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Digital transformation, demographic changes and labor markets: Projected implications for 100 European regions*

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Abstract

The ongoing substitution of labor with automated technologies generates widespread fears about the future working conditions for millions of workers. As technological progress accelerates and replaces new tasks, employees can witness a decline in their wages, face job displacement, and may even be compelled to move to another location. In this paper, we aim to quantify the magnitude of macroeconomic and welfare effects that robotization and automation can bring to European regions in the coming decades. Using a spatial general equilibrium model that incorporates projected automation scenarios, our methodology offers new insights into the geographical, sectoral, and occupational distribution of gains and losses resulting from technological progress. We find that , from a macroeconomic perspective, Europe is expected to experience significant gains from robotization and automation over the next 15 years. However, these welfare effects are highly heterogeneous across job types and sectors, leading to many individuals facing adverse outcomes. We emphasize these disparities and the diverse repercussions that different segments of the population are poised to encounter. Understanding these implications is crucial in formulating effective policies to address the challenges and opportunities arising from digital transformation.

Keywords: automation, robotization, labor markets, migration.
JEL codes: J24, O33, R12, E24

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1 Introduction

Technological progress has had a varying impact across different sectors, occupations, and tasks. While it has the potential to improve productivity and create synergies for certain workers, it may also introduce competition from substitutable technologies for others (Goos et al., 2014). Historical records demonstrate that technological transformations over the past decades primarily resulted in the disappearance of middle-skilled jobs. As a consequence, labor market polarization has significantly influenced the distribution of workers across occupations, remuneration growth, and the overall macroeconomic performance in many developed countries' local economies. However, it is important to recognize that current and future technological innovations are expected to impact highly skilled cognitive tasks, as emphasized by Brynjolfsson et al. (2018b). This raises the question of how future technological advancements will affect workers' mobility and wages across occupations, sectors, and regions. Understanding this is essential for addressing the challenges and opportunities presented by technological progress.

The main contribution of this paper lies in constructing projection scenarios to assess the impact of future technological progress on European labor markets. Our focus lies on waves 1.0 to 3.0 of the digital revolution, as defined by Arntz et al. (2019), and we use data on two types of capital. ICT capital, such as IT equipment, software, and databases, is available from EU-KLEMS data, and data on industrial robots is provided by IFR data. While there have been tremendous advancements in AI, and in particular in generative AI technology, in recent months and years, the lack of detailed data on its spread across occupations, sectors and regions prevents us from taking it into account at this stage. Our scenarios encompass various effects arising from task automation and the utilization of industrial robots in different sectors of regional economies. Our methodology takes into account the implications of automation on the shares of labor income, changes in productivity for different occupational tasks, and the direct substitution between labor and technology within sectors. By extrapolating these relationships, we present a comprehensive analysis of the potential consequences that automation and robotization could have on labor markets. These diverse effects are then translated into variations in wage distributions specific to different occupations across European regions, subsequently influencing the economic incentives for people to consider mobility across sectors, occupations, and regions.

Several papers within the H2020 UNTANGLED project have studied the distributional effects of past technological adoptions. Doorley et al. (2023) find that robots had minimal impact on income inequality across 14 European countries (2006-2018) whereas Stehrer (2022) argue that the accumulation of ICT assets have generally insignificant effects on income shares in the European economy (2007-2018). Capello et al. (2023) noted that digital transformation contributed to wage inequalities within 164 European regions

(2009-2016). There is a notable scarcity of projection exercises that specifically address the distributional impacts of automation and robotization. Our projections enable us to identify the workers, sectors and regions that are likely to benefit or be harmed by the digital transformation. Such an exercise is crucial to help better target policies in order to support those who are adversely affected. Our work thus complements Capello and Caragliu (2023), who present scenarios on Europe's regional economic development over the next 15 years assuming different evolutions in Global Value Chains and national digital plans.

We adopt a general equilibrium framework, combined with projection scenarios, in order to shed new light on how future technological progress may reshape European labor markets. In particular, we extend the models proposed by Acemoglu and Autor (2011), Acemoglu and Restrepo (2018), Autor et al. (2003) to incorporate the multidimensional heterogeneity of workers, following the self-selection model presented by Roy (1951). This theoretical approach allows us to quantify the average wage effects and changes in wage dispersion resulting from automation and robotization across various occupations, sectors, geographical areas, and different worker groups. Our approach not only builds upon recent applications of Fréchet-based models (Burstein et al., 2020, 2019, Costinot and Vogel, 2015) but also offers novel insights into how automation influences the sorting of workers into different occupations and impacts all moments of wage distributions in a non-uniform manner. Moreover, we explicitly model key adjustment mechanisms that come into play as technological shocks affect individual occupational choices, cross-sectoral mobility, and the costly process of spatial migration. By considering these important factors, our analysis provides a comprehensive understanding of the broader implications of automation on the labor market and worker outcomes.

We calibrate our model on data for 100 European regions in the year 2018. In our benchmark simulation, we assume a continuation of past trends in automation and robotization over the next 15 years (medium automation scenario) and a medium education scenario (E2). We observe accelerated growth in most European regions over the next 15 years, but the benefits from automation are distributed heterogeneously across regions and sectors. These benefits result from the sorting of workers across different occupations and sectors, where labour shifts towards more labour-intensive occupations within sectors that adopt new technologies at a slower pace. As more efficient and cheaper production processes reduce marginal costs and lead to more firms entering the markets, prices decrease and the mass of available consumer goods increases. This results in an improvement of consumers' purchaising power and welfare.

However, assuming the process of technological adoption follows patterns similar to those of the last two decades, implies significant divergent effects across European regions from automation and robotization. Not only will regions with a history of successful automation adoption solidify their positions, but the widening gap between high and low-income areas will also lead to increased worker migration toward technology hubs, further exacerbating inequality. This finding highlights the potential challenges associated with the uneven distribution of the gains from automation, and it underscores the need for proactive policies to address regional disparities and ensure that the benefits of technological progress are shared more inclusively across the European economy.

Part of the benefits derived from automation stems from the reassignment of workers across occupations and sectors. Our projections take into account the spatial and sectoral variations in the adoption of automation technologies and recognize that automation affects occupations differently. Consequently, we reach the conclusion that workers tend to be displaced from sectors that embrace automation more readily, such as finance, and gravitate towards sectors that experience a slower pace of technological task substitution, like public services. Simultaneously, our analysis projects that automation will elevate the relative significance of professional occupations, prompting workers to switch job types as wages increase. It is worth noting that the reduction in employment in other occupations is not uniform. As skills required in various occupations differ and are unequally correlated with each other, the outflow of workers is most significant from managerial occupations that share similarities with professional job types. Furthermore, we find substantial movements between two less complex occupations, namely service and elementary occupations, driven by wage effects of opposing signs. However, there is no consistent pattern of this bidirectional occupational mobility across European regions. Instead, the regional specificity in sectoral structures becomes the determining factor in the fluctuation of demand for less complex tasks. These findings emphasize the importance of considering the unique characteristics of each occupation and sector when assessing the impact of automation on the labor market. They also underscore the significance of regional factors in shaping the dynamics of occupational mobility and the demand for particular skill sets as automation continues to reshape the European job landscape.

These region-, sector-, and occupation-specific characteristics lead to highly diverse effects on overall native welfare. In our benchmark scenario, changes in average native welfare range from a decrease of 10% (observed in Paris, Ile de France) to an increase of 20% (seen in Province de Liège, Belgium). Approximately 80 out of the 100 NUTS1 regions experience a boost in their average workers' welfare due to automation. Consequently, automation represents more of an opportunity than a risk for the majority of European regions. Despite the often costly and demanding nature of labor market mobility, it plays a crucial role in the overall production potential and helps mitigate the losses caused by technological task displacement. As a result, we observe an overall increase in production capacity, thus reaffirming the potential benefits of automation for the broader European economy. In summary, the varying impacts of automation across regions and sectors underscore the need for targeted policy measures to support workers in regions that may experience adverse effects, while also capitalizing on the opportunities presented by automation to enhance overall welfare and productivity.

We also examine the sensitivity of our benchmark results to alternative automation projections. By reducing or accelerating the speed of adopting automation technologies by 50%, we observe that more intense automation increases the number of regions where native workers, on average, experience gains in their real wages. Furthermore, the distribution of these effects across regions becomes more dispersed, with gains increasing linearly, while losses are more limited and evolve at a slower rate than linear. Consequently, faster automation can lead to a potential upside for many European regions, and the losses in specific areas are not exacerbated as automation becomes more widespread. Furthermore, our projections encompass education scenarios, in which we modify the share of college-educated workers in all European regions. This allows us to shed light on the interaction between the supply side of labor market skills and the demand for specific types of workers. Our findings indicate that, in comparison to automation shocks, education scenarios have a relatively small impact on the aggregated production in the European economy, employment, and migration. Although a more educated workforce does contribute to accelerated growth, slightly reduced average wages, and increased employment, the magnitude of these effects is significantly smaller when compared to the impacts of technological scenarios. In conclusion, our research highlights the significant influence of automation on regional and sectoral dynamics, while emphasizing the relatively limited effects of education scenarios on the broader European economy. Understanding these complexities is vital for policymakers to formulate effective strategies that address the challenges and opportunities brought about by automation and workforce education.

The rest of the paper is organized as follows. In the following section we review the related literature. Section 3 presents our theoretical framework. Section 4 defines our calibration strategy and describes the data used. We further detail therein our methodology for automation projections. Section 5 presents the results for our benchmark simulations whereas in Section 6 we discuss alternative scenarios in which the benchmark trends are reinforced or mitigated. Section 7 concludes.

2 Literature Review

In this section, we detail the different strands of the literature to which we contribute to. In Section 2.1, we discuss the underlying task-based and self-selection models upon which our framework builds on. We then summarize the empirical literature on the effects of robotization (in Section 2.2) and new technological advancements (in Section 2.3) on the labor markets. In Section 2.4, we summarize existing projection studies.

2.1 Skill-Task Modelling

The economic thinking and related modelling paradigms on the relationship between technological progress, labor markets and inequality have evolved over recent decades (Autor, 2022). Our theoretical framework builds on an extensive literature using task-based models to study the effects of technological change on labor demand (Acemoglu and Autor, 2011, Acemoglu and Restrepo, 2018, 2020, 2022, Autor and Dorn, 2013, Autor et al., 2003, Deming, 2017, Goos et al., 2014, Gregory et al., 2022). This type of framework puts the task-content of production at its core. Automation can generate different effects on the labor market, acting in opposite direction (see Acemoglu and Restrepo, 2019 for a detailed exposition of the mechanisms). The first order impact of automation is a displacement effect, as it shifts some tasks executed by labor towards capital. Automation thereby reduces the labor share of these tasks and workers switch to tasks where they have a comparative advantage.

Automation can reduce the returns associated with specific skills or, in some cases, render them entirely obsolete. Focussing on skills obtained during higher education, Deming and Noray (2020) show that the return of science, technology, engineering and mathematics (STEM) degrees declines by more than 50 percent in the ten years following the entrance on the labor market. Allen and van der Velden (2002) document that a third of the skills obtained by tertiary education graduates in The Netherlands were obsolete seven years after their graduation. Using Dutch panel data on older workers (above 40 years) in the late 1990, Allen and de Grip (2012) show that skill obsolescence is more prominent in technologically- and learning-intensive jobs. Automation can also increase demand for complementary non-automatable tasks (Autor, 2015) or even lead to the creation of new tasks. Acemoglu et al. (2022) argue that while some tasks become obsolete as they are taken over by algorithms (e.g. customer services, sales), the demand for new skills simultaneously increases (e.g. analysis, engineering, business or information technology).

One important feature of labor markets that is missing in existing skill-task models is the multidimensional heterogeneity of workers' skills and its impact on occupational sorting. As motivated by Autor and Handel (2013), and Firpo et al. (2011), the self-selection models in the vein of Roy (1951) provide the most suitable framework for analyzing labor market mobility and the evolution of wage distributions in a context of worker heterogeneity. These models recognize that individuals possess multidimensional vectors of skills, distributed continuously. Jobs reward these skills differently, prompting workers to self-select into different occupations and sectors. A similar theory has recently been applied to different contexts (e.g. Burstein et al., 2019, Costinot and Vogel, 2015, and Burstein et al., 2020), which make use of a self-selection model with a Fréchet distribution of labor productivity (types). The novelty of our approach lies in endogenizing changes in locations and the dispersion of wage distributions by reformulating the multidimensional self-selection model using normal distributions.

2.2 The Impact of Robotization on the Labor Market

A growing empirical literature studies the impact of robot adoption on labor markets, with a particular focus on the manufacturing sector. Within countries, the analyzes are conducted at the regional (Acemoglu and Restrepo, 2020, Dauth et al., 2021, Grimm and Gathmann, 2022) or worker (Dottori, 2021, Koch et al., 2021) level, whereas some researchers work at the cross-country industry level (de Vries et al., 2020, Graetz and Michaels, 2018, Klenert et al., 2020).

Acemoglu and Restrepo (2020) find negative employment effects from the adoption of robots in local US labor markets. Results for the European context tend to be more optimistic as firms that adopted robots were found to experience a rise in labour demand in France (Daron Acemoglu and Claire Lelarge and Pascual Restrepo, 2020, Domini et al., 2021) and in Spain (Koch et al., 2021).

Dauth et al. (2021) use German administrative data to study the adjustment of local labor markets to industrial robots in Germany as well as individual labor market trajectories. They find displacement effects in manufacturing associated with robot exposure, but these are fully offset by job creation in services. Incumbent workers benefit from a certain job stability by transiting to new occupations within their workplace. Workers in occupations with complementary tasks, such as managers or technical scientists, benefit from the introduction of industrial robots. In contrast, labor market entrants and young workers are more likely to be displaced.

Grimm and Gathmann (2022) develop a patent-based measure of robotics (and AI) for the period ranging from 1990 to 2018. They use it to analyze the effects of exposure to these two technologies on local labor markets in Germany. Regarding robotics, they find an overall negative effect on employment, with employment decreasing in manufacturing but increasing in services (albeit less than the decrease in manufacturing). Wages in contrast increase modestly in the manufacturing sector but are not significantly affected in the services sector.

In the context of Italy, Dottori (2021) finds an overall positive employment effect of robot adoption at the local labor market level. In particular, incumbent workers in the manufacturing sector did not experience negative effects. Instead, they benefited from longer job tenures within the same firms and, for those who stayed with their original employer, saw an increase in wages. However, robot diffusion affected the distribution of new labour inflows towards less robot intensive sectors. Koch et al. (2021) use panel data on robot adoption in the Spanish manufacturing sector from 1990 to 2016 and find that robotization led to a net job creation of 10%.

de Vries et al. (2020) combine data on robot adoption and occupations by industry in 37 countries for the period 2005 to 2015. They find that an increase in robot adoption is significantly associated with a decrease in the employment share of routine manual task-intensive jobs. This relationship is observed in high-income countries, but not in emerging and transition economies. Graetz and Michaels (2018) use a panel data on robot adoption at the industry-country level in seventeen countries from 1993 to 2007. They find no significant impact from robot adoption on aggregate hours worked, but a reduction in the share of hours worked by low-skilled workers relative to more educated workers. Robotization boosts total factor productivity (TFP) and, to a lesser extent, average wages. Using data from 26 EU countries over the period between 1993 to 2016, Klenert et al. (2020) find that the robot adoption did not reduce low-skilled employment in the manufacturing sector. Focusing on labor market transitions in Europe over the period 1998-2017, Bachmann et al. (2022) conclude that robot adoption increased employment and reduced job separation, especially in European countries with low or average levels of labor costs.

2.3 The Impact of Automation on the Labor Market

Frey and Osborne (2017) develop a measure of the probability of computerisation for 702 occupations in the US. They report that 47% of the US labor force in 2013 held jobs that faced a high risk of being automated. Arntz et al. (2016) use the automation risk defined by Frey and Osborne (2017) but use a probabilistic method to estimate which tasks that can be automated for each occupation. Applying their method to PIAAC data for 21 OECD countries, they find that, on average, 9% of jobs are automatable. However, the share of automatable jobs varies across countries: while it is 6% in Korea, it reaches 12% in Austria. Using a similar methodology, Nedelkoska and Quintini (2018) estimate that 14% of all jobs across 32 OECD countries have a high risk of automation.

Stehrer (2022) does not find significant effects of the accumulation of ICT assets on labour demand in the European economy (2007-2018). Albinowski and Lewandowski (2022) argue that the adoption of ICT (and robots) is advantageous for young and prime-aged women, as well as for older men, whereas negative effects on relative labour market outcomes are concentrated among older women and prime-aged men. Between 2010 and 2018, the growth in ICT capital had a substantially greater impact on labor market outcomes than robotization. Gaggl and Wright (2017) rely on a natural experiment arising from a tax allowance on ICT investments in the UK. They find that the principal impact of ICT is to complement non-routine, cognitive-intensive tasks. Moreover, ICT investments resulted in organizational changes that correlated with a rise in wage inequality within the firm. In the case of French manufacturing firms, Domini et al. (2021) find that periods with increased imports of capital goods embedding automation technologies are associated with a lower separation rate and a higher hiring rate at the firm level. Webb (2020) finds that exposure to software (and robots) is associated with a 7 to 11% (9-18%) decline in within-industry employment shares, and a 2 to 6% (8-14%) decline in wages over the period 1980 to 2010 in the US.

Akerman et al. (2015) exploit a plausibly exogenous roll-out of broadband internet access in Norway to analyze how its adoption affects firm-level labor market outcomes. They find that broadband internet has a positive impact on the labor market outcomes and productivity of skilled workers, while it negatively affects less skilled workers. In particular, broadband adoption seems to substitute for the need for unskilled workers for the execution of routine tasks. Mann and Püttmann (2023) use a patent-based classification of automation at a detailed industry level and use an instrumental variable strategy that relies on innovations developed outside of the U.S. to analyze the effect of automation on U.S. local labor markets. They find positive employment effects generated by job growth in services, whereas workers in the manufacturing sector do not benefit from automation. In addition, they find that commuting zones with a low routine-task share experience positive effects on wages, while in other commuting zones, the effects are negative.

Recent research focuses on investigating the way in which automation of more complex non-routine tasks affects labor markets. Even if AI technologies are progressing fast, they are built to perform certain tasks, rather than the entire work-content of specific occupations (see e.g., Arntz et al., 2017). A growing strand of literature develops different approaches to define which occupations and tasks are most susceptible to be executed by Machine Learning and Artificial Intelligence. Existing measures rely on experts or crowd-sourced evaluations to identify tasks that can be affected by automation or AI (Brynjolfsson et al., 2018a, Felten et al., 2018, Frey and Osborne, 2017, Tolan et al., 2021) or use contents described in patent application to recover the automation potentials of different tasks (Danzer et al., 2020, Dechezleprêtre et al., 2019, Grimm and Gathmann, 2022, Mann and Püttmann, 2023). More recent approaches combine patent-based definitions with information of tasks performed on the job (Felten et al., 2021, Webb, 2020) or rely on AI to implement task classifications. In on-going work, Eloundou et al. (2023) employ a Generative Pre-trained Transformer (GPT-4) to define the potential exposure of tasks in the US to GPT.

A growing literature studies the impact of AI on labor markets and firm-level outcomes. Brynjolfsson et al. (2018a) analyze the potential effects of applying Machine Learning to 2.069 work activities, 18.156 tasks, and 964 occupations in the US. As most occupations have at least some tasks that are suitable for machine learning, they only find a weak correlation between an occupation's suitability for machine learning and its log median wage and total wage bill percentiles. Webb (2020) shows that 'male' jobs are much more exposed to AI than 'female' jobs, due to a lower exposition of tasks requiring more interpersonal skills. Contrary to robots and software, the exposure to AI is increasing in education and thus mostly impacts high-skilled tasks. This could lead to a reduction in wage inequality. Using an estimation based on robot (software) adoption, Webb (2020) finds a 9% (4%) decrease in the ratio of the 90th to the 10th percentile of wages. Felten et al. (2019) find that AI-affected occupations witness a slight increase in wages, but no significant change in employment. More generally, they observe a robust positive relationship between their AI impact measure and both employment and wages in higher-income occupations.

Acemoglu et al. (2022) build an establishment-level data set of AI activity based on the detailed skill requirements from online job-vacancies. They find that AI alters the task structure of jobs, as AI exposure is associated with a significant decline in some skills and the emergence of new skills in job postings. Some human-performed tasks are replaced by AI while newly generated tasks raise the demand for new skills. They further observe significant decreases in hiring between 2014 and 2018, coinciding with the period of increased AI activity. At the establishment-level, however, they do not find significant impacts on employment in industries with greater AI exposure, nor employment or wage effects in occupations that are less exposed to AI. Relying on two different measures of AI exposure and EU-LFS data, Albanesi et al. (2023) study the link between AI, employment shares and relative wages by occupations in 16 European countries for the period 2011-2019. Regardless of the proxy used, they find a positive correlation between AI-enabled automation and changes in employment shares, with this effect being driven solely by young and high-skilled workers. This positive impact is consistent across countries, with only a few exceptions, although the magnitude of the estimates varies considerably. The authors posit that this variation may reflect different structural characteristics, such as the rate of technology diffusion, the educational structure of the population, or policy environments such as employment protection laws. The effects on wages are generally not statistically significant. Additionally, the authors do not find a statistically significant impact of software exposure for Europe as a whole, but they do observe a significant negative effect in a subset of countries.

The latest advancements in AI include generative AI built on new large language models (LLMs), which have the potential to innovate and create new content. ChatGPT, an AI chatbot released in November 2022, is the most well-known example. However, its impact on employment is still in the early stages (Felten et al., 2023, Gmyrek et al., 2023). Without accounting for new jobs that will be created, Gmyrek et al. (2023) estimate that generative AI will both have an automation and an augmentation (i.e. automated tasks liberate time to dedicated to other work) effect of employment. In high income countries, they estimate that 5.5% of jobs can be automated whereas augmentation could affect 13.4% of employment. Accounting for anticipated advancements in GPT-powered software, Eloundou et al. (2023) estimate that about 19% of jobs could have at least 50% of their tasks exposed to GPTs. These advancements in AI are so recent that the detailed data needed for our framework is not yet available. However, the overall effect that automation has on labor markets is complex and strongly depends on sectoral, occupational and local contexts. The value added of our approach is that it allows for sector and occupation-specific shocks that heterogeneously affect the distribution of returns to labor and generate a distributive effects across job types.

2.4 Projections of the Impact of Digital Transformation

Projection exercises on the production and distributional impacts of robotization and automation have mainly been produced by consultancies (e.g. PWC, McKinsey Global Institute or Roland Berger) or international agencies (e.g. Cedefop and Eurofound, 2018) and have received little attention in the academic literature.

Regarding robotization, a report by the consultant firm Berger (2016) covering the United States, Japan, China, South Korea, Brazil and Western Europe (France, Germany, Italy, Spain, United Kingdom), provides a forecast for the period from 2015 to 2035. Their methodology is based on returns on capital employed and they focus on Industry 4.0 robots (including virtual factories, automated flows, smart machines, predictive maintenance, and the cyber-production system). They predict that a 50% adoption rate by 2035 will result in a 33% reduction of jobs in the manufacturing sector (affecting 8.3 million out of the 25 million current workers), while generating approximately 10 million new jobs (3 million in manufacturing and 7 million in new service activities).

Following a report by McKinsey (Manyika et al., 2017), nearly half of all work activities worldwide could be automated using existing technology. However, less than 5% of occupations can be entirely automated, while about 60% of occupations possess at least 30% of tasks that are automatable. These technically automatable activities potentially affect 1.2 billion workers in the world, with China, India, Japan, and the United States together accounting for over half of them. Under different automation adoption scenarios, the authors conclude that automation has the potential to increase global productivity by 0.8–1.4% annually over the course of decades. In another recent report by the McKinsey Global Institute (Smit et al., 2020), the midpoint scenario of the evolution of the European labor market predicts that 22 percent of current labor market activities (equivalent to 53 million jobs) could be automated by 2030. In particular, the authors predict that technology will automate 20 percent of current activities which may require 94 million workers to be retrained and 21 million workers to change occupations by 2030.

The H2020 project Technequality has produced several reports on future automation scenarios for Europe, at the heart of which lie different trajectories for the penetration of automation in industries and occupations. In Heald et al. (2020), the authors use the Cedefop Skills Forecast model 2018 that allows to project future trends in employment by industry sector and occupational groups. Their scenarios postulate an automation risk (low, mid, high), a full technology adoption date (by 2035, 2055, 2075; which can be region-specific) and barriers to automation (no protection, employment protection, regional specific). Depending on the scenario, total job losses in Europe range from a few % to 43.8%. They further provide forecasts at the EU-27 country level, at the (NACE 1 digit) sector level and at the (ISCO 1 digit) occupation level.

3 Theoretical Framework

In this section, we develop a general equilibrium model of the European economy that is tailored for investigating the impact of automation on wage inequality, occupational mobility and migration. The advantages of four approach are based on several critical modeling decisions. First, labor markets are decomposed by regions and occupations, allowing for a detailed occupation-specific spatial analysis. We model 100 regional economies in Europe, corresponding to NUTS1 areas, and four occupations. Each of the four occupations faces its own regional level of demand and supply, which determine prices of occupation-specific skills. Second, individuals are characterized by continuously distributed multidimensional skills that represent regional supplies of four market skills (relevant in four distinct occupations) and one non-market skill (representing preferences for inactivity). Third, firms are continuously heterogeneous and operate in one of eight aggregated sectors. Given the level of technology and prices, firms decide about the optimal employment of production factors and their allocation across tasks. Fourth, people spend their income on consumption of sector-specific goods that are traded across all European regions. Finally, each individual sorts into their income-maximizing occupation, and chooses the region where their utility is maximized. In particular, every shock in the economy generates new job switchers and migrants, who generate occupational and spatial equilibrium forces in equalizing skill supply to changed demand for skills.

In the following sections, we provide a detailed description of each module of our theoretical model, including the production technology, individual consumption decisions, firms' decision processes, labor market design, and individuals' migration decisions.

3.1 Producers' Perspective

Each firm employs capital and labor as its primary production inputs. The production technology differs across sectors and regions in terms of factor intensity, relative productivities, and factor prices. The latter are driven by the available supply of capital and workers' skills. We assume that physical capital exists in two distinct forms: structures and automation capital. The former group includes dwellings, vehicles, and other non-ICT factors, which are imperfect substitutes for labor tasks. The latter category comprises ICT capital, including hardware and software, which we consider to be a perfect substitute for workers performing labor tasks. As a result, the production function takes the form of a constant elasticity of substitution (CES), with structures and perfectly substitutable labor and automation as the two aggregated inputs. Within each sector, the production process requires firms to complete a specific set of occupational tasks. These tasks are performed by workers who possess occupation-specific skills, which they apply upon entering a particular occupation. Workers exhibit heterogeneous skills both across different occupations, each characterized by distinct skill sets, and within occupations themselves. This dual-tier heterogeneity allows us to aggregate all workers into a multidimensional continuous distribution, summarizing the supply of skills within a regional labor market. Based on the available skill supply, firms hire workers to fulfill occupation-specific tasks, which leads to equilibrium wage rates for each occupational skill type. By assyumption, the structure of occupation-specific tasks within the sectoral labor composite is predetermined, requiring a predefined set of basic inputs for production. We further assume that the aggregated input of tasks follows a Cobb-Douglas function, which implies complementarity across all occupational inputs. Specifically, all relevant tasks must be fulfilled to produce a unit of value added, and the marginal product of each occupation tends to infinity when the supply of skills assigned to that occupation approach zero.

We further assume that workers with different levels of education are capable of performing all tasks. As a result, the total supply of workers active in each occupation can be broken down into the sum of less-educated and college-educated workers. However, individuals with different levels of education possess different quantities of occupation-specific skills, giving rise to distinct comparative advantages across tasks. Consequently, low- and high-educated workers are imperfect substitutes within the production function, as they represent opposite ends of the skills distribution and are assigned to different tiers of occupation-specific tasks. Similarly, in the final labor decomposition, native workers and immigrant workers of both education types are also treated as imperfect substitutes due to their divergent characteristics and qualifications. Hence, within the framework of the task-based production function, they exhibit disparities in both skill supplies and wage rates.

We assume that there are no barriers restricting the mobility of workers across sectors within the same region and occupation. Therefore, by design, the remunerations for performing occupation-specific tasks within sectors are equal for workers belonging to the same education and origin group.

3.2 Labor Market

The labor market is composed of workers who face the demand for their occupation-specific skills set by firms operating within sectors and regions. Our approach towards formalizing these interactions builds upon the model developed by Roy (1951), Heckman and Sedlacek (1985), and Borjas (1987). Recalling the double heterogeneity of workers, we assume that in each regional labor market, the natives are characterized by a continuous distribution of multidimensional skills. Each individual possesses a specific bundle of market skills that they utilize in occupation-specific jobs, along with one non-market skill that represents their preference for inactivity. This discrete set of distinct occupational skills forms the first tier of labor heterogeneity. Then, workers exhibit heterogeneity in their skill endowments, and we assume that the logarithms of these endowments follow a continuous normal distribution within each region-specific worker population. The key feature of this model boils down to each individual selecting a single occupation in which they are active. This choice is driven by demand factors (the market returns to different skills) and by supply factors (individual endowments of discrete skills). Each individual aims to maximize their gains from supplying occupation-specific skills, which leads to occupational sorting based on workers' comparative advantage in one of the occupation-specific tasks.

In the absence of workers' sorting, the wage distributions resulting from the distribution of workers' skills would follow a log-normal pattern. However, when workers choose only one occupation according to their comparative advantage, the subset of individuals who select a specific occupation becomes non-random within the overall population. This self-selection bias impacts all moments of the observed wage distributions after workers' sorting occurs. In mathematical terms, individuals optimize their wage maximization program across all occupational job types, considering their individual skill endowments and the market prices for skills. Consequently, the post-sorting log wage distributions across occupations can be expressed as a normal distribution conditioned on a set of other (yet necessarily correlated) normal distributions. This set of conditions defines a Unified Skew-Normal distribution (abbreviated as SUN), which has been developed and analyzed by Arellano-Valle and Azzalini (2006), Azzalini (2005). This SUN distribution fully characterizes the post-sorting wage distributions across occupations and regions.

3.3 Consumers' Perspective

Each individual allocates their earned labor income to purchase sector-specific goods that are produced across all regions. When making their optimal consumption choices, individuals take into account the triple heterogeneity of consumption goods. This heterogeneity arises from the specificity of sectors and regions, as well as the differentiation of firms within sectors. To ensure tractability, we divide the consumption problem into outer and inner decisions.

First, individuals determine their sectoral spending by maximizing the utility from aggregated consumption. They select the optimal expenditure shares given market prices of goods, and preferences for sector-specific goods. We implicitly assume that individuals residing in a given region share identical consumption preferences for all good types. Additionally, we assume a common elasticity of substitution between sector-specific goods, which enables us to summarize the outer utility as a CES function. Finally, individuals are constrained by their budget condition, which equalizes consumption expenditures with income. The solution of this program yields sector-specific demands, and determines the level of sectoral prices.

Upon solving the outer utility maximization problem, consumers proceed to determine the consumption structure within each sector. Within sectors, goods exhibit heterogeneity based on their region of origin and the firms that produce them. Consequently, the inner utility maximization problem reduces to selecting the consumption structure within each region-sector pair, given sectoral prices and demands for sectoral goods determined in the previous step. The sectoral goods from various origins exhibit imperfect substitution, thus the inner utility is characterized by a constant elasticity of substitution which takes a higher value than the elasticity within the outer utility. Note also that importing one unit of a sector-specific good from a different region requires the payment of an iceberg trade cost that is sector- as well as destination-origin-specific.

The combination of the solutions to the inner and the outer utility maximization problems, allows us to formulate a standard definition of the equilibrium on the goods' market that imposes equalization of the total supply of goods produced in a given sector of a given region to the demand for those good.

3.4 Firms

Similar to the framework developed in Melitz (2003), firms operating in a given region are subject to a homogeneous, sector-specific fixed cost of production. However, firms differentiate themselves based on their variable costs of production, which are indicative of their productivity. Due to their local monopoly power, firms have the ability to internalize the demand for their products and determine the optimal price, which is set as a constant markup over the marginal cost of production. The latter is a function of factor costs (labor, structures and automation capital), firm-specific productivity, and the elasticity of substitution across goods within a region-sector basket.

There is an infinite pool of potential entrepreneurs, who are required to pay an entry cost in order to draw their productivity level from a given distribution. Firms, encouraged by the perspective of positive profits, pay the fixed cost of entry to discover their productivity level, and stay active on the market as long as their productivity level is high enough to generate positive operational profit (the free entry condition). However, the expected net profit also includes the sunk cost, and no firm would choose to enter the market as long as expected net profits are negative (the zero expected profit condition).

While the free entry condition leads to a natural cutoff point on the productivity level that divides the firms that paid the entry cost into leavers and stayers, the zero profit condition sets the total mass of firms within the region-sector-specific cell. These two conditions jointly determine the equilibrium market size of firms.

We assume that within sector-region distributions of firms' productivities are Pareto with a determined minimal level of productivity. This enables us to compute the distributions of firms' characteristics conditional on staying on the market, and aggregate them into sector-region-specific averages that determine expected revenues, operational profits and net profits.

3.5 Migration

Native workers can respond to labor market shocks by moving across regions. The worker's utility function in each region is a sum of three elements. First, an objective welfare measure in the form of the log of the expected real wages attainable for everyone active in a specific occupation in a given region. Second, a subjective taste shock described with a random variable that incorporates idiosyncratic preferences of living in specific regions. The third element of workers' utility applies to migrants, and represents a utility cost of moving between regions. These costs are education-specific, and include both measurable and non-measurable factors that prevent free mobility (e.g. language barriers, distance costs, as well as the attachment to the local community or costs of leaving family and friends). Overall, every individual solves their spatial utility maximization problem by selecting their preferred place of residence given economic conditions, migration costs and the realizations of individual preference shocks. Assuming that these shocks take the specific functional form of an extreme value type one probability distribution (also known as Gumbel distribution), the solution to the spatial utility maximization problem has a simple analytical form. Following McFadden (1973), the probability of moving to any destination region relative to staying in the region of origin equals the ratio of real wage rates in the destination and origin multiplied by the residual of migration costs between origin and destination.

When a shock hits a regional labor market, labor supplies of native workers (in origin and destination regions of the same country) and within-EU immigrants (in destination regions of different countries) adjust. The equilibrium condition imposes that the marginal individual is indifferent between staying in their current place of residence and moving to any other region, which is equivalent to saying that expected utilities equalize across all regions. Formally, the labor market equilibrium can be expressed as an equalization of demand and supply of efficient labor composites across all occupation-sector cells in a specific region. The latter is possible due to occupational sorting of workers within sectors and regional migration of workers within a specific occupation.

3.6 General Equilibrium

The general equilibrium is a straightforward conjunction of goods', firms', and labor market equilibria, completed with a macro income consistency criterion. In formal terms, the economy is in a general equilibrium if and only if all markets clear and total expenditure in a given region equals total income earned by workers in that region.

4 Calibration and Data

In this section, we discuss the data used to calibrate the model parameters to represent the European economy in 2018 and beyond. Our theoretical framework allows us to analyze changes in worker location and wage distributions across labor markets defined by a spatial, occupational, and educational dimension:

- **Regions**: Our baseline calibration decomposes the European economy into 100 geographical regions corresponding to NUTS1 areas within 31 European countries. The regions, their codes as well as the countries they belong to are provided in Appendix Table A7.

- **Occupations**: We define four market occupation aggregates and a non-market occupation referred to as inactivity. Our aggregates include managerial, professional, service and elementary occupations, which can be thought of as sorted according to a decreasing complexity of tasks. Table 1 illustrates the assignment of occupations based on the ISCO 1-digit classification to our five categories.

- **Sectors**: In order to exploit as much detail as possible while also limiting the need to impute missing values from the available data, we use eight aggregated production sectors. These sectors can be broadly defined as follows: manufacturing, constructions, sales, transportation, low-skilled services, financial services, professional services, and public services. Table 1 details the assignment of sectors based on the NACE 1-digit classification to our eight categories.

- **Worker characteristics**: Workers belong to one of two education groups: less-educated and college-educated. Additionally, within each education group, we differentiate workers by origin, including natives, EU-immigrants and non-EU immigrants. Thus, workers belong to one of six origin-education groups, which are imperfect substitutes within each occupation.

4.1 Data Sources

Labor Market The main data sources for the numerical exercise are derived from Eurostat. First, we use the Labor Force Survey (LFS) to calculate the supply of 24 types of workers across all NUTS1 geographical regions. These worker types are defined by the combination of three observable dimensions: origin (native, EU immigrants, non-EU

Table 1: The Structure of the Economy: Occupations and Sectors

Occ. Number	Occ. Code	ISCO1D	Sec. Number	Sec. Code	NACE1D
1	MAN	1	1	MANU	A, B, C, D, E
2	PRO	2, 3	2	CONS	F
3	SER	4, 5	3	SALE	G
4	ELE	6, 7, 8, 9	4	TRAN	H
5	INA	0*	5	LSER	I, N, R, S
			6	FSER	K, L
			7	PSER	J, M
			8	PUBL	O, P, Q

Notes: Occupations 1: Managers; 2: Professionals, 3: Clerical, Service and Sale Workers, 4: Less-Skilled and Elementary Occ., 5: Inactive on Labor Market. Sectors: 1: Manufacturing, 2: Construction, 3: Wholesale and Retail Trade, 4: Transport and Storage, 5: Low-Skilled Services, 6: Financial Services, 7: Professional Services, 8: Public Administration, Education, and Health. Source: ISCO, NACE (Eurostat).

immigrants), education level (non-college and college educated), and market occupation (four aggregates).

In order to estimate the continuous distributions of worker skills, we use an algorithm which aims at minimizing distances between empirical (i.e. observed in the data) and model wage distributions. Using the Structure of Earnings Survey (SES), we construct non-parametric kernel estimates of occupational wage distributions for native workers of all education and occupation types in 100 regions.[1] These densities serve as references for estimating the parameters of the labor market module. Additionally, we compute average wage rates by region and occupation, and using sectoral wage bills and employment, we compute shares of occupational inputs across sectors and regions.

Using the European Union Statistics on Income and Living Conditions (EU-SILC) database, we calculate the differentials in location and spread of wage distributions between natives, EU immigrants and non-EU immigrants for all regions and occupations. Finally, using the aggregated LFS data from Eurostat, we determine region-specific inactivity rates.

Migration The objective of this step is to obtain numbers of movers across all European regions by education level, which are not readily available from existing data sources.

First, in stage 1 of our imputation, we collect data on migration across all European countries from Eurostat (based on census 2010) and supplement it with OECD DIOC database for 2010. Then, using the DIOC database, we divide total migrants into two education groups: below college and college-educated. Next, we collect the data on country-pair-specific common border ($Cont$), language ($Lang$), and Schengen area dummies (EU) from CEPII (Head and Mayer, 2014). We also compute log-distances across all countries ($logDist$), and set country-specific wages by education using the data from

[1] The empirical distributions are censored at 1st and 99th percentile to eliminate outliers; we also set the smoothing parameter for the Epanechnikov kernel estimation at 2.

Eurostat's SES. We then estimate the following regression:

$$Migr_{ij}^e = \beta_1 \ln \frac{w_j^e}{w_i^e} + \beta_2 logDist_{ij} + \beta_3 Cont_{ij} + \beta_4 Lang_{ij} + \beta_5 EU_i + FE(i) + FE(j) + \beta_0, \quad (1)$$

where $Migr_{ij}^e$ represents the probability that an individual with education level $e = L, H$ moves from country i to country j, divided by the probability of staying in i. $FE(\cdot)$ represent origin and destination fixed effects. The estimated parameters are reported in Table A1 and are used to impute all international movements across NUTS1 regions.

Then, in stage 2, we apply a similar procedure to compute migration movements within countries. The LFS allows us to summarize recent flows of native workers across NUTS1 regions within their countries of origin. We generate country-specific matrices that aggregate the number of internal movers by education level. With this data, supplemented by the data on regional wage ratios, distances and contiguity, we estimate:

$$Migr_{cij}^e = \beta_1 \ln \frac{w_j^e}{w_i^e} + \beta_2 logDist_{ij} + \beta_3 Cont_{ij} + FE(c) + FE(i) + \beta_0, \quad (2)$$

where $Migr_{cij}^e$ represents the probability that an individual with education level $e = L, H$ moves from region i to region j within country c, divided by the probability of staying in region i. The estimated parameters are reported in Table A2. We use these parameters to impute all within-country movements across NUTS1 regions.

Finally, Stage 3 joins the two imputed data sets and enables to generate the full matrix of migration across 100 European regions for two education groups.

Regional Trade by Sectors We use a two-step approach in computing trade matrices by region pairs and eight aggregated sectors. Stage 1: we generate country-pair-specific flows of value added by sectors using the Trade in Value Added (TiVA) dataset by the OECD. Stage 2: we use the EU regional trade database created by JRC and PBL (Thissen et al., 2015), that publishes data by NUTS2 regions and 59 product categories. We aggregate this data to NUTS1 and eight sectors, and we use it to decompose the country-pair flows from TiVA into region-pair flows. This stage provides unbalanced sector-specific trade matrices across all 100 NUTS1 regions in Europe and the rest of the world. Finally, in stage 3: we unify the matrices in a way that (i) sums of produced value added (consumed locally or exported) coincide with regional GDP measures, (ii) sums over all regions of production by sector coincide with sums over all regions of consumption by sector, (iii) total production in each region coincides with total consumption in each region.

Macro Indicators The final data inputs for the calibration procedure are the macroeconomic data for European economies. From Eurostat, we collect data on stocks of labor and capital by sectors (including structures and automation capital), as well as the 2018 sectoral GDP values followed by its decomposition into employees compensation, capital compensations, and corporate profits by eight aggregated sectors. This is complemented with the data on price levels (PPP indexes), interest rates and firm demography (stocks of active firms, survival and exit rates).

Exogenous Parameters To complete the reference data input for the model, we have to set values of several external parameters. Two of them are the elasticities of substitution between sector-specific goods and between goods within each sector. Following a large body of literature in industrial organization and trade, e.g Simonovska and Waugh (2014), we take the values of 3 and 4 respectively. Then, we assume that the minimal productivity level in each sector is normalized to one. In order to define sector-specific elasticities of substitution between capital and labor, we refer to Chirinko and Mallick (2017) and set the vector of $\sigma_s = (0.6, 0.41, 0.74, 0.36, 0.63, 1.16, 0.24, 0.27)$. Finally, following Ottaviano and Peri (2012), we set the elasticities of substitution between education and origin groups to 2 and 20, respectively.

4.2 Calibration of Projections

In this section, we explain the procedure of generating projection scenarios for the European economies. In our model, automation affects the structure of the economy through different channels. First, it changes the relative productivity of capital and labor in the aggregated production function. Second, automation affects the relative importance of occupations in generating value added. Third, automation is reflected in a direct change in the supply of automation capital that perfectly substitutes labor. Finally, it affects the pattern of capital accumulation in terms of structures. Below, we discuss each of these dimensions separately and provide estimates of projected trajectories of relevant parameters. Importantly, in addition to automation scenarios, we also project other key variables that define the state of the European economy in the future: population, education shares, and capital stocks, which evolve in the reference as well as in the counterfactual scenarios.

The Reference Scenario Our aim is to provide reasonable projections for the future state of the European economy in the horizon of 15 years. Thus, all the simulation results refer to the new equilibrium of the European economy in 2033, as the core of our model is calibrated using the data for 2018. We therefore start by describing the reference projection for the year 2033, which serves as a no-automation baseline and assumes no change in automation patterns between 2018 and 2033.

To built our reference scenario, we project trends in two macroeconomic variables. First, we determine the future working-age population counts using the projections of the Wittgenstein Centre for Demography and Global Human Capital (2023). Column one in Table 2 summarizes the changes in total workforce across European countries. Most figures are significantly below zero, which indicates that the ongoing ageing and low fertility rates of younger generations will significantly reduce the labor component of the production capacity with respect to 2018 values. In particular, population is only expected to grow in France, Iceland, Ireland, Luxembourg, Norway and Sweden, whereas it will decrease between 1% in Denmark to 14.6% in Lithuania.

The second macroeconomic variable projected in the reference scenario is the future stock of structures (non-automation capital) in all countries. Using the sector- and country-specific trends in Total Assets as well as ICT Equipment over 2001-2018, we construct the contemporary and future stocks of Structures as differences between these two variables. According to column two in Table 2, only Cyprus and Portugal show stagnation in fixed capital accumulation, while in many European economies, we extrapolate strong increases in structures that range up to 30-40% over the period of 15 years.

Education Scenarios The Wittgenstein Centre for Demography and Global Human Capital (2023) publish projections of the evolution of educational attainment of the workforce (see Lutz et al., 2018). This database allows us to determine country-specific education scenarios, labelled E1, E2, E3 for low, medium and high acquisition of higher education. We use the Wittgenstein Center population projections by education level for three Shared Socioeconomic Pathways (SSPs) that correspond to a slow (SSP3), medium (SSP2) and fast (SSP1) evolution of college-education shares (columns 3-5 in Table 2). In many countries, the SSP scenarios project significantly different relative changes in education shares, which correspond to various potentials of socio-economic development assumed in these SSPs. For example, the medium scenario predicts an increase in the share of highly educated individuals ranging between 16.8% (in Greece) and 47% (in Italy).

Automation Scenarios Three model objects are affected by automation in our model: the relative productivity of labor compared to capital, the relative inputs of occupations across sectors, and the stock of automation capital. To form projections over the period of 15 years, we identify key relationships between core macroeconomic variables as follows: (1) We identify the relationship between the intensity of automation and the labor share using data on compensation to value added (the left hand side variable) and the share of IT and software capital in total capital (right hand side variable). The data is collected from Eurostat and is aggregated into eight model sectors for each of the 31 European countries over the period of 2001 - 2018. We run separate regressions for each of the eight

Table 2: Definition of the Reference Scenario for 2033

Variables:	**Δ Population**	**Δ Structures**	**Δ Share of College-Edu**		
Scenarios:	All	All	E1	E2	E3
AT	-5,5%	20,7%	25,8%	34,4%	40,6%
BE	-2,2%	18,7%	18,0%	32,0%	35,0%
BG	-13,0%	20,7%	11,5%	22,6%	21,1%
CH	-2,6%	21,5%	21,8%	33,3%	38,0%
CY*	-5,0%	-5,0%	18,5%	30,0%	32,4%
CZ	-4,7%	23,6%	15,6%	26,6%	27,2%
DE	-9,0%	15,8%	8,0%	17,9%	20,7%
DK	-1,0%	8,8%	12,0%	29,1%	31,3%
EE	-5,5%	37,9%	9,4%	17,3%	20,9%
EL	-4,7%	20,7%	10,0%	16,8%	17,9%
ES	-4,2%	18,0%	15,0%	25,8%	28,8%
FI	-4,7%	18,9%	23,3%	44,6%	43,2%
FR	0,3%	2,4%	23,5%	35,8%	37,4%
HR	-9,6%	9,7%	22,8%	38,6%	40,0%
HU	-5,9%	15,8%	18,0%	24,0%	24,5%
IE	3,6%	46,3%	22,9%	27,3%	28,4%
IS	0,9%	3,0%	9,9%	27,8%	35,2%
IT	-8,2%	15,3%	26,8%	47,0%	53,6%
LT	-14,6%	26,5%	17,7%	24,3%	24,3%
LU	4,3%	33,5%	20,4%	29,2%	33,6%
LV	-9,8%	9,8%	16,8%	26,0%	29,8%
MT*	-7,8%	15,5%	18,5%	30,0%	32,4%
NL	-3,3%	15,8%	22,1%	38,3%	42,2%
NO	1,9%	32,7%	14,7%	25,5%	30,9%
PL	-8,8%	26,7%	31,3%	43,9%	43,1%
PT	-9,6%	-2,1%	20,4%	30,6%	36,7%
RO	-9,1%	20,7%	27,6%	38,3%	41,1%
SE	1,6%	27,6%	20,6%	29,0%	31,7%
SI	-6,2%	19,9%	27,0%	40,9%	40,1%
SK	-8,1%	20,6%	19,8%	31,5%	31,5%
UK	-1,7%	13,1%	16,4%	25,9%	30,2%

Notes: Column 1, Δ Population, shows relative deviations in native workforce in 2033 compared to 2018. Column 2, Δ Structures, presents relative deviations in the value of accumulated non-automation capital in 2033 compared to 2018. Columns 3-5, Δ Share of College-Edu, summarize relative changes in the share of high-educated workers in scenarios E1 (low education, SSP3), E2 (medium education, SSP2), and E3 (high education, SSP1).

sectors adding country and year fixed effects:

$$\frac{Comp_{cst}}{VA_{cst}} = \alpha + \beta_1(s)\frac{(Cap\_IT_{cst} + Cap\_Soft_{cst})}{Cap\_Tot_{cst}} + \gamma_c + \gamma_t + \epsilon_{cst}. \quad (3)$$

The coefficient of interest, $\beta_1(s)$, indicates how sector-specific labor shares evolve with the automation-related share of capital in sector s, see Table A3.

(2) In addition, we also want to account for the impact of robotization on the evolution of labor shares in production. To do so, we assess the average relationship between the number of robots and the share of employee compensation in total value added for a subset of countries and sectors MANU, CONS, and PUBL, for which the data on installed

industrial robots is available from the International Federation of Robotics (IFR, 2020).[2]

We add the stock of industrial robots to equation (3) and regress it for all sectors simultaneously. This allows us to obtain the coefficient of change in labor share due to robots, see Table A4.

(3) Next, after imputing missing data points (for details see Section A in the appendix), we compute country-sector specific time trends in the share of computer hardware and software within the total capital stock, as well as the trends in the total number of industrial robots:

$$\frac{(Cap\_IT_{cst} + Cap\_Soft_{cst})}{Cap\_Tot_{cst}} = \alpha + \delta_1(s,c)t, \tag{4}$$

$$Rob_{cst} = \alpha + \delta_2(s,c)t. \tag{5}$$

(4) Using the estimates from the equations detailed above, we calculate the change in the country-sector labor share for our medium automation scenario. These changes, caused solely by future trends in automation technologies, are summarized in Table 3. For the purpose of simulation convergence, we impose a 10% lower and upper bound on the change in projected labor shares in 2033. According to our estimates, financial services is the only sector with a positive (unweighted) average change in labor share. Sectors that are the most exposed to automation-driven loss in labor income are manufacturing, construction and transport. Finally, the changes in labor shares serve as key inputs for computing the deviations in production function parameters that represent the relative productivity of labor and automation capital versus structures capital. These deviations are then used for our medium automation scenario, labelled by A2. We take a -50% (deceleration) in scenario A1 (slow automation) and +50% (acceleration) in scenario A3 (fast automation).

(5) Regarding changes of occupational inputs in sectoral production functions, we use microdata on occupation-sector shares of income from the Structure of Earnings Survey by Eurostat. We estimate time trends in these relative income structures in a panel of all European countries over 2010, 2014, and 2018, and extrapolate them for the year 2033 using a country- and sector-fixed effect regression, see Table A5 for a summary of estimation results. Table 4 summarizes the changes in occupational inputs across all eight aggregated sectors in the medium automation scenario A2 (as before, the numbers for scenarios A1 and A3 equal -50% and +50% of changes reported in the A2 scenario). Note that these numbers are changes in structures, therefore they sum to zero within each row. Clearly, in all sectors automation increases the demand for professional occupations, while it reduces the input share of managerial occupations. For service and elementary

[2] An industrial robot is defined as “An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications” (IFR, 2020).

Table 3: Projected Changes in Labor Shares due to Automation and Robotization in the Reference Scenario

	MANU	CONS	SALE	TRAN	LSER	FSER	PSER	PUBL
AT	-5,6%	-6,6%	-4,8%	-9,4%	-2,7%	0,8%	0,0%	-4,5%
BE	-4,2%	-3,6%	-1,6%	-1,9%	-2,6%	0,1%	-1,3%	-1,3%
BG	-1,3%	-2,8%	-7,4%	-3,8%	-10,0%	3,5%	-0,5%	-2,4%
CH	-3,1%	-6,5%	-4,8%	-9,4%	-2,7%	0,8%	0,0%	-4,1%
CY	-6,4%	-10,0%	-3,4%	0,0%	-10,0%	3,4%	0,6%	-7,6%
CZ	-6,6%	-8,1%	-2,4%	-3,5%	-2,1%	0,9%	-3,0%	-1,0%
DE	-6,0%	-4,6%	-1,3%	-1,6%	-0,6%	0,1%	-1,2%	-0,5%
DK	-2,6%	-4,9%	-2,3%	-1,1%	-0,7%	0,5%	-2,5%	-1,8%
EE	-1,4%	-2,3%	-1,6%	-4,8%	-3,3%	0,6%	-4,2%	-2,8%
EL	-1,0%	0,3%	-1,2%	-0,6%	-3,9%	0,6%	-0,9%	-0,7%
ES	-5,6%	0,0%	-1,2%	-6,1%	-3,4%	0,2%	-2,7%	-1,8%
FI	-2,3%	-7,0%	-4,5%	-7,3%	-2,6%	0,3%	-0,6%	-0,8%
FR	-7,2%	-10,0%	-5,1%	-9,1%	-5,3%	0,8%	-2,5%	-2,1%
HR	-2,5%	-1,4%	-1,6%	-5,2%	-6,5%	1,0%	0,0%	-4,5%
HU	-2,7%	-3,5%	-0,9%	-3,6%	-7,5%	0,7%	-1,5%	-1,2%
IE	-0,9%	-1,4%	-2,6%	-2,5%	-1,4%	0,5%	-1,1%	-1,8%
IS	1,2%	0,0%	-1,6%	-3,8%	-10,0%	1,2%	0,3%	2,3%
IT	-5,6%	-7,3%	-1,5%	-1,7%	-2,3%	0,1%	-1,5%	-0,8%
LT	-3,5%	-9,0%	-4,4%	-7,1%	-6,7%	0,9%	-0,9%	-1,0%
LU	-0,3%	-5,3%	-1,4%	-2,3%	-1,2%	0,5%	-2,0%	-0,5%
LV	-0,5%	-0,8%	-1,2%	-10,0%	-2,3%	0,2%	-1,6%	-2,3%
MT	-7,1%	-1,1%	0,6%	-3,6%	-10,0%	5,5%	0,3%	-2,8%
NL	-4,7%	-10,0%	-5,5%	-6,7%	-2,0%	0,6%	-1,8%	-3,1%
NO	-0,3%	-7,1%	-3,5%	-6,5%	-2,7%	0,4%	-1,8%	-0,6%
PL	-5,0%	-7,1%	-3,7%	-5,2%	-5,0%	1,2%	-2,1%	-2,9%
PT	-2,0%	-2,9%	-2,7%	-4,5%	-2,0%	0,7%	-0,2%	-2,4%
RO	-1,5%	-1,1%	-2,8%	-7,9%	-4,0%	0,6%	-1,5%	-1,4%
SE	-3,3%	-1,8%	-2,0%	-2,5%	-1,7%	0,8%	-1,8%	-1,5%
SI	-1,5%	0,1%	-1,1%	-3,0%	-0,7%	0,3%	-1,4%	-0,6%
SK	-2,3%	-9,5%	-0,7%	-3,3%	-2,4%	0,1%	-1,4%	-1,6%
UK	-2,4%	-0,5%	-1,8%	-5,5%	-1,9%	0,5%	-2,2%	-1,6%
AVG	**-3,2%**	**-4,4%**	**-2,6%**	**-4,6%**	**-3,9%**	**0,9%**	**-1,3%**	**-1,9%**

Notes: All columns illustrate relative changes in labor shares across eight aggregated sectors and 31 countries (the last row summarizes the unweighted average across countries).

occupations the outcomes are mixed and dependent on the specificity of each sector.

Table 4: Changes in Occupational Inputs in the Reference Scenario

	MAN	PRO	SER	ELE
MANU	-1,0%	3,1%	0,0%	-2,1%
CONS	-0,5%	2,6%	2,9%	-4,9%
SALE	-2,0%	2,8%	1,2%	-2,0%
TRAN	-0,8%	0,8%	-5,3%	5,3%
LSER	-2,2%	0,1%	0,8%	1,2%
FSER	-1,2%	2,3%	-1,4%	0,3%
PSER	-1,7%	4,4%	-0,5%	-2,1%
PUBL	-0,7%	3,9%	-2,0%	-1,2%

Notes: All columns illustrate relative changes in occupational input shares across eight aggregated sectors. For each sector (row), the sum of changes in inputs across occupations (columns) equals zero.

(6) A direct implication of automation in our model is a rise in the stock of automation capital, which includes ICT equipment, software and databases. This type of capital is assumed to be perfectly substitutable with labor, and according to our analysis, has increased considerably in the last two decades. Using the updated EU-KLEMS dataset, compiled as part of the H2020 project UNTANGLED, we observe that in the period 2001-2018 across eight aggregated sectors and 31 European countries, the average (unweighted) growth rate of ICT capital was 5.7%. Additionally, over the same period, the relative productivity of automation capital versus labor increased visibly by on average 0.25% year over year, according to the EU-KLEMS data. While the former computations were done using a straightforward extrapolation of the ICT capital services index for all countries and sectors separately ($CAPICT\_QI$), the latter required to run the following regressions for all NACE 1-digit sectors:

$$\frac{VA\_ICT_{cst} + VA\_Soft_{cst}}{VA\_Lab_{cst}} : \frac{\Delta Cap\_ICT_{cst}}{\Delta Lab_{cst}} = \alpha + \delta_3(s)t + \gamma_c, \tag{6}$$

and aggregating them into eight sectors using the stock of ICT capital as weights, see Table A6 for details. Note that the left hand side includes the ratio of value added gained from ICT capital and labor (in p.p.), divided by the ratio of changes in stocks of ICT capital and labor (expressed in percent). This structure enables us to include the trend in the intensive margin of ICT productivity, controlling for the changes in the extensive margin (larger stock of capital versus labor). Overall, Table 5 presents the factors of change of automation capital across all countries and sectors in scenario A2 (+/- 50% deviations in A1 and A3 scenarios, respectively). The professional services sector dominates in terms of the average unweighted increase in ICT capital, while manufacturing and sales/trade sectors see the slowest projections of ICT implementations.

5 Projections: the Benchmark Scenario

In this section, we use our model to project the effects of automation on the European economy for 2033. In all our simulations, we use the parameters calibrated on the baseline year 2018 as described in Section 4.1, as well as projections for the population structure and capital stocks, detailed in Section 4.2. Our main (benchmark) simulation compares the reference scenario for 2033 (summarized in Table 2, assuming education E2) to a projection which accounts for three automation-related changes in the production functions at A2 levels: (i) the relative productivity of labor compared to capital (provided in Table 3), (ii) the relative inputs of occupations across sectors (provided in Table 4), and (iii) the stock of automation capital (provided in Table 5). The difference between this scenario and the reference allows us to dele into the geographical as well as occupation-sector specific impacts of automation-driven changes on different outcomes. In what follows, we

Table 5: Change in Automation Capital for the Benchmark Scenario A2 (expressed as growth factor)

	MANU	CONS	SALE	TRAN	LSER	FSER	PSER	PUBL
AT	2,64	2,39	2,36	2,87	2,29	3,01	2,47	2,54
BE	2,34	2,87	2,35	2,10	2,33	1,62	2,51	2,38
BG	2,10	2,32	2,97	2,15	2,34	3,01	4,07	1,97
CH	2,63	2,39	2,36	2,87	2,28	3,36	2,43	2,59
CY	2,65	3,09	2,12	1,10	2,39	2,89	3,06	2,40
CZ	2,62	3,34	2,80	2,75	2,63	2,90	3,42	2,21
DE	2,07	1,89	1,84	2,07	1,72	2,32	2,54	1,94
DK	2,31	2,55	2,11	1,67	1,80	2,64	2,68	2,20
EE	2,49	2,54	2,50	2,34	2,86	2,81	3,43	2,61
EL	1,84	0,92	1,88	2,55	2,10	3,08	1,87	2,13
ES	2,59	1,29	2,08	3,28	2,68	1,97	3,11	2,39
FI	2,09	2,56	2,09	1,83	2,33	2,74	2,87	2,25
FR	2,06	2,40	2,30	2,28	2,29	2,55	2,64	2,02
HR	1,92	1,51	1,66	2,24	2,56	2,40	2,32	2,28
HU	2,08	2,46	2,08	2,42	4,41	2,60	2,60	2,45
IE	2,37	1,24	2,25	2,61	4,05	2,74	3,23	2,51
IS	2,44	1,24	2,25	2,61	4,04	2,62	2,98	2,52
IT	2,04	2,27	1,96	1,82	2,15	1,57	2,12	1,91
LT	3,58	3,53	3,14	2,66	3,26	3,38	4,05	2,31
LU	2,05	2,78	2,62	2,85	2,56	1,94	4,17	2,61
LV	2,50	2,14	2,46	3,41	3,59	2,53	3,24	3,14
MT	2,82	2,19	1,09	1,99	3,81	3,23	2,77	2,27
NL	2,20	2,30	2,17	2,19	1,71	2,45	2,56	2,36
NO	1,66	2,90	1,95	1,98	1,93	2,95	2,59	2,11
PL	2,69	2,86	2,62	2,97	3,00	3,07	3,06	2,94
PT	2,25	1,81	2,12	1,88	2,02	2,18	2,38	2,05
RO	2,14	2,29	3,09	2,58	2,59	1,88	3,41	2,64
SE	1,71	2,90	1,95	1,98	1,93	2,86	2,59	2,09
SI	1,99	0,99	2,06	2,78	1,66	2,08	2,61	1,98
SK	2,20	4,32	2,33	2,28	3,26	1,53	2,20	2,57
UK	1,64	2,15	1,72	1,95	1,82	2,41	2,45	2,56
AVG	**2,28**	**2,34**	**2,24**	**2,36**	**2,59**	**2,56**	**2,85**	**2,35**

All columns illustrate growth factors in ICT (automation) capital across eight aggregated sectors and 31 countries (the last row summarizes the unweighted average across countries).

analyze the effects of automation on macroeconomic aggregates, production and labor across sectors, and labor and real wages of workers by education and occupation type.

5.1 Effects of Automation across Regions

To start with, we provide an overview of the spatial distribution of the macroeconomic effects caused by automation. Figure 1 illustrates changes in regional levels of nominal GDP, efficient labor, price indexes and net migration across European NUTS1 regions. Automation has a nearly uniformly positive impact on regional economies across Europe. Panel (a) provides relative deviations in nominal GDP induced by automation in the general equilibrium of our model. While a strong majority of regions benefit from automation, its effect is quite heterogeneous, both across and within countries. The Paris area, Austria, Switzerland, as well as Nordic regions belong to the main winners of automation, followed by the rest of France, the south of Germany, Benelux and Ireland. A positive but weaker impact is observed in the UK, southern and eastern European regions. Clearly, our benchmark simulation projects automation-driven divergence across Europe, as richer European regions benefit most from the projected trends, while poorer areas struggle to cope with the pace of implementation of new technologies.

The gains from automation are partially driven by the reallocation of workers across occupations and sectors that increases their efficient labor supply. Panel (b) illustrates changes in the size of the labor composite across NUTS1 regions. Most areas see an increase in their efficient workforce, as labor moves to jobs that are more labor-intensive and to growing sectors with a slower intensity of automation. These processes are highly visible in Belgium, Switzerland, Lithuania and Austria.

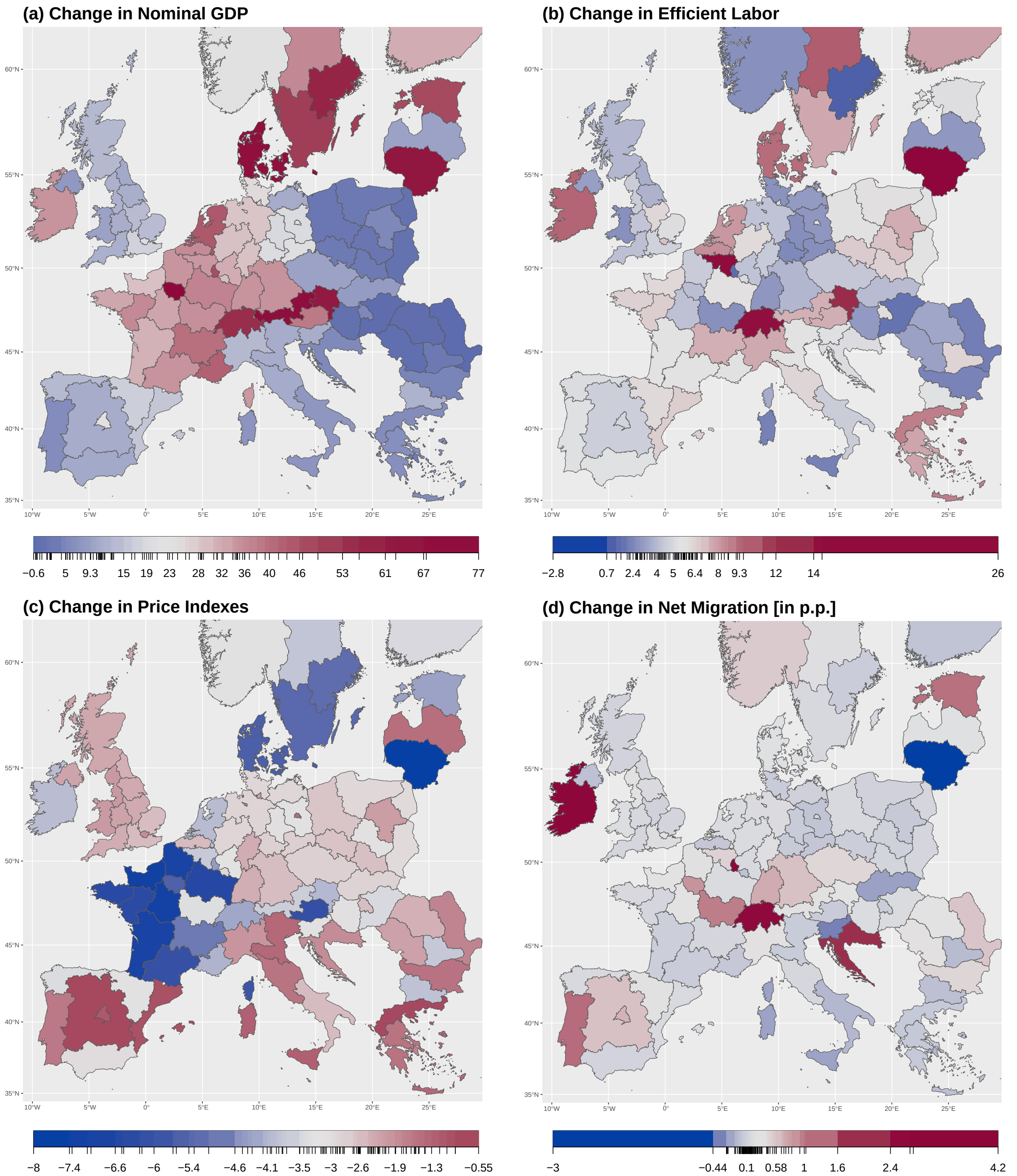
Another dimension through which automation benefits the European economy are price levels. Accelerated growth goes hand in hand with reduced prices, as depicted in Panel (c). We find the highest benefits in France, Nordic and Alpine countries, where prices fall by more than 5%, whereas southern and eastern Europe see price drops limited to 1-3%. More efficient and cheaper production processes allow to reduce marginal costs, which has a two-fold impact on the economy. First, lower costs increase firms' profits and attracts more producers into the market. This positive market size effect increases the mass of available consumption goods, which benefits consumers who exhibit a love for variety. In addition, it also generates an indirect negative impact on price indexes. The positive spillovers from this market size effect are reinforced by the direct reduction in prices which further improves the purchasing power of consumers.

As a result, regions with higher GDP per capita and lower prices tend to attract more intra-European immigrants. In Panel (d), we highlight changes in net immigration, measured as percentage points changes relative to the regional population. Ireland, Switzerland, Croatia, Luxembourg and Portugal are among the regions that attract the most new foreign workers while retaining their incumbent native population. In contrast, Lithuania experiences a significant drop in population, while for the majority of European regions we find no substantial changes in migration patterns due to automation.

5.2 Effects across Sectors and Occupations

Automation has a significantly distinct impact across economic sectors in Europe. The left panel of Figure 2 disentangles regional changes in GDP into effects across sectors. Manufacturing tends to be the key beneficiary of automation in most of Belgian and German regions. Professional and public services are dominating in France, Nordic and Alpine countries. Transportation experiences the highest growth in value added in eastern European countries and the UK. In contrast, construction and financial services tend to

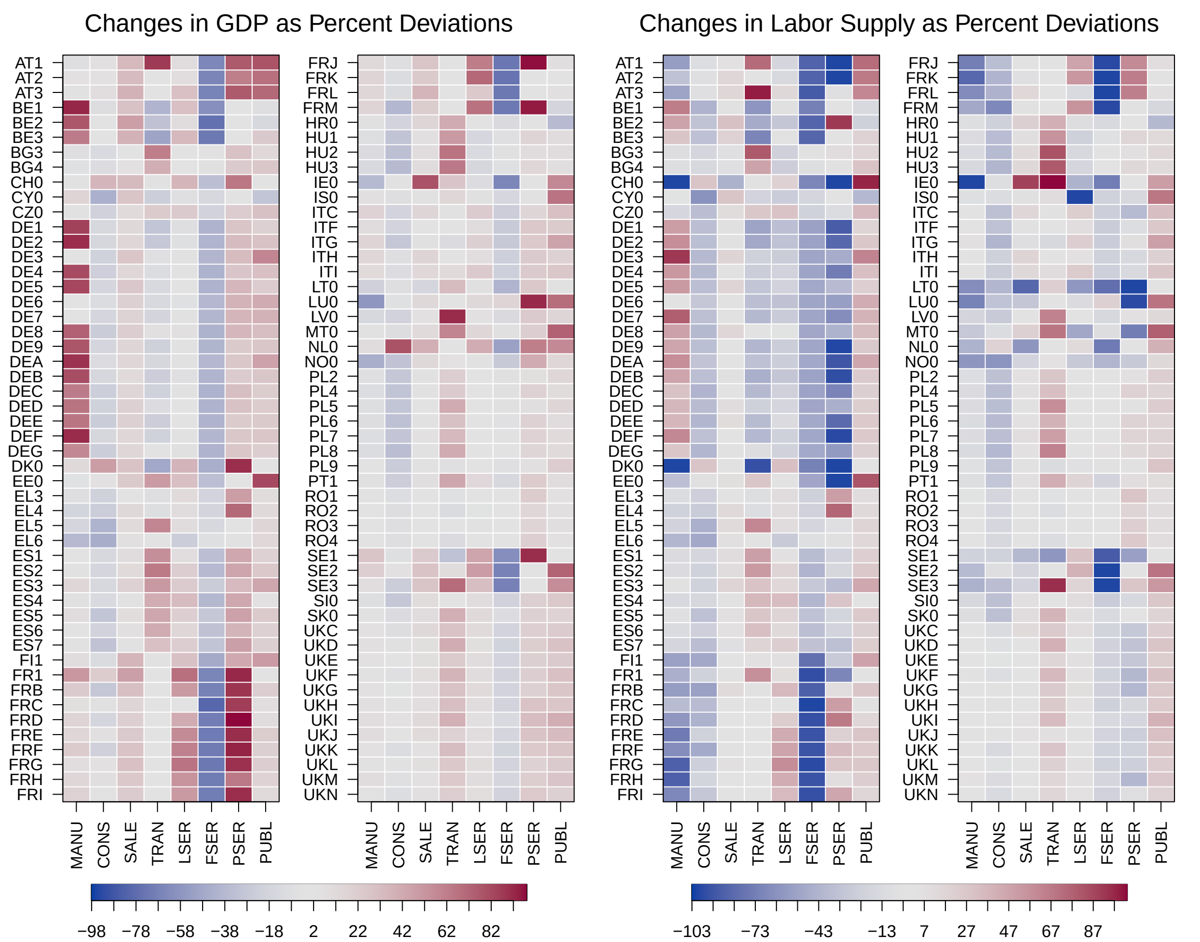
Figure 1: Effects of Robotization and Automation on GDP, Prices, Labor Composite and Net Migration in the Benchmark Scenario



Note: Panel (a) shows changes in regional GDP (in %); Panel (b) shows changes in regional efficient labor composite (in %); Panel (c) shows changes in regional price indexes (in %); and Panel (d) shows changes in the net immigration, calculated as the differences in stocks immigrants and emigrants relative to the native population in the region (in percentage points). All results include the difference between the A2 automation scenario, versus the reference scenario for 2033.

shrink in the majority of regions. While the former sector experiences outflows of workers to manufacturing and low-skilled services, finance attracts substantial investments in automation capital (due to high initial levels in 2018) but it generates few investments in structures. This fact, on the one hand, lowers wages for incumbents, and on the other hand displaces workers from many tasks in finance, which encourages them to move to professional and public services that use similar occupational inputs (see the right panel of Figure 2). Interestingly, public services is the only sector that consistently increases the efficient labor supply throughout European regions. Overall, European regions can be divided into manufacturing-dominant economies (namely Germany and Belgium), in which automation generates inflows of workers to production, and service-dominant economies (predominantly Spain, France, Poland), in which automation increases the efficient supply of workers across (mostly advanced) services.

Figure 2: Effects of Robotization and Automation on Sector-Specific Aggregates in the Benchmark Simulation



Note: Figure 2 details the change in nominal GDP (left panel) and efficient labor supply (right panel) by regions and sectors (in %). Sectors are denoted as: MANU: Manufacturing, CONS: Construction, SALE: Wholesale and Retail Trade, TRAN: Transport and Storage, LSER: Low-Skilled Services, FSER: Financial Services, PSER: Professional Services, PUBL: Public Administration, Education, and Health. For the region codes, please refer to Table A7. All results display the difference between the A2 automation scenario, versus the reference scenario for 2033. Source: authors' calculations.

From the workers' perspective, automation has a significant impact on returns to occupational skills across education groups. The left panel of Figure 3 shows that there is a heterogeneous reallocation of regional labor across job types. Managerial occupations tend to lose workers in most regions (mostly in Denmark, France, Italy, Luxembourg and

Sweden) and in particular among the highly educated workers. These workers reallocate to professional occupations because there is a strong positive correlation between the skill sets required for these job types. With the exception of a few regions, service and elementary occupations experience a slight decrease of active workers as a consequence of automation. Driven by changes in labor productivity (through interactions with structures and automation capital), labor mobility across occupations is mainly affected by equilibrium real wages for workers of different skills, as depicted in the right panel of Figure 3. Managerial occupations face significant decreases in real wages in Ireland, Spain, France, Italy, Poland and the United Kingdom. In contrast, wages in managerial positions tend to increase in Austria, the Benelux countries and Germany, even though workers still leave these jobs. Professional occupations benefit from an increase in real wages in many regions, and in particular in regions with high automation: Alpine, Nordic and Central European countries. The increase is also higher for highly-educated workers (except in parts of France and Lithuania). The impact of automation on wages in service and elementary occupations is more scattered, but shows a consistent pattern across all regions. Namely, the changes across these two occupations move predominantly in opposite directions, showing that the mobility of workers takes place across these two job types. Depending on the characteristics of local economies, one of these two occupations generates positive wage effects, while the other loses in relative terms.

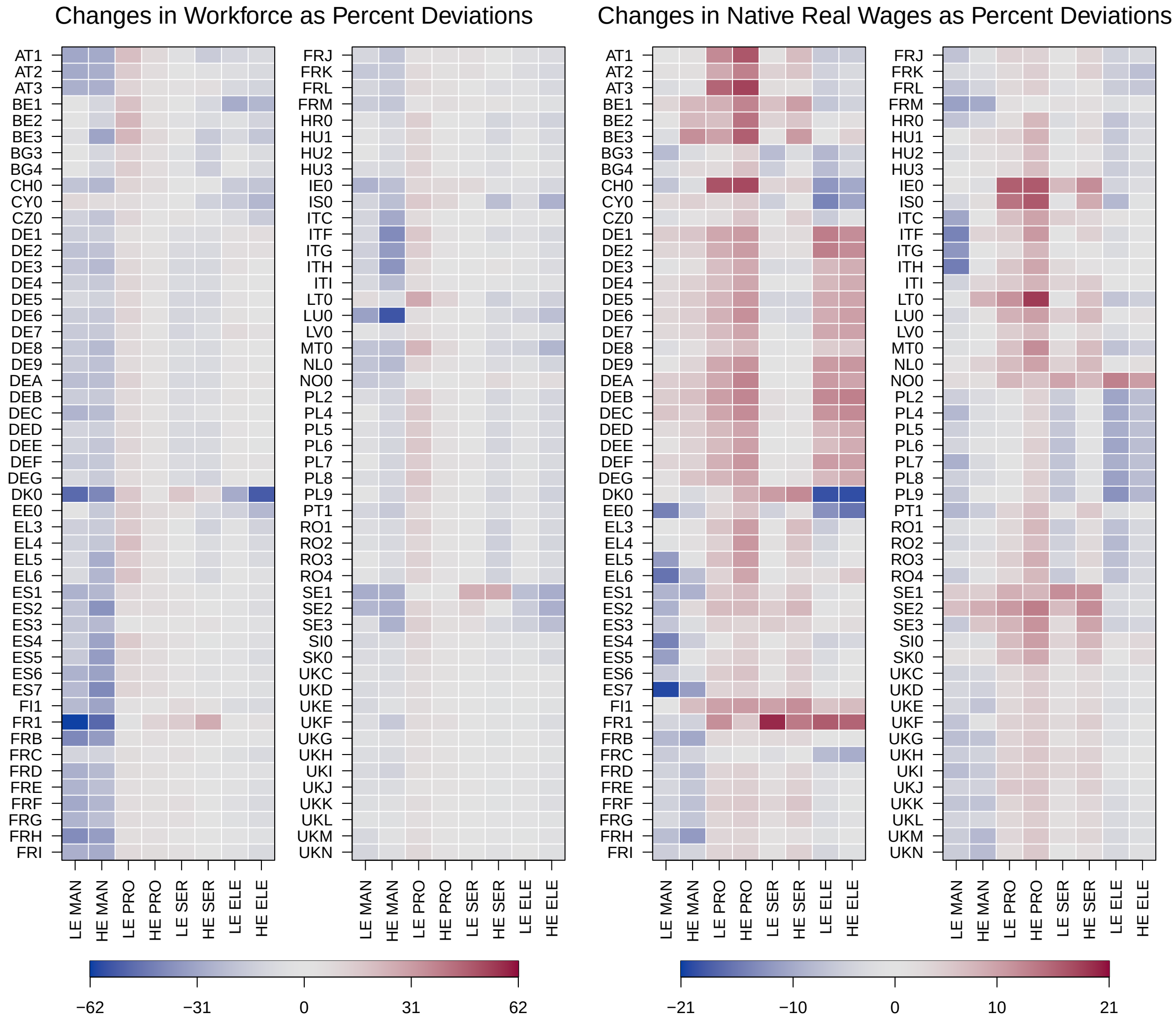
6 Projections: Alternative Scenarios

In this section, we use our model to evaluate the impact of automation on the European labor markets using alternative projections for the technological and demographic scenarios. Our projections built on scenarios for automation (labelled with prefix A) and education (labelled with prefix E). To generate low- and high-impact scenarios, we take the benchmark projection (labelled as A2E2) and apply a uniform reduction/increase of key automation variables by 50%. We also take advantage of alternative projections for the education structure of European populations by the Wittgenstein Center, as highlighted in Table 2. This enables us to run nine projections spanning over all combinations of A1-A3 and E1-E3 scenarios.

We are interested in the way that accelerated/decelerated automation and education affect aggregated outputs for the European economy. Each of the four panels of Figure 4 studies the effect of these 9 scenarios on a specific variable of interest: average European GDP, average European wage rate, average employment levels and average net migration rate. Each scenario is thereby compared to the reference simulation for 2033 (without automation), which means that the central squares in each cube show the effects for the A2E2 scenario analyzed in the previous section.

Figure 4a shows that total average GDP unambiguously increases with automation.

Figure 3: Effects of Robotization and Automation on Labor Groups in the Benchmark Simulation



Note: Figure 3 details the change in labor (left panel) and real wages (right panel) by region and skill-occupation (in %). The two skill levels are LE (less-educated) and HE (highly-educated) and the four occupation types are: MAN: Managerial; PRO: Professionals, SER: Clerical, Service and Sale Workers, ELE: Less-Skilled and Elementary Occupations. For the region codes, please refer to Table A7. All results display the difference between the A2 automation scenario, versus the reference scenario for 2033. Source: authors' calculations.

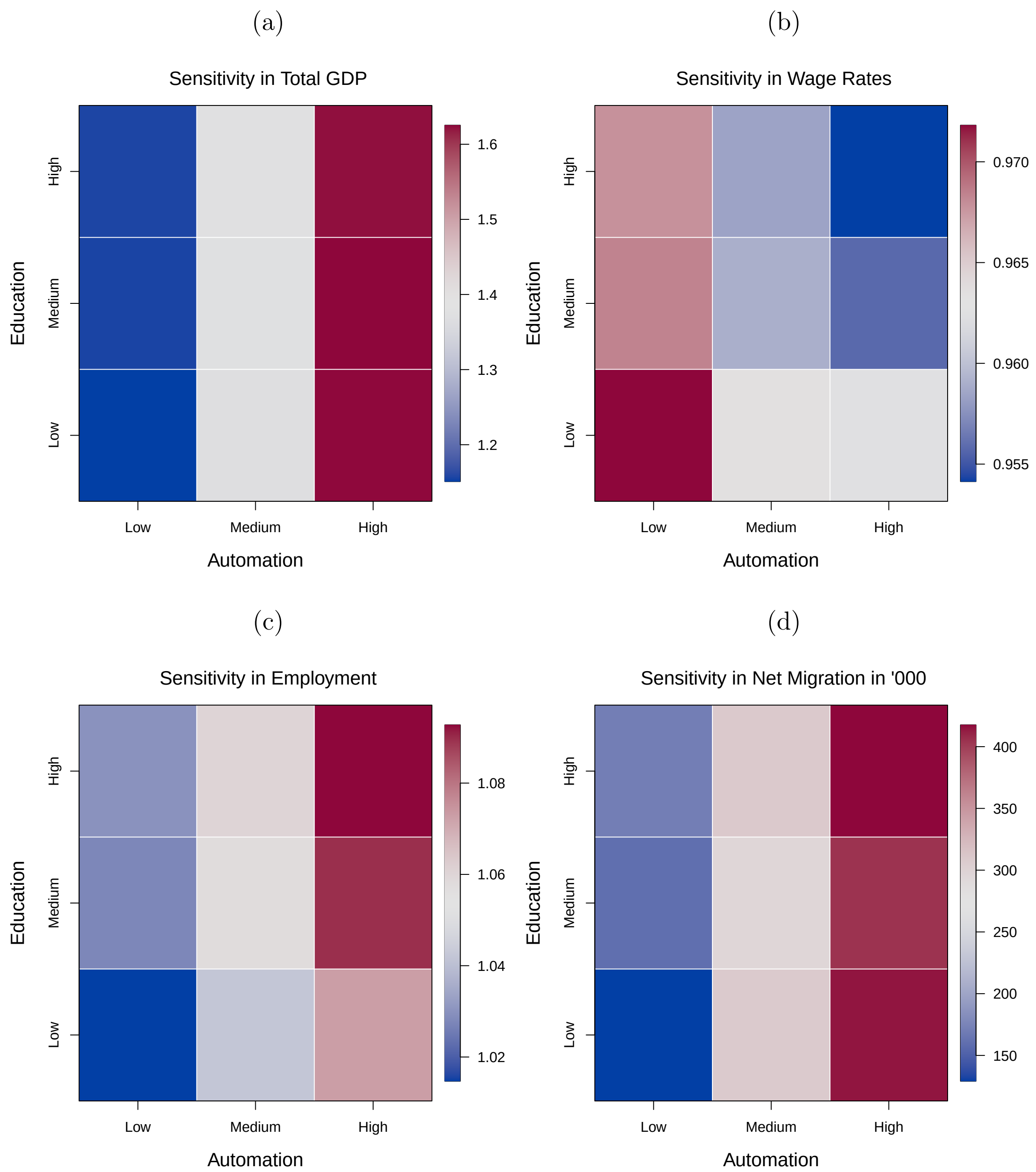
These effects are only slightly affected by changes in the education structure of the workforce. Thus, we conclude that from the macroeconomic point of view automation brings a substantially more pronounced impact on the size of the economy than the quality of employed labor. However, aggregated real wage rates show non-monotonic deviations across scenarios. Both low education and slower automation seem to slightly increase wage rates, as illustrated in Figure 4b. Part of this effect is due to the fact that less automation and education tends to increase inactivity, as highlighted in Figure 4c, so that the remaining active workers are positively self-selected. More broadly, we conclude that education and, to a larger extent, automation visibly increase employment. As more people join the labor market, they necessarily possess lower skill levels than formerly active workers, which leads to a slight reduction in average wages due to the labor composition effect. We observe that worker mobility tends to significantly increase with automation, as highlighted by in Figure 4d, expressed in 1,000 persons. At the same time, net migration tends to increase with the share of educated workers, as more educated workers face lower mobility barriers than less-educated ones. In conclusion, at the aggregate European level, the interactions between labor and automation, and the consequential reallocation of workers, seem to outweigh negative effects caused by labor-automation substitution and lead to higher employment with more intensive worker mobility and only a marginal change in average European wage rates.

Our final focus is on analyzing the effect of automation, under alternative automation-education scenarios, on the welfare of workers with different origins, education levels and skills. Each of the three panels in Figure 5 highlights one automation scenario: low (A1), medium (A2) and high (A3), respectively. Within each of these three panels, we show the change in average welfare of all workers active in each European region, assuming three education scenarios: low-education (E1) with triangles, high-education (E3) with circles, and medium-education (E2) with thick lines. Note that regions are sorted in descending order of welfare effects in the medium education scenario.

Starting with the medium automation scenario in the second panel of Figure 5, we note that average native welfare improves in most regions, except for roughly twenty regions predominantly in France and Poland. Automation causes considerable heterogeneous effects on worker welfare across regions: while average welfare decreases by around 10% in Paris, it increases by more than 20% in Liège. Changing the education scenarios generates variation within regions to different extents, with the low education scenario leading to lower gains or higher losses in most regions, although the regional ordering is only slightly affected. The main winners from automation are workers in Belgium, Germany and Alpine countries, notably those who work in manufacturing-intensive economies that are subject to high automation. Economies rich in service-intensive automation tend to gain, although the magnitudes of these benefits are more limited.

In the low automation scenario, average native welfare decreases in around half of the regions (see the upper Panel of Figure 5). Note that the spread of the distribution of welfare effects is also negatively affected, reducing the range of changes by approximately 50%. In the fast automation scenario (the bottom panel of Figure 5), average native welfare increases above 40% in Copenhagen and decreases by more than 10% in Paris. In this case, the distribution of the effects is affected only on the positive end, while losses in the negatively affected regions are similar to those reported in the medium automation scenario. Thus, one can expect that faster implementation of new technologies can generate an upside potential for many regions in Europe, while the losses incurred in specific regions are not aggravated.

Figure 4: Macroeconomic Effects of Alternative Scenarios on Automation and Education



Note: Each panel shows different combinations of automation (horizontal axis) and an education (vertical axis) scenarios in relation to the reference scenario for 2033. The variables of interest include nominal GDP in Panel 4a, nominal wages in Panel 4b, efficient labor in Panel 4c and net migration expressed in 1,000 persons in Panel 4d.

7 Conclusion

In the past, technological innovations have primarily impacted certain types of tasks and occupations, particularly those performed by middle-skilled workers. However, as automation continues to progress, it is increasingly probable that it will impact workers who have, thus far, been relatively unaffected. Therefore, it is important to gain a deeper understanding of the heterogeneous effects that innovation can have on workers with diverse educational backgrounds and skill sets, working in different sectors and occupations, and living in heterogeneous geographical regions.

We employ a comprehensive general equilibrium framework to simulate different automation and population scenarios for 100 regional European labor markets. We find that the overwhelming majority of regions benefit from automation. However, workers in different sectors and occupations experience opposite effects on their wages, whereas all clearly benefit from the resulting decline in equilibrium prices of goods. These heterogeneous effects across regions and occupations are likely to drive significant labor market mobility, with people moving across NUTS1 areas and transitioning between different job types. Most of our results are proportional to the speed of implementing automation technologies. Most of our results are proportional to the speed of implementing automation technologies. An important exception is the spatial distribution of welfare effects across natives. This distribution improves and becomes more dispersed as automation accelerates, but its lower bound is less affected than its upper bound.

Our study highlights the significance of taking regional and occupation-specific contexts into account when analyzing the effects of automation on the labor market. Overall, the heterogeneity of the effects of automation warrants careful consideration in policy discussions. By acknowledging and addressing the disparities that arise from technological progress, policymakers can formulate measures that promote a more inclusive and equitable distribution of the benefits generated by technological progress across regions, sectors, and workers in Europe. Our framework has the potential to be further expanded to incorporate additional channels and analyze alternative scenarios or shocks, such as changes in immigration policies, environmental policies, or the emergence of more advanced technologies like generative AI. This flexibility opens up promising avenues for exploring additional factors that could influence economic and labor market dynamics in Europe over the next decades.

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A Imputing migration data - estimation results

Table A1: Stage 1: International Migration Gravity Estimates

VARIABLES	(1) LS PPML	(2) LS PPML	(3) LS PPML	(4) HS PPML	(5) HS PPML	(6) HS PPML
w_j^l/w_i^l	0.521***	0.685***	1.603***			
	(0.0836)	(0.0942)	(0.250)			
w_j^h/w_i^h				0.504***	0.652***	1.731***
				(0.0830)	(0.0907)	(0.240)
log-distance	-1.037***	0.0517	-1.093***	-0.916***	-0.108	-1.312***
	(0.177)	(0.298)	(0.214)	(0.170)	(0.230)	(0.201)
contiguity		1.977***	0.846**		1.236***	0.0877
		(0.519)	(0.383)		(0.372)	(0.374)
common language		1.216***	0.963**		1.534***	1.196***
		(0.379)	(0.379)		(0.284)	(0.257)
EU		0.355	1.083*		0.490**	1.192**
		(0.264)	(0.582)		(0.220)	(0.543)
constant	6.276***	-1.854	4.148**	6.530***	-0.0602	6.083***
	(1.300)	(2.045)	(1.665)	(1.561)	(1.528)	(1.372)
Observations	930	930	930	930	930	930
R-squared	0.074	0.212	0.606	0.106	0.293	0.615
Origin FE	NO	NO	YES	NO	NO	YES
Destination FE	NO	NO	YES	NO	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2: Stage 2: Internal Migration Gravity Estimates

VARIABLES	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML
w_j^l/w_i^l	0.602	0.593	1.236***			
	(0.472)	(0.424)	(0.313)			
w_j^h/w_i^h				1.610***	1.605***	2.419***
				(0.345)	(0.311)	(0.230)
log-distance	-0.699***	-0.675***	-0.762***	-0.554***	-0.623***	-0.815***
	(0.0964)	(0.0897)	(0.0779)	(0.0858)	(0.0851)	(0.0816)
contiguity		-0.253	-0.220		0.0423	0.0230
		(0.297)	(0.169)		(0.192)	(0.140)
constant	-0.994*	-1.387***	1.301***	-1.181**	-1.619***	-0.724
	(0.538)	(0.450)	(0.322)	(0.476)	(0.489)	(0.465)
Observations	682	682	679	682	682	676
R-squared	0.081	0.278	0.795	0.091	0.266	0.648
Country FE	NO	YES	YES	NO	YES	YES
Origin FE	NO	NO	YES	NO	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B Generating Projection Scenarios

Table A3: Change in Labor Share as a Function of ICT Intensity

	(1) MANU	(2) CONS	(3) SALE	(4) TRAN	(5) LSER	(6) FSER	(7) PSER	(8) PUBL
ICT	-1.103***	-2.847***	-0.841***	-4.890***	-1.470***	1.391***	-0.165***	-1.369***
	(0.381)	(0.386)	(0.159)	(0.672)	(0.152)	(0.442)	(0.0566)	(0.277)
year	0.0018***	0.0046***	0.0053***	0.0024***	0.0066***	-0.0020***	0.0046***	0.00064***
	(0.0002)	(0.0006)	(0.0003)	(0.0004)	(0.0003)	(0.0001)	(0.0003)	(0.0002)
Const	-3.086***	-8.699***	-10.17***	-4.206***	-12.61***	4.395***	-8.778***	-0.503
	(0.600)	(1.222)	(0.727)	(0.971)	(0.603)	(0.227)	(0.614)	(0.407)
Obs	282	294	294	294	294	294	294	294
R-sq	0.863	0.875	0.937	0.876	0.953	0.943	0.970	0.860
Cou FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Change in Labor Share as a Function of ICT Intensity and Robotization

	(1) ALL SECTORS
ICT	-2.739***
	(0.283)
robot_stock	-2.09e-05***
	(1.76e-06)
year	0.00391***
	(0.000635)
Const	-7.120***
	(1.275)
Obs	807
R-sq	0.462
Cou FE	YES
Sec FE	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Changes in Occupational Inputs across Sectors - Coefficients

Estimated Coefficients	OCCUPATION			
	MAN	**PRO**	**SER**	**ELE**
MANU	-0,000678	0,00206*	-0,0000089	-0,00138
CONS	-0,000363	0,00171	0,00191***	-0,00326**
SALE	-0,00135**	0,00187**	0,00083	-0,00135
TRAN	-0,000561	0,000546	-0,00351***	0,00353***
LSER	-0,00144***	0,0000728	0,000558	0,00081
FSER	-0,000793	0,00155	-0,000958	0,000206
PSER	-0,00114	0,00290***	-0,000356	-0,00141***
PUBL	-0,000476	0,00258***	-0,00132**	-0,000785**

Table A6: Trends in ICT-Labor Relative Productivities [x1000] by NACE 1-Digit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	A	B	C	D	E	F	G	H	I	J
year	-0.112	-4.132	-0.799	10.24	4.543	1.702	-0.429	0.0291	-0.829**	22.86*
	(0.363)	(7.255)	(1.902)	(18.16)	(7.418)	(1.581)	(1.903)	(3.774)	(0.402)	(11.70)
Const	0.227	8.356	1.614	-20.61	-9.079	-3.442	0.878	0.0209	1.680**	-45.87*
	(0.732)	(14.62)	(3.832)	(36.59)	(14.95)	(3.185)	(3.835)	(7.604)	(0.809)	(23.57)
Obs	270	274	307	302	262	306	307	307	283	307
R-sq	0.049	0.035	0.046	0.028	0.054	0.066	0.043	0.053	0.115	0.064
Cou FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
	K	L	M	N	O	P	Q	R	S
year	25.33	-0.760	-3.047	-1.171	8.017	2.729	-1.201**	-5.930	-1.737
	(36.57)	(2.923)	(4.901)	(1.881)	(6.676)	(4.146)	(0.533)	(9.969)	(2.007)
Const	-50.84	1.714	6.150	2.368	-16.33	-5.515	2.421**	11.90	3.539
	(73.68)	(5.890)	(9.873)	(3.789)	(13.45)	(8.351)	(1.073)	(20.08)	(4.043)
Obs	304	292	295	275	305	259	294	290	283
R-sq	0.036	0.089	0.062	0.062	0.053	0.028	0.132	0.019	0.105
Cou FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B.1 Capital Imputation: Stocks and Flows

In order to calibrate the evolution of ICT and Total capital stocks, we start by imputing missing capital flows and stocks by type: computer (hardware), software and total. We use sector-specific regressions that impute the specific capital type flows on total capital flows. These regressions take the form:[3]

$$Flow\_Cap_{is} = \alpha + \beta_3 Flow\_Cap\_Total_{is},\ \forall s, \& i = \{IT, Soft\} \quad (7)$$

$$Stock\_Cap_{is} = \alpha + \beta_4 Stock\_Cap\_Total_{is},\ \forall s, \& i = \{IT, Soft\} \quad (8)$$

We then replace missing data points by $\max(0, Flow\hat{\_}Cap_{is})$ and $\max(0, Stock\hat{\_}Cap_{is})$, $\forall s, \& i = \{IT, Soft\}$ as capital cannot be negative. We predict total stocks using flows

[3]If the constant is negative, we replace a specification without it.

data:

$$Stock\_Cap\_Total_s = \alpha + \beta_5 Flow\_Cap\_Total_s,\ \forall s. \tag{9}$$

In a next step, when predictions with flow data are unavailable, we impute missing data points using a relationship between capital stocks and GDP:

$$Stock\_Cap_{is} = \alpha + \beta_6 GDP_{is},\ \forall s, \&i = \{IT, Soft, Total\} \tag{10}$$

Using the predictions from equation 10, we replace missing databpoints by $\max(0, Stock\hat{\_}Cap_{is})$, $\forall s, \&i = \{IT, Soft, Total\}$. The updated capital stock series are then used to recompute the share of computer hardware and software within the total capital stock $((Stock\_Cap\_IT_{cst} + Stock\_Cap\_Softw_{cst})/(Stock\_Cap\_Total_{cst}))$.

Table A7: Regions and Countries

Code 2021	NUTS1 Region	Country
AT1	Ostösterreich	Austria
AT2	Südösterreich	Austria
AT3	Westösterreich	Austria
BE1	Région de Bruxelles-Capitale	Belgium
BE2	Vlaams Gewest	Belgium
BE3	Région wallonne	Belgium
BG3	Severna i yugoiztochna Bulgaria	Bulgaria
BG4	Yugozapadna i yuzhna tsentralna Bulgaria	Bulgaria
CH0	Schweiz/Suisse/Svizzera	Switzerland
CY0	Kypros	Cyprus
CZ0	Czechia	Czechia
DE1	Baden-Württemberg	Germany
DE2	Bayern	Germany
DE3	Berlin	Germany
DE4	Brandenburg	Germany
DE5	Bremen	Germany
DE6	Hamburg	Germany
DE7	Hessen	Germany
DE8	Mecklenburg-Vorpommern	Germany
DE9	Niedersachsen	Germany
DEA	Nordrhein-Westfalen	Germany
DEB	Rheinland-Pfalz	Germany
DEC	Saarland	Germany
DED	Sachsen	Germany
DEE	Sachsen-Anhalt	Germany
DEF	Schleswig-Holstein	Germany
DEG	Thüringen	Germany
DK0	Danmark	Denmark
EE0	Eesti	Estonia
EL3	Attiki	Greece
EL4	Nisia Aigaiou, Kriti	Greece
EL5	Voreio Aigaio	Greece
EL6	Notio Aigaio	Greece
ES1	Noroeste (ES)	Spain
ES2	Noreste (ES)	Spain
ES3	Comunidad de Madrid	Spain
ES4	Centro (ES)	Spain
ES5	Este (ES)	Spain
ES6	Sur (ES)	Spain
ES7	Canarias	Spain
FI1	Manner-Suomi	Finland
FR1	Ile-de-France	France
FRB	Centre — Val de Loire	France
FRC	Bourgogne-Franche-Comté	France

Continues on next page

Table A7 – continued

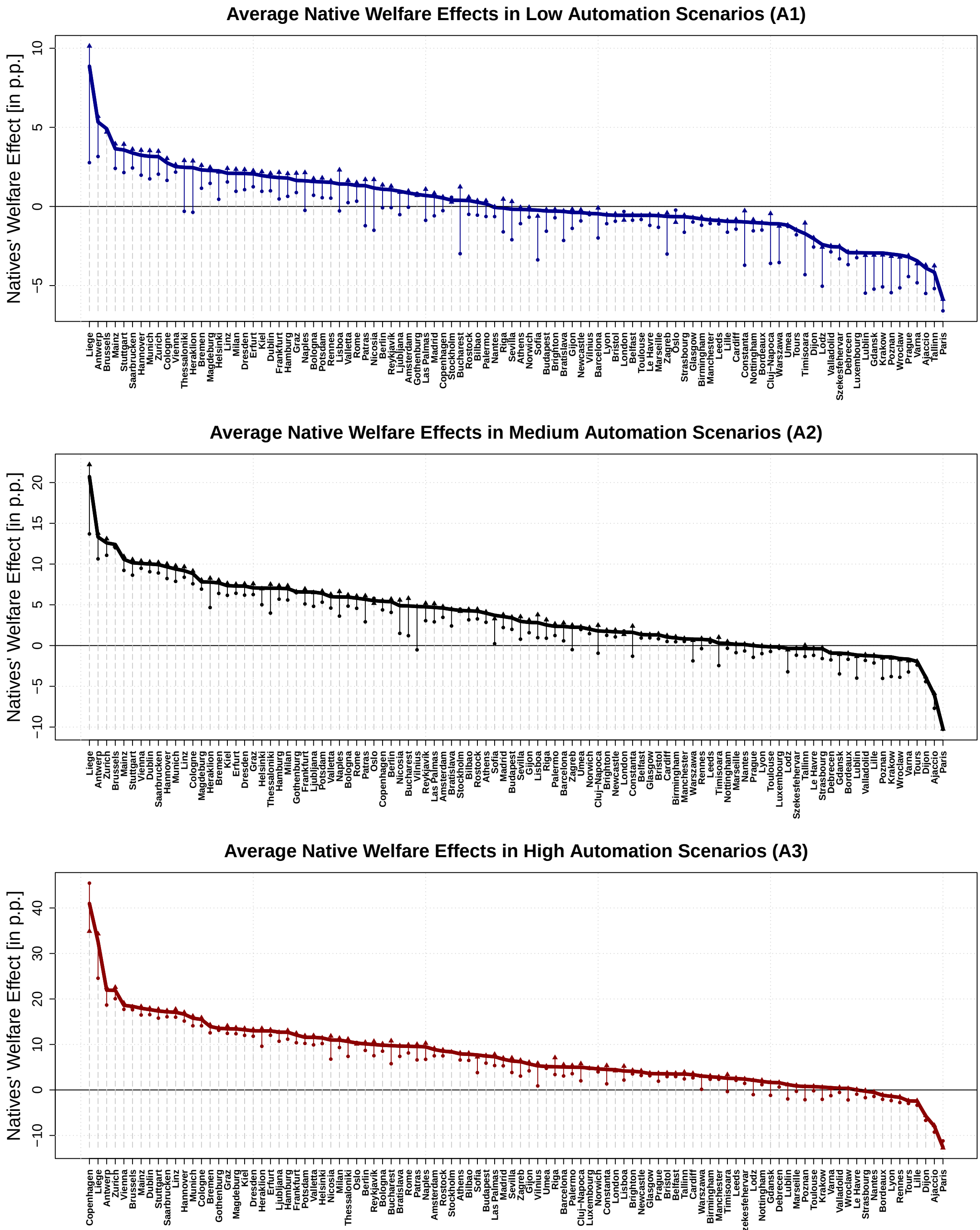
Code 2021	NUTS1 Region	Country
FRD	Normandie	France
FRE	Hauts-de-France	France
FRF	Grand Est	France
FRG	Pays de la Loire	France
FRH	Bretagne	France
FRI	Nouvelle-Aquitaine	France
FRJ	Occitanie	France
FRK	Auvergne-Rhône-Alpes	France
FRL	Provence-Alpes-Côte d'Azur	France
FRM	Corse	France
HR0	Hrvatska	Croatia
HU1	Közép-Magyarország	Hungary
HU2	Dunántúl	Hungary
HU3	Alföld és Észak	Hungary
IE0	Ireland	Ireland
IS0	Ísland	Island
ITC	Nord-Ovest	Italy
ITF	Sud	Italy
ITG	Isole	Italy
ITH	Nord-Est	Italy
ITI	Centro (IT)	Italy
LT0	Lietuva	Lithuania
LU0	Luxembourg	Luxembourg
LV0	Latvija	Latvia
MT0	Malta	Malta
NL0	Neerlands	Netherlands
NO0	Norge	Norway
PL2	Makroregion południowy	Poland
PL4	Makroregion północno-zachodni	Poland
PL5	Makroregion południowo-zachodni	Poland
PL6	Makroregion północny	Poland
PL7	Makroregion centralny	Poland
PL8	Makroregion wschodni	Poland
PL9	Makroregion województwo mazowieckie	Poland
PT1	Continente	Portugal
RO1	Macroregiunea Unu	Romania
RO2	Macroregiunea Doi	Romania
RO3	Macroregiunea Trei	Romania
RO4	Macroregiunea Patru	Romania
SE1	Östra Sverige	Sweden
SE2	Södra Sverige	Sweden
SE3	Norra Sverige	Sweden
SI0	Slovenija	Slovenia
SK0	Slovensko	Slovakia
UKC	North East (UK)	United Kingdom

Continues on next page

Table A7 – continued

Code 2021	NUTS1 Region	Country
UKD	North West (UK)	United Kingdom
UKE	Yorkshire and the Humber	United Kingdom
UKF	East Midlands (UK)	United Kingdom
UKG	West Midlands (UK)	United Kingdom
UKH	East of England	United Kingdom
UKI	London	United Kingdom
UKJ	South East (UK)	United Kingdom
UKK	South West (UK)	United Kingdom
UKL	Wales	United Kingdom
UKM	Scotland	United Kingdom
UKN	Northern Ireland (UK)	United Kingdom

Figure 5: Native Welfare Effects of Alternative Scenarios on Robotization, Automation and Education



Note: In Figure 5, the upper panel depicts a low automation scenario; the middle panel a medium automation scenario and the bottom panel a fast automation scenario. Within each panel, and for each regions, the triangle focuses on the high education scenario whereas the circle relates to the low-education scenario defined in Table 2. The bold line defines average native welfare according to the medium education scenario. Regions are sorted according to the welfare level in the medium education scenario.

UNTANGLED Partners:

UNTANGLED is a three-year interdisciplinary Horizon 2020 research project that seeks to examine the interconnected trends of globalisation, demographic change and technological transformation, and their effects on labour markets in the European Union and beyond. By engaging a broad range of stakeholders, including companies and civil society organisations, we will develop practical policy proposals to help governments cushion the negative impacts of these trends and ensure their benefits are enjoyed fairly across regions and sectors.

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