour markets. *European Sociological Review*, *29*(3), 616–629.

Dahrendorf, R. (1959). *Class and Class Conflict in Industrial Society*. Stanford: Stanford University Press.

Dallinger, U. (2013). The endangered middle class? A comparative analysis of the role played by income redistribution. *Journal of European Social Policy*, *23*(1), 83–101.

Damian, O., Serena, Y. and Buchanan, J. (2019). Political Economy of Vocational Education and Training, in Guile, D. and Unwin, L. (eds) *The Wiley Handbook of Vocational Education and Training*. New York: Wiley-Blackwell, pp. 115–137.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2018). Adjusting to robots: Worker-level evidence. *Opportunity and Inclusive Growth Institute Working Papers*, *13*.

Davis, K. (1955). Social and Demographic Aspects of Economic Development in India, in S. Kuznets, W. E. Moore, and J. J. Spengler (eds) *Economic Growth: Brazil, India, Japan*. Durham, NC: Duke University Press, pp. 263–315

De Boef, S., and Keele, L. (2008). Taking time seriously. *American Journal of Political Science*, *52*(1), 184–200.

de Vries, G. J., Gentile, E., Miroudot, S. and Wacker, K. M. (2020). The rise of robots and the fall of routine jobs. *Labour Economics, 66*, 101885.

De Witte, M., and Steijn, B. (2000). Automation, job content, and underemployment. *Work, Employment and Society 14*(2), 245–264.

Denice, P., and Rosenfeld, J. (2018). Unions and Nonunion Pay in the United States, 1977-2015. *Sociological Science*, *5*, 541–561.

Desjardins, R. and Rubenson, K. (2013). Participation Patterns in Adult Education. *European Journal of Education 48*, 262–280.

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica: Journal of the Econometric Society*, 1001–1044.

DiPrete, T. and McManus, P. (1996) Institutions, Technical Change, and Diverging Life Changes: Earnings Mobility in The United States and Germany. *American Journal of Sociology, 102*, 34–79.

Dobbin, F., and Boychuk, T. (1999). National employment systems and job autonomy. *Organization Studies 20*(2), 257–291.

Edlund, J., and Grönlund, A. (2008). Protection of mutual interests? Employment protection and skill formation in different labour market regimes. *European Journal of Industrial Relations 14*(3), 245–264.

Edlund, J., and Lindh, A. (2015). The democratic class struggle revisited: The welfare state, social cohesion and political conflict. *Acta Sociologica*, *58*(4), 311–328.

Eichhorst, W. and Marx, P. (2011). Reforming German labour market institutions: A dual path to flexibility, *Journal of European Social Policy, 21*(1), pp. 73–87.

Eichhorst, W., and Marx, P. (2010). Whatever works: dualisation and the service economy in Bismarckian welfare states. In Emmenegger, P. et al. (eds) *The Age of Dualization*, Oxford, Oxford University Press.

Elliott, C. S., and Long, G. (2016). Manufacturing rate busters: computer control and social relations in the labour process. *Work, employment and society*, *30*(1), 135-151.

Elsby, M. W. L., Hobijn, B., and Şahin, A. (2013). The decline of the US labor share. *Brookings Papers on Economic Activity*, *2013*(2), 1–63.

Emmenegger, P., Häusermann, S., Palier, B., and Seeleib-Kaiser, M. (2012). *The age of dualization: the changing face of inequality in deindustrializing societies*. New York, Oxford University Press.

Erikson, R. and Goldthorpe, J. H. (1992). *The Constant Flux: A Study of Class Mobility in Industrial Societies*. Oxford: Oxford University Press.

Erikson, R., Goldthorpe, J. H., and Hällsten, M. (2012). No way back up from

ratcheting down? A critique of the 'microclass' approach to the analysis of social mobility. *Acta Sociologica*, *55*(3), 211–229.

Erikson, R., Goldthorpe, J. H., and Portocarero, L. (1979). Intergenerational class mobility in three Western European societies: England, France and Sweden. *The British Journal of Sociology*, *30*(4), 415–441.

Esping-Andersen, G. (1990) *The Three Worlds of Welfare Capitalism*. Princeton, NJ: Princeton Univ. Press

Esping-Andersen, G. (1993). *Changing Classes: Stratification and mobility in post-industrial societies*. Beverly Hills, Calif.: Sage.

Esping-Andersen, G., and Regini, M. (2000). *Why deregulate labour markets?* New York: Oxford University Press.

Esposito, P., and Robert, S. (2008). The sector bias of skill-biased technical change and the rising skill premium in transition economies. *Empirica, 36*(3), 351–364.

Estevez-Abe, M., Iversen, T. and Soskice, D. (2001). Social Protection and the Formation of Skills. in Hall, P. A. and Soskice, D. (eds) *Varieties of Capitalism: The Institutional Foundations of Comparative Advantage*. Oxford: Oxford University Press.

European Union. (2019). *The changing nature of work and skills in the digital age*. Luxembourg: Publications Office of the European Union.

Evans, G. (1992). Testing the validity of the Goldthorpe class schema. *European Sociological Review*, *8*(3), 211–232.

Evans, G. (2000). The continued significance of class voting. *Annual Review of Political Science*, *3*(1), 401–417.

Fagan, C., Brendan H., and J. O'Reilly. (2005). Service sector employment in Germany and the UK. *Schmollers Jahrbuch, 125*(1), 97–107.

Featherman, D. L. and Hauser, R. M. (1978). *Opportunity and Change.* New York: Academic Press.

Ferragina, E and Seeleib-Kaiser, M (2011) Thematic review. Welfare regime debate: Past, present, futures? Policy and Politics 39(4): 583–611.

Ferragina, E, Seeleib-Kaiser, M and Tomlinson, M (2013) Unemployment protection and family policy at the turn of the 21st century: A dynamic approach to welfare regime theory. Social Policy & Administration 47(7): 783–805.

Ferragina, E., and Filetti, F. D. (2022). Labour market protection across space and time: A revised typology and a taxonomy of countries' trajectories of change. Journal of European Social Policy, 09589287211056222.

Ferragina, E., Seeleib-Kaiser, M., and Spreckelsen, T. (2015). The four worlds of 'Welfare Reality'–Social risks and outcomes in Europe. Social Policy and Society, 14(2),

287-307.

Fernández-macías, E. (2012). Job Polarization in Europe ? Changes in the Employment Structure and Job Quality, 1995-2007. *Work and Occupations, 39*(2), pp. 157–182.

Fernández-Macías, E. and Hurley, J. (2017). Routine-biased technical change and job polarization in Europe. *Socio-Economic Review*, *15*(3), 563–585.

Fleming, P. (2019). Robots and organization studies: Why robots might not want to steal your job. *Organization Studies*, *40*(1), 23-38.

Flood, S., King, M., Rodgers, R., Ruggles, S. and Robert, W. J. (2020). *Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset].* IPUMS.

Fonseca, T., Francisco L. and Sonia C. P. (2018). Job polarization, technological change and routinization. *Labour Economics, 51*, 317–339.

Ford, M. (2015). *Rise of the Robots: Technology and the Threat of a Jobless Future*. Basic Books.

Fox, A. (1974). *Beyond contract: Work, power and trust relations*. London: Faber and Faber.

Freeman, R. B. (1980). Unionism and the Dispersion of Wages. *ILR Review*, *34*(1), 3–23.

Freeman, R. B. (1984). Longitudinal analyses of the effects of trade unions. *Journal of Labor Economics*, *2*(1), 1–26.

Freeman, R. B. (2005). What Do Unions Do? *Journal of Labor Research*, *26*(4), 641–668.

Frey, C. B. (2019). *The technology trap: Capital, labor, and power in the age of automation*. Princeton, NJ: Princeton University Press.

Frey, C. B. and Michael, A. O. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254–280.

Friedmann, G. (1946). *Problèmes humains du machinisme industriel*. Paris: Gallimard.

Friedmann, G. (1961). *The anatomy of work*. London: Heinemann.

Gallie, D. (1978). *In Search of the New Working Class.* New York: Cambridge University Press

Gallie, D. (1991). Patterns of skill change: upskilling, deskilling or the polarization of skills? *Work, Employment and Society, 5*(3), 319–351.

Gallie, D. (2007). Production regimes and the quality of employment in Europe. *Annual Review Sociology, 33*, 85–104.

Gallie, D. (2011). *Production regimes, employee job control and skill development*. LLAKES Research Paper, 31. London: Centre for Learning and Life Chances in Knowledge Economies and Societies.

Gallie, D., Felstead, A. and Green, F. (2003). Skill, task discretion and new technology. *L'Année Sociologique, 53*(2), 401–430.

Gallie, D., White, M., Cheng, Y. and Tomlinson; M. (1998). *Restructuring the Employment Relationship*. Oxford: Oxford University Press.

Ganzeboom, H. B. G., and Treiman, D. J. (2003). Three internationally standardised measures for comparative research on occupational status. In J.H. P. Hoffmeyer-Zlotnik and C. Wolf (Eds.), *Advances in cross-national comparison: A European working book for demographic and socio-economic variables* (pp. 159–193). New York: Kluwer Academic/Plenum.

Garson, B. (1989). *The electronic sweatshop: How Computers are Transforming the Office of the Future.* New York: Simon and Schuster.

Goedemé, T., Paskov, M., Weisstanner, D. and Nolan, B. (2020). *Social class and earnings: a cross-national study*. INET Oxford Working Paper.

Goedemé, T., Nolan, B., Paskov, M., and Weisstanner, D. (2022). Occupational social class and earnings inequality in Europe: a comparative assessment. *Social Indicators Research*, *159*(1), 215-233.

Gebel, M., and Giesecke, J. (2011). Labor market flexibility and inequality: the changing skill-based temporary employment and unemployment risks in Europe. *Social Forces*, *90*(1), 17-39.

George, J. F., and King, J. L. (1991). Examining the computing and centralization debate. Communications of the ACM, *34*(7), 62-72.

Golden, H. H. (1957). Illiteracy and urban industrialization. *World Illiteracy at Mid-Century*.

Goldin, C. and Katz, L., (1998). The origins of technology-skill complementarity, Quarterly Journal of Economics, 113, 693-732.

Goldin, C. and Katz, L. (2007) 'The Race between Education and Technology: The Evolution of U.S. Educational Wage Differentials 1890 to 2005', *NBER Working Paper No.12984, Cambridge, National Bureau of Economic Research*.

Goldin, C. and Katz, L. F. (1998). The Origins of Technology-Skill Complementarity. *The Quarterly Journal of Economics 113*(3), 693–732.

Goldin, C., and Katz, L.F. (2008). *The Race between Education and Technology*. Cambridge, MA: Harvard University Press.

Goldthorpe, J. H., and Hope, K. (1974). *The social grading of occupations: A new approach and scale*. Oxford: Clarendon Press.

Goldthorpe, J. H. and McKnight, A. (2006). The Economic Basis of Social Class. In M. S., D. B. Grusky, and F. G. S. (Eds.), *Mobility and Inequality: Frontiers of Research from Sociology and Economics* (pp. 109–136). CA: Stanford University Press.

Goldthorpe, J. H. (1984). *Order and conflict in contemporary capitalism*. Clarendon Press Oxford.

Goldthorpe, J. H. (2000). Social Class and the Differentiation of Employment Contracts. In Goldthorpe, J. H. On Sociology: Numbers, Narratives, and the Integration of Research and Theory. Oxford University Press, pp. 206–229.

Goos, B. M., Manning, A. and Salomons, A. (2014). Explaining Job Polarization: Routine-Biase Technological Change and Offshoring. *The American Economic Review*, *104*(8), pp. 2509–2526.

Goos, B. M., Manning, A. and Salomons, A. (2009). Job Polarization in Europe. *The American Economic Review*, *99*(2), 58–63.

Gordon, J. R. (2014). *The Demise of US Economic Growth.* Working Paper no. 19895, NBER, Cambridge, MA.

Green F., Felstead, A., Gallie, D. and Henseke, G. (2021). Working Still Harder. ILR Review.

Green, F. (2004) Why Has Work E¤ort Become More Intense? *Industrial Relations, 43*(4), pp. 709–741.

Green, F. (2012). Employee involvement, technology and evolution in job skills. *ILR Review, 65*(1), 36–67.

Green, F. and McIntosh, S. (2001). The Intensification of Work in Europe. *Labour Economics*, 8(2), pp. 291–308.

Green, F., Alan, F. and Gallie, D. (2003). Computers and the changing skill-intensity of jobs. *Applied Economics, 35*(14), 1561–1576.

Green, F. and Tsitsianis, N. (2005). An investigation of national trends in job satisfaction in Britain and Germany. *British Journal of Industrial Relations, 43*(3), 401–429.

Green, F. and McIntosh, S. (2001). The Intensification of Work in Europe. *Labour Economics, 8*(2), 291–308.

Grimshaw D., Bosch G., Rubery J. (2014). "Minimum wages and collective bargaining: What types of pay bargaining can foster positive pay equity outcomes?" British Journal of Industrial Relations, Vol. 52, Issue. 3, pp. 470-498

Guy, F. and Skott, P. (2008). Communications Technology and the Distribution of Income. *Journal of Income Distribution, 17*(3–4), pp. 71–92.

Guy, F., and Skott, P. (2013). *Technology, power and the political economy of inequality*. Economics Department Working Paper Series. 162

Haakestad, H. and Friberg, J. H. (2017). Deskilling revisited. *Economic and Industrial Democracy 41*(3), 630–651.

Hall, P.A. (2015). Varieties of Capitalism. In Emerging Trends in the Social and Behavioral Sciences, in R.A. Scott and S.M. Kosslyn (eds) *Emerging trends in the social and behavioral sciences: An interdisciplinary, searchable, and linkable resource*. [Hoboken, N.J.]: John Wiley & Sons.

Hall, P. A., and Gingerich, D. W. (2009). Varieties of capitalism and institutional complementarities in the political economy: An empirical analysis. British journal of political science, 39(3), 449-482.

Hall, P. A. and Soskice, D. (2001) 'An Introduction to Varieties of Capitalism', in Hall, P. A. and Soskice, D. (eds) *Varieties of Capitalism: The Institutional Foundations of Comparative Ad- vantage*. Oxford: Oxford University Press, pp. 1–70.

Hall, P. A., and Taylor, R. C. (1996). Political science and the three new institutionalisms. *Political studies*, *44*(5), 936-957.

Hall, P. A., and Thelen, K. 2008. "Institutional Change in Varieties of Capitalism." Socio-Economic Review 7: 7–34.

Handel, M. J. (2012). *Trends in job skill demands in OECD countries*. OECD Social, Employment and Migration Working Papers, No. 143, OECD Publishing.

Hancké, B., Rohdes, M., and Thacher, M. (2007). Beyond varieties of capitalism. Oxford University Press

Hardin, E. (1960). Computer automation, work environment, and employee satisfaction. *ILR Review, 13*(4), 559–567.

Hardy, W., Keister, R. and Lewandowski, P. (2016). Technology or upskilling? Trends in the task composition of jobs in Central and Eastern Europe. *IBS Working Paper Series, Institute of Structural Research (IBS). HKUST IEMS Working Paper No. 2016-40*

Haslberger, M. (2021). Routine-biased technological change does not always lead to polarisation: Evidence from 10 OECD countries, 1995–2013. Research in Social Stratification and Mobility, 74, 100623.

Hassel, A. (2014). The paradox of liberalization - understanding dualism and the recovery of the German political economy. *British Journal of Industrial Relations*, *52*(1), pp. 57–81.

Hassel, A. 2017. "No Way to Escape Imbalances in the Eurozone? Three Sources for Germany's Export Dependency: Industrial Relations, Social Insurance and Fiscal Federalism." German Politics 26(3): 360–79.

Hassel, A., and Palier, B. (Eds.). (2021). Growth and Welfare in Advanced Capitalist Economies: How Have Growth Regimes Evolved?. Oxford University Press.

Hassel, A., Wiss, T., and Naczyk, M. 2019. “The Political Economy of Pension Financialisation: Public Policy Responses to the Crisis.” Journal of European Public Policy 26(4): 483–500.

Häusermann, S., and Schwander, H. (2012). Varieties of dualization? Labor market segmentation and insider-outsider divides across regimes. *The age of dualization: The changing face of inequality in deindustrializing societies*, 27-51.

Hay, C (2004) Common trajectories, variable paces, divergent outcomes? Models of European capitalism under conditions of complex economic interdependence. Review of International Political Economy 11(2): 231–262.

Heisig, J.P. and Solga, H. (2015) ‘Secondary Education Systems and the General Skills of Less- and Intermediate-educated Adults a Comparison of 18 Countries’, Sociology of Education 88(3): 202–25.

Herrigel, G., and Sabel, C. F. (1999). Craft production in crisis. In P. Culpepper and D. Finegold (Eds), *The German Skills Machine* (pp. 77–114). New York: Berghahn.

Hobsbawn, E. J. (1952). The Machine Breakers. *Past and Present, 1*, pp. 57–70.

Holm, J. R., Lorenz, E., Lundvall, B. and Valeyre, A. (2010). Organizational learning and systems of labor market regulation in Europe. *Industrial and Corporate Change, 19*(4), 1141–1173.

Holman, D. (2013). Job types and job quality in Europe. *Human Relations*, *66*(4), 475-502.

Hope, D., and Soskice, D. 2016. “Growth Models, Varieties of Capitalism, and Macroeconomics.” Politics and Society 44(2): 209–26.

Hunter, L. W., and Lafkas, J. J. (2003). Opening the box: Information technology, work practices, and wages. *ILR Review*, *56*(2), 224–243.

Huws, U. (2014). *Labor in the Global Digital Economy*. New York: Monthly Review Press.

Iacono, S., and Kling, R. (1991). Computerization, office routines, and changes in clerical work. In R. Kling (Ed.), *Computerization and controversy* (pp. 213–220). New York: Academic Press.

IPUMS USA. (2018). *Integrated Occupation and Industry Codes and Occupational Standing Variables In The IPUMS*. Minnesota Population Center.

Iversen, T. and Wren, A. (1998). Equality, Employment, and Budgetary Restraints: The Trilemma of the Service Economy. *World politics*, *50*(4), pp. 507–546.

Iversen, T., and Stephens, J. D. (2008). Partisan politics, the welfare state, and three worlds of human capital formation. *Comparative Political Studies*, *41*(4–5), 600–637.

Jacobs, D., and Dirlam, J. C. (2016). Politics and economic stratification: Power

resources and income inequality in the United States. *American Journal of Sociology*, *122*(2), 469–500.

Jaques, E. (1956). *Measures of responsibility*. London: Tavistock.

Jaques, E. (1967). *Equitable Payment. (revised edition.).* Harmondsworth: Penguin Books.

Jenkins, C., and Sherman, B. (1979). *The collapse of work*. London: Eyre Methuen.

Jonsson, J. O., Grusky, D. B., Di Carlo, M., Pollak, R. and Brinton, M. C. (2009). Microclass mobility: Social reproduction in four countries. *American Journal of Sociology*, *114*(4), 977–1036.

Karabarbounis, L., and Neiman, B. (2014). The global decline of the labor share. *The Quarterly journal of economics*, *129*(1), 61-103.

Kalleberg, A. L., Wallace, M. and Raffalovich, L. E. (1984). Accounting for Labor's Share: Class and Income Distribution in the Printing Industry. *Industrial and Labor Relations Review*, *37*, pp. 386–402.

Katz, L. and Murphy, K. (1992). Changes in relative wages: supply and demand factors. *Journal of Economics*, CVII, pp. 35–78.

Keister, R. and Lewandowski, P. (2017). A routine transition in the digital era? *Transfer: European Review of Labour and Research 23*(3), 263–279.

Kelley, M. (1990) New process technology, job design and work organization: A contingency model. American Sociological Review 55:191-20

Kim, C. and Sakamoto, A. (2008). The rise of intra-occupational wage inequality in the United States, 1983 to 2002. *American Sociological Review*, *73*(1), 129–157.

Korpi, T. and Tåhlin, M. (2009). Educational mismatch, wages, and wage growth: Overeducation in Sweden, 1974–2000. *Labour Economics*, *16*(2), 183–193.

Korpi, W. (1983) *The Democratic Class Struggle*. London: Routledge Kegan Paul.

Korpi, W. (1985). Power Resources Approach vs Action and Conflict : On Causal and Intentional Explanations in the Study of Power. *Sociological Theory*, *3*(2), pp. 31–45.

Kremer, M. (1993). The O-Ring Theory of Economic Development. *Quarterly Journal of Economics*, *108*(3), pp. 551–75.

Kristal, T. (2013). The Capitalist Machine: Computerization, Workers' Power, and the Decline in Labor's Share within U. S. Industries. *American Sociological Review*, *78*(3), pp. 361–389.

Kristal, T. (2019). Computerization and the Decline of American Unions : Is Computerization Class-Biased ? *Work and Occupations*, *46*(4), pp. 371–410.

Kristal, T. (2020). Why Has Computerization Increased Wage Inequality? Information, Occupational Structural Power, and Wage Inequality. *Work and*

Occupations, *47*(4), 466–503.

Kristal, T. and Cohen, Y. (2017). The causes of rising wage inequality : the race between institutions and technology. *Socio-Economic Review, 15*(1), pp. 187–212.

Kristal, T. and Cohen, Y. (2015). What do computers really do? Computerization, fading pay-setting institutions and rising wage inequality. *Research in Social Stratification and Mobility*, *42*, 33–47.

Kristal, T., and Edler, S. (2021). Computers meet politics at wage structure: an analysis of the computer wage premium across rich countries. *Socio-Economic Review*, *19*(3), 837-868.

Krueger, A., 1993. How computers have changed the wage structure: evidence from micro data 1984-1989, Quarterly Journal of Economics, 108, 33-60.

Kuznets, S. (1957). Quantitative aspects of the economic growth of nations: II. industrial distribution of national product and labor force. *Economic Development and Cultural Change*, *5*(S4), 1–111.

Kyndt, E., and Onghena, P. (2014). The integration of work and learning. In C. Harteis, A. Raush, and J. Seifried (Eds), *Discourses on professional learning* (pp. 255–291). Dordrecht: Springer.

Lawrence, M., Roberts, C. and King, L. (2017). *Managing automation: Employment, inequality and ethics in the digital age*, *IPPR*. http://www.ippr.org/publications/managing-automation.

Le Grand, C. and Tåhlin, M. (2013). Class, occupation, wages, and skills: The iron law of labor market inequality. Comparative Social Research 30:3–46.

Leavitt, H. J. and T.L. Whisler. 1958. Management in the 1980's. *Harvard Business Review, 36*(6), 1–11.

Leicht, K. T. (1989). On the estimation of union threat effects. *American Sociological Review*, 1035–1047.

Levy, F. and Temin, P. (2007). Inequality and Institutions in 20th Century America. *Working Paper No. 07-002, Cambridge, MIT Industrial Performance Center.*

Levy, F. and Murnane, R. J. (1992). US earnings levels and earnings inequality: A review of recent trends and proposed explanations. *Journal of Economic Literature*, *30*(3), 1333–1381.

Levy, F. and Murnane, R. J. (2012). *The new division of labor: How computers are creating the next job market*. Princeton University Press.

Lewandowski, P., Keister, R., Hardy, W.,and Górka, S. (2017). *Routine and ageing? The intergenerational divide in the deroutinisation of jobs in Europe*. IZA Discussion Papers, No. 10732, Institute of Labor Economics (IZA), Bonn

Lieberman, Robert C. 2002. "Ideas, Institutions, and Political Order: Explaining

Political Change." American Political Science Review 96:697–712

Lin, K.-H. and Tomaskovic-Devey, D. (2013). Financialization and US income inequality, 1970–2008. *American Journal of Sociology*, *118*(5), 1284–1329.

Lincoln, J. R. and Kalleberg, A. (1990). *A Study of Work Organization and Work Attitudes in the USA and Japan*. Cambridge, MA: Cambridge University Press.

Lindbeck, A., and Snower, D. J. (2000). Multitask learning and the reorganization of work. *Journal of Labor Economics, 18*(3), 353–376.

Lipset, S. M. (1960). *Political man: the social bases of politics*. Doubleday.

Lopes, H., Lagoa, S., and Calapez, T. (2014). Work autonomy, work pressure, and job satisfaction. *The Economic and Labour Relations Review, 25*(2), 306–326.

Lopes, H., Calapez, T. and Lopes, D. (2017). The determinants of work autonomy and employee involvement. *Economic and Industrial Democracy, 38*(3), 448–472.

Mahnkopf, B. (1992). The 'Skill-oriented' strategies of German Trade Unions: Their Impact on Efficiency and Equality Objectives. *British Journal of Industrial Relations*, *30*(1), 61–81.

Mandel, H. (2012). Winners and Losers : The Consequences of Welfare State Policies for Gender Wage Inequality. *European Sociological Review*, 28(2), pp. 241–262.

Mandel, H. and Semyonov, M. (2006). A Welfare State Paradox : State Interventions and Women's Employment Opportunities in 22 Countries 1. *American Journal of Sociology*, 111(6).

Mandel, H. and Shalev, M. (2009) "How welfare states shape the gender pay gap: A theoretical and comparative analysis." *Social Forces* 87(4), 1873-1911.

March, J. G., and Olsen, J. P. (1983). The new institutionalism: Organizational factors in political life. *American political science review*, *78*(3), 734-749.

Martinaitis, Ž., Christenko, A. and Antanavičius, J. (2021). Upskilling, Deskilling or Polarisation? *Work, Employment and Society*, *35*(3), 451-469.

Maurice, M., Sellier, F. and Silvestre, J. (1986). *The social foundations of industrial power: A comparison of France and Germany*. Cambridge, MA: MIT Press.

Maxwell, N. L. (2008). Wage differentials, skills, and institutions in low-skill jobs. *ILR Review*, *61*(3), 394–409.

Mazmanian, M., Orlikowski, W. J., and Yates, J. (2013). The autonomy paradox: The implications of mobile email devices for knowledge professionals. *Organization Science*, *24*(5), 1337-1357.

McCall, L. and Percheski, C. (2010). Income inequality: New trends and research directions. *Annual Review of Sociology*, *36*, 329–347.

McCollum, D. and Findlay, A. (2015). Flexible'workers for 'flexible' jobs? The

labour market function of A8 migrant labour in the UK. *Work, Employment and Society*, *29*(3), 427–443.

Menon, S., Salvatori, A., and Zwysen, W. (2020). The Effect of Computer Use on Work Discretion and Work Intensity: Evidence from Europe. *British Journal of Industrial Relations*, *58*: 1004-1038.

Milanovic, B. (2016). *Global inequality: A new approach for the age of globalization*. Harvard University Press.

Milkman, R. (1995). *Farewell to the Factory: Auto Workers in the Late Twentieth Century.* Berkeley: University of California Press.

Mishel, L., Bivens, J., Gould, E. and Shierholz, H. (2012). *The state of working America*. Cornell University Press.

Mokyr, J., Vickers, C. and Ziebarth, N. L. (2015). The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different?, *Journal of Economic Perspectives*, *29*(3), pp. 31–50.

Mokyr, J., Vickers, C., and Ziebarth, N. L. (2015). The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different? *Journal of Economic Perspectives*, *29*(3), 31–50.

Morgan, S. L. (2017). A coding of social class for the general social survey. *Chicago, Illinois: GSS Methodological Report*, *125*.

Morgan, S. L. and McKerrow, M. W. (2004). Social class, rent destruction, and the earnings of black and white men, 1982–2000. *Research in Social Stratification and Mobility*, *21*, 215–251.

Morgan, S. L. and Tang, Z. (2007). Social class and workers' rent, 1983–2001. *Research in Social Stratification and Mobility*, *25*(4), 273–293.

Mouw, T. and Kalleberg, A. L. (2010). Occupations and the Structure of Wage Inequality in the United States, 1980s to 2000s. *American Sociological Review*, *75*(3), 402–431.

Murphy, E. C. and Oesch, D. (2018). Is Employment Polarisation Inevitable ? Occupational Change in Ireland and. *Work, Employment and Society, 32*(6), pp. 1099–1117.

Myles, J. (1990). *Job skills and the service economy*. Ottawa: Economic Council of Canada.

Nassab, R. (2008). Factors influencing job satisfaction amongst plastic surgical trainees. *European Journal of Plastic Surgery, 31*, 55–58.

Nee, V., and Swedberg, R. (2005). Economic sociology and new institutional economics. In *Handbook of new institutional economics* (pp. 789-818). Springer, Boston, MA.

Nellas, V. and Olivieri, E. (2012). *The Change of Job Opportunities: The Role of Computerization and Institutions*, *Quadetni-Working Paper DSE N 804*.

Nelson, J. I. (2001). Inequality in America: The case for post-industrial capitalism. *Research in Social Stratification and Mobility*, *18*(C), pp. 39–62.

Noon, M., Blyton, P. and Morrell, K. (2013). *The realities of work*. London: Macmillan International Higher Education.

North, D, C. (1990). *Institutions, Institutional Change And Economic Performance.* New York: Cambridge University Press.

Oberfield, E. and Raval, D. (2014). Micro Data and Macro Technology. *NBER Working Paper No. 20452.*

Oesch, D. (2003). Labour market trends and the Goldthorpe class schema: a conceptual reassessment. *Revue Suisse de Sociologie*, *29*(2), 241–262.

Oesch, D. (2013). *Occupational change in Europe: how technology and education transform the job structure*. Oxford University Press.

Oesch, D. (2015). Welfare regimes and change in the employment structure : Britain, Denmark and Germany since 1990. *Journal of European Social Policy*, *25*(1), pp. 94–110.

Oesch, D. and Menés, J. R. (2011). Upgrading or polarization? Occupational change in Britain, Germany, Spain and Switzerland, 1990-2008. *Socio-Economic Review*, *9*, pp. 503–531.

Oesch, D. and Piccitto, G. (2019). The Polarization Myth: Occupational Upgrading in Germany, Spain, Sweden, and the UK, 1992–2015. *Work and Occupations*, *46*(4), pp. 441–469.

Palier, B. and Thelen, K. (2008). Dualizing CMEs: Flexibility and change in coordinated market economies. *16th Conference of the Council for European Studies*, 6–8.

Palier, B. and Thelen, K. (2010). Institutionalizing dualism: Complementarities and Change in France and Germany. *Politics and Society*, *38*(1), 119–148.

Parayitam, S., Desai, K. J., Desai, M. S. and Eason, M. K. (2010). Computer attitude as a moderator in the relationship between computer anxiety, satisfaction, and stress. *Computers in Human Behavior 26*(3), 345–352.

Parolin, Z. (2021). Automation, occupational earnings trends, and the moderating role of organized labor. *Social Forces*, *99*(3), 921–946.

Pavitt, K. (1984) Sectoral pattern of technical change: Towards a taxonomy and a theory. *Research and Politics*, *13*, pp. 347–74.

Piketty, T. and Saez, E. (2003). Income inequality in the United States, 1913–1998. *The Quarterly Journal of Economics*, *118*(1), 1–41.

Powell, J. J., and Solga, H. (2010). Analyzing the nexus of higher education and vocational training in Europe: a comparative-institutional framework. *Studies in Higher Education*, *35*(6), 705-721.

Pressman, S. (2007). The decline of the middle class: an international perspective. *Journal of Economic Issues*, *41*(1), 181–200.

Pressman, S. (2009). *Public Policies and the Middle Class throughout the World in the Mid 2000s*. LIS Cross-National Data Center in Luxembourg.

Radner, R. (1993). The organization of decentralized information processing. *Econometrica, 62*, 1109–1146.

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S. and Tu, Q. (2008). The consequences of technostress for end users in organizations. *Information Systems Research, 19*(4), 417–433.

Regini, M. (2000). Between deregulation and social pacts: The responses of European economies to globalisation. Politics & Society, 28(1), 5-33.

Rigby, M. and García Calavia, M. Á. (2018). Institutional resources as a source of trade union power in Southern Europe. *European Journal of Industrial Relations*, *24*(2), pp. 129–143.

Rolfe, H. (1986). Skill, deskilling and new technology in the non-manual labour process. *New Technology, Work and Employment, 1*(1), 37–49.

Rolfe, H. (1990). In the name of progress? Skill and attitudes towards technological change. *New Technology, Work and Employment, 5*(2), 107–121.

Rose, D., and Harrison, E. (2007). The European socio-economic classification: a new social class schema for comparative European research. *European Societies*, *9*(3), 459–490.

Rosenfeld, J. (2006). Widening the gap: The effect of declining unionization on managerial and worker pay, 1983–2000. *Research in Social Stratification and Mobility*, *24*(3), 223–238.

Rubin, B. (1986). Trade Union Organization, Labor Militancy, and Labor's Share of National Income in the United States, 1949–1978. *Research in Social Stratification and Mobility*, *5*, pp. 223–42.

Sabel, C. F. (1982). *Work and politics: the division of labour in industry*. Cambridge University Press.

Saint-Arnaud, S., and Bernard, P. (2003). Convergence or resilience? A hierarchical cluster analysis of the welfare regimes in advanced countries. Current sociology, 51(5), 499-527.

Scherer, S. (2005). Patterns of labour market entry–long wait or career instability? An empirical comparison of Italy, Great Britain and West Germany. *European Sociological*

Review, *21*(5), 427-440.

Schmitt, J. (2003). Creating a consistent hourly wage series from the Current Population Survey's Outgoing Rotation Group, 1979-2002. *Version 0.9 (August). Washington DC: Center for Economic and Policy Research*.

Schumpeter, J. (1912). *The theory of economic development*. Cambridge, Mass: Harvard University Press.

Schwander, H., and Häusermann, S. (2013). Who is in and who is out? A risk-based conceptualization of insiders and outsiders. *Journal of European Social Policy*, *23*(3), 248-269.

Scopp, T. S. (2003). *The relationship between the 1990 census and census 2000 industry and occupation classification systems*. Washington, DC: US Census Bureau

Scott, R. H., and Pressman, S. (2011). A double squeeze on the middle class. *Journal of Economic Issues*, *45*(2), 333–342.

Shalev, M. (1983) Class politics and the Western welfare state. In *Evaluating the Welfare State: Social and Political Perspectives*, ed. S. E. Spiro, E. Yuchtman- Yaar, pp. 27-50. New York: Academic Press.

Shalev, M. (1992). The Resurgence of Labour Quiescence, in M. Regini (ed.) *The Future of Labour Movements,* pp.102-32. London: Sage.

Shalev, M., and Korpi, W. (1980). Working class mobilization and American exceptionalism. *Economic and Industrial Democracy*, *1*(1), 31-61.

Shepard, J. M. (1977). Technology, alienation, and job satisfaction. *Annual Review of Sociology, 3*(1), 1–21.

Skott, P. (2010). Power Biased Technical Change, Endogenous Mismatch and Institutional Change. *New School Economic Review*, *4*, pp. 50–64.

Skott, P., and Guy, F. (2007). A model of power-biased technological change. *Economics Letters*, *95*(1), 124–131.

Smith, A., and Anderson, M. (2017). Automation in everyday life. *Pew Research Center*.

Smith, C., and Thompson, P. (1998). Re-evaluating the labour process debate. *Economic and industrial democracy*, *19*(4), 551-577.

Soares, G. A. D. (1966). Economic development and class structure. In R. Bendix and S. Lipset (Eds.) *Class, Status, and Power: Social Stratification in Comparative Perspective.* New York: The Free Press.

Solga, H. (2002). 'Stigmatization by negative selection': explaining less-educated people's decreasing employment opportunities. *European sociological review*, *18*(2), 159-178.

Solga, H. (2014). Education, economic inequality and the promises of the social investment state. *Socio-Economic Review*, *12*(2), 269-297.

Sorge, A., and Streeck, W. (2018). Diversified quality production revisited: Its contribution to German socio-economic performance over time. Socio-Economic Review, 16(3), 587-612.

Soskice, D. (1990). Wage determination: The changing role of institutions in advanced industrialized countries. *Oxford Review of Economic Policy*, *6*(4), pp. 36–61.

Soskice, D. (1999). Divergent Production Regimes: Coordinated and Uncoordinated Market Economies in the 1980s and 1990s. In Kitschelt, H., Lange, P., Marks, G., and Stephens, J. D. (eds) *Continuity and Change in Contemporary Capitalism*. Cambridge: Cambridge University Press.

Soskice D. 2005. Varieties of capitalism and cross-national gender differences. *Soc. Polit.*12(2):170–79

Soskice, D. (2007). Macroeconomics and varieties of capitalism. *',* in B. Hancke´, M. Rhodes and M. Thatcher (eds), *Beyond Varieties of Capitalism.* Oxford: Oxford University Press, 2007, pp.89–121.

Spencer, D. (2016). Work in and beyond the Second Machine Age: the politics of production and digital technologies. *Work, Employment and Society, 1*(16).

Spenner, K. I. (1983). Deciphering Prometheus: Temporal change in the skill level of work. *American Sociological Review, 48*(6), 824–837.

Spenner, K. I. (1990). Skill: meanings, methods, and measures. *Work and Occupations, 17*(4), 399–421.

Spitz-Oener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure. *Journal of Labor Economics*, *24*(2), 235–270.

Srnicek, N. and Williams, A. (2015). *Inventing the Future: Postcapitalism and a World Without Work*. London: Verso Books.

Steinmo, S., Thelen, K., Longstreth, F. (1992). *Structuring Politics: Historical Institutionalism in Comparative Analysis*. New York: Cambridge Univ. Press.

Streeck, W. (1991) 'On the Institutional Conditions of Diversified Quality Production'. In Matzner, E. and Streeck, W. (eds) *Beyond Keynesianism: The Socio-Economics of Production and Full Employment*, Aldershot, Edward Elgar, pp. 21–61.

Streeck, W. (1992). *Social Institutions and Economic Performance. Studies of Industrial Relations in Advanced Capitalist Economies*. London: Sage

Streeck, W. (2009). *Re-Forming Capitalism: Institutional Change in the German Political Economy*. Oxford: Oxford University Press.

Streeck, W. and Recchi, E. (1994). Vincoli benefici : sui limiti economici dell' attore razionale. *Stato e Mercato*, *2*(41), pp. 185–213.

Streeck, W., and Thelen, K. (2005). Beyond continuity: Institutional change in advanced political economies. Oxford University Press.

Susskind, R. and Susskind, D. (2015). *The Future of the Professions: How Technology Will Transform the Work of Human Experts*. Oxford University Press.

Sutherland, J. (2016). Job quality in Scotland. *Scottish Affairs, 25*(3), 337–371.

Taber, T. D., and Alliger. G. M. (1995). A Task-Level Assessment of Job Satisfaction. *Journal of Organizational Behavior, 16*(2), 101–121.

Tåhlin, M. (2007). Class clues. *European Sociological Review*, *23*(5), 557–572.

Thelen, K. (1999). Historical institutionalism in comparative politics. Annual review of political science, 2(1), 369-404.

Thelen, K. (2001). Varieties of labour politics in the developed democracies. In Hall, P. . and Soskice, D. (eds) *Varieties of Capitalism and the Institutional Foundations of Comparative Advantage*. Oxford: Oxford University Press, pp. 71–103.

Thelen, K. (2004). *How Institutions Evolve.* New York: Cambridge University Press.

Thelen, K. (2012). Varieties of Capitalism: Trajectories of liberalisation and the new politics of social solidarity. Annual Review of Political Science, 15, 137-159.

Thelen, K. (2014). *Varieties of Liberalization and the New Politics of Social Solidarity*. New York: Cambridge University Press.

Tinbergen, J. (1975). *Income Difference: Recent Research*. Amsterdam: North-Holland Publishing Company.

Treiman, D. J. (1970). Industrialization and social stratification. *Sociological Inquiry*, *40*(2), 207–234.

U.S. Census Bureau. (2013). *1990-2012 Census Industry Codes with Crosswalk*. https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html

Vallas, S. P. and Beck, J. P. (1996). The Transformation of Work Revisited: The Limits of Flexibility in America n Manufacturing, *Social Problems*, *43*, pp. 339–61.

Vallas, S.P. (1993). *Power in the workplace*. Albany, NY: State University of New York Press.

VanHeuvelen, T. (2018). Moral economies or hidden talents? A longitudinal analysis of union decline and wage inequality, 1973–2015. *Social Forces*, *97*(2), 495–530.

Waddington, N. (2004). *The Europeanisation of Corporate Governance in Germany and the UK*. Archive of European Integration, http://aei.pitt.edu/6119/.

Wallace, M., Leicht, K. and Raffalovich, L. E. (1999). Unions, Strikes, and Labor's Share of Income: A Quarterly Analysis of the United States, 1949–1992. *Social Science Research*, *28*, pp. 265–88.

Weeden, K. A. and Grusky, D. B. (2005). The Case for a New Class Map. *American Journal of Sociology*, *111*, pp. 141–212.

Weeden, K. A., Kim, Y.-M., Di Carlo, M. and Grusky, D. B. (2007). Social class and earnings inequality. *American Behavioral Scientist*, *50*(5), 702–736.

Welch, F. (1973). Black-white differences in returns to schooling. *American Economic Review*, *63*, pp. 893–905.

Western, B. and Rosenfeld, J. (2011). Unions, norms, and the rise in US wage inequality. *American Sociological Review*, *76*(4), 513–537.

Wilkinson, R. and Pickett, K. (2011). *The spirit level: Why greater equality makes societies stronger*. Bloomsbury Publishing USA.

Williams, M. and Bol, T. (2018). Occupations and the wage structure: The role of occupational tasks in Britain. *Research in Social Stratification and Mobility*, *53*, 16–25.

Wodtke, G. T. (2017). Social Class and Income Inequality in the United States: Ownership, Authority, and Personal Income Distribution from 1980 to 2010. *American Journal of Sociology*, *121*(5), pp. 1–39.

Wolbers, M. H. (2007). Patterns of labour market entry: A comparative perspective on school-to-work transitions in 11 European countries. *Acta sociologica*, *50*(3), 189-210.

World Economic Forum (2015). *Deep Shift: Technology Tipping Points and Societal Impact*. https://www.weforum.org/reports/deep-shift-technology-tipping-points-and-societal-impact

Wright, E. O. (1979). *Class Structure and Income Determination*. New York: Academic.

Wright, E. O. (1997). *Class counts: Comparative studies in class analysis*. Cambridge University Press.

Wright, E. O. (2005). *Approaches to class analysis*. Cambridge University Press.

Wyner, G., and Malone, T. (1996). Cowboys or commanders: Does information technology lead to decentralization? *ICIS 1996 Proceedings,* 4, 63-79.

Zhou, X., and Wodtke, G. T. (2019). Income stratification among occupational classes in the United States. *Social Forces*, *97*(3), 945–972.

Zuboff, S. (1988). *In the age of the smart machine*. New York: Basic books.

Appendix to Chapter II

AII.1 Occupational Quintiles

Analysis of occupational change typically starts from ranking and grouping jobs according to their quality and then analyze changes in the share or number of workers employed in each of these tiers. Literature has usually ranked occupations according to their median wage, considering that wages are one of the best correlates of job quality. This chapter uses ISEI level rather than wages for the reasons presented in the paper.

As Fernandez-Macias (2012) argued, the concept of job quality in these types of analysis is purely relative and static. It is relative because it only entails the relative position of one job against the others and not the scale of difference between jobs. Static because it considers only the change in employment shares between jobs defined by different levels of quality and not changes in job quality within jobs. Therefore, jobs are ranked only one time, and ranking is kept constant through the analysis. To construct the five quintiles, the110 three-digit isco-88 occupations from the EU-LFS are ranked according to their ISEI level and then grouped in five ISEI quintiles representing five job quality tiers. Each employed individual in the labour force survey is thus assigned an occupational quintile based on its isco-88 code.

Occupational classification was subjected to major changes in 2011 due to changes from ISCO-88 to ISCO-08. To assign the appropriate ranking through time, all occupational codes are converted to ISCO-88 using the crosswalk provided by Ganzeboom and Treiman (2019). When specific conversions are ambiguous, some modifications are applied to the original crosswalk to adapt it to the labour force survey and minimize breaks in time series between 2010 and 2011 so that the distribution of occupations in 2011 is most similar to the one in 2010. Precisely, 522 in ISCO-08 is converted to 522 in ISCO-88 if they are not self-employed rather than convert all to 1310, 312 in ISCO-08 are converted to 82 in ISCO-88 instead of 122, 226 in ISCO-08 to 322 in ISCO-88 rather than 321, 234 in ISCO-08 to 332 in ISCO-88 if they have a medium level of education rather than all to 233.

A second issue is that few individuals in the EU-LFS are assigned a 2-digit ISCO code rather than three digits. For these individuals, it is impossible to directly match an occupational quintile based on the isco-3-digit distribution. To avoid dropping these units, they are assigned a specific quintile based on the isco-2-digit ISEI level. Once each individual is assigned a position in the occupational structure, the percentage of people

unemployed or employed in one of the five groups is computed for country-year combinations and region-year

Finally, the occupational employment shares at the country-level and the regional level are adjusted for several breaks apparent in the time series. The same approach as Goos, Manning and Salomons (2014) is adopted; when an occupation's employment jumps up or down in a specific year, the post-break year-to-year employment growth is applied (for all quintiles or classes) to the employment level before the break.

In other words, the level shifts are removed by equating the mean occupational share values in the two years surrounding the classification changes, which allows studying the overall changes in a consistent manner (Hardy et al., 2016, 2018). This is the case for Finland in 2002, Portugal 1998, Germany in 2012, Austria and Italy 2004, and all countries in 2011. In general, the same adjustments as Goos et al. (2014) are performed

AII.2 Task measures

To connect the findings on class and quintiles to the literature on RBTC, the impact of robotics on regional task distribution is investigated. Five indexes representing the original dimension proposed by Autor, Levy, and Murnane (2003) are investigated, using items suggested by Acemoglu and Autor (2011) reported in Table A2.1. The only difference in items is "Structured v. Unstructured work" which is not available in O*net 3.0 and which was substituted with "Entering, transcribing, recording, storing, or maintaining information in either written form or by electronic/magnetic recording". Transcribing values into matrixes and software is a highly repetitive and routine task performed in many clerical occupations.

Each item has a value from 1 to 5 for each O*Net-soc occupation, thus to translate them into isco-88 several cross-walk are necessary. First, O*net-soc are transformed to soc-2000, using the cross-walk provided by O*net. Each item is then standardized based on the distribution of occupations, and the five indexes are generated by summing the items belonging to each domain. Soc2000 codes are therefore translated to isco-88 following the cross-walk and approach from Hardy, Keister, and Lewandowski (2018).

In this way, a score for each ISCO-88 occupation is obtained. As in the case of occupational rank based on ISEI, the main interest is in the relative and static aspects of task content. Therefore, the110 occupations are ranked in 100 percentiles, so that each occupation has a value from 1 to 100 indicating its position in terms of the task dimension of interest.

Table A2.1 O*Net 3.0 items used for each of the five tasks indexes

Non-Routine Cognitive Analytical
Analyzing data/information
Interpreting information for others
Thinking creatively
Non-Routine Cognitive Interpersonal
Establishing and maintaining personal relationship
Guiding directing and motivating subordinate
Coaching/Developing other
Routine Cognitive
Importance of repeating the same task
Importance of being exact or accurate
Entering, transcribing, recording, storing, or maintaining information in either written form or by electronic/magnetic recording
Routine Manual
Pace determined by the speed of equipment
Controlling machines and processes
Spend time making repetitive motion
Non-Routine Manual
Running, maneuvering, navigating, or driving vehicles or mechanized equipment
Spend time using hands to handle control or feel objects tools or controls
Manual dexterity
Spatial Orientation

As mentioned above, few individuals in the EU-LFS are assigned an ISCO-2-digit code, and it is, therefore, impossible to assign them a value based on the distribution of the 3-digit occupation. To overcome this limit, for each 2-digit occupation, a task score based on the average value of all the 3-digit occupations which compose it is computed.

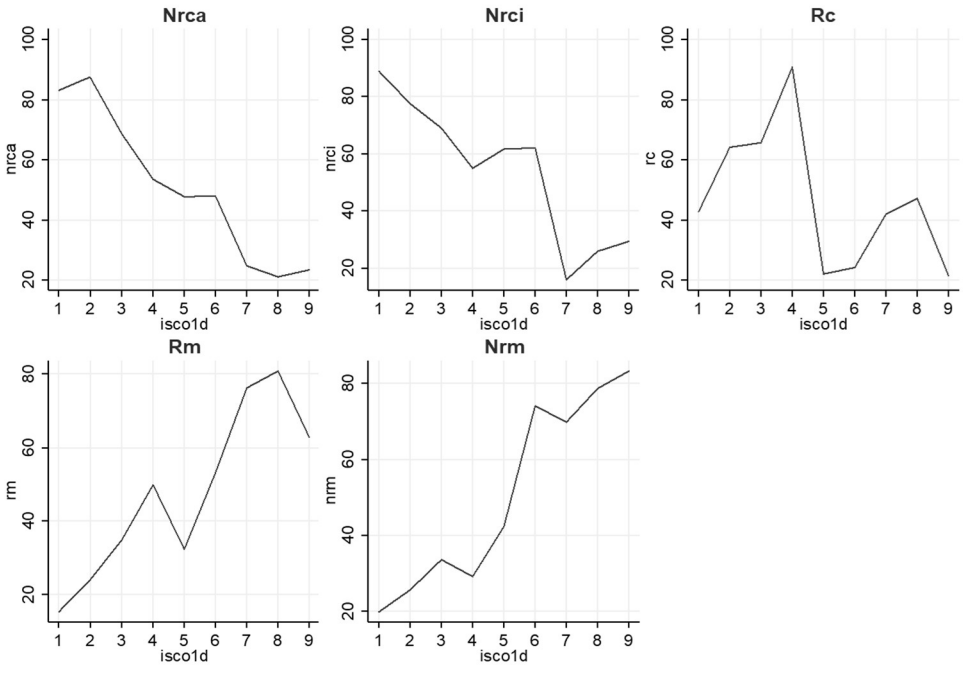
These values are then averaged at the country-year level and region-year level. The same adjustments applied to the time-series of occupational quintiles are applied to task indexes at the regional and national levels. We removed the level shifts by equating the mean tasks indexes values in the two years surrounding the occupational classification changes.

Figure A2.1 reports the distribution of task indexes across 1-digit occupations. The values for each occupation are given by the average of all the lower level 3-digit occupations' scores.

Scores reflect theoretical considerations from RBTC. The highest levels of non-routine cognitive tasks are concentrated in the highest ISCO occupation. Manual tasks are high

towards the bottom, while routine-cognitive has the highest level in white-collar occupations.

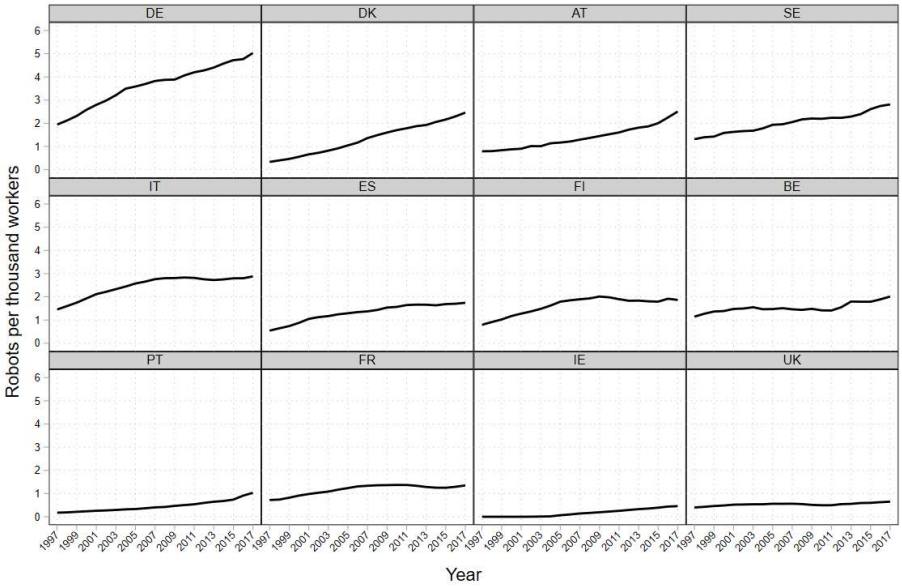
Figure A2. 1 Distribution of the five task indexes across one-digit ISCO-88 occupations



Nrca: Non-routine cognitive analytic; Nrci: Non-routine cognitive interpersonal; RC: Routine cognitive; Rm: Routine manual; Nrm: Non routine manual

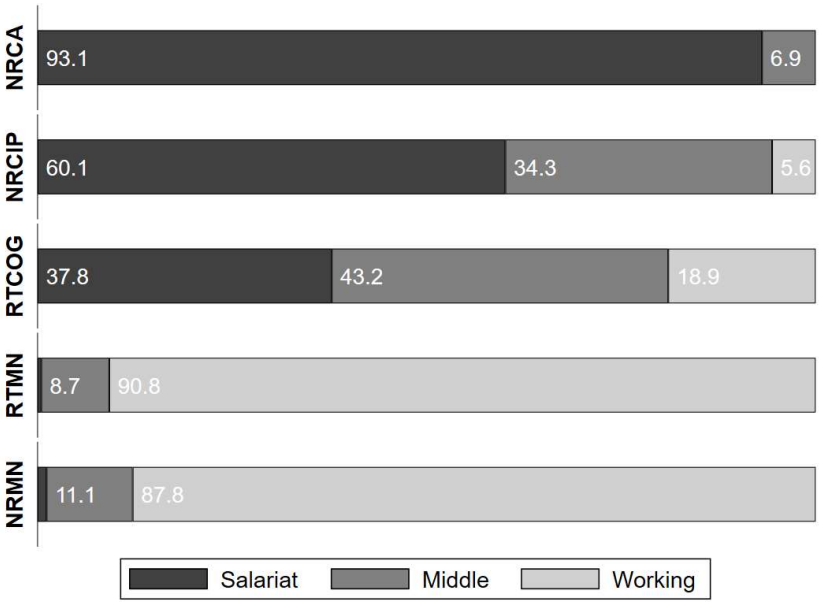
AII. 3 Additional figures

Figure A2.2 Trends in robots per thousand workers in western Europe (1997-2017)



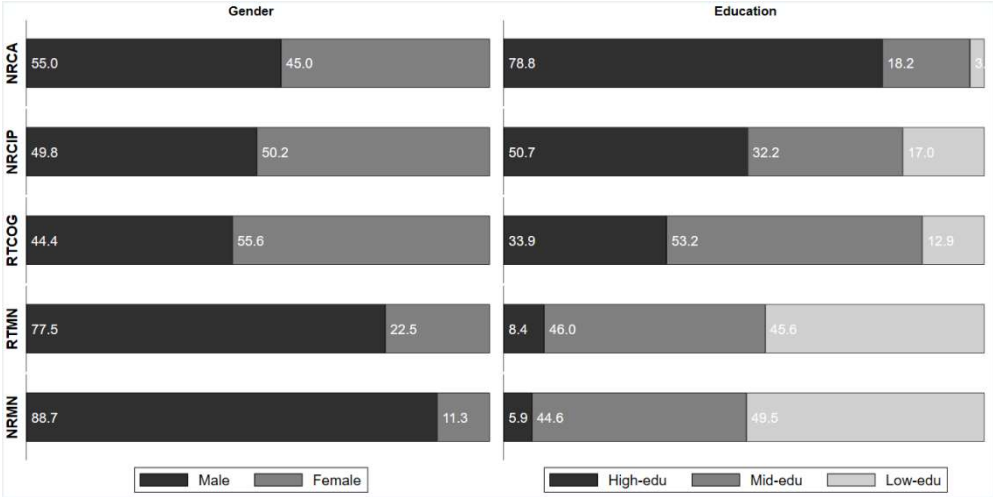
Own calculations from EU-LFS and IFR data. Countries are ranked based on their growth in robot density from 1997 to 2017.

Figure A2.3 Composition of occupations defined by their task content in terms of ESEC classes in western Europe (1997-2017)



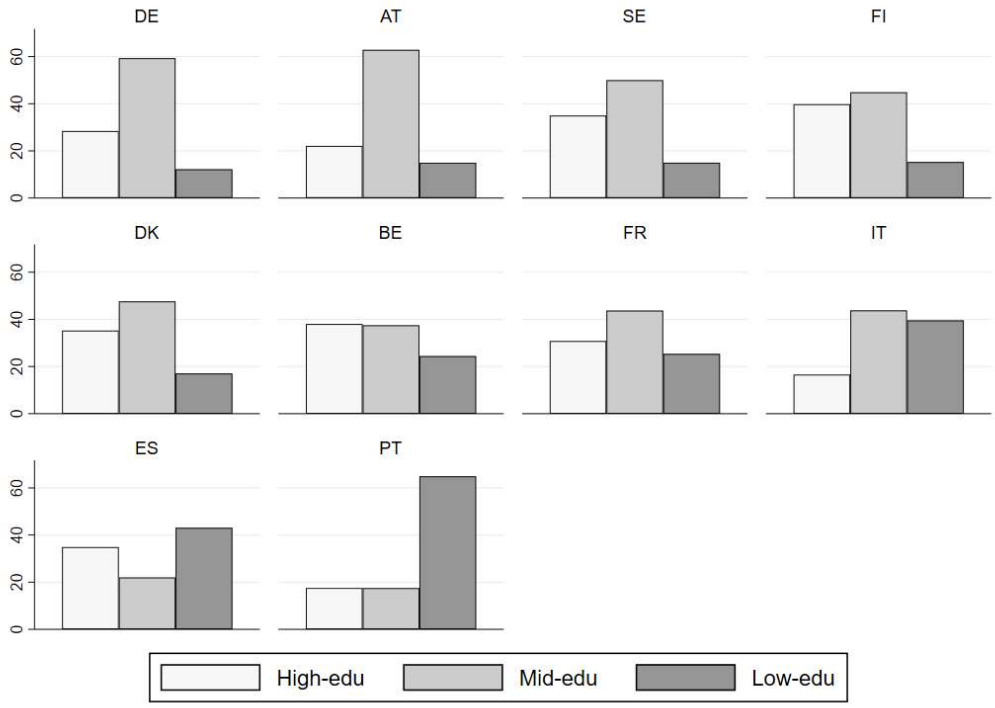
Notes: Own calculations from weighted EU-LFS 1997-2017. Non-routine manual (NRMN), Routine manual (RTMN), Routine cognitive (RTCOG), Non-routine cognitive interpersonal (NRCIP), Non-routine cognitive analytic (NRCA). Groups of occupations are defined according to five separate indexes described above. Each group is composed of occupations over the 80th percentile of each index.

Figure A2.4 Composition of occupations defined by their task content in terms of gender and level of education in western Europe (1997-2017)



Notes: Own calculations from weighted EU-LFS 1997-2017. Non-routine manual (NRMN), Routine manual (RTMN), Routine cognitive (RTCOG), Non-routine cognitive interpersonal (NRCIP), Non-routine cognitive analytic (NRCA). Groups of occupations are defined according to five separate indexes described above. Each group is composed of occupations over the 80th percentile of each index.

Figure A2.5 Share of the active population at different levels of education in the period from 1997 to 2017 across western European countries



Notes: Own calculations from weighted EU-LFS 1997-2017

AII. 4 Tables

Table A2.2 Regional panel fixed-effects estimates of regional robotics exposure on the regional unemployment rate and regional share of workers employed in five ISEI quintiles. Interactions with country clusters

VARIABLES	Unempl	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Robotics*Continental	-0.005	-0.004	-0.004*	-0.004	0.010**	0.008**
	(0.004)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)
Robotics*Nordic	-0.008	-0.005	-0.014***	-0.009**	0.018**	0.021**
	(0.011)	(0.003)	(0.004)	(0.004)	(0.008)	(0.010)
Robotics*Southern	0.006	0.015***	-0.007***	0.001	-0.008	-0.010**
	(0.004)	(0.005)	(0.002)	(0.003)	(0.006)	(0.005)
High-edu supply*Continental	0.150**	-0.096**	-0.126**	0.027	-0.102	0.214***
	(0.066)	(0.045)	(0.051)	(0.033)	(0.063)	(0.052)
High-edu supply*Nordic	0.309**	-0.345***	-0.020	0.044	-0.150**	0.200**
	(0.119)	(0.046)	(0.052)	(0.038)	(0.062)	(0.093)
High-edu supply*Southern	0.071	-0.397***	-0.073	0.071	0.197*	0.261***
	(0.100)	(0.084)	(0.054)	(0.053)	(0.104)	(0.081)
Youth unemp*Continental	0.387***	-0.056**	-0.017	-0.041	-0.184***	-0.026
	(0.045)	(0.024)	(0.024)	(0.033)	(0.034)	(0.037)
Youth unemp*Nordic	0.260***	-0.011	-0.032*	-0.069***	-0.083*	-0.040
	(0.024)	(0.015)	(0.018)	(0.022)	(0.044)	(0.036)
Youth unemp*Southern	0.440***	-0.062***	-0.138***	-0.036***	-0.091***	-0.037**
	(0.043)	(0.023)	(0.017)	(0.013)	(0.015)	(0.017)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	954	954	954	954	954	954
R-squared	0.776	0.348	0.607	0.284	0.250	0.586
Number of ids	49	49	49	49	49	49

Cluster robust standard errors at the regional level in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A2.3 Regional panel fixed-effects estimates of regional robotics exposure on the regional share of workers employed in five ESeC classes. Interactions with country clusters

VARIABLES	Salariat	Intermediate employee	Self-employed	Lower service	Lower technical and routine
Robotics*Continental	0.002	-0.000	-0.002	0.009***	-0.009***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Robotics*Nordic	0.022***	0.008	0.002	-0.008**	-0.024***
	(0.004)	(0.006)	(0.004)	(0.003)	(0.006)
Robotics*Southern	-0.014**	0.001	0.003	0.002	0.008
	(0.006)	(0.006)	(0.005)	(0.003)	(0.006)
High-edu supply*Continental	0.341***	0.064	0.057*	-0.224***	-0.238***
	(0.071)	(0.043)	(0.028)	(0.051)	(0.059)
High-edu supply*Nordic	0.253***	0.100	0.026	-0.216***	-0.163**
	(0.060)	(0.069)	(0.031)	(0.038)	(0.068)
High-edu supply*Southern	0.408***	0.215**	-0.339***	0.058	-0.342***
	(0.094)	(0.094)	(0.067)	(0.072)	(0.097)
Youth unemp*Continental	0.034	-0.001	0.039**	-0.067*	-0.007
	(0.044)	(0.044)	(0.019)	(0.035)	(0.034)
Youth unemp*Nordic	-0.025	0.024	0.027***	-0.029	0.003
	(0.018)	(0.021)	(0.010)	(0.022)	(0.024)
Youth unemp*Southern	0.033*	0.018	0.026**	-0.005	-0.073***
	(0.018)	(0.016)	(0.011)	(0.016)	(0.020)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	954	954	954	954	954
R-squared	0.656	0.166	0.616	0.491	0.579
Number of ids	49	49	49	49	49

Cluster robust standard errors at the regional level in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A2.4 Regional panel fixed-effects estimates of regional robotics exposure on regional indexes of task composition. Interactions with country clusters

VARIABLES	NRCA	NRCI	RC	RM	NRM
Robotics*Continental	0.395***	0.313**	0.330	-0.545***	-0.628***
	(0.131)	(0.154)	(0.259)	(0.147)	(0.122)
Robotics*Nordic	1.530***	1.192***	0.433	-1.031***	-1.148***
	(0.339)	(0.260)	(0.465)	(0.228)	(0.292)
Robotics*Southern	-0.243	-0.185	-0.889**	0.487	0.683
	(0.270)	(0.355)	(0.381)	(0.357)	(0.421)
High-edu supply*Continental	19.073***	13.141***	4.789	-12.123***	-11.310***
	(3.403)	(3.310)	(3.301)	(2.386)	(2.386)
High-edu supply*Nordic	17.348***	9.935***	18.482***	-15.644***	-13.438***
	(3.273)	(2.842)	(5.022)	(3.781)	(3.342)
High-edu supply*Southern	24.702***	17.103***	27.713***	-26.678***	-35.814***
	(4.778)	(5.762)	(6.706)	(5.716)	(6.744)
Youth unemp*Continental	0.803	1.294	-1.807	-2.531	-1.285
	(1.751)	(1.801)	(2.859)	(1.592)	(1.246)
Youth unemp*Nordic	-1.037	-1.529	-3.363**	0.539	1.330
	(1.553)	(1.686)	(1.343)	(1.249)	(1.368)
Youth unemp*Southern	5.989***	7.358***	1.820*	-5.381***	-4.382***
	(1.002)	(1.139)	(1.059)	(0.899)	(1.070)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	954	954	954	954	954
R-squared	0.676	0.613	0.212	0.706	0.692
Number of ids	49	49	49	49	49

Cluster robust standard errors at the regional level in parentheses *** p<0.01, ** p<0.05, * p<0.1. NRCA: Non-routine cognitive analytical; NRCI: Non-routine cognitive interpersonal; RTCOG: Routine cognitive; RTMN: Routine manual; NRTMN: Non-routine manual.

Table A2.5 Pseudo-individual panel fixed-effects estimates of regional robotics exposure on pseudo- individuals' unemployment rate and ISEI level. Interactions with country clusters, gender, and level of education

			ISEI		Unemployment	
VARIABLES			Coef	se	Coef	se
Robots*	Continental	*Male*High-edu	0.727***	(0.175)	0.004	(0.004)
Robots*	Continental	*Male*Mid-edu	0.489**	(0.184)	-0.010**	(0.005)
Robots*	Continental	*Male*Low-edu	0.062	(0.180)	-0.018***	(0.006)
Robots*	Continental	*Female*High-edu	1.082***	(0.235)	0.003	(0.004)
Robots*	Continental	*Female*Mid-edu	1.130***	(0.197)	-0.008	(0.005)
Robots*	Continental	*Female*Low-edu	-0.014	(0.215)	-0.010*	(0.005)
Robots*	Nordic	*Male*High-edu	1.920***	(0.503)	-0.001	(0.009)
Robots*	Nordic	*Male*Mid-edu	1.822***	(0.347)	-0.018	(0.017)
Robots*	Nordic	*Male*Low-edu	1.478***	(0.548)	-0.003	(0.009)
Robots*	Nordic	*Female*High-edu	3.216***	(0.801)	0.006	(0.008)
Robots*	Nordic	*Female*Mid-edu	2.060**	(0.816)	-0.010	(0.011)
Robots*	Nordic	*Female*Low-edu	1.974	(1.357)	-0.018**	(0.007)
Robots*	Southern	*Male*High-edu	-0.512	(0.539)	0.003	(0.004)
Robots*	Southern	*Male*Mid-edu	-0.222	(0.246)	0.017***	(0.006)
Robots*	Southern	*Male*Low-edu	0.054	(0.124)	0.028***	(0.010)
Robots*	Southern	*Female*High-edu	-1.357	(0.814)	-0.011	(0.009)
Robots*	Southern	*Female*Mid-edu	-0.996**	(0.422)	-0.008	(0.009)
Robots*	Southern	*Female*Low-edu	-0.236	(0.205)	-0.004	(0.006)
High-edu supply*	Continental	*Male*High-edu	-12.454**	(5.336)	0.184***	(0.063)
High-edu supply*	Continental	*Male*Mid-edu	1.522	(2.636)	0.321***	(0.075)
High-edu supply*	Continental	*Male*Low-edu	4.451	(2.747)	0.429***	(0.087)
High-edu supply*	Continental	*Female*High-edu	1.807	(8.188)	0.154**	(0.065)
High-edu supply*	Continental	*Female*Mid-edu	-9.457***	(3.048)	0.149**	(0.072)
High-edu supply*	Continental	*Female*Low-edu	-6.269	(3.833)	0.129	(0.089)
High-edu supply*	Nordic	*Male*High-edu	-11.641	(9.725)	0.321***	(0.112)
High-edu supply*	Nordic	*Male*Mid-edu	-4.506	(4.138)	0.299*	(0.150)
High-edu supply*	Nordic	*Male*Low-edu	-3.551	(4.444)	0.619***	(0.194)
High-edu supply*	Nordic	*Female*High-edu	3.234	(4.735)	0.235**	(0.095)
High-edu supply*	Nordic	*Female*Mid-edu	-3.658	(6.340)	0.251**	(0.111)
High-edu supply*	Nordic	*Female*Low-edu	-16.694*	(9.294)	0.989***	(0.177)
High-edu supply*	Southern	*Male*High-edu	-4.992	(7.273)	0.188**	(0.092)
High-edu supply*	Southern	*Male*Mid-edu	-8.318	(5.050)	0.130	(0.111)
High-edu supply*	Southern	*Male*Low-edu	7.524**	(3.510)	0.212	(0.149)
High-edu supply*	Southern	*Female*High-edu	3.659	(8.485)	-0.001	(0.141)
High-edu supply*	Southern	*Female*Mid-edu	-18.096**	(8.415)	-0.124	(0.149)
High-edu supply*	Southern	*Female*Low-edu	1.243	(4.476)	0.007	(0.136)
Youth unemp. *	Continental	*Male*High-edu	-5.547**	(2.757)	0.168***	(0.025)
Youth unemp. *	Continental	*Male*Mid-edu	-4.900***	(1.682)	0.390***	(0.059)
Youth unemp. *	Continental	*Male*Low-edu	-3.136	(2.359)	0.585***	(0.075)
Youth unemp. *	Continental	*Female*High-edu	-10.233***	(3.251)	0.196***	(0.039)
Youth unemp. *	Continental	*Female*Mid-edu	-7.127***	(1.818)	0.423***	(0.068)
Youth unemp. *	Continental	*Female*Low-edu	3.388	(4.370)	0.608***	(0.088)
Youth unemp. *	Nordic	*Male*High-edu	-5.886*	(3.379)	0.119***	(0.026)
Youth unemp. *	Nordic	*Male*Mid-edu	-0.733	(2.373)	0.239***	(0.046)

Youth unemp. *	Nordic	*Male*Low-edu	-0.959	(1.495)	0.446***	(0.037)
Youth unemp. *	Nordic	*Female*High-edu	10.329*	(5.155)	0.165***	(0.025)
Youth unemp. *	Nordic	*Female*Mid-edu	10.189**	(4.950)	0.254***	(0.029)
Youth unemp. *	Nordic	*Female*Low-edu	-6.630**	(3.293)	0.362***	(0.071)
Youth unemp. *	Southern	*Male*High-edu	1.817	(1.209)	0.249***	(0.036)
Youth unemp. *	Southern	*Male*Mid-edu	0.894	(0.743)	0.403***	(0.040)
Youth unemp. *	Southern	*Male*Low-edu	-0.140	(0.579)	0.579***	(0.059)
Youth unemp. *	Southern	*Female*High-edu	5.888***	(1.954)	0.281***	(0.040)
Youth unemp. *	Southern	*Female*Mid-edu	0.989	(2.017)	0.441***	(0.037)
Youth unemp. *	Southern	*Female*Low-edu	-1.929**	(0.918)	0.535***	(0.047)
Year fixed effects			Yes		Yes	
Observations			5,724		5,724	
R-squared			0.294		0.556	
Number of ids			294		294	

Cluster robust standard errors at the regional level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.6 Pseudo-individual panel fixed-effects estimates of regional robotics exposure on pseudo-individuals' unemployment rate and ISEI level. Interactions with training participation, gender, and level of education

				ISEI		Unemployment	
VARIABLES				Coef	se	Coef	se
Robot	*Train	*High-edu	*Male	5.586***	(1.331)	-0.018	(0.016)
Robot	*Train	*High-edu	*Female	6.291***	(1.953)	-0.036**	(0.017)
Robot	*Train	*Mid-edu	*Male	6.710***	(2.006)	-0.153***	(0.047)
Robot	*Train	*Mid-edu	*Female	9.234***	(2.657)	-0.163***	(0.035)
Robot	*Train	*Low-edu	*Male	6.769*	(3.384)	-0.445***	(0.103)
Robot	*Train	*Low-edu	*Female	8.576	(5.698)	-0.368***	(0.083)
High-edu supply	*Train	*High-edu	*Male	-71.272**	(30.082)	0.931***	(0.319)
High-edu supply	*Train	*High-edu	*Female	-15.072	(35.078)	0.398	(0.288)
High-edu supply	*Train	*Mid-edu	*Male	-11.802	(21.863)	2.572***	(0.718)
High-edu supply	*Train	*Mid-edu	*Female	-85.197***	(24.894)	1.043	(0.670)
High-edu supply	*Train	*Low-edu	*Male	78.868**	(38.755)	9.004***	(1.435)
High-edu supply	*Train	*Low-edu	*Female	-81.337*	(44.107)	5.674***	(1.432)
Youth unemp	*Train	*High-edu	*Male	-1.310	(9.077)	1.476***	(0.201)
Youth unemp	*Train	*High-edu	*Female	9.192	(8.692)	1.214***	(0.162)
Youth unemp	*Train	*Mid-edu	*Male	-19.465**	(8.242)	4.177***	(0.427)
Youth unemp	*Train	*Mid-edu	*Female	-23.024*	(11.733)	3.309***	(0.417)
Youth unemp	*Train	*Low-edu	*Male	5.029	(20.981)	12.444***	(2.186)
Youth unemp	*Train	*Low-edu	*Female	-16.398	(17.986)	7.778***	(1.649)
Year fixed effects				YES		YES	
Constant				46.764***	(0.539)	-0.026*	(0.015)
Observations				5,724		5,724	
R-squared				0.173		0.420	
Number of ids				294		294	

Cluster robust standard errors at the regional level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.7 Regional fixed-effects estimates of regional robotics exposure on the regional unemployment rate and regional share of employed in five ISEI quintiles. Interactions with country clusters, excluding controls for youth unemployment and tertiary educated supply.

VARIABLES	Unemployment	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Robotics*Continental	-0.018***	0.001	-0.004*	-0.004	0.007	0.006**
	(0.007)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
Robotics*Nordic	0.008	-0.015***	-0.007**	-0.009*	0.010	0.018**
	(0.010)	(0.004)	(0.003)	(0.005)	(0.008)	(0.007)
Robotics*Southern	-0.028***	0.001	-0.005**	0.003	0.005	-0.007*
	(0.008)	(0.005)	(0.002)	(0.003)	(0.005)	(0.004)
High-edu supply*Continental	0.149					
	(0.126)					
High-edu supply*Nordic	0.038					
	(0.126)					
High-edu supply*Southern	0.870***					
	(0.213)					
Youth unemp*Continental		-0.069**	-0.037	-0.037	-0.200***	0.007
		(0.029)	(0.027)	(0.034)	(0.041)	(0.034)
Youth unemp*Nordic		0.012	-0.031**	-0.071***	-0.066	-0.054
		(0.031)	(0.014)	(0.025)	(0.052)	(0.041)
Youth unemp*Southern		-0.098***	-0.133***	-0.030**	-0.051**	-0.030
		(0.020)	(0.015)	(0.013)	(0.023)	(0.022)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	954	954	954	954	954	954
R-squared	0.327	0.236	0.582	0.279	0.205	0.531
Number of ids	49	49	49	49	49	49

Cluster robust standard errors at the regional level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A2.8 Regional panel fixed-effects estimates of regional robotics exposure on the share of workers employed in five ESeC classes. Interactions with country clusters, excluding controls for tertiary educated supply.

VARIABLES	Salariat	Intermediate employees	Self-employed	Lower service	Lower tech & routine
Robotics*Continental	0.001	-0.002	0.003	0.006**	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Robotics*Nordic	0.013**	0.007	0.007*	-0.011**	-0.016***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
Robotics*Southern	-0.010**	0.008*	-0.014***	0.014***	0.003
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Youth unemp*Continental	0.088*	0.009	0.048**	-0.101**	-0.044
	(0.045)	(0.044)	(0.021)	(0.040)	(0.040)
Youth unemp*Nordic	-0.041**	0.019	0.019*	-0.009	0.012
	(0.017)	(0.017)	(0.010)	(0.015)	(0.024)
Youth unemp*Southern	0.044**	0.037	-0.025	0.031*	-0.088***
	(0.021)	(0.022)	(0.021)	(0.017)	(0.019)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	954	954	954	954	954
R-squared	0.575	0.130	0.514	0.386	0.522
Number of ids	49	49	49	49	49

Cluster robust standard errors at the regional level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A2. 9 Regional panel fixed-effects estimates of regional robotics exposure on regional indexes of task composition. Interactions with country clusters. Excluding controls for tertiary educated supply.

VARIABLES	NRCA	NRCI	RC	RM	NRM
Robotics*Continental	0.269**	0.231	-0.011	-0.315**	-0.282*
	(0.129)	(0.140)	(0.243)	(0.143)	(0.154)
Robotics*Nordic	1.213***	0.845***	0.876**	-0.932***	-0.793***
	(0.328)	(0.265)	(0.434)	(0.213)	(0.225)
Robotics*Southern	0.064	0.032	0.149	-0.201	-0.456
	(0.244)	(0.295)	(0.356)	(0.228)	(0.280)
Youth unemp*Continental	3.804*	3.378*	-1.153	-4.409**	-3.056*
	(2.150)	(1.993)	(2.954)	(1.797)	(1.591)
Youth unemp*Nordic	-2.162*	-2.129	-4.480**	1.458	1.898*
	(1.106)	(1.537)	(2.033)	(1.524)	(0.947)
Youth unemp*Southern	6.777***	7.944***	4.604***	-7.243***	-7.565***
	(0.956)	(0.903)	(1.618)	(1.165)	(1.632)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	954	954	954	954	954
R-squared	0.585	0.567	0.109	0.641	0.595
Number of ids	49	49	49	49	49

Cluster robust standard errors at the regional level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. NRCA: Non-routine cognitive analytical; NRCI: Non-routine cognitive interpersonal; RTCOG: Routine cognitive; RTMN: Routine manual; NRTMN: Non-routine manual.

Appendix to Chapter III

Table A3.1 Descriptive statistics of the industry-class panel (1984-2019)

Variables	Mean	SD.	Min	Max
Computer investments	12.3	11.4	0.2	68.5
Union density	12.9	10.3	1.0	49.0
Mean of log earnings				
I-II	6.8	0.2	6.2	7.2
III	6.2	0.2	5.6	6.8
V-VI	6.4	0.2	5.8	6.9
VII	6.1	0.2	5.4	6.8
Share of tertiary educated				
I-II	59.1	13.7	17.7	92.0
III	22.8	9.8	0.0	60.3
V-VI	16.1	10.6	0.0	62.4
VII	5.6	4.5	0.0	35.0
Share of Female				
I-II	36.7	17.2	4.8	84.2
III	64.7	13.1	23.3	95.9
V-VI	20.0	16.7	0.2	78.9
VII	29.6	18.1	0.3	83.3
Average age				
I-II	41.3	2.8	30.1	49.3
III	39.8	3.5	29.8	51.9
V-VI	40.3	3.1	29.3	52.1
VII	39.5	3.2	30.5	50.8
Share of white non-Hispanic workers				
I-II	81.7	8.2	55.8	99.2
III	75.0	11.0	44.3	100.0
V-VI	73.9	9.1	35.8	96.5
VII	58.0	12.2	17.7	89.7
Log of real value added	12.0	1.2	9.0	14.9

Figure A3.1 Trends in computerisation, union density and social class earnings by broad industries (1984-2019)

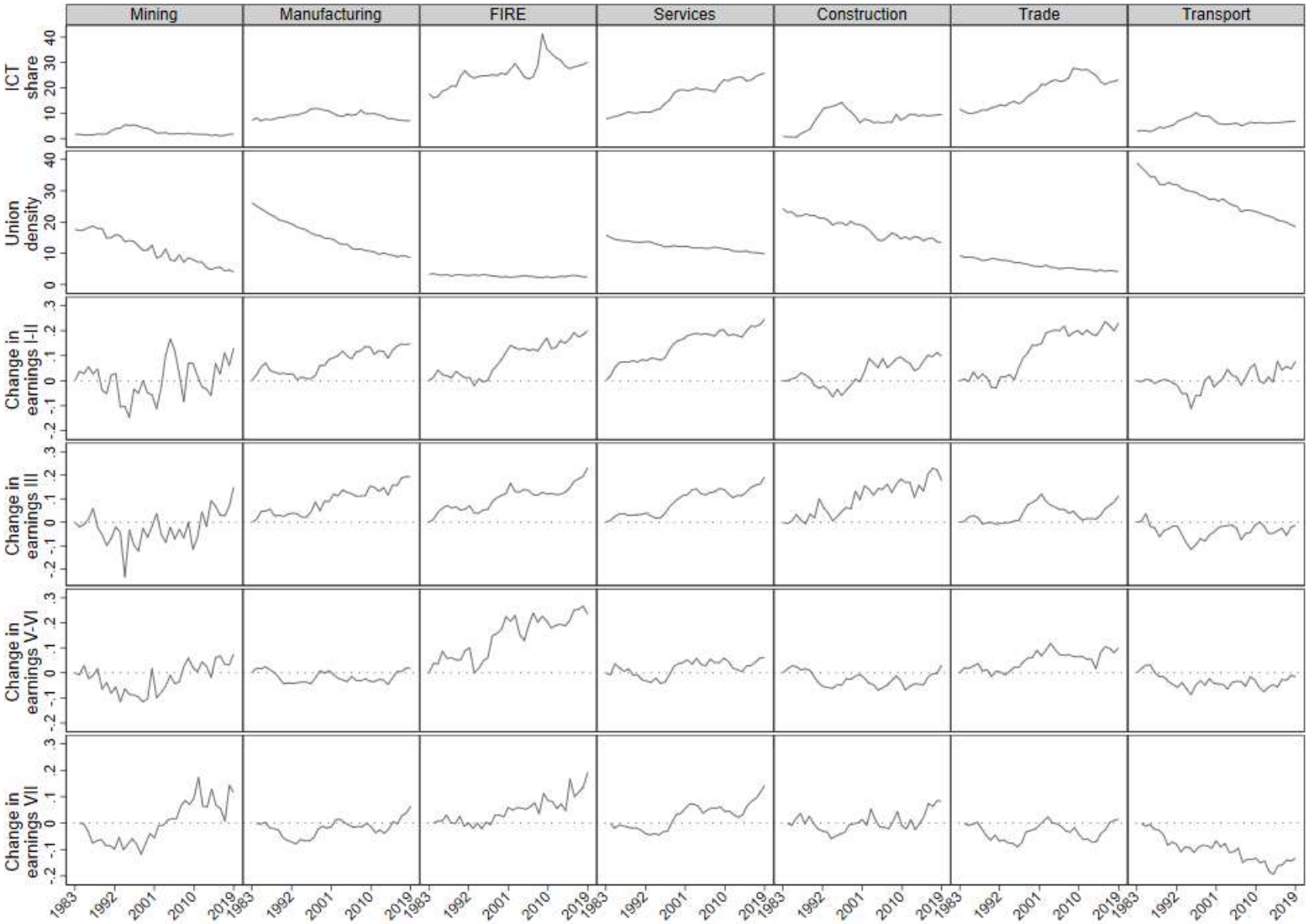


Table A3.2 Two-way fixed-effect models fully interacted with EGP classes (M1), robustness checks for top-codes (M2) and cell-size (M3-M5)

VARIABLES	M1 Main model interacted	M2 Median earnings	M3 N>49	M4 N>99	M5 Weighted by cell size
ICT shares	0.0002	0.0004	0.0002	0.0000	0.0002
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
III*ICT shares	0.0003	0.0002	0.0002	0.0002	-0.0002
	(0.0005)	(0.0007)	(0.0004)	(0.0004)	(0.0004)
V-VI*ICT shares	-0.0007	-0.0007	-0.0007	-0.0006	-0.0004
	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)
VII*ICT shares	-0.0004	-0.0005	-0.0006	-0.0007*	-0.0002
	(0.0005)	(0.0006)	(0.0005)	(0.0004)	(0.0004)
Union density	0.0019***	0.0023***	0.0021***	0.0020***	0.0018***
	(0.0006)	(0.0008)	(0.0006)	(0.0005)	(0.0005)
III*Union density	0.0014	0.0020	0.0018**	0.0022**	0.0013*
	(0.0010)	(0.0012)	(0.0009)	(0.0008)	(0.0008)
V-VI*Union density	0.0024**	0.0031**	0.0019**	0.0024***	0.0024***
	(0.0010)	(0.0012)	(0.0009)	(0.0008)	(0.0008)
VII*Union density	0.0031***	0.0044***	0.0024***	0.0023**	0.0028***
	(0.0008)	(0.0010)	(0.0009)	(0.0009)	(0.0006)
Share of high educated	0.0032***	0.0035***	0.0031***	0.0032***	0.0025***
	(0.0003)	(0.0005)	(0.0003)	(0.0005)	(0.0004)
III*Share of high educated	0.0013**	0.0011	0.0010**	0.0003	-0.0000
	(0.0005)	(0.0009)	(0.0005)	(0.0007)	(0.0006)
V-VI*Share of high educated	-0.0003	-0.0009	-0.0002	0.0001	0.0001
	(0.0005)	(0.0008)	(0.0005)	(0.0008)	(0.0006)
VII*Share of high educated	0.0010	0.0002	0.0006	-0.0019*	-0.0001
	(0.0010)	(0.0013)	(0.0012)	(0.0011)	(0.0009)
Share of female	-0.0019***	-0.0026***	-0.0018***	-0.0015***	-0.0014**
	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0006)
III*Share of female	-0.0008	0.0006	-0.0005	-0.0012*	-0.0009
	(0.0006)	(0.0008)	(0.0006)	(0.0006)	(0.0007)
V-VI*Share of female	0.0010	0.0011	0.0005	-0.0004	0.0003
	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0007)
VII*Share of female	-0.0010	-0.0007	-0.0009	-0.0007	-0.0012*
	(0.0008)	(0.0010)	(0.0009)	(0.0007)	(0.0007)
Share of white non-Hispanic	0.0004	-0.0000	0.0007*	0.0005	0.0003
	(0.0005)	(0.0008)	(0.0004)	(0.0006)	(0.0004)
III*Share of white non-Hispanic	0.0000	0.0006	-0.0002	-0.0004	-0.0004
	(0.0006)	(0.0008)	(0.0006)	(0.0008)	(0.0006)
V-VI*Share of white non-Hispanic	0.0005	0.0011	0.0001	0.0006	0.0009
	(0.0005)	(0.0008)	(0.0005)	(0.0007)	(0.0005)
VII*Share of white non-Hispanic	0.0008	0.0013	0.0001	-0.0001	0.0006
	(0.0007)	(0.0012)	(0.0007)	(0.0008)	(0.0005)
Log of real value added	0.0048	-0.0090	0.0086	0.0068	0.0043
	(0.0096)	(0.0147)	(0.0077)	(0.0082)	(0.0061)
III*Log of real value added	-0.0244**	-0.0157	-0.0278***	-0.0257***	-0.0225**
	(0.0119)	(0.0118)	(0.0102)	(0.0081)	(0.0098)
V-VI*Log of real value added	-0.0084	-0.0045	-0.0061	0.0055	0.0039
	(0.0078)	(0.0095)	(0.0087)	(0.0113)	(0.0101)
VII*Log of real value added	-0.0207*	-0.0120	-0.0194	-0.0148	-0.0231***
	(0.0109)	(0.0151)	(0.0118)	(0.0124)	(0.0080)
Average age	0.0085***	0.0105***	0.0078***	0.0090***	0.0069***
	(0.0017)	(0.0021)	(0.0020)	(0.0020)	(0.0013)
III*Average age	-0.0029	-0.0037	-0.0036	-0.0043*	-0.0052***
	(0.0030)	(0.0024)	(0.0022)	(0.0023)	(0.0019)
V-VI*Average age	-0.0004	-0.0004	-0.0013	-0.0033	0.0005
	(0.0027)	(0.0025)	(0.0020)	(0.0025)	(0.0023)
VII*Average age	-0.0066***	-0.0051*	-0.0040	-0.0061***	-0.0034*
	(0.0022)	(0.0030)	(0.0026)	(0.0020)	(0.0017)
L. Mean of ln earnings	0.2866***		0.2919***	0.3741***	0.4485***
	(0.0391)		(0.0416)	(0.0424)	(0.0456)
III*L. Mean of ln earnings	-0.1096*		0.0096	0.0129	0.0950**
	(0.0605)		(0.0414)	(0.0425)	(0.0386)
V-VI*L. Mean of ln earnings	-0.0059		0.0264	-0.0577	-0.0613
	(0.0596)		(0.0555)	(0.0618)	(0.0671)
VII*L. Mean of ln earnings	0.1181		0.1340*	0.1200**	0.0651
	(0.0833)		(0.0729)	(0.0535)	(0.0472)
L. Median of ln earnings		0.2345***			
		(0.0456)			
III*L. Median of ln earnings		-0.1147			
		(0.0953)			
V-VI*L. Median of ln earnings		-0.0827			
		(0.0860)			
VII*L. Median of ln earnings		0.1255			
		(0.0871)			
Year-Class FE	Yes	Yes	Yes	Yes	Yes
Observations	5,760	5,760	5,410	4,721	5,760
R-squared	0.5759	0.4470	0.6369	0.7101	0.8164
Number of ids	160	160	159	150	160

Cluster robust standard errors at the industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A3.3 Stepwise regressions from baseline two-way fixed-effects models fully interacted

VARIABLES	M6	M7	M8	M9	M10	M11	M12
ICT shares	0.0011***	0.0007*	0.0003	0.0001	0.0001	0.0003	0.0002
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
III*ICT shares	-0.0000	-0.0000	0.0001	0.0001	0.0001	-0.0000	0.0003
	(0.0007)	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
V-VI*ICT shares	0.0001	-0.0005	-0.0006	-0.0004	-0.0004	-0.0008	-0.0007
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
VII*ICT shares	-0.0003	-0.0006	-0.0004	-0.0005	-0.0004	-0.0006	-0.0004
	(0.0006)	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0005)
Union density		0.0019***	0.0023***	0.0023***	0.0024***	0.0020***	0.0019***
		(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)
III*Union density		-0.0000	0.0003	0.0006	0.0008	0.0011	0.0014
		(0.0011)	(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.0010)
V-VI*Union density		0.0026**	0.0023**	0.0024**	0.0025**	0.0023**	0.0024**
		(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
VII*Union density		0.0014	0.0013	0.0024**	0.0025***	0.0028***	0.0031***
		(0.0013)	(0.0010)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
Share of high educated			0.0034***	0.0031***	0.0031***	0.0032***	0.0032***
			(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
III*Share of high educated			0.0016***	0.0015***	0.0014***	0.0012**	0.0013**
			(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
V-VI*Share of high educated			-0.0008	-0.0003	-0.0003	-0.0003	-0.0003
			(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
VII*Share of high educated			0.0008	0.0008	0.0008	0.0007	0.0010
			(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Share of female				-0.0023***	-0.0023***	-0.0020***	-0.0019***
				(0.0005)	(0.0005)	(0.0005)	(0.0005)
III*Share of female				-0.0001	-0.0002	-0.0006	-0.0008
				(0.0007)	(0.0007)	(0.0006)	(0.0006)
V-VI*Share of female				0.0012	0.0011	0.0011	0.0010
				(0.0007)	(0.0007)	(0.0007)	(0.0007)
VII*Share of female				-0.0007	-0.0006	-0.0010	-0.0010
				(0.0009)	(0.0009)	(0.0009)	(0.0008)
Share of white non-Hispanic					0.0008*	0.0003	0.0004
					(0.0004)	(0.0004)	(0.0005)
III*Share of white non-Hispanic					0.0001	0.0001	0.0000
					(0.0005)	(0.0006)	(0.0006)
V-VI*Share of white non-Hispanic					0.0004	0.0006	0.0005
					(0.0005)	(0.0005)	(0.0005)
VII*Share of white non-Hispanic					0.0004	0.0008	0.0008
					(0.0007)	(0.0007)	(0.0007)
Average age						0.0086***	0.0085***
						(0.0017)	(0.0017)
III*Average age						-0.0028	-0.0029
						(0.0031)	(0.0030)
V-VI*Average age						-0.0004	-0.0004
						(0.0027)	(0.0027)
VII*Average age						-0.0066***	-0.0066***
						(0.0022)	(0.0022)
Log of real value-added							0.0048
							(0.0096)
III*Log of real value-added							-0.0244**
							(0.0119)
V-VI*Log of real value-added							-0.0084
							(0.0078)
VII*Log of real value-added							-0.0207*
							(0.0109)
L. Mean of ln earnings	0.3935***	0.3719***	0.3168***	0.2908***	0.2956***	0.2877***	0.2866***
	(0.0508)	(0.0496)	(0.0430)	(0.0416)	(0.0413)	(0.0393)	(0.0391)
III*L. Mean of ln earnings	-0.1317*	-0.1207	-0.1180*	-0.1019*	-0.1138*	-0.1095*	-0.1096*
	(0.0723)	(0.0730)	(0.0680)	(0.0595)	(0.0593)	(0.0611)	(0.0605)
V-VI*L. Mean of ln earnings	0.0136	-0.0414	-0.0223	-0.0011	-0.0131	-0.0068	-0.0059
	(0.0685)	(0.0694)	(0.0582)	(0.0588)	(0.0612)	(0.0606)	(0.0596)
VII*L. Mean of ln earnings	0.1428	0.1116	0.1374	0.1201	0.1101	0.1211	0.1181
	(0.0969)	(0.1041)	(0.0979)	(0.0875)	(0.0866)	(0.0877)	(0.0833)
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,760	5,760	5,760	5,760	5,760	5,760	5,760
R-squared	0.4728	0.4884	0.5369	0.5583	0.5624	0.5741	0.5759
Number of ids	160	160	160	160	160	160	160

Cluster robust standard errors at the industry level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A3.4 ECM models fully interacted with EGP classes (M13), robustness checks for top-codes (M14) and cell-size (M15-M16)

	M13	M14	M15	M16	M17
VARIABLES	Main model interacted	Median earnings	N>49	N>99	Weighted by average cell size
L. ICT investments	0.0001	0.0003	0.0001	-0.0001	0.0001
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0002)
III*L. ICT investments	0.0003	0.0003	0.0002	0.0001	-0.0002
	(0.0005)	(0.0007)	(0.0004)	(0.0003)	(0.0003)
V-VI*L. ICT investments	-0.0006	-0.0007	-0.0005	-0.0004	-0.0004
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
VII*L. ICT investments	-0.0003	-0.0005	-0.0006	-0.0006	-0.0001
	(0.0005)	(0.0006)	(0.0005)	(0.0004)	(0.0004)
Δ ICT investments	0.0017**	0.0025**	0.0014**	0.0012**	0.0006
	(0.0008)	(0.0011)	(0.0006)	(0.0006)	(0.0005)
III*Δ ICT investments	0.0006	-0.0008	0.0004	-0.0004	0.0003
	(0.0009)	(0.0013)	(0.0007)	(0.0008)	(0.0005)
V-VI*Δ ICT investments	-0.0010	-0.0012	-0.0003	-0.0007	0.0005
	(0.0013)	(0.0020)	(0.0015)	(0.0016)	(0.0010)
VII*Δ ICT investments	-0.0011	-0.0011	0.0004	-0.0012	-0.0002
	(0.0015)	(0.0021)	(0.0012)	(0.0008)	(0.0008)
L.Union density	0.0018**	0.0022***	0.0018***	0.0020***	0.0015***
	(0.0007)	(0.0008)	(0.0006)	(0.0004)	(0.0004)
III*L. Union density	0.0011	0.0016	0.0012	0.0014*	0.0007
	(0.0012)	(0.0014)	(0.0011)	(0.0008)	(0.0007)
V-VI* L'union density	0.0024**	0.0029**	0.0020**	0.0023***	0.0026***
	(0.0010)	(0.0011)	(0.0009)	(0.0008)	(0.0008)
VII* L. Union density	0.0030***	0.0046***	0.0022**	0.0019**	0.0025***
	(0.0009)	(0.0010)	(0.0009)	(0.0008)	(0.0006)
Δ Union density	0.0007	0.0012	0.0003	0.0011	0.0017*
	(0.0010)	(0.0019)	(0.0010)	(0.0014)	(0.0009)
III*Δ Union density	0.0030**	0.0049**	0.0021*	0.0026	0.0007
	(0.0015)	(0.0021)	(0.0011)	(0.0019)	(0.0014)
V-VI*Δ Union density	0.0031*	0.0034	0.0027*	0.0012	0.0016
	(0.0016)	(0.0023)	(0.0015)	(0.0016)	(0.0012)
VII*Δ Union density	0.0042***	0.0041*	0.0043***	0.0038**	0.0031***
	(0.0015)	(0.0023)	(0.0014)	(0.0018)	(0.0011)
L.Share of high-edu	0.0026***	0.0031***	0.0023***	0.0027***	0.0020***
	(0.0005)	(0.0006)	(0.0004)	(0.0005)	(0.0004)
III*L. Share of high-edu	0.0018*	0.0020**	0.0004	-0.0002	-0.0004
	(0.0011)	(0.0009)	(0.0007)	(0.0008)	(0.0006)
V-VI*L. Share of high-edu	0.0001	-0.0003	-0.0003	-0.0002	0.0001
	(0.0006)	(0.0008)	(0.0006)	(0.0008)	(0.0005)
VII*L. Share of high-edu	0.0003	-0.0002	-0.0003	-0.0032**	-0.0013
	(0.0010)	(0.0013)	(0.0013)	(0.0015)	(0.0010)
Δ Share of high-edu	0.0035***	0.0035***	0.0034***	0.0036***	0.0036***
	(0.0004)	(0.0005)	(0.0003)	(0.0004)	(0.0003)
III*Δ Share of high-edu	0.0010**	0.0008	0.0012**	0.0006	0.0004
	(0.0004)	(0.0009)	(0.0005)	(0.0007)	(0.0005)
V-VI*Δ Share of high-edu	-0.0004	-0.0013	0.0001	0.0003	-0.0005
	(0.0007)	(0.0009)	(0.0004)	(0.0007)	(0.0007)
VII*Δ Share of high-edu	0.0008	0.0000	0.0007	-0.0019*	-0.0007
	(0.0010)	(0.0013)	(0.0012)	(0.0010)	(0.0009)
L.Share of female	-0.0013**	-0.0021***	-0.0013**	-0.0011**	-0.0010
	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)
III*L. Share of female	-0.0009	-0.0001	-0.0009	-0.0010	-0.0006
	(0.0008)	(0.0011)	(0.0007)	(0.0006)	(0.0006)
V-VI*L. Share of female	0.0011	0.0015	0.0002	-0.0003	0.0003
	(0.0009)	(0.0009)	(0.0010)	(0.0011)	(0.0008)
VII*L. Share of female	-0.0017	-0.0018	-0.0009	-0.0005	-0.0014**
	(0.0011)	(0.0014)	(0.0011)	(0.0008)	(0.0007)
Δ Share of female	-0.0020***	-0.0028***	-0.0019***	-0.0015***	-0.0019***
	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
III*Δ Share of female	-0.0008	0.0007	-0.0006	-0.0013*	-0.0010
	(0.0007)	(0.0008)	(0.0006)	(0.0007)	(0.0006)
V-VI*Δ Share of female	0.0010	0.0011	0.0003	-0.0011	0.0001
	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0006)
VII*Δ Share of female	-0.0007	-0.0003	-0.0010	-0.0011	-0.0010*
	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0006)
L.Average age	0.0060***	0.0092***	0.0056***	0.0049***	0.0047***
	(0.0015)	(0.0020)	(0.0015)	(0.0018)	(0.0012)
III*L. Average age	-0.0003	0.0009	-0.0030	-0.0023	-0.0048**
	(0.0035)	(0.0035)	(0.0022)	(0.0026)	(0.0018)
V-VI*L. Average age	-0.0001	-0.0022	-0.0025	-0.0024	-0.0009
	(0.0037)	(0.0032)	(0.0016)	(0.0024)	(0.0025)
VII*L. Average age	-0.0087***	-0.0091***	-0.0048**	-0.0046**	-0.0034*
	(0.0022)	(0.0024)	(0.0019)	(0.0021)	(0.0018)
Δ Average age	0.0111***	0.0126***	0.0104***	0.0139***	0.0124***

	(0.0017)	(0.0024)	(0.0022)	(0.0019)	(0.0013)
III*Δ Average age	-0.0052	-0.0068**	-0.0039	-0.0070***	-0.0058***
	(0.0032)	(0.0026)	(0.0026)	(0.0023)	(0.0017)
V-VI*Δ Average age	-0.0011	-0.0001	-0.0012	-0.0055**	-0.0016
	(0.0023)	(0.0028)	(0.0023)	(0.0025)	(0.0020)
VII*Δ Average age	-0.0077***	-0.0052	-0.0045	-0.0091***	-0.0069***
	(0.0027)	(0.0035)	(0.0032)	(0.0025)	(0.0020)
L.Share of white	0.0002	-0.0005	0.0005	0.0001	-0.0003
	(0.0006)	(0.0011)	(0.0006)	(0.0009)	(0.0005)
III*L. Share of white	-0.0006	-0.0003	-0.0005	-0.0005	-0.0003
	(0.0008)	(0.0011)	(0.0009)	(0.0011)	(0.0008)
V-VI*L. Share of white	0.0004	0.0014	0.0001	0.0010	0.0014**
	(0.0008)	(0.0010)	(0.0007)	(0.0011)	(0.0007)
VII*L. Share of white	0.0003	0.0010	-0.0002	-0.0000	0.0010
	(0.0008)	(0.0012)	(0.0008)	(0.0010)	(0.0006)
Δ Share of white	0.0004	0.0002	0.0008**	0.0009	0.0003
	(0.0004)	(0.0008)	(0.0004)	(0.0005)	(0.0003)
III*Δ Share of white	0.0003	0.0007	0.0003	-0.0003	0.0007
	(0.0006)	(0.0009)	(0.0005)	(0.0008)	(0.0005)
V-VI*Δ Share of white	0.0008	0.0013	0.0005	0.0004	0.0012**
	(0.0005)	(0.0009)	(0.0006)	(0.0007)	(0.0005)
VII*Δ Share of white	0.0012	0.0016	0.0004	-0.0002	0.0011**
	(0.0008)	(0.0012)	(0.0007)	(0.0008)	(0.0005)
L.Log of real value added	0.0084	-0.0071	0.0122*	0.0069	0.0046
	(0.0087)	(0.0145)	(0.0073)	(0.0080)	(0.0048)
III*L. Log of real value added	-0.0240*	-0.0176	-0.0255**	-0.0171*	-0.0145
	(0.0125)	(0.0134)	(0.0114)	(0.0092)	(0.0095)
V-VI*L. Log of real value added	-0.0095	-0.0039	-0.0069	0.0063	0.0041
	(0.0079)	(0.0090)	(0.0079)	(0.0113)	(0.0081)
VII*L. Log of real value added	-0.0189	-0.0096	-0.0208*	-0.0129	-0.0195***
	(0.0118)	(0.0173)	(0.0104)	(0.0114)	(0.0062)
Δ Log of real value added	0.0051	-0.0131	0.0022	0.0174	0.0003
	(0.0233)	(0.0324)	(0.0239)	(0.0207)	(0.0120)
III*Δ Log of real value added	-0.0450**	0.0010	-0.0106	-0.0550	-0.0101
	(0.0195)	(0.0290)	(0.0331)	(0.0345)	(0.0217)
V-VI*Δ Log of real value added	0.0009	0.0210	-0.0034	-0.0023	0.0206
	(0.0251)	(0.0369)	(0.0247)	(0.0216)	(0.0202)
VII*Δ Log of real value added	-0.0406	0.0051	-0.0389	-0.0528	-0.0132
	(0.0362)	(0.0445)	(0.0367)	(0.0393)	(0.0206)
L.Mean log earnings	-0.6658***		-0.6590***	-0.5789***	-0.4906***
	(0.0405)		(0.0445)	(0.0498)	(0.0493)
III*L. Mean log earnings	-0.1452		0.0290	0.0310	0.1025**
	(0.0871)		(0.0450)	(0.0474)	(0.0433)
V-VI*L. Mean log earnings	-0.0241		0.0268	-0.0720	-0.0827
	(0.0699)		(0.0586)	(0.0621)	(0.0739)
VII*L. Mean log earnings	0.0976		0.1257	0.1021*	0.0417
	(0.0877)		(0.0760)	(0.0604)	(0.0495)
L.Median log earnings		-0.7377***			
		(0.0411)			
III*L.Median log earnings		-0.1828*			
		(0.1052)			
V-VI*L.Median log earnings		-0.0720			
		(0.0869)			
VII*L.Median log earnings		0.1046			
		(0.0898)			
Year-class fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	5,600	5,600	5,253	4,580	5,600
R-squared	0.4919	0.4844	0.4781	0.4692	0.4565
Number of ids	160	160	159	149	160

Cluster robust standard errors at the industry level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3.5 Stepwise regression of fully interacted ECM

VARIABLES	M18	M19	M20	M21	M22	M23	M24
L. ICT investments	0.0010**	0.0006	0.0002	0.0001	0.0002	0.0002	0.0001
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
III*L. ICT investments	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0003
	(0.0008)	(0.0008)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
V-VI*L. ICT investments	0.0001	-0.0004	-0.0006	-0.0005	-0.0007	-0.0007	-0.0006
	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
VII*L. ICT investments	-0.0002	-0.0005	-0.0004	-0.0005	-0.0006	-0.0005	-0.0003
	(0.0007)	(0.0007)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0005)
Δ ICT investments	0.0020**	0.0017*	0.0018**	0.0014*	0.0018**	0.0018**	0.0017**
	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0008)
III*Δ ICT investments	0.0004	0.0004	0.0003	0.0008	0.0004	0.0003	0.0006
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
V-VI*Δ ICT investments	-0.0005	-0.0010	-0.0015	-0.0010	-0.0010	-0.0010	-0.0010
	(0.0018)	(0.0018)	(0.0017)	(0.0016)	(0.0013)	(0.0013)	(0.0013)
VII*Δ ICT investments	-0.0010	-0.0013	-0.0011	-0.0011	-0.0014	-0.0014	-0.0011
	(0.0017)	(0.0016)	(0.0016)	(0.0016)	(0.0015)	(0.0015)	(0.0015)
L.Union density		0.0020**	0.0022***	0.0022***	0.0019**	0.0018**	0.0018**
		(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
III*L. Union density		-0.0002	0.0003	0.0004	0.0008	0.0007	0.0011
		(0.0013)	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
V-VI*L.Union density		0.0026**	0.0024**	0.0024**	0.0022**	0.0023**	0.0024**
		(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
VII*L.Union density		0.0012	0.0012	0.0025**	0.0029***	0.0028***	0.0030***
		(0.0013)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0009)
Δ Union density		0.0021*	0.0018*	0.0016	0.0007	0.0007	0.0007
		(0.0012)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
III*Δ Union density		0.0009	0.0018	0.0021	0.0027*	0.0028*	0.0030**
		(0.0013)	(0.0015)	(0.0015)	(0.0014)	(0.0015)	(0.0015)
V-VI*Δ Union density		0.0025	0.0029*	0.0031*	0.0030*	0.0031*	0.0031*
		(0.0017)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
VII*Δ Union density		0.0029	0.0032*	0.0037**	0.0040**	0.0040**	0.0042***
		(0.0019)	(0.0017)	(0.0017)	(0.0015)	(0.0015)	(0.0015)
L.Share of high-edu			0.0030***	0.0028***	0.0027***	0.0026***	0.0026***
			(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
III*L. Share of high-edu			0.0021**	0.0015	0.0017*	0.0017	0.0018*
			(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0011)
V-VI*L. Share of high-edu			-0.0004	-0.0001	-0.0000	0.0000	0.0001
			(0.0006)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
VII*L. Share of high-edu			0.0004	0.0001	0.0002	-0.0000	0.0003
			(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0010)
Δ Share of high-edu			0.0036***	0.0034***	0.0035***	0.0035***	0.0035***
			(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
III*Δ Share of high-edu			0.0013***	0.0012***	0.0010**	0.0009**	0.0010**
			(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
V-VI*Δ Share of high-edu			-0.0010	-0.0004	-0.0004	-0.0005	-0.0004
			(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
VII*Δ Share of high-edu			0.0008	0.0008	0.0007	0.0006	0.0008
			(0.0012)	(0.0010)	(0.0011)	(0.0010)	(0.0010)
L.Share of female				-0.0017***	-0.0014**	-0.0015**	-0.0013**
				(0.0005)	(0.0006)	(0.0006)	(0.0006)
III*L. Share of female				-0.0004	-0.0006	-0.0006	-0.0009
				(0.0008)	(0.0007)	(0.0007)	(0.0008)
V-VI*L. Share of female				0.0012	0.0013	0.0012	0.0011
				(0.0009)	(0.0009)	(0.0008)	(0.0009)
VII*L. Share of female				-0.0016	-0.0018	-0.0017	-0.0017
				(0.0012)	(0.0012)	(0.0011)	(0.0011)
Δ Share of female				-0.0025***	-0.0021***	-0.0021***	-0.0020***
				(0.0006)	(0.0005)	(0.0005)	(0.0005)
III*Δ Share of female				-0.0000	-0.0005	-0.0007	-0.0008
				(0.0008)	(0.0007)	(0.0007)	(0.0007)
V-VI*Δ Share of female				0.0012	0.0011	0.0011	0.0010
				(0.0008)	(0.0008)	(0.0007)	(0.0008)
VII*Δ Share of female				-0.0003	-0.0008	-0.0007	-0.0007
				(0.0009)	(0.0008)	(0.0008)	(0.0008)
L.Average age					0.0061***	0.0061***	0.0060***
					(0.0015)	(0.0015)	(0.0015)
III*L. Average age					-0.0005	-0.0003	-0.0003
					(0.0032)	(0.0035)	(0.0035)
V-VI*L. Average age					0.0002	-0.0002	-0.0001
					(0.0036)	(0.0038)	(0.0037)
VII*L. Average age					-0.0086***	-0.0087***	-0.0087***
					(0.0022)	(0.0023)	(0.0022)
Δ Average age					0.0112***	0.0111***	0.0111***
					(0.0017)	(0.0017)	(0.0017)
III*Δ Average age					-0.0046	-0.0051	-0.0052
					(0.0031)	(0.0033)	(0.0032)
V-VI*Δ Average age					-0.0009	-0.0011	-0.0011
					(0.0023)	(0.0023)	(0.0023)
VII*Δ Average age					-0.0076***	-0.0077***	-0.0077***
					(0.0027)	(0.0026)	(0.0027)

L.Share of white						0.0001	0.0002
						(0.0005)	(0.0006)
III*L. Share of white						-0.0004	-0.0006
						(0.0008)	(0.0008)
V-VI*L. Share of white						0.0005	0.0004
						(0.0008)	(0.0008)
VII*L. Share of white						0.0004	0.0003
						(0.0007)	(0.0008)
Δ Share of white						0.0004	0.0004
						(0.0004)	(0.0004)
III*Δ Share of white						0.0003	0.0003
						(0.0007)	(0.0006)
V-VI*Δ Share of white						0.0008*	0.0008
						(0.0005)	(0.0005)
VII*Δ Share of white						0.0013*	0.0012
						(0.0008)	(0.0008)
L.Log of real value-added							0.0084
							(0.0087)
III*L. Log of real value-added							-0.0240*
							(0.0125)
V-VI*L. Log of real value-added							-0.0095
							(0.0079)
VII*L. Log of real value-added							-0.0189
							(0.0118)
Δ Log of real value-added							0.0051
							(0.0233)
III*Δ Log of real value-added							-0.0450**
							(0.0195)
V-VI*Δ Log of real value-added							0.0009
							(0.0251)
VII*Δ Log of real value-added							-0.0406
							(0.0362)
L.Mean log earnings	-0.6174***	-0.6370***	-0.6760***	-0.6892***	-0.6676***	-0.6651***	-0.6658***
	(0.0485)	(0.0473)	(0.0455)	(0.0430)	(0.0402)	(0.0405)	(0.0405)
III*L. Mean log earnings	-0.1399*	-0.1276*	-0.1420	-0.1164	-0.1426	-0.1407	-0.1452
	(0.0722)	(0.0723)	(0.0870)	(0.0829)	(0.0856)	(0.0877)	(0.0871)
V-VI*L. Mean log earnings	0.0202	-0.0336	-0.0297	-0.0165	-0.0208	-0.0247	-0.0241
	(0.0644)	(0.0662)	(0.0616)	(0.0601)	(0.0668)	(0.0706)	(0.0699)
VII*L. Mean log earnings	0.1516	0.1258	0.1460	0.1089	0.0920	0.0995	0.0976
	(0.0948)	(0.1003)	(0.0993)	(0.0960)	(0.0895)	(0.0911)	(0.0877)
Year-class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,600	5,600	5,600	5,600	5,600	5,600	5,600
R-squared	0.3527	0.3717	0.4324	0.4599	0.4830	0.4901	0.4919
Number of ids	160	160	160	160	160	160	160

Cluster Robust standard errors at the industry level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3.6 Results for two-way fixed-effects models for EGP classes including an interaction term between union density and computer investments, the dependent variable is the mean of ln weekly earnings

	I-II		III		V-VI		VII	
VARIABLES	Coef	se	Coef	se	Coef	se	Coef	se
ICT investments	0.0002	(0.0004)	0.0010	(0.0006)	-0.0011	(0.0007)	-0.0005	(0.0006)
Union density	0.0019***	(0.0007)	0.0037***	(0.0012)	0.0039***	(0.0008)	0.0048***	(0.0009)
ICT investments*Union density	0.0000	(0.0000)	-0.0001	(0.0000)	0.0001*	(0.0000)	0.0000	(0.0000)
Share of high-edu	0.0032***	(0.0004)	0.0045***	(0.0004)	0.0031***	(0.0006)	0.0042***	(0.0010)
Share of female	-0.0019***	(0.0005)	-0.0026***	(0.0003)	-0.0009**	(0.0004)	-0.0030***	(0.0005)
White non-Hispanic workers	0.0004	(0.0005)	0.0004	(0.0004)	0.0009**	(0.0003)	0.0012**	(0.0006)
Average age	0.0085***	(0.0017)	0.0056**	(0.0024)	0.0083***	(0.0020)	0.0020	(0.0014)
Ln of real VA	0.0048	(0.0096)	-0.0200	(0.0120)	-0.0030	(0.0130)	-0.0155	(0.0120)
Mean ln Earning t-1	0.2866***	(0.0388)	0.1718***	(0.0561)	0.2779***	(0.0437)	0.4037***	(0.0737)
Year fixed effects	Yes		Yes		Yes		Yes	
Observations	1,440		1,440		1,440		1,440	
R-squared	0.6731		0.6077		0.4547		0.5388	
Number of ids	40		40		40		40	

Cluster Robust standard errors at the industry level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3.7 Results for fixed-effects ECMs for EGP classes including an interaction term between union density and computer investments, the dependent variable is the mean of ln weekly earnings

	I-II		III		V-VI		VII	
VARIABLES	Coef	se	Coef	se	Coef	se	Coef	se
L. ICT investments	0.0002	(0.0004)	0.0007	(0.0006)	-0.0009	(0.0006)	-0.0003	(0.0006)
L.Union density	0.0018**	(0.0008)	0.0031**	(0.0013)	0.0039***	(0.0009)	0.0048***	(0.0010)
L. ICT investments* L.Union density	-0.0000	(0.0000)	-0.0000	(0.0000)	0.0001	(0.0000)	0.0000	(0.0000)
Δ ICT investments	0.0019**	(0.0008)	0.0024**	(0.0011)	0.0009	(0.0011)	0.0006	(0.0014)
Δ Union density	0.0006	(0.0011)	0.0036**	(0.0013)	0.0038***	(0.0012)	0.0049***	(0.0010)
Δ ICT investments* Δ Union density	0.0008**	(0.0004)	0.0005	(0.0015)	0.0001	(0.0007)	-0.0000	(0.0009)
L.Share of high-edu	0.0026***	(0.0005)	0.0045***	(0.0009)	0.0028***	(0.0006)	0.0029***	(0.0008)
Δ Share of high-edu	0.0035***	(0.0004)	0.0045***	(0.0004)	0.0031***	(0.0006)	0.0044***	(0.0010)
L.Share of female	-0.0013**	(0.0006)	-0.0022***	(0.0005)	-0.0003	(0.0006)	-0.0031***	(0.0009)
Δ Share of female	-0.0020***	(0.0005)	-0.0028***	(0.0003)	-0.0010**	(0.0005)	-0.0028***	(0.0004)
L.Average age	0.0059***	(0.0015)	0.0056**	(0.0026)	0.0060*	(0.0034)	-0.0027	(0.0022)
Δ Average age	0.0111***	(0.0017)	0.0058**	(0.0027)	0.0101***	(0.0013)	0.0034**	(0.0016)
L.Share of white	0.0002	(0.0006)	-0.0004	(0.0005)	0.0006	(0.0006)	0.0005	(0.0005)
Δ Share of white	0.0004	(0.0004)	0.0007	(0.0005)	0.0012***	(0.0003)	0.0017**	(0.0006)
L.Log of real value added	0.0083	(0.0086)	-0.0158	(0.0123)	-0.0009	(0.0117)	-0.0104	(0.0118)
Δ Log of real value added	0.0049	(0.0234)	-0.0413*	(0.0236)	0.0082	(0.0370)	-0.0349	(0.0241)
L.Mean log earnings	-0.6653***	(0.0406)	-0.8135***	(0.0841)	-0.6933***	(0.0587)	-0.5687***	(0.0793)
Year fixed effects	Yes		Yes		Yes		Yes	
Observations	1,400		1,400		1,400		1,400	
R-squared	0.5059		0.5573		0.4599		0.4188	
Number of ids	40		40		40		40	

Cluster Robust standard errors at the industry level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3. 8 Two-way fixed-effect models fully interacted with EGP classes excluding controls for union density and share of tertiary educated

VARIABLES	Excluding union density	Excluding tertiary educated
ICT shares	0.0006	0.0005
	(0.0004)	(0.0004)
III*ICT shares	0.0006	0.0003
	(0.0004)	(0.0005)
V-VI*ICT shares	-0.0003	-0.0003
	(0.0005)	(0.0006)
VII*ICT shares	0.0001	-0.0004
	(0.0004)	(0.0006)
Union density		0.0014*
		(0.0007)
III*Union density		0.0008
		(0.0011)
V-VI*Union density		0.0023**
		(0.0009)
VII*Union density		0.0024**
		(0.0010)
Share of high educated	0.0031***	
	(0.0004)	
III*Share of high educated	0.0012**	
	(0.0005)	
V-VI*Share of high educated	-0.0002	
	(0.0006)	
VII*Share of high educated	0.0006	
	(0.0011)	
Share of female	-0.0018***	-0.0023***
	(0.0005)	(0.0005)
III*Share of female	-0.0007	-0.0008
	(0.0006)	(0.0007)
V-VI*Share of female	0.0013*	0.0022***
	(0.0007)	(0.0007)
VII*Share of female	-0.0004	-0.0006
	(0.0008)	(0.0009)
Share of white non-hispanic	0.0002	0.0002
	(0.0005)	(0.0005)
III*Share of white non-hispanic	-0.0001	0.0006
	(0.0007)	(0.0008)
V-VI*Share of white non-hispanic	0.0005	0.0008
	(0.0005)	(0.0005)
VII*Share of white non-hispanic	0.0009	0.0010
	(0.0007)	(0.0007)
Average age	0.0095***	0.0085***
	(0.0016)	(0.0018)
III*Average age	-0.0036	-0.0025
	(0.0031)	(0.0032)
V-VI*Average age	0.0002	-0.0003
	(0.0027)	(0.0028)
VII*Average age	-0.0066***	-0.0065**
	(0.0021)	(0.0024)
Log of real value added	0.0098	0.0092
	(0.0095)	(0.0132)
III*Log of real value added	-0.0216*	-0.0192
	(0.0114)	(0.0144)
V-VI*Log of real value added	-0.0050	-0.0069
	(0.0078)	(0.0097)
VII*Log of real value added	-0.0139	-0.0146
	(0.0114)	(0.0159)
L. Mean of ln earnings	0.2927***	0.3210***
	(0.0396)	(0.0443)
III*L. Mean of ln earnings	-0.1098*	-0.1202*
	(0.0638)	(0.0641)
V-VI*L. Mean of ln earnings	0.0519	0.0003
	(0.0589)	(0.0702)
VII*L. Mean of ln earnings	0.2003**	0.1265
	(0.0841)	(0.0860)
Year fixed-effects	Yes	Yes
Observations	5,600	5,600
R-squared	0.5475	0.5186
Number of ids	160	160

Cluster robust standard errors by industry in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3.9 ECM models fully interacted with EGP classes excluding controls for union density and share of tertiary educated

VARIABLES	Excluding union density	Excluding tertiary educated
L. ICT investments	0.0005	0.0003
	(0.0003)	(0.0004)
III*L. ICT investments	0.0005	0.0003
	(0.0005)	(0.0006)
V-VI*L. ICT investments	-0.0002	-0.0003
	(0.0005)	(0.0006)
VII*L. ICT investments	0.0002	-0.0004
	(0.0005)	(0.0006)
Δ ICT investments	0.0020**	0.0015*
	(0.0007)	(0.0007)
III*Δ ICT investments	0.0007	0.0008
	(0.0009)	(0.0009)
V-VI*Δ ICT investments	-0.0005	-0.0005
	(0.0012)	(0.0013)
VII*Δ ICT investments	-0.0007	-0.0013
	(0.0014)	(0.0016)
L.Union density		0.0016**
		(0.0007)
III*L.Union density		0.0008
		(0.0012)
V-VI*L.Union density		0.0026**
		(0.0010)
VII*L.Union density		0.0031***
		(0.0011)
Δ Union density		0.0010
		(0.0012)
III*Δ Union density		0.0022*
		(0.0013)
V-VI*Δ Union density		0.0028
		(0.0017)
VII*Δ Union density		0.0040**
L.Share of high-edu	0.0024***	
	(0.0005)	
III*L.Share of high-edu	0.0017	
	(0.0011)	
V-VI*L.Share of high-edu	0.0000	
	(0.0007)	
VII*L.Share of high-edu	-0.0006	
	(0.0011)	
Δ Share of high-edu	0.0035***	
	(0.0004)	
III*Δ Share of high-edu	0.0010**	
	(0.0004)	
V-VI*Δ Share of high-edu	-0.0004	
	(0.0007)	
VII*Δ Share of high-edu	0.0006	
	(0.0010)	
L.Share of female	-0.0013**	-0.0020***
	(0.0006)	(0.0005)
III*L.Share of female	-0.0007	-0.0009
	(0.0008)	(0.0008)
V-VI*L.Share of female	0.0013	0.0022***
	(0.0008)	(0.0008)
VII*L.Share of female	-0.0009	-0.0013
	(0.0010)	(0.0012)
Δ Share of female	-0.0020***	-0.0025***
	(0.0005)	(0.0006)
III*Δ Share of female	-0.0008	-0.0008
	(0.0007)	(0.0008)
V-VI*Δ Share of female	0.0011	0.0021**
	(0.0007)	(0.0009)

VII*Δ Share of female	-0.0003	-0.0002
	(0.0007)	(0.0009)
L.Average age	0.0067***	0.0050***
	(0.0014)	(0.0018)
III*L.Average age	-0.0009	0.0009
	(0.0034)	(0.0033)
V-VI*L.Average age	0.0010	0.0003
	(0.0037)	(0.0036)
VII*L.Average age	-0.0084***	-0.0080***
	(0.0023)	(0.0025)
Δ Average age	0.0115***	0.0104***
	(0.0018)	(0.0019)
III*Δ Average age	-0.0054	-0.0046
	(0.0033)	(0.0032)
V-VI*Δ Average age	0.0001	-0.0007
	(0.0022)	(0.0025)
VII*Δ Average age	-0.0073**	-0.0072***
	(0.0028)	(0.0027)
L.Share of white	-0.0000	-0.0001
	(0.0005)	(0.0007)
III*L.Share of white	-0.0008	-0.0001
	(0.0008)	(0.0010)
V-VI*L.Share of white	0.0000	0.0007
	(0.0007)	(0.0007)
VII*L.Share of white	0.0002	0.0004
	(0.0007)	(0.0008)
Δ Share of white	0.0004	0.0004
	(0.0004)	(0.0005)
III*Δ Share of white	0.0001	0.0007
	(0.0007)	(0.0008)
V-VI*Δ Share of white	0.0006	0.0009*
	(0.0005)	(0.0005)
VII*Δ Share of white	0.0013	0.0012
	(0.0008)	(0.0008)
L.Log of real value added	0.0111	0.0094
	(0.0083)	(0.0116)
III*L.Log of real value added	-0.0198	-0.0194
	(0.0119)	(0.0144)
V-VI*L.Log of real value added	-0.0053	-0.0072
	(0.0079)	(0.0100)
VII*L.Log of real value added	-0.0113	-0.0159
	(0.0115)	(0.0160)
Δ Log of real value added	0.0051	-0.0031
	(0.0232)	(0.0223)
III*Δ Log of real value added	-0.0397**	-0.0170
	(0.0195)	(0.0223)
V-VI*Δ Log of real value added	0.0055	0.0098
	(0.0277)	(0.0224)
VII*Δ Log of real value added	-0.0399	-0.0131
	(0.0369)	(0.0349)
L.Mean log earnings	-0.6445***	-0.6464***
	(0.0433)	(0.0476)
III*L.Mean log earnings	-0.1356	-0.1346*
	(0.0922)	(0.0735)
V-VI*L.Mean log earnings	0.0253	-0.0070
	(0.0727)	(0.0770)
VII*L.Mean log earnings	0.1741**	0.0850
	(0.0837)	(0.0933)
Year-class FE	Yes	Yes
Observations	5,600	5,600
R-squared	0.4705	0.4379
Number of ids	160	160

Cluster robust standard errors by industry in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure A3.2 Distribution of workers in each social class by quintiles of industries ordered by the change in union density from 1984 to 2019

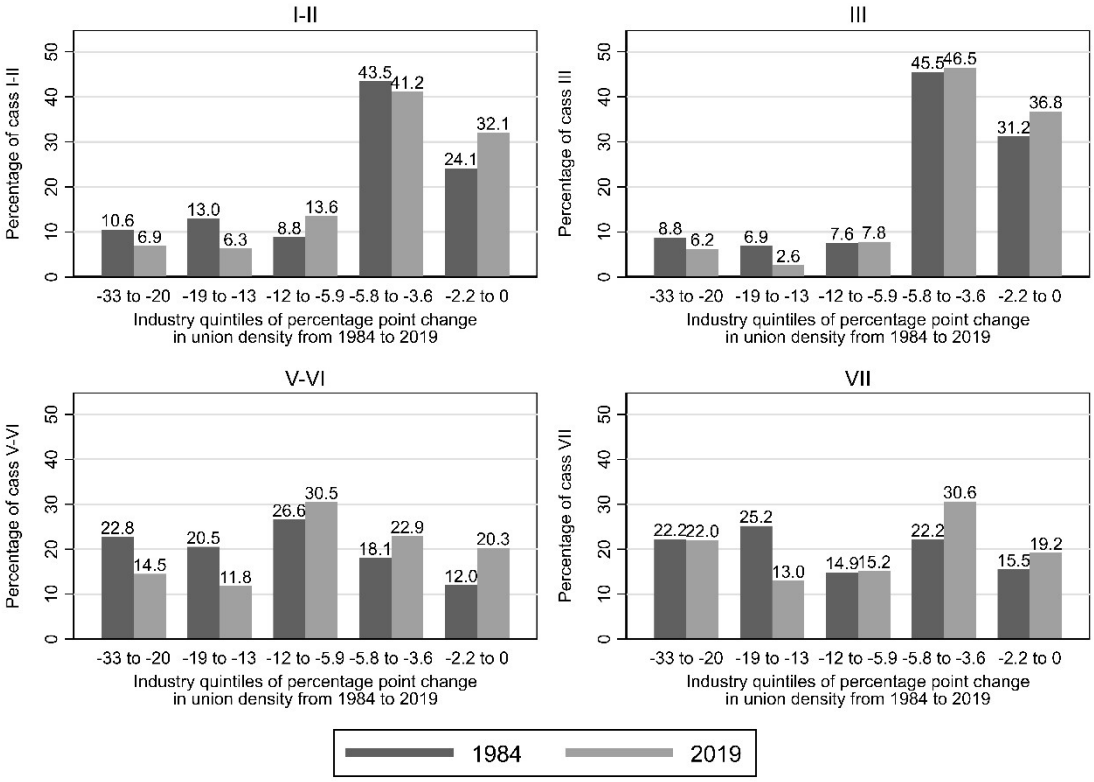
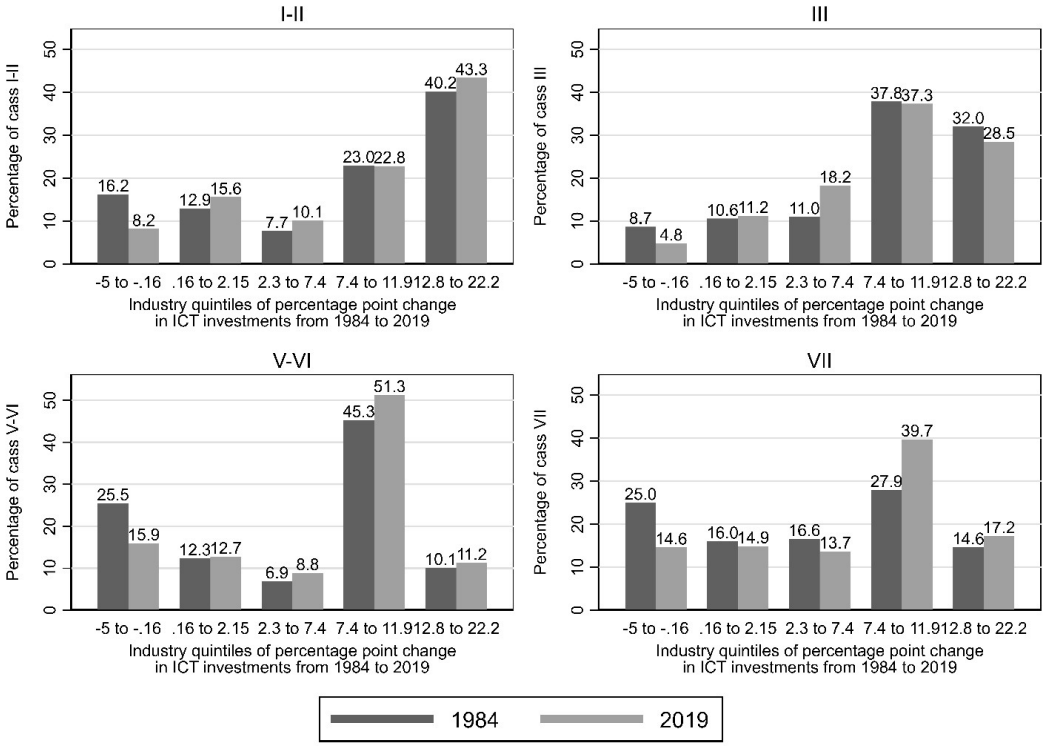


Figure A3.3 Distribution of workers in each social class by quintiles of industries ordered by the change in ICT investments from 1984 to 2019



Occupational and industry harmonisations

In the period from 1984 to 2019, both industries and occupational classification underwent a number of revisions. Occupational codes underwent three revisions, in 1991-1992, 2002-2003, and 2010-2011. Given that EGP is constructed based on workers' occupation, these codes are first harmonised to a common 2010 classification. The common 2010 code was developed utilising a series of technical papers issued by the Census Bureau immediately after each census was conducted. These publications give a thorough analysis of how each census year's occupational coding scheme differs from the preceding year's system. These occupational "crosswalks" are based on case samples that have been "twice coded" into the occupational schemes of the current and preceding census years. First, the 1980 occupational code is harmonised to the 1990. This transition involves only minor transformation and mainly in the labelling of occupations. In a second step, the 1990 codes are recoded to a common 2000 occupational classification. Here occupation in the 1990 classification is translated to the 2000 occupation where the largest share of workers would have been coded according to the "double coding" provided by the census. Finally, the 2000 occupational code is translated to a common 2010, which implies only minor changes. All documents for the cross-walks are collected in the Census Bureau website (https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html)

The crosswalks, especially from the 1990 to 2000 code, are not always straightforward, meaning that some occupations from the previous classification could be translated into more than one of the new classifications, or single occupational codes from the previous classification are split in more than one code. However, these are not major problems for the present study since it uses broad social classes, and in almost all cases, the ambiguous recoding options fall within the same aggregate social class.

Nevertheless, to maximise consistency in the observed time series, a number of corrections are applied to the original crosswalks. These choices are not exclusively informed by the BLS crosswalks but also by the observation of brakes in the class employment distribution in the CPS. However, models tested without these adjustments or with only partial adjustments return substantively identical results.

First, a number of occupations after 2002 are placed in class I-II despite indications from Morgan (2007). This is because they made up considerable parts of occupations 22 and 21 of the 1990 classification, which are placed in class I-II. Occupation 22 "managers and administrators not elsewhere classified" and 21 "managers service organisation, n.e.c"

are in fact translated into occupations 43 and 42 of the 2000/2010 occupational classification, which belongs to class I-II. However, after 2002 occupational codes 21 and 22 are split into a number of other 2000 codes, which in some cases are located in different EGP classes based on Morgan (2007). These are occupations 10 33 22 60 430 which are exclusively made up of individuals who in the 1990 classification would have been coded class I-II, and occupations 471 and 462, which could be recorded both in class I-II or in V-VI and III respectively, but their positioning outside class I-II results in visible jumps in time series.

Finally, occupation 17 of 1990 occupational classification and the corresponding 310 and 340 of the 2000 classification are located in class I-II instead of class IIIa. This is because occupation 17 is part of occupation 19 of the 1980 classification. After 1990 occupation 19 is divided into 17, 21, and 22, most of which belongs to class I-II. Given that before 1990 17 was part of 19, the two occupations are kept together in class I-II to increase consistency.

Industry classification changed in 1991-1992 2002-2003 2008-2009 2013-2014. Data in investments in computer and communication technologies are provided by the BEA at the naics2012 level, mainly at the three digits level. The starting point is the harmonisation provided by IPUMS to a common 1990 code (IPUMS USA, 2018). The common 1990 code is then translated into NAICS based on crosswalks from the Census Bureau. In order to match data on investments from the BEA and due to ambiguities in the crosswalks, some three-digit industries are reaggregated to broader two-digit ones. Furthermore, some adjustments are made to increase consistency in classifications. Industry code 212 prior to 2003 is kept with Naics 326 as indicated by the US Census Bureau. Following IPUMS crosswalk 212 would have been placed in a residual "not specified" category, resulting in a substantial break in the time series. Industry 237, which is the direct translation of 212 after 2002, is also kept in Naics 326 following indications from Census.

Employment in Naics 512 motion pictures and sound suddenly drops after 2002, and this is because its main 1990 component 800 is broken down into two 2000 components 657 and 856. 856 comprises previous parts of both 800 and 810 (NAICS 713). Since it is impossible to distinguish them, they are combined in a single 71 Naics.

Finally, industry 288 after 2003 is placed in Naics 333 instead of 332. After 2000 the new code 288 can be reconnected to both 331, which is part of Naics 333 and 290, which is part of Naics 332. However, after 2000, code 290 shows a sudden increase in employment and code 331 a sudden drop. for this reason, 288 is kept together with 331 of

the 1990 code into Naics 333. Finally, code 392 of 1990 classification, which is a small industry of residual "not specified manufacturing" in the CPS is excluded.

Table A3.10. Full list of industries used in the analysis

Naics	title	Naics	title
211-213	Oil and gas extraction and supporting activities to mining	339	Miscellaneous manufacturing
212	Mining, except oil and gas	420	Wholesale trade
22	Utilities	44-45	Retail trade
23	Construction	48-49	Transportation and warehousing
311-312	Food, beverage, and tobacco products	511	Publishing industries (including software)
313-314	Textile mills and textile product mills	515-517	Broadcasting and telecommunications
315-316	Apparel and leather and allied products	518-519	Information and data processing services
321	Wood products	52-55	Finance and insurance
322	Paper products	53	Real estate and rental and leasing
323	Printing and related support activities	541	Professional, scientific, and technical services
324	Petroleum and coal products	560	Administrative and waste management services
325	Chemical products	61	Educational services
326	Plastics and rubber products	621	Ambulatory health care services
327	Non-metallic mineral products	622	Hospitals
331	Primary metals	623	Nursing and residential care facilities
332	Fabricated metal products	624	Social assistance
333	Machinery	71-512	Arts, entertainment, and recreation, motion picture and sound recording
334-335	Electronic products	721	Accommodation
336	Motor vehicles, bodies and trailers, parts and other transportation equipment	722	Food services and drinking places
337	Furniture and related products	81	Other services, except government

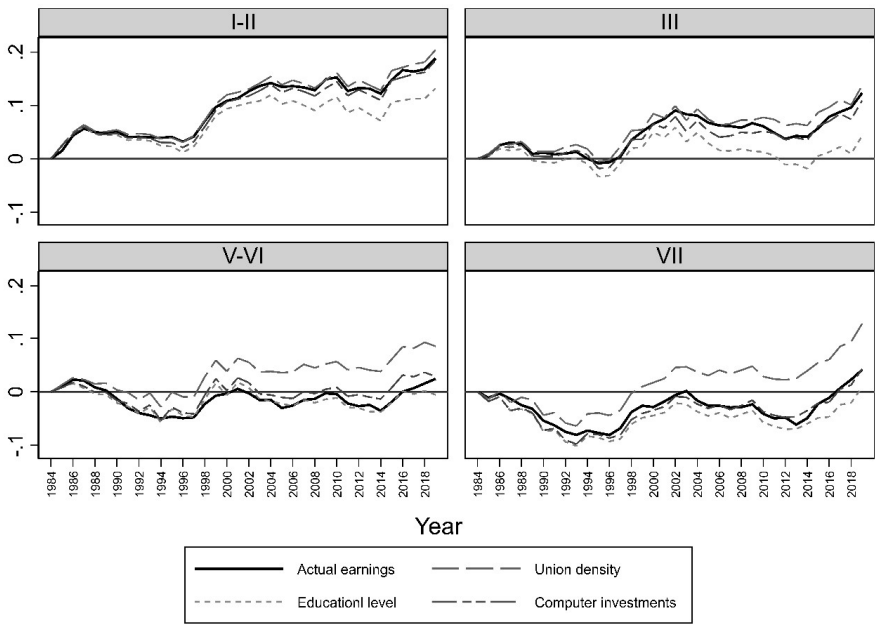
Counterfactual estimates

Counterfactual estimates are obtained by estimating model 1 using bootstrapped standard errors and predicting values of the dependent variable holding unionisation, investments in technology and share of tertiary educated constant at the 1984 levels for each social class. Because Y is path-dependent in the data generating process, the predicted value of Y_{cit} are predicted sequentially, that is Y_{cit} is used to predict $\hat{Y}_{cit+1}$ and $\hat{Y}_{cit+1}$ is used to predict $\hat{Y}_{cit+}$ and so on. Second, counterfactual estimates of each industry-social class combination are reaggregated to represent the whole non-agricultural private sector using industry-class-year weights reflecting the employment size of each cell, computed as the sum of sampling weights. Estimates for the actual earnings computed this way are therefore identical to the ones computed from weighted microdata as in Figure 3.1.

Upper and lower prediction bounds are computed through a simulation that repeatedly solves the models, each time accounting for the uncertainty associated with the estimated coefficient vector. Since the objective of the study is the analysis of differences in earnings growth between classes in the period analysed, as reported in the second panel of Figure

3.1, the reported results in figure 3. 4 are computed as the difference between 2019 and 1984 in the counterfactual estimates for each social class, upper and lower prediction bounds of the difference are computed as the 2019-1984 change in the estimated upper and lower bounds in levels. Estimates are thus interpretable as the change in earnings from 1984 to 2019 had the level of indicated covariate remained at the 1984 values. Cumulative changes over the whole period are reported in figure A3.4. It is important to note that counterfactual estimates assume independent relations among explanatory variables. Given that variables are likely associated with one another, the counterfactual estimates should be interpreted cautiously and mainly as instruments to interpret the results from the main model. The main idea is that even similar functional effects in union density would have a different impact on the overall earnings growth of different social classes due to different exposure to the phenomena.

Figure A3.4 Counterfactual estimates of cumulative change in ln weekly earnings by EGP classes



Appendix to Chapter IV

Table A4.1 Factor analysis of comparable skills items for the UK and Germany

	C.ANL	DISCRET	PHYS	C.INT	ROUT	Uniq.
The UK						
Importance of						
… working out causes of problems	0.925					0.132
… spotting problems	0.892					0.198
… thinking of solutions to problems	0.847					0.219
Influence personally have on						
… what task to do		0.806				0.302
… how to do the tasks		0.793				0.333
… how hard to work		0.714				0.462
How much choice have over way in which job is done		0.675				0.438
Importance of						
… physical stamina			0.941			0.108
… physical strength			0.935			0.114
… counselling, and advising				0.812		0.311
… dealing with people				0.742		0.390
… selling a product of service				0.683		0.479
How often work involves short and repetitive tasks					0.819	0.297
How much variety in job					0.681	0.354
Eigenvalues	*3.690*	*2.095*	*1.583*	*1.469*	*1.028*	
Germany	C.ANL	PHYS	DISCRET	ROUT	C.INT	Uniq.
Confronted with new tasks	0.740					0.430
Recognize and close your own gaps in knowledge	0.688					0.508
React to problems and solve them	0.682					0.506
Improve existing procedures or try something new	0.645					0.498
Work standing up		0.858				0.254
Lift and carry heavy load		0.827				0.300
Influence the amount of work assigned to you			0.745			0.409
Plan and schedule your own work yourself			0.689			0.425
Decide for yourself when to take a break			0.644			0.481
Execution of work is prescribed in every detail				0.812		0.282
One and the same operation is repeated in every detail				0.799		0.296
Purchasing, procuring, selling					0.822	0.292
Advertising, Marketing, Public Relations, PR					0.748	0.360
Eigenvalues	*2.934*	*1.622*	*1.253*	*1.113*	*1.038*	

Notes: Factor loadings estimated using the principal-component-factor method. Orthogonal rotation applied. Weighted. Blanks represent abs(loadings) < 0.35.
Sources: UK Skills Survey (2006, 2012, 2017) for the UK and BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany; authors' calculations.

Table A4.2 OLS regression results of total and direct effects of computer use on task discretion and job satisfaction – the UK

	Total effect on Discretion	Direct effect on Discretion	Total effect on Satisfaction	Direct effect on Satisfaction
Computer Use	0.096**	-0.065^{+}	0.045	-0.084*
	(0.035)	(0.033)	(0.037)	(0.036)
Task indicators				
Cognitive-analytical		0.157***		0.091***
		(0.013)		(0.012)
Cognitive-interpersonal		0.098***		0.030*
		(0.013)		(0.014)
Physical		-0.006		0.022
		(0.014)		(0.014)
Routine		-0.242***		-0.241***
		(0.013)		(0.014)
Discretion				0.313***
				(0.013)
Educational attainment (reference: less-educated (ISCED 0–2))				
Intermediately educated (ISCED 3–4)	0.138***	0.104**	-0.095**	-0.159***
	(0.036)	(0.035)	(0.036)	(0.033)
Highly educated (ISCED 5+)	0.122**	0.041	-0.223***	-0.328***
	(0.040)	(0.038)	(0.042)	(0.039)
Occupation (reference: managers)				
Professionals	-0.376***	-0.312***	-0.057	0.093*
	(0.035)	(0.035)	(0.041)	(0.038)
Technicians and associate professionals	-0.455***	-0.360***	-0.163***	0.049
	(0.038)	(0.037)	(0.041)	(0.038)
Clerical-support workers	-0.653***	-0.408***	-0.423***	-0.023
	(0.044)	(0.043)	(0.049)	(0.043)
Service- and sales workers	-0.693***	-0.487***	-0.372***	-0.007
	(0.040)	(0.040)	(0.046)	(0.044)
Skilled agriculture-, forestry-, and fishery workers	-0.399*	-0.254^{+}	-0.139	0.067
	(0.155)	(0.143)	(0.239)	(0.231)
Craft- and related-trades workers	-0.604***	-0.494***	-0.184***	0.042
	(0.049)	(0.050)	(0.051)	(0.049)
Plant- and machine operators and assemblers	-1.092***	-0.767	-0.601***	-0.042
	(0.064)	(0.062)	(0.063)	(0.060)
Elementary occupations	-0.935***	-0.560***	-0.698***	-0.163*
	(0.054)	(0.058)	(0.061)	(0.064)
Industry (reference: agriculture and fishery)				
Energy and water	-0.090	-0.124	-0.123	-0.121
	(0.147)	(0.133)	(0.219)	(0.182)
Manufacturing	-0.217	-0.177	-0.199	-0.088
	(0.133)	(0.120)	(0.205)	(0.167)
Construction	-0.084	-0.130	0.040	0.037
	(0.140)	(0.126)	(0.208)	(0.171)
Distribution, hotels, & restaurants	-0.263*	-0.218^{+}	-0.204	-0.048
	(0.132)	(0.119)	(0.204)	(0.166)

Transport & communication	-0.395**	-0.376**	-0.096	0.066
	(0.139)	(0.126)	(0.207)	(0.169)
Banking, finance, & insurance, etc.	-0.275*	-0.253*	-0.142	-0.018
	(0.133)	(0.120)	(0.203)	(0.165)
Public admin, education, & health	-0.246+	-0.253*	-0.039	0.039
	(0.132)	(0.119)	(0.203)	(0.165)
Other services	-0.124	-0.130	0.066	0.120
	-0.137	(0.125)	(0.207)	(0.172)
Further-training participation	0.071**	-0.011	0.052*	-0.028
	(0.023)	(0.022)	(0.026)	(0.024)
Age (reference: 20–35)				
35–49	0.150***	0.089***	0.120***	0.019
	(0.026)	(0.025)	(0.028)	(0.026)
> 49	0.178***	0.124***	0.170***	0.064*
	(0.029)	(0.028)	(0.030)	(0.028)
Female	0.001	0.035	0.125***	0.157***
	(0.025)	(0.024)	(0.028)	(0.026)
Non-white workers	-0.163***	-0.093*	-0.174***	-0.066
	(0.042)	(0.039)	(0.044)	(0.042)
Survey year (reference: 2006)				
2012	-0.028	-0.003	-0.117***	-0.084**
	(0.027)	(0.026)	(0.029)	(0.026)
2017	-0.068**	-0.038	0.024	0.067**
	(0.025)	(0.024)	(0.026)	(0.024)
	0.502***	0.541***	0.343+	0.190
	(0.140)	(0.127)	(0.205)	(0.170)
Constant	0.502	0.541	0.342	0.19
	(0.140)	(0.127)	(0.205)	(0.169)
Observations	11,281	11,281	11,281	11,281
Rsquared	0.139	0.225	0.073	0.258

Notes: All continuous index variables are predicted scores from factor analyses. Sampling weights included. Robust standard errors in parentheses. + p<0.1,* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: UK Skills Survey (2006, 2012, 2017); authors' calculations.

Table A4.3 OLS regression results of total and direct effects of computer use on task discretion and job satisfaction – Germany

	Total effect on Discretion	Direct effect on Discretion	Total effect on Satisfaction	Direct effect on Satisfaction
Computer use	0.225***	0.121***	0.093***	0.006
	(0.017)	(0.017)	(0.016)	(0.016)
Task indicators				
Cognitive-analytical		0.194***		0.088***
		(0.007)		(0.008)
Cognitive-interpersonal		0.113***		0.020**
		(0.006)		(0.006)
Physical		-0.090***		-0.067***
		(0.007)		(0.007)
Routine		-0.140***		-0.117***
		(0.006)		(0.006)
Discretion				0.160***
				(0.007)
Educational attainment (reference: less-educated (ISCED 0–2))				
Intermediately educated (ISCED 3–4)	0.177***	0.132***	-0.136***	-0.181***
	(0.033)	(0.032)	(0.031)	(0.031)
Highly educated (ISCED 5+)	0.302***	0.142***	-0.208***	-0.345***
	(0.035)	(0.033)	(0.034)	(0.034)
Occupation (reference: managers)				
Professionals	-0.249***	-0.203***	-0.060*	-0.022
	(0.020)	(0.020)	(0.030)	(0.029)
Technicians and associate professionals	-0.316***	-0.134***	-0.216***	-0.083**
	(0.020)	(0.020)	(0.030)	(0.030)
Clerical-support workers	-0.456***	-0.207***	-0.373***	-0.181***
	(0.024)	(0.024)	(0.034)	(0.033)
Service- and sales workers	-0.497***	-0.263***	-0.291***	-0.078*
	(0.027)	(0.027)	(0.036)	(0.035)
Skilled agriculture-, forestry-, and fishery workers	-0.462***	-0.142*	-0.124	0.127
	(0.071)	(0.068)	(0.076)	(0.078)
Craft- and related-trades workers	-0.705***	-0.381***	-0.289***	-0.013
	(0.027)	(0.028)	(0.035)	(0.035)
Plant- and machine operators and assemblers	-0.919***	-0.504***	-0.496***	-0.149***
	(0.034)	(0.035)	(0.040)	(0.040)
Elementary occupations	-0.891***	-0.402***	-0.612***	-0.232***
	(0.040)	(0.040)	(0.044)	(0.045)
Industry (reference: agriculture/mining/electricity/gas & water supply)				
Other manufacturing	-0.137***	-0.110**	-0.017	0.028
	(0.037)	(0.035)	(0.038)	(0.037)
Manufacturing of basic metals and fabricated metal products and electrical equipment	-0.279***	-0.264***	-0.009	0.040
	(0.035)	(0.034)	(0.037)	(0.036)
Construction	0.038	0.018	0.094*	0.089*
	(0.041)	(0.040)	(0.042)	(0.041)
Trade	-0.235***	-0.227***	-0.108**	-0.041
	(0.039)	(0.037)	(0.040)	(0.039)
Personal-service activities	-0.185***	-0.178***	-0.043	-0.002
	(0.038)	(0.036)	(0.039)	(0.038)
Financial intermediation	0.004	-0.014	-0.029	-0.048
	(0.038)	(0.037)	(0.043)	(0.042)
Business activities	-0.004	-0.029	-0.092*	-0.114**
	(0.037)	(0.036)	(0.042)	(0.041)
Public administration/education	-0.242***	-0.215***	-0.015	0.038
	(0.034)	(0.033)	(0.036)	(0.035)

	Total effect on Discretion	Direct effect on Discretion	Total effect on Satisfaction	Direct effect on Satisfaction
Health- and social work	-0.335***	-0.257***	-0.009	0.100**
	(0.037)	(0.036)	(0.038)	(0.037)
Further-training participation	0.172***	0.089***	0.170***	0.108***
	(0.013)	(0.012)	(0.013)	(0.013)
Age (reference: 20–35)				
36–50	0.042**	0.070***	0.012	0.019
	(0.014)	(0.014)	(0.015)	(0.015)
51–65	0.088***	0.135***	0.034*	0.038*
	(0.016)	(0.015)	(0.016)	(0.016)
Female	-0.125***	-0.102***	0.028*	0.063***
	(0.013)	(0.012)	(0.014)	(0.013)
Migration background	0.025	0.051**	-0.147***	-0.134***
	(0.020)	(0.019)	(0.021)	(0.020)
Survey year (reference: 2006)				
2012	0.034*	0.013	0.021	0.008
	(0.013)	(0.013)	(0.013)	(0.013)
2018	-0.060***	-0.088***	0.062***	0.057***
	(0.014)	(0.014)	(0.015)	(0.015)
Constant	0.227***	0.159**	0.240***	0.163**
	(0.052)	(0.051)	(0.058)	(0.057)
Observations	49,446	49,446	49,446	49,446
R-squared	0.153	0.220	0.046	0.101

Notes: All continuous index variables are predicted scores from factor analyses. Sampling weights included. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: BIBB/BAuA Employment Survey (2006, 2012, 2018); authors' calculations.

Table A4.4 SEM of direct and total effects of computer use on job tasks, task discretion, and job satisfaction, separated by occupational class position, including tests for the parameter invariance of direct effects

	The UK				Germany			
	Lower ESeC		Higher ESeC		Lower ESeC		Higher ESeC	
	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect
DV: Cognitive-analytical tasks								
Computer use	0.403*** (0.023)	*No Ind. Path*	0.338*** (0.059)	*No Ind. Path*	0.126*** (0.010)	*No Ind. Path*	0.352*** (0.010)	*No Ind. Path*
DV: Cognitive-interpersonal tasks								
Computer use	0.420*** (0.024)	*No Ind. Path*	0.069 (0.063)	*No Ind. Path*	0.035* (0.014)	*No Ind. Path*	0.201*** (0.010)	*No Ind. Path*
DV: Physical tasks								
Computer use	-0.473*** (0.023)	*No Ind. Path*	-0.519*** (0.071)	*No Ind. Path*	-0.659*** (0.020)	*No Ind. Path*	-0.737*** (0.011)	*No Ind. Path*
DV: Routine tasks								
Computer use	-0.111*** (0.011)	*No Ind. Path*	-0.098** (0.034)	*No Ind. Path*	0.025 (0.016)	*No Ind. Path*	0.006 (0.012)	*No Ind. Path*
DV: Task discretion								
Computer use	-0.047** (0.017)	0.113*** (0.017)	-0.061 (0.045)	0.062 (0.046)	0.060*** (0.013)	0.246*** (0.011)	0.042* (0.018)	0.394*** (0.013)
Cognitive-analytical	0.109*** (0.011)	*No Ind. Path*	0.065*** (0.013)	*No Ind. Path*	0.145*** (0.017)	*No Ind. Path*	0.488*** (0.017)	*No Ind. Path*
Cognitive-interpersonal	0.067*** (0.013)	*No Ind. Path*	0.080*** (0.022)	*No Ind. Path*	0.264*** (0.015)	*No Ind. Path*	0.236*** (0.023)	*No Ind. Path*
Physical	-0.011 (0.010)	*No Ind. Path*	-0.062*** (0.014)	*No Ind. Path*	-0.244*** (0.010)	*No Ind. Path*	-0.183*** (0.014)	*No Ind. Path*
Routine	-0.738*** (0.046)	*No Ind. Path*	-0.641*** (0.053)	*No Ind. Path*	-0.100*** (0.011)	*No Ind. Path*	-0.363*** (0.017)	*No Ind. Path*
DV: Job satisfaction								
Computer use	-0.110*** (0.025)	0.111*** (0.025)	-0.109 (0.061)	-0.014 (0.065)	-0.038 (0.022)	0.059** (0.019)	-0.025 (0.016)	0.182*** (0.011)
Cognitive-analytical	0.071*** (0.015)	0.130*** (0.016)	0.043* (0.017)	0.071*** (0.018)	0.174*** (0.030)	0.262*** (0.029)	0.232*** (0.016)	0.322*** (0.014)
Cognitive-interpersonal	0.053** (0.018)	0.090*** (0.020)	-0.007 (0.027)	0.027 (0.030)	-0.070* (0.029)	0.091*** (0.024)	0.006 (0.020)	0.050* (0.020)
Physical	-0.024 (0.014)	-0.031 * (0.015)	0.059** (0.018)	0.033 (0.021)	0.101*** (0.020)	-0.047** (0.015)	-0.071*** (0.012)	-0.105*** (0.012)
Routine	-0.866*** (0.066)	-1.269*** (0.072)	-0.868*** (0.079)	-1.151*** (0.083)	-0.249*** (0.018)	-0.310*** (0.018)	-0.180*** (0.015)	-0.247*** (0.015)
Task discretion	0.546(0.030)	*No Ind. Path*	0.439*** (0.039)	*No Ind. Path*	0.610*** (0.048)	*No Ind. Path*	0.185*** (0.014)	*No Ind. Path*
Goodness-of-fit statistics								
CFI				0.954				0.921
RMSEA				0.048				0.047
SRMR				0.039				0.038

Notes: DV dependent variable. Underlined coefficient estimates indicate rejection of the null hypothesis of equality between groups. All continuous variables are z-standardised to have a mean of 0 and a standard deviation of 1. Controlled for educational attainment. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: UK Skills Survey (2006, 2012, 2017) for the UK and BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany; authors' calculations.

Table A4.5 SEM of direct and total effects of computer use on job tasks, task discretion, and job satisfaction, separated by training participation, including tests for the parameter invariance of direct effects

	The UK				Germany			
	Trained		Non-trained		Trained		Non-trained	
	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect
DV: Cognitive-analytical tasks								
Computer use	0.217*** (0.033)	*No Ind. Path*	0.501*** (0.025)	*No Ind. Path*	0.175*** (0.008)	*No Ind. Path*	0.430*** (0.013)	*No Ind. Path*
DV: Cognitive-interpersonal tasks								
Computer use	0.211*** (0.033)	*No Ind. Path*	0.513*** (0.027)	*No Ind. Path*	0.067*** (0.007)	*No Ind. Path*	0.152*** (0.010)	*No Ind. Path*
DV: Physical tasks								
Computer use	-0.637*** (0.037)	*No Ind. Path*	-0.496*** (0.025)	*No Ind. Path*	-0.652*** (0.013)	*No Ind. Path*	-0.798*** (0.015)	*No Ind. Path*
DV: Routine tasks								
Computer use	-0.207*** (0.024)	*No Ind. Path*	-0.181*** (0.016)	*No Ind. Path*	-0.000 (0.008)	*No Ind. Path*	-0.097*** (0.012)	*No Ind. Path*
DV: Task discretion								
Computer use	-0.033 (0.025)	0.121*** (0.024)	-0.037 (0.020)	0.198***(0.019)	0.096*** (0.014)	0.302*** (0.011)	0.067** (0.023)	0.487*** (0.016)
Cognitive-analytical	0.070*** (0.012)	*No Ind. Path*	0.100*** (0.012)	*No Ind. Path*	0.377*** (0.019)	*No Ind. Path*	0.424*** (0.019)	*No Ind. Path*
Cognitive-interpersonal	0.043* (0.018)	*No Ind. Path*	0.084*** (0.014)	*No Ind. Path*	0.233*** (0.021)	*No Ind. Path*	0.264*** (0.032)	*No Ind. Path*
Physical	-0.012 (0.012)	*No Ind. Path*	-0.030** (0.012)	*No Ind. Path*	-0.190*** (0.011)	*No Ind. Path*	-0.199*** (0.017)	*No Ind. Path*
Routine	-0.595*** (0.041)	*No Ind. Path*	-0.701*** (0.043)	*No Ind. Path*	0.067*** (0.023)	*No Ind. Path*	-0.400*** (0.025)	*No Ind. Path*
DV: Job satisfaction								
Computer use	-0.089* (0.036)	0.123*** (0.037)	-0.133*** (0.029)	0.170*** (0.029)	-0.012 (0.015)	0.106*** (0.012)	-0.049* (0.021)	0.214*** (0.015)
Cognitive-analytical	0.056*** (0.017)	0.087*** (0.018)	0.057*** (0.016)	0.107*** (0.017)	0.179*** (0.021)	0.283*** (0.020)	0.174*** (0.019)	0.266*** (0.018)
Cognitive-interpersonal	0.012 (0.026)	0.030 (0.028)	0.041* (0.020)	0.082*** (0.022)	0.005 (0.021)	0.069** (0.021)	-0.009 (0.029)	0.049 (0.029)
Physical	0.048** (0.017)	0.042* (0.018)	-0.014 (0.016)	-0.030 (0.018)	-0.004 (0.012)	-0.056*** (0.011)	-0.066*** (0.017)	-0.109*** (0.016)
Routine	-0.843*** (0.066)	-1.102*** (0.065)	-0.818*** (0.064)	-1.167*** (0.066)	-0.222*** (0.014)	-0.287*** (0.014)	-0.313*** (0.024)	-0.400*** (0.023)
Task discretion	0.435*** (0.039)	*No Ind. Path*	0.498*** (0.033)	*No Ind. Path*	0.276*** (0.017)	*No Ind. Path*	0.217*** (0.018)	*No Ind. Path*
Goodness-of-fit statistics								
CFI				0.954				0.921
RMSEA				0.05				0.047
SRMR				0.04				0.036

Notes: DV dependent variable. Underlined coefficient estimates indicate rejection of the null hypothesis of equality between groups. All continuous variables are z-standardised to have a mean of 0 and a standard deviation of 1. Controlled for educational attainment. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: UK Skills Survey (2006, 2012, 2017) for the UK and BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany; authors' calculations.

Table A4.6 Factor analysis of all relevant skill items – the UK and Germany

The UK	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniq.
Importance of						
… working out causes of problems	0.901					0.169
… spotting problems or faults	0.854					0.253
… thinking of solutions to problems	0.839					0.224
… analysing complex problems in depth	0.662					0.368
Influence personally have on						
… how to do the tasks		0.795				0.312
… what tasks to do		0.747				0.388
… quality standards to work to		0.710				0.480
… how hard to work		0.682				0.510
How much choice have over way in which job is done		0.645				0.483
Importance of						
… physical strength			0.864			0.238
… physical stamina			0.859			0.254
… skill or accuracy using hands			0.798			0.322
… knowledge of use of operational tools			0.718			0.405
… counselling, and advising others				0.769		0.384
… dealing with people				0.699		0.462
… selling a product or service				0.650		0.484
… persuading or influencing others				0.577		0.422
… teaching people				0.552		0.495
How much variety in job					-0.673	0.414
How often work involves short and repetitive tasks					-0.615	0.556
My job requires that I keep learning new things					0.584	0.505
Importance of planning own activities		0.392			0.434	0.487
Importance of organising own time		0.353			0.392	0.536
Eigenvalues	6.000	3.056	1.952	1.684	1.159	
Germany	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**	**Uniq.**
Confronted with new tasks	0.698					0.477
React to problems and solve them	0.650					0.536
Recognize and close your own gaps in knowledge	0.615					0.606
Work under strong deadline or performance pressure	0.597					0.552
Improve existing procedures or try something new	0.577					0.539
Organizing, planning and preparing work processes	0.424			0.356		0.601
Work standing up		0.708				0.383
Measuring, testing, quality control		0.658				0.487
Lift and carry heavy load		0.639				0.493
Monitoring, control of machines, plants, technical processes		0.636				0.483
Manufacturing, producing goods and commodities		0.616				0.544
Influence the amount of work assigned to you			0.696			0.467
Decide for yourself when to take a break			0.674			0.490
Plan and schedule your own work yourself			0.648			0.473
Purchasing, procuring, selling				0.746		0.413
Advertising, Marketing, Public Relations, PR				0.613		0.543
Providing advice and information	0.434			0.559		0.456
Execution of work is prescribed in every detail					0.789	0.320
One and the same operation is repeated in every detail					0.784	0.319
Eigenvalues	3.610	2.473	1.354	1.278	1.105	

Notes: Factor loadings estimated using the principal-component factor method. Orthogonal rotation applied. Weighted. Blanks represent abs(loadings) < 0.30.
Sources: UK Skills Survey (2006, 2012, 2017) for the UK and BIBB/BAuA Employment Survey (2006, 2012, 2018) for Germany; authors' calculations

Table A4.7 Correlation matrix of individual-level predictors – the UK

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Computer use	1																		
Importance of																			
2. … spotting problems or mistakes	0.201	1																	
3. … working out causes of problems/mistakes	0.223	0.759	1																
4. … thinking of solutions to problems	0.303	0.631	0.754	1															
5. … counselling […]	0.217	0.164	0.171	0.238	1														
6. … dealing with people	0.256	0.142	0.143	0.223	0.504	1													
7. … selling a product or service	0.170	0.094	0.133	0.157	0.345	0.264	1												
8. … physical stamina	-0.293	0.086	0.076	0.011	0.032	-0.046	0.012	1											
9. … physical strength	-0.350	0.059	0.050	-0.038	-0.043	-0.098	-0.003	0.770	1										
10. How much variety exists in the job	-0.142	-0.011	-0.043	-0.130	-0.065	-0.097	-0.020	0.188	0.213	1									
11. How often work involves short repetitive tasks	-0.260	-0.192	-0.217	-0.318	-0.251	-0.284	-0.084	0.083	0.144	0.329	1								
Personal influence on																			
12. … how hard to work	0.099	0.152	0.158	0.197	0.129	0.145	0.107	-0.023	-0.028	-0.062	-0.230	1							
13. … how to do the task	0.150	0.157	0.194	0.266	0.156	0.183	0.117	-0.068	-0.081	-0.172	-0.341	0.444	1						
14. … what tasks to do	0.169	0.139	0.178	0.245	0.177	0.200	0.171	-0.078	-0.094	-0.146	-0.311	0.426	0.617	1					
15. Amount of choice over how to do the job	0.131	0.132	0.167	0.238	0.104	0.138	0.094	-0.108	-0.113	-0.187	-0.374	0.343	0.520	0.458	1				
Satisfaction with																			
16. … the opportunity to use abilities	0.098	0.131	0.171	0.217	0.157	0.170	0.056	-0.006	-0.041	-0.166	-0.362	0.226	0.285	0.274	0.301	1			
17. … the ability to use own initiative	0.081	0.152	0.182	0.242	0.147	0.160	0.068	-0.022	-0.048	-0.171	-0.352	0.294	0.385	0.357	0.407	0.746	1		
18. … the work itself	0.011	0.075	0.106	0.135	0.116	0.119	0.027	0.009	-0.017	-0.147	-0.310	0.199	0.212	0.209	0.255	0.593	0.555	1	
19. Education	0.393	0.109	0.131	0.242	0.181	0.226	0.041	-0.238	-0.321	-0.214	-0.275	0.087	0.159	0.150	0.150	0.051	0.046	-0.001	1

Sources: UK Skills Survey (2006, 2012, 2017); authors' calculations.

Table A4.8 Correlation matrix of individual-level predictors – Germany

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1.	Computer use	1																	
2.	Purchasing, procuring, selling	0.037	1																
3.	Advertising, marketing, public relations, PR	0.176	0.261	1															
4.	Reacting to problems and solving them	0.232	0.095	0.179	1														
5.	Recognising and closing own gaps in knowledge	0.207	0.060	0.156	0.357	1													
6.	Execution of work is prescribed in every detail	-0.068	-0.074	-0.114	-0.070	-0.043	1												
7.	The exact same operation is repeated in every detail	-0.135	-0.011	-0.138	-0.181	-0.155	0.381	1											
8.	Being confronted with new tasks	0.256	0.036	0.162	0.330	0.321	-0.057	-0.224	1										
9.	Improving existing procedures or trying something new	0.178	0.097	0.190	0.302	0.272	-0.125	-0.200	0.420	1									
10.	Working while standing	-0.371	0.096	-0.072	-0.028	-0.052	0.108	0.100	-0.105	-0.009	1								
11.	Lifting and carrying heavy loads	-0.370	0.086	-0.080	-0.029	-0.047	0.154	0.153	-0.084	-0.042	0.518	1							
12.	Planning and scheduling own work oneself	0.253	0.103	0.163	0.210	0.162	-0.241	-0.170	0.219	0.262	-0.163	-0.165	1						
13.	Influencing the amount of work assigned	0.083	0.122	0.153	0.123	0.111	-0.160	-0.123	0.138	0.214	-0.026	-0.053	0.330	1					
14.	Deciding for oneself when to take a break	0.211	0.057	0.106	0.092	0.086	-0.147	-0.091	0.116	0.093	-0.274	-0.180	0.302	0.221	1				
15.	Satisfaction with the type and content of work	0.105	0.052	0.097	0.106	0.087	-0.156	-0.143	0.135	0.158	-0.050	-0.082	0.160	0.141	0.103	1			
16.	Satisfaction with opportunities for applying skills	0.096	0.046	0.082	0.123	0.098	-0.145	-0.135	0.157	0.174	-0.038	-0.069	0.169	0.156	0.111	0.576	1		
17.	Satisfaction with work on the whole	0.059	0.034	0.059	0.031	0.033	-0.148	-0.082	0.070	0.106	-0.062	-0.105	0.144	0.160	0.122	0.509	0.471	1	
18.	Education	0.312	0.004	0.204	0.252	0.197	-0.199	-0.310	0.259	0.231	-0.192	-0.283	0.234	0.129	0.123	0.081	0.064	0.025	1

Sources: BIBB/BAuA Employment Survey (2006, 2012, 2018); authors' calculations.

Table A4.9 The UK – Descriptive statistics of the individual-level variables used

	Mean	SD	Min	Max
Job satisfaction (fac)	0	1	-4.520	1.513
Satisfaction with the opportunity to use own abilities	0.748	0.199	0	1
Satisfaction with being able to use own initiative	0.763	0.188	0	1
Satisfaction with the work itself	0.737	0.183	0	1
Task discretion (fac)	0	1	-3.355	1.351
Personal influence on how hard to work	0.793	0.239	0	1
Personal influence on what tasks to do	0.629	0.308	0	1
Personal influence on how to do the tasks	0.726	0.277	0	1
Amount of choice over how the job is done	0.696	0.276	0	1
Cognitive-analytical tasks (fac)	0	1	-3.032	1.075
Importance of spotting problems or mistakes	0.765	0.256	0	1
Importance of working out causes of problems	0.709	0.284	0	1
Importance of thinking of solutions to problems	0.739	0.272	0	1
Cognitive-interpersonal tasks (fac)	0	1	-3.075	1.274
Importance of counselling, advising, or caring for customers and clients	0.641	0.369	0	1
Importance of dealing with people	0.878	0.214	0	1
Importance of selling a product or service	0.425	0.397	0	1
Physical tasks (fac)	0	1	-1.299	1.714
Importance of physical stamina	0.459	0.353	0	1
Importance of physical strength	0.403	0.351	0	1
Routine tasks (fac)	0	1	-1.957	2.364
How much variety exists in the job	0.316	0.283	0	1
How often the work involves short and repetitive tasks	0.589	0.281	0	1
Working with computers	0.789	0.408	0	1
Education				
less-educated (ISCED 0–2)	0.163	0.369	0	1
intermediately educated (ISCED 3–4)	0.415	0.493	0	1
highly educated (ISCED 5+)	0.422	0.494	0	1
Occupation (ISCO-08)				
Managers	0.164	0.370	0	1
Professionals	0.165	0.371	0	1
Technicians and associate professionals	0.124	0.330	0	1
Clerical-support workers	0.129	0.335	0	1
Service- and sales workers	0.184	0.388	0	1
Skilled agricultural-, forestry-, and fishery workers	0.005	0.068	0	1
Craft- and related-trades workers	0.074	0.262	0	1
Plant- and machine operators and assemblers	0.063	0.243	0	1
Elementary occupations	0.092	0.289	0	1
Industry (SIC92)				
Agriculture & fishing	0.009	0.092	0	1
Energy & water supply	0.012	0.107	0	1
Manufacturing	0.132	0.338	0	1
Construction	0.045	0.207	0	1
Distribution, hotels, & restaurants	0.183	0.387	0	1
Transport & communication	0.061	0.239	0	1
Banking, finance, & insurance	0.177	0.382	0	1
Public admin, education, & health	0.341	0.474	0	1
Other services	0.041	0.198	0	1
Attendance of job-related training in the previous year	0.454	0.498	0	1
Age				
20–34	0.347	0.476	0	1
35–49	0.383	0.486	0	1
> 49	0.270	0.444	0	1
Gender	0.491	0.500	0	1
Non-white	0.100	0.300	0	1
Survey year				
2006	0.331	0.471	0	1
2012	0.322	0.467	0	1
2017	0.348	0.476	0	1

Sources: U.K. Skill Survey (2006, 2012, 2017); authors' calculations. Weighted.

Table A4.10 Germany – Descriptive statistics of the individual-level variables used

	Mean	SD	Min	Max
Job satisfaction (fac)	0	1	-4.234	1.620
Satisfaction with type and content of work	0.733	0.199	0	1
Satisfaction with opportunities for applying skills	0.707	0.224	0	1
Satisfaction with work on the whole	0.729	0.203	0	1
Task discretion (fac)	0	1	-2.663	1.144
Planning and scheduling own work oneself	0.812	0.312	0	1
Influence on the amount of work assigned	0.546	0.387	0	1
Deciding for oneself when to take a break	0.703	0.397	0	1
Cognitive-analytical tasks (fac)	0	1	-3.391	1.485
Reacting to problems and solving them	0.799	0.283	0	1
Recognising and closing own gaps in knowledge	0.613	0.297	0	1
Being confronted with new tasks	0.717	0.280	0	1
Improving existing procedures or trying something new	0.643	0.293	0	1
Cognitive-interpersonal tasks (fac)	0	1	-0.909	2.572
Purchasing, procuring, selling	0.308	0.395	0	1
Advertising, marketing, public relations, PR	0.222	0.330	0	1
Physical tasks (fac)	0	1	-1.676	1.327
Working while standing	0.703	0.372	0	1
Lifting and carrying heavy loads	0.405	0.394	0	1
Routine tasks (fac)	0	1	-2.094	1.325
Execution of work is prescribed in every detail	0.529	0.356	0	1
The exact same operation is repeated in every detail	0.695	0.353	0	1
Working with computers	0.660	0.474	0	1
Education				
less-educated (ISCED 0–2)	0.063	0.243	0	1
intermediately educated (ISCED 3–4)	0.630	0.483	0	1
highly educated (ISCED 5+)	0.307	0.461	0	1
Occupation (ISCO-08)				
Managers	0.045	0.206	0	1
Professionals	0.182	0.386	0	1
Technicians and associate professionals	0.234	0.424	0	1
Clerical-support workers	0.114	0.318	0	1
Service- and sales workers	0.122	0.327	0	1
Skilled agricultural-, forestry-, and fishery workers	0.010	0.100	0	1
Craft- and related-trades workers	0.158	0.364	0	1
Plant- and machine operators and assemblers	0.077	0.267	0	1
Elementary occupations	0.059	0.236	0	1
Industry (NACE)				
Agriculture/mining/electricity/gas & water supply	0.029	0.167	0	1
Other manufacturing	0.117	0.321	0	1
Manufacturing basic metals and fabricated metal products and electricity	0.184	0.388	0	1
Construction	0.061	0.239	0	1
Trade	0.099	0.298	0	1
Personal-service activities	0.114	0.318	0	1
Financial intermediation	0.035	0.183	0	1
Business activities	0.070	0.256	0	1
Public administration/education	0.167	0.373	0	1
Health- and social work	0.125	0.331	0	1
Attendance of job-related training in the previous 2 years	0.598	0.490	0	1
Age				
20–35	0.301	0.459	0	1
36–50	0.427	0.495	0	1
51–65	0.272	0.445	0	1
Gender (male)	0.546	0.498	0	1
Migration background	0.157	0.364	0	1
Survey year				
2006	0.343	0.475	0	1
2012	0.321	0.467	0	1
2018	0.336	0.472	0	1
Observations	49,446			

Sources: BIBB/BAuA Employment Survey (2006, 2012, 2018); authors' calculations. Weighted.

Table A4.11 OLS regression results of total effects of computer use on task indexes – UK

	Cognitive-analytical	Cognitive-interpersonal	Physical	Routine
Computer Use	0.492***	0.374***	-0.127***	-0.191***
	(0.036)	(0.033)	(0.031)	(0.035)
Educational attainment (reference: less-educated (ISCED 0–2))				
Intermediately educated (ISCED 3–4)	0.138***	0.051	-0.034	-0.030
	(0.038)	(0.035)	(0.032)	(0.035)
Highly educated (ISCED 5+)	0.132**	-0.005	-0.202***	-0.246***
	(0.042)	(0.039)	(0.036)	(0.040)
Occupation (reference: managers)				
Professionals	-0.116**	-0.368***	-0.072*	0.039
	(0.036)	(0.037)	(0.035)	(0.037)
Technicians and associate professionals	-0.060	-0.269***	0.129***	0.245***
	(0.037)	(0.036)	(0.039)	(0.040)
Clerical-support workers	-0.333***	-0.515***	-0.322***	0.593***
	(0.042)	(0.041)	(0.037)	(0.041)
Service- and sales workers	-0.363***	-0.249***	0.588***	0.503***
	(0.040)	(0.034)	(0.041)	(0.042)
Skilled agriculture-, forestry-, and fishery workers	-0.125	-0.464*	0.867***	0.310
	(0.169)	(0.219)	(0.125)	(0.195)
Craft- and related-trades workers	0.217***	-0.858***	1.023***	0.225***
	(0.044)	(0.057)	(0.047)	(0.050)
Plant- and machine operators and assemblers	-0.289***	-0.969***	0.818***	0.746***
	(0.059)	(0.058)	(0.051)	(0.063)
Elementary occupations	-0.540***	-1.031***	0.934***	0.761***
	(0.055)	(0.055)	(0.052)	(0.055)
Industry (reference: agriculture and fishery)				
Energy and water	-0.151	0.007	-0.633***	-0.224
	(0.174)	(0.168)	(0.136)	(0.206)
Manufacturing	-0.170	0.016	-0.489***	0.075
	(0.154)	(0.147)	(0.094)	(0.190)
Construction	-0.213	0.339*	-0.304**	-0.187
	(0.161)	(0.155)	(0.101)	(0.193)
Distribution, hotels, & restaurants	-0.417**	0.743***	-0.232*	0.219
	(0.153)	(0.145)	(0.094)	(0.188)
Transport & communication	-0.328*	0.417**	-0.444***	0.044
	(0.158)	(0.149)	(0.098)	(0.193)
Banking, finance, & insurance, etc.	-0.356*	0.233	-0.805***	-0.025
	(0.155)	(0.146)	(0.094)	(0.189)
Public admin, education, & health	-0.382*	0.379**	-0.276**	-0.118
	(0.153)	(0.145)	(0.094)	(0.188)
Other services	-0.321*	0.499**	-0.277**	-0.023
	(0.158)	(0.152)	(0.102)	(0.193)
Further-training participation	0.176***	0.192***	0.004	-0.149***
	(0.023)	(0.022)	(0.021)	(0.024)
Age (reference: 20–35)				
35–49	0.061*	0.026	-0.026	-0.201***
	(0.026)	(0.026)	(0.024)	(0.026)
> 49	0.020	0.023	-0.033	-0.201***

	(0.030)	(0.028)	(0.026)	(0.029)
Female	-0.091***	0.070**	-0.039+	0.108***
	(0.026)	(0.024)	(0.023)	(0.024)
Non-white workers	-0.133**	-0.033	0.071+	0.187***
	(0.047)	(0.040)	(0.040)	(0.040)
Survey year (reference: 2006)				
2012	-0.077**	0.047+	-0.023	0.074**
	(0.027)	(0.025)	(0.024)	(0.026)
2017	-0.065*	-0.054*	0.053*	0.062*
	(0.026)	(0.024)	(0.023)	(0.024)
Constant	0.021	-0.387*	0.332**	0.011
	(0.163)	(0.151)	(0.102)	(0.193)
N	11,281	11,281	11,281	11,281
R-squared	0.165	0.260	0.348	0.232

All continuous index variables are predicted scores from factor analyses. Sampling weights included. Robust standard errors in parentheses. + p<0.1,* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: UK Skills Survey (2006, 2012, 2017); authors' calculations.

Table A4. 12 OLS regression results of total effects of computer use on task indexes – Germany

	Cognitive-analytical	Cognitive-interpersonal	Physical	Routine
Computer Use	0.320***	0.102***	-0.434***	0.065***
	(0.015)	(0.013)	(0.013)	(0.015)
Educational attainment (reference: less-educated (ISCED 0–2))				
Intermediately educated (ISCED 3–4)	0.181***	0.099***	0.021	-0.002
	(0.032)	(0.023)	(0.026)	(0.028)
Highly educated (ISCED 5+)	0.347***	0.236***	-0.227***	-0.325***
	(0.034)	(0.027)	(0.028)	(0.030)
Occupation (reference: managers)				
Professionals	0.011	-0.566***	0.004	-0.113***
	(0.022)	(0.031)	(0.024)	(0.027)
Technicians and associate professionals	-0.288***	-0.640***	0.061*	0.342***
	(0.022)	(0.030)	(0.024)	(0.027)
Clerical-support workers	-0.585***	-0.643***	-0.115***	0.525***
	(0.025)	(0.034)	(0.028)	(0.029)
Service- and sales workers	-0.459***	-0.312***	0.550***	0.428***
	(0.027)	(0.035)	(0.027)	(0.031)
Skilled agriculture-, forestry-, and fishery workers	-0.444***	-0.663***	0.948***	0.522***
	(0.066)	(0.069)	(0.046)	(0.065)
Craft- and related-trades workers	-0.338***	-1.027***	0.760***	0.529***
	(0.027)	(0.033)	(0.027)	(0.031)
Plant- and machine operators and assemblers	-0.741***	-1.202***	0.286***	0.780***
	(0.034)	(0.035)	(0.034)	(0.035)
Elementary occupations	-1.092***	-1.154***	0.672***	0.617***
	(0.039)	(0.036)	(0.033)	(0.037)
Industry (reference: agriculture/mining/electricity/gas & water supply)				
Other manufacturing	0.048	-0.024	0.171***	0.135***
	(0.036)	(0.038)	(0.032)	(0.038)
Manufacturing of basic metals and fabricated metal products and electrical equipment	0.068*	-0.177***	-0.007	0.063
	(0.034)	(0.037)	(0.031)	(0.037)
Construction	0.148***	0.134**	0.237***	0.013
	(0.040)	(0.041)	(0.034)	(0.043)
Trade	-0.088*	0.439***	0.283***	0.100*
	(0.037)	(0.040)	(0.033)	(0.039)
Personal-service activities	0.011	0.066	0.028	0.102**
	(0.036)	(0.039)	(0.033)	(0.039)
Financial intermediation	0.067	-0.165***	-0.380***	0.081
	(0.039)	(0.045)	(0.035)	(0.043)
Business activities	0.097**	-0.173***	-0.333***	0.034
	(0.037)	(0.041)	(0.033)	(0.040)
Public administration/education	0.065	-0.149***	0.184***	0.042
	(0.034)	(0.037)	(0.030)	(0.037)
Health- and social work	0.116***	-0.169***	0.636***	0.168***
	(0.035)	(0.038)	(0.032)	(0.039)
Further-training participation	0.309***	0.164***	0.044***	-0.060***
	(0.012)	(0.012)	(0.011)	(0.012)
Age (reference: 20–35)				
35–49	-0.126***	-0.014	-0.020	0.026
	(0.013)	(0.013)	(0.012)	(0.014)
> 49	-0.250***	-0.050***	-0.103***	0.015
	(0.014)	(0.014)	(0.013)	(0.015)
Female	-0.156***	0.077***	-0.171***	0.117***
	(0.012)	(0.012)	(0.011)	(0.012)

Non-white workers	-0.045*	-0.040*	-0.032*	0.116***
	(0.019)	(0.019)	(0.016)	(0.019)
Survey year (reference: 2006)				
2012	0.160***	-0.023	0.033**	0.032*
	(0.012)	(0.013)	(0.011)	(0.013)
2017	0.183***	-0.068***	0.044***	-0.027*
	(0.013)	(0.013)	(0.012)	(0.014)
Constant	-0.216***	0.455***	0.012	-0.433***
	(0.053)	(0.053)	(0.047)	(0.054)
Observations	49,446	49,446	49,446	49,446
R-squared	0.283	0.180	0.358	0.151

Notes: All continuous index variables are predicted scores from factor analyses. Sampling weights included. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: BIBB/BAuA Employment Survey (2006, 2012, 2018); authors' calculations.