Automation, Techies, and Labor Market Restructuring[1]

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Abstract

While job polarization was a salient feature in European economies in the decade up to 2010, this phenomenon has all but disappeared, except in a handful of Southern-European economies. The decade following 2010 is characterized by occupational upgrading, where low-paid jobs shrink and high paid jobs expand. We show that this is associated with automation: employment shares in low paid, highly automatable jobs shrinks, while employment shares of better paid jobs that are unlikely to be automated expands. Techies (engineers and technicians with strong STEM skills) help explain cross country variation in occupational upgrading: economies that are abundant in techies or exhibit high growth of techies see strong skill upgrading; in contrast, polarization is observed in economies with few techies. Robotization is associated with skill upgrading in manufacturing. We discuss the additional roles of globalization, structural change and labor market institutions in driving these phenomena. Hitherto, artificial intelligence (AI) seems to have similar impacts as other automation technologies. However, there is uncertainty about what new AI technologies harbor.

Keywords: automation, robots, techies, tasks, STEM, occupations, employment, polarization

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Introduction

The phenomenon of labor market restructuring has caught the attention of economists and policymakers since the 1980s, a period in which large changes started to emerge. This has been extensively documented in the United States and in European countries, and has been studied due to the important implications this confers on inequality and social stability. We can broadly identify three distinct periods of labor market restructuring: 1980 to early 1990s, mid-1990s to 2010, and 2010 to today. In this chapter, we focus our attention to the last period and make some cautious predictions for the future. But before that, it is worthwhile to briefly discuss the first two periods in order to give context to our analysis.

The 1980s and early 1990s are broadly characterized by "job upgrading", where employment shares of high skilled workers increased and those of low skill workers decreased, while the relative wage of high skilled workers increased or, in several European economies, did not decrease. This phenomenon is largely attributed to skill-biased technological change (Berman, Bound & Griliches, 1994; Machin & Van Reenen 1998). This theory suggests that new technologies, such as computers and ICTs, have complemented workers with high skills,

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increasing demand for their labor services. While increasing inequality in the short run, in the long run this trend could, in principle, bring general improvement, as low wage jobs slowly disappear.

Since the mid-1990s and roughly up to 2010 a new phenomenon is observed: job polarization. This means that the share of medium-wage occupations declined, while employment shares of both high and low wage workers increased. Scholars such as Autor, Katz, and Kearney (2006) and Autor and Dorn (2013) have conducted in-depth research on this topic in the United States. Similarly, Goos and Manning (2007) have investigated job polarization in the United Kingdom, while Spitz-Oener (2006) and Dustmann, Ludsteck, and Schönberg (2009) have examined it in Germany. Furthermore, Goos, Manning, and Salomons (2009, 2014) and Michaels, Natraj & Van Reenen (2014) studied on job polarization across several countries.

The leading theory that explains this is broadly called the "routinization hypothesis". This theory suggests that new technologies directly replaced middle-wage workers that performed routine cognitive tasks, all the while complementing high-wage workers that perform non-routine abstract tasks. Employment in low-wage jobs increased because of worker displacement, or because new entrants – many of which had moderate levels of education – were no longer able to find middle-wage jobs. Job polarization is more alarming than job upgrading for two reasons. First, it mechanically increases wage inequality, as employment of high-wage professionals and low-wage workers outpaces the employment of middle-wage workers. Second, in the long run it could lead to a bifurcation of society and the disappearance of the middle class, which is broadly considered to be the linchpin of democratic institutions.

Against this backdrop, we focus on recent times, while comparing it to the 2000-2010 period.

1. Labor market restructuring in 2000-2019: What do the data say?

Several studies have consistently highlighted the persistent nature of job polarization in the United States at least into the early 2000s (e.g., Autor 2010 and Brynjolfsson & McAfee 2011). Recent findings by Jaimovich and Siu (2020) reveal a continuous increase in high-skill (non-routine cognitive) and low-skill (non-routine manual) employment over time. This trend has coincided with a decline in middle-skill, routine occupations, resulting in a noticeable shift in employment from routine, middle-skill jobs to non-routine cognitive and manual roles. For instance, in 1982, routine occupations constituted approximately 56% of total employment, but by 2017, this share had diminished to 42%. Moreover, these shifts tend to accelerate during recessions (Jaimovich and Siu, 2020).

Our analysis examines European labor market restructuring. To do so, we primarily rely on data sourced from the European Labor Force Survey (EULFS). We consider 28 countries for which we have harmonized data across occupations and workers' characteristics, such as wages and gender, from 2000 to 2019.[2] Our sample includes employees (82.15%), self-employed

[2] The countries included in the data are Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden, Switzerland, and the United Kingdom. However, the data for Croatia, Malta, and Slovenia had to be excluded from the analysis due to limited data availability. Specifically, Croatia lacks data for the years 2000 and 2001, while Malta and Slovenia have no available data for the periods 2000 to 2008 and 2015 to 2019, respectively.

(15.92%) and family workers (1.93%) and excludes workers in the armed forces.[3] We drop observations that do not have information on the classification of economic activities.[4]

a. Job polarization before and after 2010

In order to describe job polarization across European countries, we follow Dauth (2014) and Harrigan *et al.* (2017), and study changes in occupational employment shares.[5] We classify jobs into three groups: "high-level," "low-level," and "medium-level," based on the ISCO (1-digit) occupational classification.[6] These broadly correspond to high, low and medium wages, respectively. We propose a single measure of polarization, the Job Polarization Index (JPI), which is defined as follows: $JPI = \min\{\Delta H, \Delta L\} - \Delta M$, where ΔH, ΔL and ΔM denote changes in the employment shares of high, low and medium level occupations, respectively; the first component is the minimum between the change in the employment share of high and low level occupations.

The JPI summarizes the degree to which occupational employment shares evolve over time in a polarizing fashion. A large and positive JPI suggests an increase in polarization, while a negative JPI implies a decline in polarization (i.e., an increase in the share of the middle level workers at the expense of both high and low). A JPI value close to zero indicates that the distribution of employment across occupations has not changed in a polarizing fashion (e.g., if both high and medium level workers increase their employment shares to a similar degree).

Figure 1 reports the average JPI across the 28 countries in our sample for the entire working population and by gender, for two sub-periods: one before 2010 and the other after 2010. Two features emerge from Figure 1. First, polarization was markedly more salient in the 2000-2010 period compared to the period from 2011 to 2019. While in the first period job polarization is substantial, as we move into the second decade job polarization appears to attenuate, indicating a shift in labor market dynamics.[7]

Second, during the first period of examination, the JPI demonstrates a similar impact on men and women, implying a relatively balanced effect of job polarization across genders. However, in the second period, the JPI is notably higher for men and is virtually nil for women. This implies that whatever job polarization took place (and much less than in the previous period), it is essentially driven by the employment dynamics of men. Indeed, as shown by Reshef and Toubal (2019), after the 2008 financial crisis French women reduced their employment shares in all but the highest-paying occupations, notably management, and technology-related "techie" professions (we discuss these occupations below).

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[3] Workers in the armed forces occupations account for less than 1% of total workers.

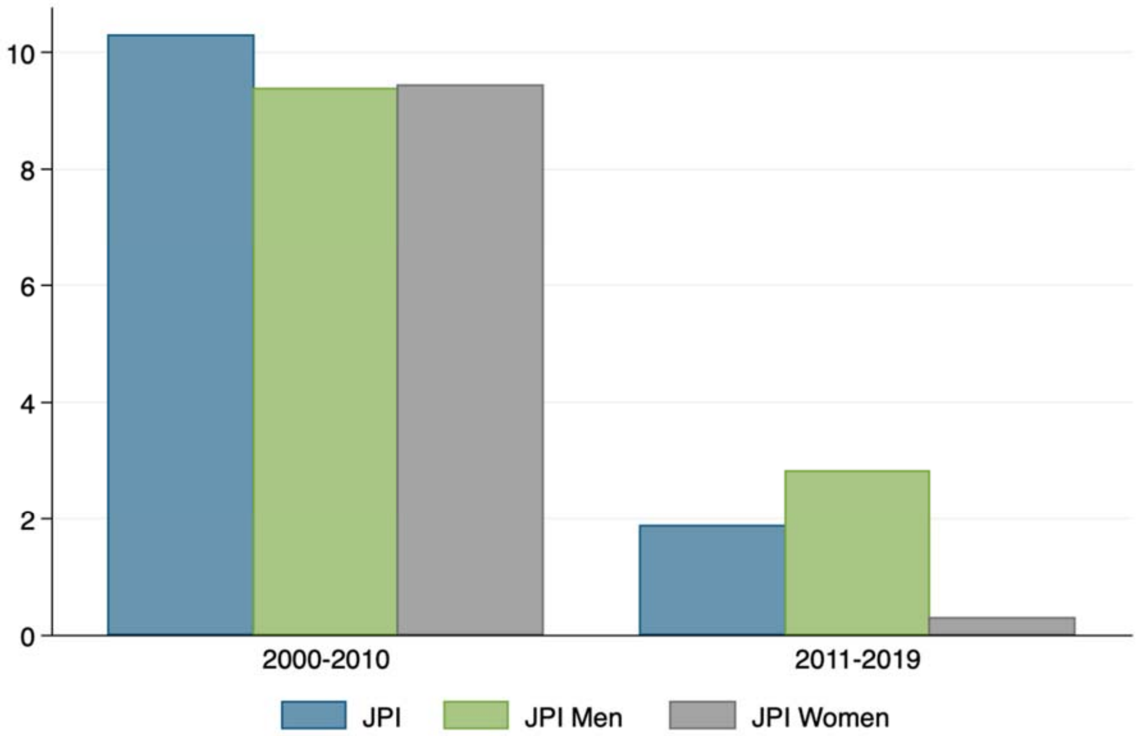
[4] The EULFS dataset uses NACE Rev. 1 for the years 2000-2007, while it uses NACE Rev. 2 from 2008 onwards. As for occupation definitions, the dataset follows the ISCO88 classification from 2000 to 2010, then, follows ISCO08 from 2011 onwards. These differences have been harmonized.

[5] Other researchers consider classifying workers by percentiles in the wage distribution (Fernández-Macías, 2012; Goos *et al.*, 2009), while others classify workers by the relative intensity of cognitive, routine, and manual tasks (Autor and Dorn, 2013; Cortes *et al.*, 2017). We prefer looking directly at occupations for transparency.

[6] The "middle jobs" group comprises clerks, skilled agricultural and fishery workers, craft and related trade workers, plant and machine operators, and assemblers. The "low-level" category includes service workers, shop and market sales workers, and elementary occupations, while the "high-level" group encompasses senior officials and managers, professionals, technicians, and associate professionals.

[7] The patterns reported in Figure 1 are qualitatively the same when we modify the JPI by considering either the average or maximum values between the growth shares of High-level and Low-level occupations.

Figure 1: Job polarization index (JPI), average of 28 European countries



Note: Authors' calculation. The JPI index is computed as JPI = min{ΔH, ΔL} – ΔM, where ΔH, ΔL and ΔM denote changes in the employment shares of high, low and medium level occupations, respectively; the first component is the minimum between the change in the employment share of high and low level occupations over the respective period. Occupational groups are defined based on the ISCO (1-digit) level, encompassing "middle jobs" – M (clerks, skilled agricultural and fishery workers, craft and related trade workers, plant and machine operators, and assemblers), "low-level" – L (service workers, shop and market sales workers, and elementary occupations), and "high-level" – H (senior officials and managers, professionals, technicians, and associate professionals).

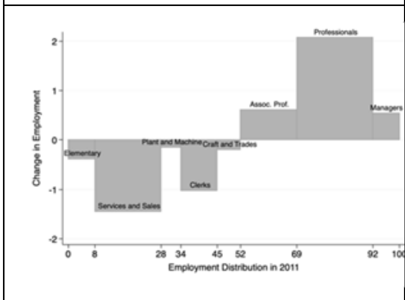
b. Job Polarization: Significant variations across geography and industries

The general decrease in the tendency toward job polarization after 2010 analysis masks differences among countries. To explore this, we group the countries in our sample based on their geographical location, distinguishing between those in the North, South, and East of Europe. This broadly corresponds to high, middle and low-income groups within Europe. We report the results in Figure 2. In each panel the vertical axis shows the percent point change in total employment of each occupational category between 2011 and 2019; these sum to zero. The horizontal axis represents the distribution of employment across occupational categories in the aggregate economy in 2011 in percent; these add up to 100. Jobs are ranked from left to right based on their position in the wage distribution. For example, in the North in 2011 Elementary workers account for approximately 8% of employment with the lowest relative wages and their share in employment declined by about 0.3 percent points; Service and sales workers in the North make up around 20% of employment (28 minus 8), have the second lowest wages on average and exhibit a 1.4 percent point drop in their employment share.

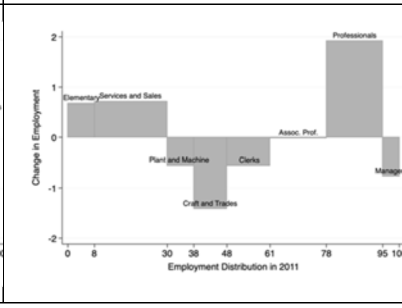
Figure 2 demonstrates that job polarization post 2011 is evident only in Southern-European countries. Countries in the north and east experienced skill upgrading during this period.

Figure 2. Change in employment composition by regions within Europe, 2011-2019

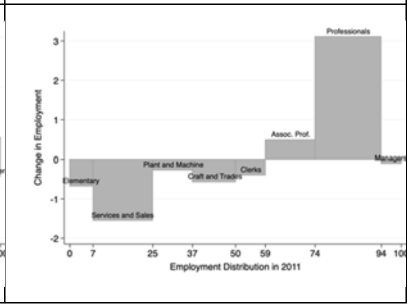
A. North



B. South



C. East

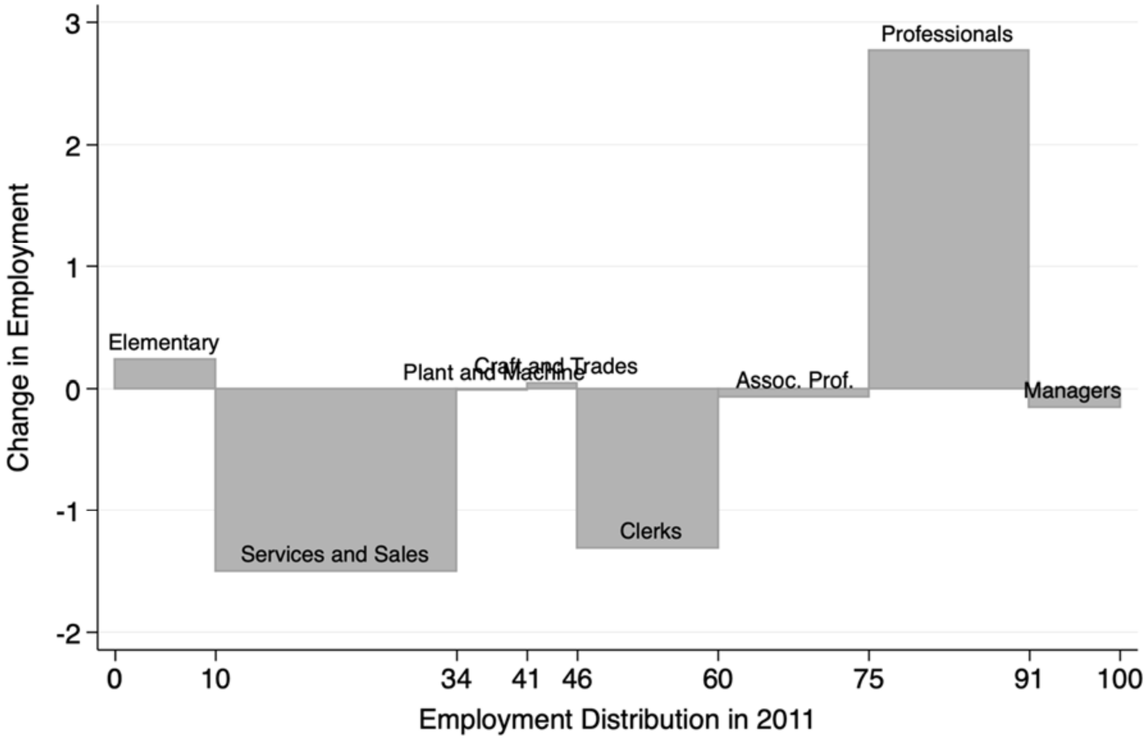


Note: Authors' calculations. Northern countries: Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Ireland, Luxembourg, Netherlands, Norway, Sweden, Switzerland, United Kingdom. Eastern countries: Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia. Southern countries: Cyprus, Greece, Italy, Portugal, Spain.

Figures 1 and 2 mask significant variations across industries, reflecting the rapid structural changes observed in European countries and in other advanced economies. Over the past decades, the share of GDP in the manufacturing sector declined from 17.51% in 2000 to 14.95% in 2019, while the services sector experienced notable employment growth, employing over seven out of ten workers. This pattern is consistent across OECD economies (World Bank, 2023). The manufacturing sector's higher productivity growth compared to the non-manufacturing sector, combined with steady demand for manufactured goods relative to services, has resulted in lower demand for workers in the manufacturing sector (Baumol, 1967). Both technological change and international factors, with significant interactions between the two, contributed to the observed shifts in employment shares towards services across Europe and other advanced economies. Since these forces do not equally affect services and manufacturing sectors, we expect to see different patterns of change within each sector.

Figures 3 and 4 report the changes in employment shares by occupations from 2011 to 2019 within services and manufacturing, respectively. They have the same structure as Figure 2.

Figure 3. Change in employment composition in non-manufacturing, 2011-2019



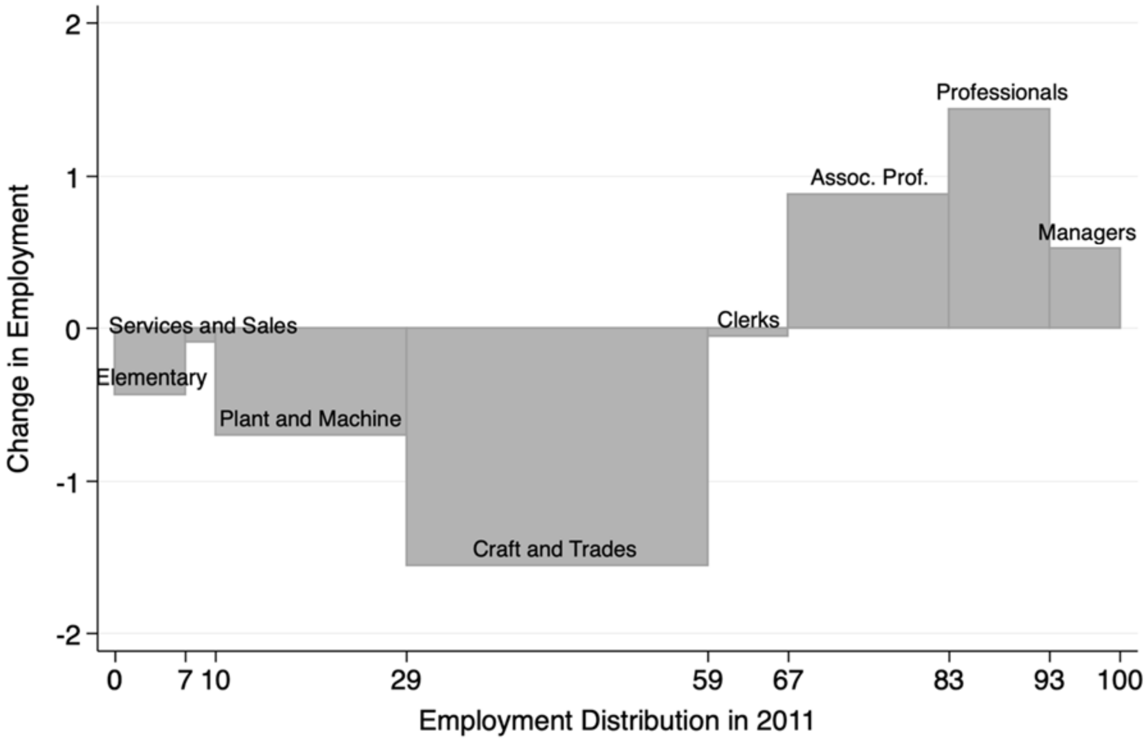
Note: Authors' calculation.

Figure 3 depicts a pattern that is consistent with a weak job polarization in the non-manufacturing sector, consistent with the low JPI values reported in Figure 1 (the lion's share of workers are employed outside of manufacturing). Apart from Managers, the shares of occupations with both high wages (Professionals) and low wages (Elementary) increase, while shares of the largest occupations with middle wages fell.

The trend in the manufacturing sector is different, as illustrated in Figure 4. First, note that the scale of changes is similar within the manufacturing sector compared to within the non-manufacturing sector – with the notable exception of the category of Professionals.

The pattern of change in 2011-2019 within the manufacturing industry is that of skills upgrading. This manifests in a notable reduction in the employment shares of Craft and Related Trades Workers, Plant and Machine Operators, and Elementary occupations. On the other hand, the employment share of Managers, Professionals (including engineers), and Associate Professionals (including technicians) increased.

Figure 4. Change in employment composition in manufacturing, 2011-2019



Note: Authors' calculation.

Additional breakdowns demonstrate the role of gender. For example, job polarization in the United States is associated with employment trends among women (Cerina *et al*. 2017). Using French administrative data, Reshef and Toubal (2019) show that, unlike the ongoing trend in the United States, both men and women contributed to the phenomenon of polarization before 2008, with significant variations across professions. For example, women are more represented in the category of Services and Sales and Clerical occupations. In contrast, women primarily drive the increase in the employment share of managerial and highly skilled professional occupations after 2008.

2. Technology and globalization

Labor and trade economists largely agree on the main causes of labor market restructuring. These are, predominantly, the differential impact of technology and globalization on various occupations. In both cases, a job's exposure to these disruptive forces is determined by occupation-specific characteristics.

Why do we expect technological progress and globalization to be significant forces driving structural change? Why do we anticipate these forces to have unequal effects on different categories of employees, e.g., different occupations? Fundamentally, both phenomena alter opportunities across various economic activities, leading to the expansion of some and the contraction of others, resulting in changes in the composition of economic activities. Since not all types of activities employ all types of workers in the same proportions, variations in the relative demand for workers arise because of these compositional changes. Moreover, technology and globalization also alter the proportions of demand for different types of workers within economic activities (regions, industries, or enterprises).

When considering the impacts of technological change, one must keep in mind the incidence of adoption. Technological progress initially increases the scope or range of production possibilities. The realization of these possibilities is mostly determined by the firms that adopt these technologies. Profit-driven firms adopt new technologies in order to reduce costs and to increase scale and market shares. Thus, the first-order impact is on firm size, and under regular conditions, overall firm employment. Outcomes across types of workers depend on how large the productivity, or cost-saving, effects are, and on the degree to which new technologies complement or substitute different types of labor. It is noteworthy that employment of a certain type of labor may rise even if technology substitutes for it, due to strong overall employment growth effects. Therefore, differential effects across worker types within firms may be secondary. Indeed, Reshef & Toubal (2019) and Harrigan, Reshef & Toubal (2021) find that job polarization in France is virtually entirely explained by changes in the composition of firms, not by within-firm changes in occupational composition. This implies that the mechanics of labor market restructuring are less straightforward than what some models suggest. Moreover, how these mechanics play out in the aggregate depends on market structure, general equilibrium conditions, and labor market institutions., giving rise to variation in outcomes across countries.

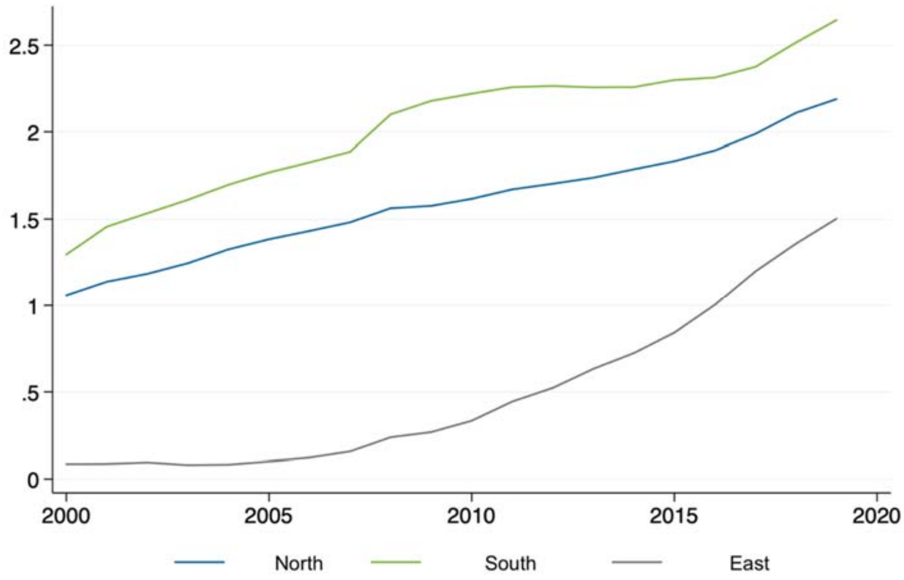
a. Indicators of technological change

Automation technologies, such as specialized software tools, computerized production equipment, and industrial robots, have been rapidly spreading across industrialized countries.[8] There is now growing evidence that these technologies not only automated tasks previously performed by workers and impacted wage structures, but also contributed to job polarization. This means that the negative effects of automation have mainly affected employment and wages in the middle of the wage distribution, which is closely related to the fact that many automated tasks were previously performed by middle-skill workers.

In various European regions, the proportion of industrial robots per workers has significantly increased, but not equally across European regions, as depicted in Figure 5. Southern regions exhibit higher robot adoption rates compared to other regions, and interestingly, they also experience job polarization (see Figure 2). Eastern European countries started adopting robots at a faster pace than those in the North or the South after 2004, which is associated with the enlargement of the European Union around that time.

[8] On the diffusion of automation technologies, see Autor (2015), Acemoglu and Restrepo (2020), Graetz and Michaels (2018).

Figure 5. Ratio of robots to employment by groups of countries



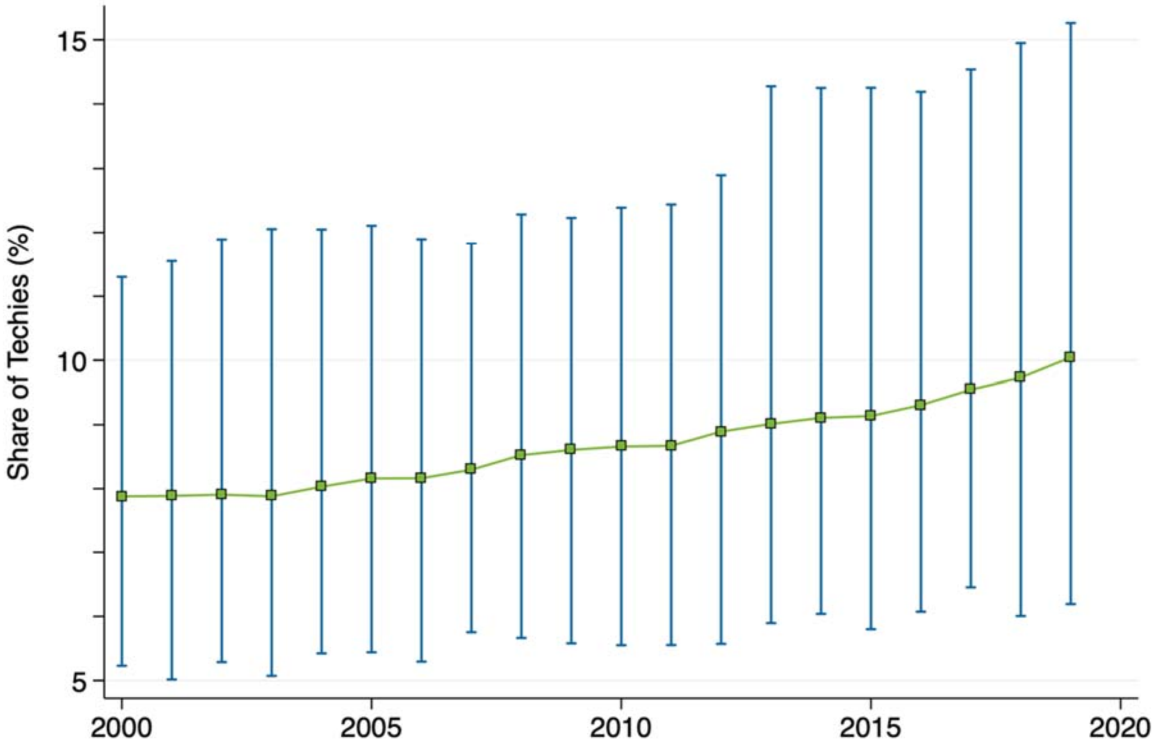
Note: Authors' calculation.

Turning to a different marker of technological change, Deming and Noray (2018) argue that "STEM jobs are the leading edge of technology diffusion in the labor market". Engineers and other technically trained workers – which we call *techies* – are particularly well equipped with STEM skills (Harrigan *et al.*, 2023).[9] The specialized technical knowledge and skills that techies possess underscores their unique role in driving technology-related advancements. They are at the heart of creating, but also adopting, implementing, and diffusing new technologies.

In Figure 6, we present the evolution of the average proportion of techies across 28 European countries and illustrate the variations among countries by considering the minimum and maximum shares in each year as lower and upper bounds. Figure 6 reveals an increasing trend in the average share of techies in the overall working population from around 8% in 2000 to 10% in 2019. Furthermore, significant differences exist among countries, with those employing a higher share of techies in 2000 showing even larger shares in 2019.

[9] Harrigan *et al.* (2023) show that techies possess a higher level of STEM education and training than workers in other occupations. Using French data, they show that approximately 63% of techies have a STEM degree and/or training. In contrast, workers in non-techie occupations have much lower levels of STEM education, in particular general management.

Figure 6: Employment shares of techies across 28 European countries

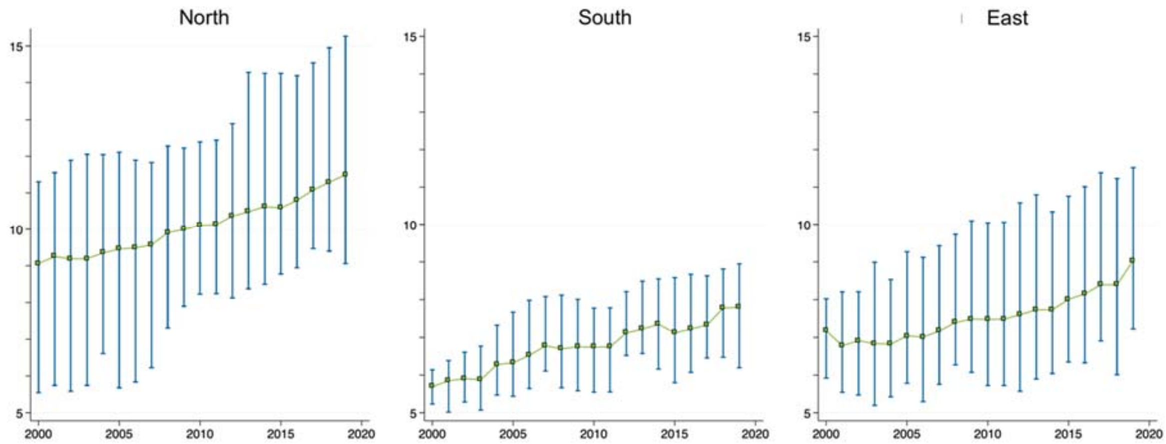


Note: Authors' calculation. This figure reports the employment share of techies in the total economy in percent (harmonized NACE Rev.2 A-U) for 28 European countries. Techies are defined as individuals working as physical, mathematical, and engineering professionals (21) and physical and engineering science associate professionals (31) according to the 2-digit ISCO-88 classification (for years 2000-2010). For years 2011-2019, techies are defined as those working as science and engineering professionals (21), information and communications technology professionals (25), science and engineering associate professionals (31), and information and communications technicians (35) based on the 2-digit ISCO-08 classification. The figure considers the minimum and maximum values of each year as lower and upper bounds, respectively.

Figure 7 illustrates the evolution of techies across European regions. We note a wide dispersion of the employment share of techies within the northern countries, ranging from 7.5% to more than 15% in 2019. In contrast, the southern and Eastern countries have a smaller average proportion of techies, reaching 7.5% and 9% in 2019, respectively, and less dispersion. However, the share of techies has increased across all regions, with the most substantial growth observed in the north, rising from 8% in 2000 to approximately 11.5% in 2019, on average.

As discussed by Harrigan, Reshef, and Toubal (2021), techies have a strong positive effect on firm-level employment growth and importantly on the occupational structure of the firm. They find that techies are associated with skill upgrading and particularly an increase in the employment share of managers. These findings should be considered in light of the broader trend in European regions, where skill upgrading has been more prevalent, except in the Southern regions.

Figure 7: Employment shares of techies across regions within Europe



Note: Authors' calculation. This figure reports the employment share of techies in the total economy in percent (harmonized NACE Rev.2 A-U) for 28 European countries. See note to Figure 7 for the definition of techies. Northern countries: Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Ireland, Luxembourg, Netherlands, Norway, Sweden, Switzerland, United Kingdom. Eastern countries: Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia. Southern countries: Cyprus, Greece, Italy, Portugal, Spain.

b. Which jobs were automated?

The central explanations for job polarization are centered around the routinization hypothesis, which builds upon the influential work of Autor *et al.* (2003). These explanations are centered around the relationship of technology to tasks. According to the routinization hypothesis, recent technology trends tended to replace workers that were engaged in routine tasks (such as clerks or production workers) because these tasks can be easily codified and executed by computers.[10] These tasks tend to be "bundled" in occupations that lie in the middle of the wage distribution. In contrast, technology augments the productivity of workers performing analytic and interactive tasks (such as managers, professionals, or researchers), thereby increasing their relative demand. The impact of these technological changes on workers performing non-routine manual tasks (such as industrial workers or personal care assistants) is limited since their jobs require substantial interpersonal or physical adaptability.[11]

The impact of technology, favoring high-skilled, highly paid employment in analytic and interactive tasks while displacing medium-skilled, medium wage routine-intensive jobs is accompanied by evidence on inter-sectoral mobility (Acemoglu and Autor, 2011; Cortes, 2016). This evidence shows that low-skilled, low-wage manual jobs absorbed the surplus labor from workers displaced from routine-based occupations. When combined, these findings provide an explanation for the clustering of employment growth at the extremes of the occupational skill distribution, resulting in a U-shaped pattern, i.e., job polarization, especially from the mid-1990s and up to 2010.

But in the previous sections we saw that the pattern of job polarization is much weaker post 2010, and is observed mostly in Southern European countries. Elsewhere, we observe a pattern

[10] Routine tasks that, in addition, do not require interpersonal face-to-face interactions can also be offshored (Blinder, 2007, Blinder & Krueger 2013), adding to the effect of automation. We discuss this below.

[11] Recent work by Autor *et al.* (2022) maps technological change in the U.S. into the labor-replacing and labor-augmenting dimensions.

of skill upgrading post 2010. This change in the pattern of labor market restructuring is consistent with the model of Acemoglu & Loebbing (2022), where automation first causes job polarization, by reducing relative demand for middle-skilled workers, but under certain conditions automation eventually replaces lower-skilled workers, giving rise to skill upgrading in the aggregate economy. This occurs if wages of low-skilled workers do not drop sufficiently, for example, if there is a binding statutory minimum wage – which is prevalent in many European economies. Initially, new automation technologies are adopted in order to replace routine tasks of middle-wage occupations, who are also relatively costly to firms compared to low-wage workers. But as these technologies become cheaper (or better) they may replace mostly low-wage workers if the latter are not "cheap enough".

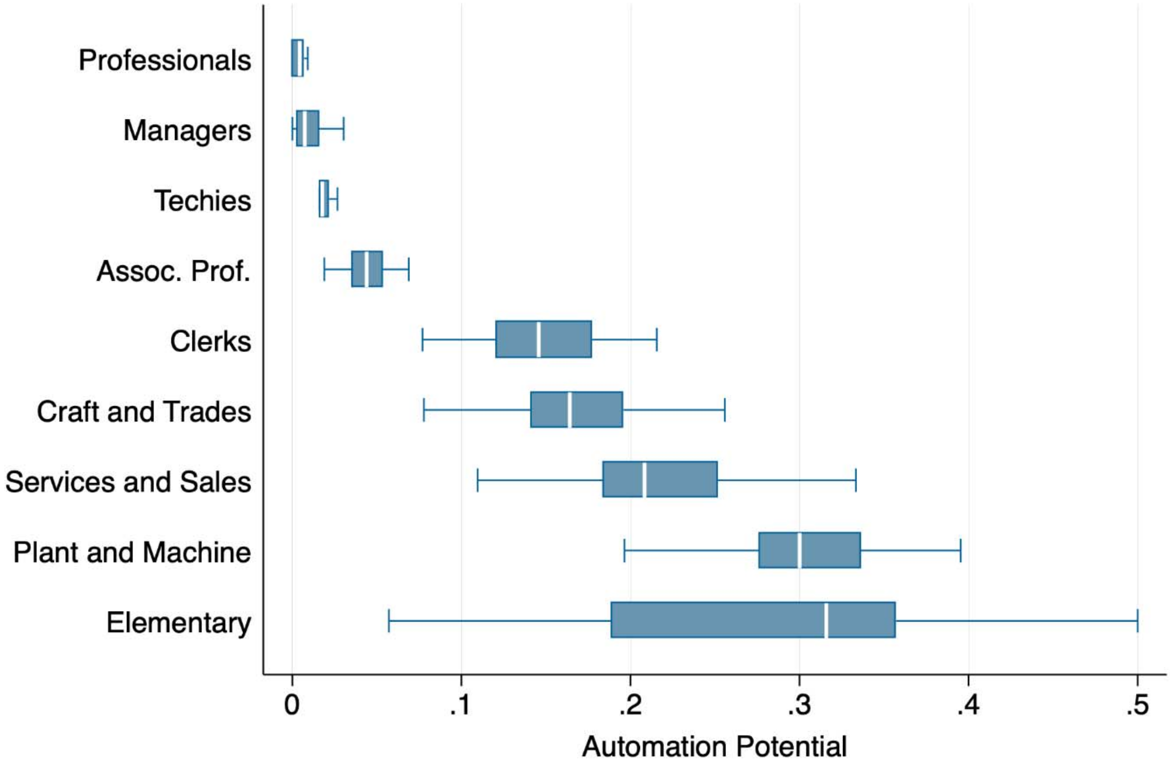
In order to understand the post-2010 trends we use a broad measure of the risk that an occupation will be replaced by some technology (robots, ICT, artificial intelligence, or other), which was developed by Arntz, Gregory and Zierahn (2017), based on data from 2010.[12] We associate the Arntz *et al.* measure to nine broad occupations that are built from the ISCO-08 classification. Figure 8 reports information on the distribution of the risk of automation across broad occupations: the median, the first and third quartiles, and extreme values.

Figure 8 delivers two main messages. The first is that professionals (associate or not), managers, and techies face low risk of automation, while other occupations face significantly higher risk. This is consistent with the idea that high skilled workers that are employed in occupations that bundle non-routine cognitive tasks. These tasks – such as analytical, creative and managerial tasks – are difficult to codify and, therefore, difficult to automate, to date.[13] The second message that Figure 8 conveys is that for the former group of occupations there is little cross-country variation in risk, compared to the large heterogeneity for other occupations, especially elementary ones. This implies that the specific task content of these occupations matters a lot for predicting their risk of automation.

[12] The advantages of the measure of Arntz, Gregory and Zierahn (2017) is that it takes into account variation in task intensity and that it varies by both occupation and country. It is an improvement over the measure by Frey and Osborne (2017), as it takes into account the heterogeneity of tasks across individuals within occupations. It also incorporates variation across countries within occupations. Frey and Osborne (2017) use expert assessments of the risk that an occupation in the United States will be replaced by technology (automated). Arntz, Gregory and Zierahn (2017) view these assessments of risk of automation as informative, but noisy. They associate these risks to underlying tasks and individual characteristics of workers that are employed in these occupations using a regression model. They then use this model to predict a task-based risk of automation. This delivers lower overall risk of automation compared to the expert assessments.

[13] Current advances in artificial intelligence may be changing this boundary to some extent.

Figure 8: Risk of Automation by Broad Occupation



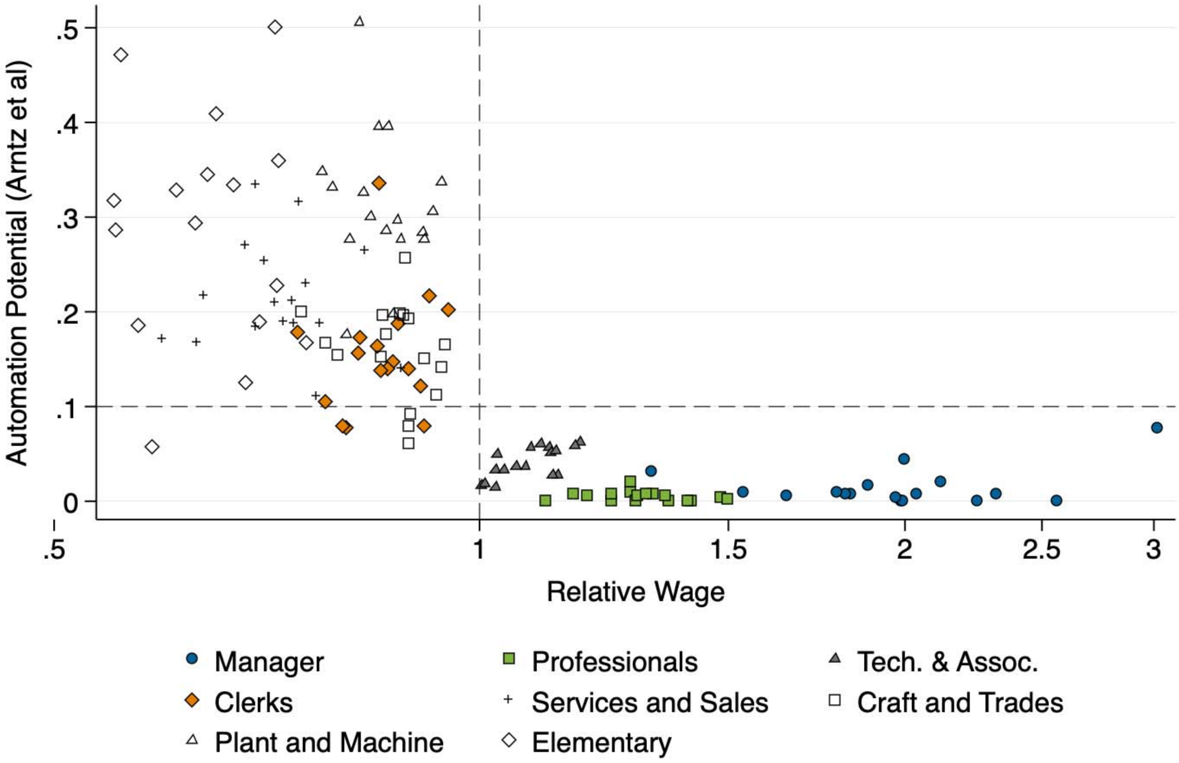
Notes. The figure reports the average risk of automation ("Automation Potential") by broad occupational categories. Risk of automation is from Arntz *et al.* (2017). For each occupation category the median is light line that lies within the box, which marks the range between the first and third quartile. The range around the box marks the lower and upper adjacent values. The lower adjacent value is the smallest value that is greater than or equal to the first quartile minus 1.5 the inter-quartile range. The upper adjacent value is the highest value that is less than or equal to the third quartile plus 1.5 the inter-quartile range. We drop "Armed Forces Occupations" and "Skilled Agricultural, Forestry and Fishery Workers", which make up a small proportion of the labor force in the sample of countries we consider. Data are from the following countries: Austria, Belgium, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Ireland, Italy, Netherlands, Norway, Poland, Sweden, Slovakia, United Kingdom. Data cover the entire economy (NACE codes A-U).

The group of occupations that face low risk of automation are also relatively better remunerated than the other occupations. We take a systematic look at this in Figure 9. We use the Structure of Earnings Survey (SES) to calculate for each occupation in each country in our data its intra-country relative wage: the occupational wage divided by the average wage in the same country.[14] We juxtapose in Figure 9 these relative wages with risk of automation. The vertical line at 1 marks the average wage in each country; observations to the left are paid less than the average wage in their respective countries and vice versa for observations to the right of the vertical line. The horizontal line is arbitrarily located at a probability of 0.1 of being automated. Due to data limitations in the SES, we cannot separate Techies from Associate Professionals; and the data cover only manufacturing, market services and non-market services.

[14] The SES covers more than 85% of the economy, compared to EU LFS coverage, since it does not report earnings for the following industries: Agriculture, Mining and quarrying, Utilities, Construction, Households as employers, and Extraterritorial organizations. This proportion rises somewhat in our dataset, since we do not use EU FLS data on workers in Households as employers, and Extraterritorial organizations.

Figure 9 demonstrates that there are two broad classes of occupations: high paid occupations have uniformly low risk of automation, and low paid occupations exhibit relatively higher risk of automation. As in Figure 8, we see that the second group exhibits significant heterogeneity in risk of automation. Interestingly, high wage occupations exhibit low risk of automation despite significant variation in relative wages. This strengthens our point above, that the task content of professionals, managers, and techies is the fundamental factor that insulates them from automation, whatever their wage.[15]

Figure 9: Risk of Automation and Relative Wages



Notes. The figure reports the average risk of automation ("Automation Potential") by broad occupational categories across countries and their relative wage. Each observation marks an occupation in a country. Average risk of automation by occupation and country is from Arntz *et al.* (2017). Relative wages are computed relative to the country average using the Structure of Earning Survey (SES). The vertical line at 1 marks the average wage in any country and the X-axis is in log scale. Data are from the following countries: Austria, Belgium, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Ireland, Italy, Netherlands, Norway, Poland, Sweden, Slovakia, United Kingdom. Due to data availability in the SES, the figure uses only data on manufacturing, market services and non-market services (NACE codes C, G-N and O-S, respectively). The SES reports incomplete or no information for Agriculture, Forestry and Fishing; Mining and Quarrying, Utilities; Construction; the Household Sector; and Extraterritorial Organizations and Bodies (NACE codes A, B, D, E, F, T, and U, respectively).

After studying how the risk of automation is associated with different occupations and with their wages, the question is then whether risk of automation predicts loss in relative employment. We study this question in Figure 10. This figure has a similar structure as Figure

[15] Frey and Osborne (2017) already documented the relationship between risk of automation and wages, but they consider only the United States.

3 and Figure 4 above. The width of each bar in the figure is proportional to the respective occupation employment share in 2011 (in percent), and the height is the change in the employment share from 2011 to 2019 (in percent points). In contrast to Figure 3 and Figure 4, occupations are positioned on the horizontal axis from high to low risk of automation (not by relative wages). Another difference is due to the sample, which here covers the entire economy and we are also able to distinguish Techies as separate category (because we do not use SES wage data here).

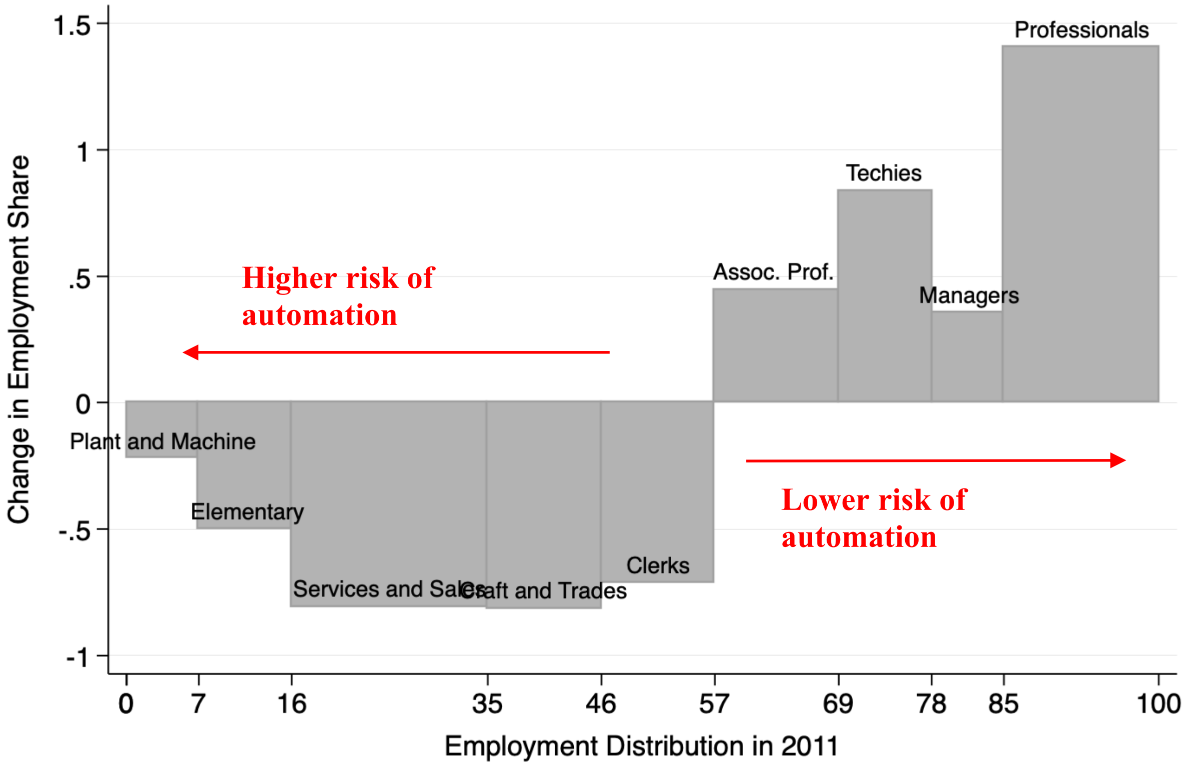
Figure 10 conveys a clear message: by and large, occupations with high risk of automation in 2010 grew less over the subsequent decade than those with low risk of automation. Although the relationship is not linear, the Arntz *et al.* (2017) measure in 2010 helps to predict which occupations grow and which shrink in the subsequent decade.

We then build similar figures, separately for manufacturing and services sectors in Figure 11. Within manufacturing Plant and Machine, Elementary and Craft and Trades occupations see their employment shares drop significantly, while Techies, Managers and Professionals rise. The picture is similar in the services sector: Services and Sales, Elementary and Clerks lose employment shares, while only Techies and Professionals rise. Interestingly, the employment share of Management does not increase much within services industries.[16]

The differences across these sectors are related to the types of technologies that are being implemented and which tasks are more prevalent. Robotization is most salient in manufacturing, replacing routine manual tasks and the occupations that are most intensive in these tasks. In contrast, in services ICT eventually reduce employment for occupations that are routine cognitive intensive. Different technologies are implemented where they can cut costs by replacing associated tasks on a large scale. Both ICTs and AI can complement workers in performing non-routine tasks, and therefore could augment demand for professionals, techies and management. We note, however, that adoption of AI is in its early stages, and may eventually replace some high-wage professionals and managers, precisely because they are costly to the firms that employ them.

[16] We obtain similar results when considering only market services, which accounts for the bulk of the overall services sector

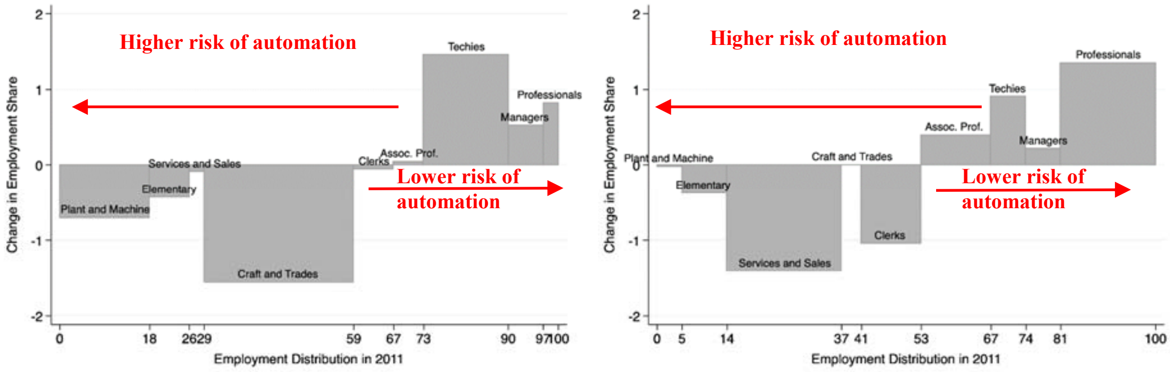
Figure 10: Risk of Automation and Occupational Change



Notes. The figure reports how changes in employment shares relate to the risk of automation. The width of each bar in the figure is proportional to the respective occupation employment share in 2011 (in percent), and the height is the change in the employment share from 2011 to 2019 (in percent points). Occupations are positioned on the Horizontal axis from high to low risk of automation. Employment data are from the EULFS. Risk of automation is from Arntz *et al.* (2017). Data are from the following countries: Austria, Belgium, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Ireland, Italy, Netherlands, Norway, Poland, Sweden, Slovakia, United Kingdom. Data cover the entire economy (NACE codes A-U).

Figure 11: Risk of Automation and Occupational Change by Sector

A. Manufacturing **B. Services**



Notes. The figure reports how changes in employment shares relate to the risk of automation within broad sectors. The width of each bar in the figure is proportional to the respective occupation employment share in 2011 (in percent), and the height is the change in the employment share from 2011 to 2019 (in percent points). Occupations are positioned on the Horizontal axis from high to low risk of automation. Employment data are from the EULFS. Risk of automation is from Arntz *et al.* (2017). Data are from the following countries: Austria, Belgium, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Ireland, Italy, Netherlands, Norway, Poland, Sweden, Slovakia, United Kingdom. Manufacturing is NACE code C; Services includes market services and non-market services, NACE codes G-N and O-S, respectively.

c. Trade, structural transformation and labor market institutions

In addition to the role of technological progress, many authors have linked the phenomenon of job polarization to globalization.[17] Globalization can be defined as an increase in the intensity of international trade in goods, services, capital, and international knowledge flows. Globalization also provides firms with the opportunity to reorganize their activities globally, either through trade or by locating all or part of their operations abroad. The question regarding the overall impact of globalization on employment or its composition can only be partially resolved. The lack of detailed data makes it challenging to jointly examine the various influences of globalization on employment. However, we have more information to analyze the specific impact of international trade in goods.

We expect a greater impact of international trade on occupations that are more directly exposed to it. Imports could explain the decline of intermediate-wage jobs as they substitute tasks that can be performed by cheaper labor abroad, a phenomenon known as offshoring (See Blinder, 2007; Blinder and Krueger, 2013). Since the tasks involved are carried out over long distances, they are more likely to be offshored if they require fewer face-to-face interpersonal interactions. International trade can also benefit high-wage workers by increasing the demand for non-routine intellectual tasks, tasks associated with organizational changes at the company

[17] Several significant contributions have been made on this topic, including those by Autor *et al*. (2013a,b), and Autor *et al*. (2015). Goos *et al*. (2014), Harrigan *et al*. (2017), Malgouyres, (2018), and Reshef and Toubal, (2019).

level, or tasks related to management and communication among company subsidiaries located in different countries.

Another force that may affect job polarization is structural transformation, i.e., the phenomenon of the decline in manufacturing employment shares and the commensurate rise in the employment share of services (together with the long run trend in the decline in the agriculture sector). This is driven by faster productivity growth in manufacturing, as discussed above (Baumol, 1967). Bárány and Siegel (2018) establish a connection between job polarization and structural transformation because manufacturing had relatively more middle-wage jobs, whereas the services sector has both relatively more low wage jobs and high wage jobs.[18] Importantly, they emphasize that this phenomenon was already present prior to the extensive global integration of the economy and to the extensive proliferation of robots and ICTs in the 1980s. Therefore, structural change is an additional, separate vector that drives job polarization.

Labor market institutions mediate the impacts of both technological change and globalization across occupations and different segments of the labor market. Oesch (2010) studies the influence of diverse regulations and economic policies on unskilled employment opportunities across European and Anglo-Saxon countries from 1991 to 2006. His findings underscore the efficacy of effective job placement assistance and adapted financial strategies in enhancing the employability prospects of unskilled workers. Subsequently, Oesch (2013) embarks on a comprehensive examination aimed at comprehending the factors shaping the occupational composition within five specific economies – namely, Britain, Denmark, Germany, Spain, and Switzerland – spanning the years 1990 to 2008. This study identifies five driving forces of occupational labor market restructuring: technological change, globalization, supply of education, international migration, and labor market institutions.

One of the most important labor market regulations that mediate the effects of novel technologies on employment dynamics is the minimum wage. Albertini, Hairault, Langot, and Sopraseuth (2016) study this in the specific context of France. They find that minimum wage policy has a negative impact on the reallocation of jobs at the bottom of the wage distribution. In particular, the reallocation of workers from routine tasks to manual service jobs was negligible before the early 2000s due to a lack of job creation in the non-manufacturing sector. The task assignment model in Acemoglu and Loebbing (2022) predicts that higher minimum wages increase the likelihood of automation of low-wage jobs, compared to middle-wage jobs.

Employment protection legislation (EPL) is another important mediating labor market institution. While potentially having positive social effects, EPL confers an implicit cost on employers and, therefore, reduces employment and increase capital intensity (Autor, Kerr & Kugler, 2007). In line with this, Presidente (2023) finds that stronger EPL is associated with more robotization in manufacturing industries where the threat of hold-up by labor is greater (due to higher fixed costs of operation). Similarly, Acemoglu & Restrepo (2022) find some evidence supporting the notion that greater unionization increases robotization due to greater implicit labor costs.[19] Anticipating the future presents challenges, particularly with the rapid advancements in artificial intelligence, digitization, and smart robotics. Debates revolve around whether these technologies will replace human labor on an unprecedented scale or if new tasks will emerge, shaping the economic transformation. Acemoglu and Restrepo (2018) ponder the transition path and timing of these changes. Equally important is understanding which tasks, previously shielded from technology or trade, might now be replaced. This can help predicting whether the result will be job polarization, or whether future technologies will affect more jobs

[18] In fact, the services sector can be divided into two broad segments: a high-skill, high wages segment and a low wage, low skill intensive segment. This has consequences for employment and wage dynamics (Reshef, 2013).
[19] However, Cardullo, Conti & Sulis (2015) find that unionization reduces capital investment more broadly.

at the top or bottom of the wage distribution. A notable technological shift is that smart machines no longer require strict codification and contingent rules due to their ability to learn from vast data and utilize computing power and statistical procedures.

The impact of automation on job replacement remains uncertain, although there is a clear possibility that new technologies could have a significant effect in the future. Research by Graetz and Michaels (2018) suggests that industries that adopted more intensively industrial robots did not exhibit excessive job losses (beyond the general trend in manufacturing). Instead, it resulted in increased labor productivity, wages and employment – even though the employment increases were less strong for less-skilled labor. While this provides some reassurance, the potential effects of future automation remain a topic of ongoing investigation and debate.

Technological progress and adoption are influenced by various interconnected factors, such as market structure, government policies, population growth and aging. Beaudry and Green (2002) show how population growth can accelerate the adoption of new technologies, resulting in more significant changes in economic outcomes during the information technology revolution. Acemoglu and Restrepo (2022) demonstrate that aging contributes to faster adoption of automation. Slower population growth and aging are predicted to be salient features of most OECD countries. This suggests less innovation, but more rapid adoption of new technologies, albeit from a smaller pool. Therefore, it is difficult to predict how population dynamics will affect labor outcomes.

Looking forward, it is safe to say that in the coming years we will see profound changes driven by the implementation of artificial intelligence technologies (AI). Less clear is what these changes will look like. Greater exposure or adoption of AI may result in either displacement, if these technologies can completely replace tasks performed by humans – or in an increase in labor demand, if these technologies strongly complement some types of labor. Complicating the analysis is the fact that AI may lead to growth in industries that adopt it more intensively.

Uncertainty about what we can predict for the future is underscored by recent work by Acemoglu *et al.* (2022). They detect greater hiring efforts in 2010-2018 (via online job ads) directed at workers with AI-related skills in U.S. establishments that were intensive in workers that possessed such skills in the first place (AI-exposed establishments). This suggests a compositional change within establishments that favors workers that are endowed with AI-related skills. However, at the more aggregate level (occupations or industries) they find no such effects. In contrast, Copestake *et al.* (2023) do find labor-displacing effects of AI in Indian services firms, especially for highly skilled managerial and professional occupations.

Ultimately, it may be too soon to know how AI will affect labor market restructuring. But given the speed at which progress in these technologies is being made, there is urgency in making some predictions. Some clues from recent research have emerged.

Albanesi *et al.* (2023) study how AI has affected labor demand in 2011-2019. They use two recent measures of "exposure" to AI, one due to Felten, Raj & Seamans (2019), the other due to Webb (2020). These two measures differ in their methodologies, but have one important common point, which is that they map indicators of AI technologies to tasks that are then bundled in occupations.

Despite their differences, the two measures suggest similar inference: occupations that are more exposed to AI grew more. This effect is stronger for young and highly educated workers, although no detrimental effect on other workers, is detected. This suggests that AI complements skilled labor, and that younger workers are more likely to adapt this technology. Skilled and young workers are more likely to become more productive and this shifted labor demand in their favor. If this continues in the future, then we can expect similar patterns as in 2011-2019: skill upgrading. However, one should take this prediction with caution, as recent advances in AI (e.g., ChatGPT, Bard and others) break new grounds.

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