Unraveling wage inequality: tangible and intangible assets, globalization and labor market regulations

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Abstract

In this paper, we study the asymmetric effects of different types of capital-embodied technological change, as proxied by tangible and intangible assets, on relative wages (high- to medium-skilled, high- to low-skilled and medium- to low-skilled workers), relying upon the technology-skill complementarity and polarization of the labor force frameworks. We also consider two additional major channels that contribute to shaping wage differentials: globalization (in terms of trade openness and global value chains participation) and labor market institutions. The empirical analysis is carried out using a panel dataset comprising 17 mostly advanced European economies and 5 industries, with annual observations spanning the period 2008–2017. Our findings suggest that software and databases—as a proxy for intangible technologies—exert downward pressure on low-skilled wages, while robotics is associated with a polarization of the wage distribution at the expense of middle-skilled labor. Additionally, less-skilled workers' relative wages are negatively affected by trade openness and global value chain participation, but positively influenced by sector-specific labor market regulations.

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1 Introduction

We are witnessing an increasingly intense debate centered around the impact of artificial intelligence, automation technologies and robotics on economic growth, inequality and society as a whole. Economists, analysts, journalists and policymakers are split on the consequences of the introduction of these new technologies, with both optimists and pessimists. The former argue that, in the next decades, we will see a boost in productivity and new job opportunities, most of which are currently hard to envisage (e.g., Brynjolfsson and McAfee 2014; Baldwin 2019), while the latter predict significant job destruction and a sharp increase in income inequality (e.g., Freeman 2015; Frey and Osborne 2017; Berg et al. 2018).

While efforts have been made on the theoretical front to understand the mechanisms through which new technologies are shaping the functioning of modern labor markets (see, for instance, Acemoglu and Restrepo 2019, 2018; Nakamura and Zeira 2023), the empirical evidence is far from conclusive. For instance, by focusing on robots, quantitative studies (such as Graetz and Michaels 2018; Acemoglu and Restrepo 2020) capture only the 'tangible' part of technical change (Nelson and Phelps 1966), with employment, productivity and wages being affected as a result of investments 'embodied' in new machinery.

Moreover, interest has arisen in assessing the contribution of specific forms of investments previously not well acknowledged and measured, i.e., intangible assets (e.g., McGrattan and Prescott 2010, 2014). Consequently, researchers have questioned whether the labor-market effects of 'intangible' technical change (e.g., Corrado et al. 2009; Haskel and Westlake 2018), such as software and R&D, affect workers in a similar manner to tangible investments or not. In this respect, Blanas et al. (2020) provide evidence in support of the hypothesis that software displaced medium- and low-skilled workers, whereas Michaels et al. (2014) identify a negative impact of R&D on the share of the wage bill captured by medium-skilled labor, suggesting a polarizing effect of R&D. Furthermore, as stressed by Haskel and Westlake (2018), the impact of intangibles is expected to lead to a rising premium for well-educated workers, insofar as specific education and skills are required for managing these new technologies. The longstanding controversy about 'disembodied' and 'capital-embodied' technical change continues to be relevant in these discussions, with questions remaining over whether technological progress is independent of (i.e., Hicks-neutral) or tied to specific capital inputs in the economy and the consequences of this for labor market outcomes (e.g., Greenwood et al. 1997; Hercowitz 1998). Overall, the effect of technological progress may depend on how the two types of technical change—i.e., broken down into tangible and intangible capital assets—affect different kinds of workers, by either enhancing or limiting their relative importance in the production process.

A further potentially important driver of labor market outcomes addressed in a separate literature, focuses on the role of trade and particularly participation in Global Value Chains (GVCs). In this regard, as pointed out by Van Reenen (2011), trade with low-wage countries could force firms in advanced economies to 'innovate or die'—producing, among others, significant impacts on the skill structure of labor demand, wages, inequality and productivity (see, among others, Wood 1995; Hijzen

et al. 2005; Hijzen 2007; Foster-McGregor et al. 2013; Michaels et al. 2014; Lopez Gonzales 2015).

Relatedly, the contributions of labor market institutions suggest that these have significant effects on living standards, productivity and social cohesion, especially in European economies (e.g., Koeniger et al. 2007; Betcherman 2012). In addition, several studies have highlighted how labor market institutions, when expressed, for example, through increased unionization, provision of minimum wages, balanced working hours and well-structured active labor policies, can favor a reduction in wage and income disparities (e.g., Jaumotte and Buitron 2015; Salverda and Checchi 2015).

The above discussion highlights that technological progress develops in various directions, with distinctions between tangible and intangible, as well as embodied and disembodied discussed in the literature. These different forms of technology potentially impact upon labor markets, and on different types of workers in labor markets, in varied ways. Beyond these broad categories, more specific technologies, such as robots and artificial intelligence (AI), are further expected to impact upon labor markets differently, with Webb (2020) arguing that while robots impact upon lower-skilled tasks, AI is targeted at high-skilled tasks. Despite such observations, much of the existing literature focuses on only a subset of technologies or bundles various different technologies together when considering technology's impact on labor markets. This paper builds upon this existing literature by decomposing technology along different dimensions, examining the relationship between these different technologies and labor market outcomes. Specifically, we examine the relationship between relative wages and the following dimensions of technology: ICT Capital; Software and databases; R%D capital stocks; and Robots. Through this analysis, our aim is to identify and understand the relative effects of these distinct technologies on the relative wages of different types of labor, providing a more nuanced comprehension of the complex relationship between different types of capital and labor market outcomes. Moreover, when considering the relationship between these different dimensions of technology and labor market outcomes, we account for the other major drivers of labor market outcomes considered in the literature, i.e. labor market institutions and trade, further focusing on the role of GVCs in the context of trade. The approach thus builds upon the technology-skill complementarity and polarization of the labor force frameworks (e.g., Autor et al. 2006; Goos and Manning 2007; Goldin and Katz 2009; Goos et al. 2009; Acemoglu and Autor 2011), but is more comprehensive in considering and decomposing technologies that may affect labor markets. The paper thus contributes to various strands of the literature: from the "capital-embodied" technical change to technology-skill complementarity and polarization of the labor force frameworks, as well as work examining the impact of automation and digital technologies, institutions and international trade on labor market outcomes. The paper further has important policy relevance, with concerns increasing around the impacts of these diverse technologies. By improving our understanding of how distinct types of technology impact upon different types of labor, the study provides insights into the range of policy responses that may be needed to tackle the increased investments in these different technologies.

In terms of data, the research relies on a panel of 17 mostly advanced European economies and 5 industries, using annual data over the years 2008–2017. In perform-

ing the empirical investigation, we exploit the EU KLEMS (2019) database, which explicitly groups fixed capital stocks into tangible and intangible assets, according to Haskel and Westlake (2018). Additionally, by integrating data on operational stocks of industrial robots from the International Federation of Robotics (IFR), we have the opportunity to detect the influence of advances in robotics, ICT, R&D and Software & Databases (S&DB) as different, independent proxies for tangible and intangible technologies, respectively. To disentangle the effects of the above-mentioned drivers on relative wages, we adopt a two-step estimation strategy. Firstly, we simultaneously estimate a system of wage premium equations by making use of seemingly unrelated regressions (SUR) to deal with correlations in the error terms across equations. The second step involves an instrumental variable approach to address potential endogeneity concerns, using Japanese robot density as an instrument for robot adoption in the sample of European countries included in the analysis.

The empirical analysis reveals that decomposing technology and considering the independent effects of different dimensions of technology is important in understanding their overall effects on labor market outcomes. In fact, the multiple aspects of technology are found to show varied relationships with relative wages. Robots, for instance, are associated with an increase in relative wages for high-skilled labor, but also with a compressed wage gap between medium- and low-skilled workers, suggesting a polarization effect. R&D also seems to benefit higher skilled labor disproportionately. Conversely, ICT is associated with a lower wage premium for high-skilled labor, while S&DB is associated with lower relative wages for low-skilled labor. The results thus underscore the importance of decomposing technology, with the average association of technology on relative wages hiding a great deal of variation across technology types.

The paper is structured as follows: Section 2 reviews the relevant literature; Sect. 3 describes the data employed in the analysis; Sect. 4 illustrates the theoretical and empirical frameworks, as well as the estimation strategy; Sect. 5 presents the baseline findings; Sects. 6 and 7 deal with the results based on the instrumental variable approach; finally, Sect. 8 provides a set of policy recommendations and concludes.

2 Related literature

The empirical literature investigating the role of (automation) technology, globalization and institutions in affecting labor market outcomes constitutes a large and growing body of research. Starting from the influential contributions by Solow (1960) and Jorgenson (1966), the controversy of 'embodied' versus 'disembodied' technical change revolved around whether technological progress affects productivity and economic growth through changes in physical capital goods (embodied) or independently of capital (disembodied). On the one hand, embodied technical change suggests that technological advancements are tied to specific capital investments, such as machinery or equipment. This perspective implies that capital accumulation is necessary for productivity growth. On the other hand, disembodied technical change posits that technology can improve productivity independently of capital investments. According to this view, technological progress can lead to efficiency gains and productivity

improvements even without significant changes in the capital stock (e.g., Greenwood et al. 1997; Hercowitz 1998; Boucekkine et al. 2003).

Meanwhile, since the seminal work by Griliches (1969) on capital-skill complementarity, many scholars have examined the potentially biased effects of technology on the relative demand for skilled workers. In particular, the evidence in the early nineties provided by Katz and Murphy (1992) and Bound and Johnson (1992) gave a new momentum to considering the efficacy of the skill-biased technical change hypothesis in explaining the observed rising trend in wage inequality across countries and within groups (for exhaustive surveys on this subject, see Chusseau et al. 2008; Acemoglu and Autor 2011). More recently, an alternative to the skill-biased technical change hypothesis has been proposed that attempts to provide an explanation more suitable for the recent observation of declining relative demand and wages of middle-skilled workers—the so-called job polarization phenomenon—in developed countries in particular (e.g., Autor et al. 2003; Goos et al. 2009; Acemoglu and Autor 2011). The routine-biased technical change hypothesis (Autor et al. 2003) argues that recent technological change, including artificial intelligence, robots and ICT developments more generally, allows for the replacement of workers doing routine tasks, which are often tasks undertaken by middle-skilled workers.

Among the proxies for automation technologies employed in the empirical literature on the skill composition of labor demand and wages, the focus has mostly been placed on computerization, ICT, R&D expenditure and patents (e.g., Berman et al. 1994; Morrison Paul and Siegel 2001; Chennells and Van Reenen 2002; Michaels et al. 2014; Mann and Püttmann 2021). Relying upon new data from the International Federation of Robotics (IFR) on industrial robots, progress has been achieved in the study of the impact of this contemporary automation wave on labor market outcomes, albeit with mixed results. Pioneering works in this field are Acemoglu and Restrepo (2020) and Graetz and Michaels (2018), who find evidence, respectively, of negative effects of robotics on wages and employment in the US and a positive influence on labor productivity growth in a panel of 17 countries. With specific reference to European economies, the findings are even less clear-cut. For instance, Chiacchio et al. (2018) point out a significant employment reduction as a result of increasing robot density (measured as the number of robots per thousand workers), an effect that is felt most strongly by middle-educated workers. By contrast, Dauth et al. (2021), analyzing 402 German local labor markets over the years 1994–2014, observe no effect of industrial robots on total employment, but adjustments in the composition of aggregate employment—specifically, job losses in manufacturing are offset by gains in the service sector. Similarly, by using data on employment from the European Labour Force Survey, Klenert et al. (2023) find that the adoption of an additional robot is associated, on average, with the employment of five additional workers.

Although the effects of robotics on labor market outcomes have been analyzed from various angles (for recent surveys, see Mondolo 2022; Yan and Grossman 2023), the empirical literature on the effects of robots on wage inequality still appears to be scarce. In this respect, Barth et al. (2020) point out that robotization increases the wages of high-skilled workers relative to low-skilled workers within Norwegian firms. Likewise, Aksoy et al. (2021) highlight how industrial robots are associated with a significant increase in the gender pay gap across 20 European economies.

Most of the technologies so far discussed, such as computerization, ICT and robots are tangible in nature, but since the contribution of Corrado et al. (2005), a new emphasis has been placed on the incidence of so-called 'intangible' investments, previously not appropriately classified and counted by business and national accounts. As argued by Haskel and Westlake (2018), intangibles are characterized by unique economic properties, among which are their complementarity, especially with well-educated and high-paid workers, as well as their tendency to generate knowledge and/or idea spillovers among firms and to trigger a "competitive process of investments in continuous product improvement" (Haskel and Westlake 2018, p. 41). These features could help explain a variety of economic phenomena such as economic growth, secular stagnation, and rising income and wealth inequality (e.g., Corrado et al. 2009; Glaeser 2011; Bessen 2016; Song et al. 2019). In particular, relying on a panel of 10 developed countries and 30 industries over the period 1982–2005, Blanas et al. (2020) find that software, as a proxy for intangible technology, is associated with an increase in the demand for high-skilled workers only, while the tangible component of ICT has a positive impact on the demand for all workers types. However, to the best of our knowledge, nothing has been done in the empirical literature to understand whether intangibles may be strongly complementary (substitutable) to high-skilled (low-skilled) workers, thus exacerbating wage inequalities, or be associated with a polarization of the wage distribution, and whether the tangible component of ICT, by contrast, may negatively affect wage dispersion (e.g., Acemoglu and Restrepo 2020, 2022).

In addition to technological advances, the many dimensions of globalization are thought to play an important role in affecting wage and income disparities (for recent reviews of the literature see, for instance, Kurokawa 2014; Nolan et al. 2019). According to the traditional Heckscher–Ohlin–Samuelson (HOS) model, trade openness is expected to benefit the abundant factor, which in developed countries would tend to suggest a rise in demand for, and therefore the return to, skilled relative to unskilled labor. In this respect, Wood (1995) analyzed the labor market effects of north–south trade, providing evidence of a significant impact of trade in reducing low-skilled employment in manufacturing in the North. Other studies have tended to provide confirmatory evidence of an effect of trade openness and/or liberalization on the skill-premium in developed countries, although the effects tend to be smaller than those found for technology. For instance, Harrigan and Balaban (1999) observe that capital accumulation and the decline in traded goods prices increased the earnings of well-educated workers in the USA, while Robbins (1996) and Beyer et al. (1999) highlighted a growth in the skill-premium in Chile. More recently, Michaels et al. (2014) and Epifani and Gancia (2008) find results suggesting polarizing and skill-biased effects of international trade, respectively. Goos et al. (2014) also find evidence to suggest that offshoring can lead to job polarization.

In reconsidering the traditional HOS trade-based approach, which has attracted considerable criticism (e.g., Berman et al. 1998; Goldberg and Pavcnik 2007), attempts have been made to provide new explanations for the role played by different forms of trade engagement—in particular, international outsourcing and offshoring—in driving wage inequality worldwide (for a survey, see Hummels et al. 2018). As argued by Feenstra and Hanson (1996), developing economies have played an increasing

role in producing more skill-intensive inputs as a result of outsourcing by advanced economies, generating a rise in the relative demand for skilled workers and the skill-premium in both developed and developing countries. Conversely, Grossman and Rossi-Hansberg (2008) offer a different explanation: by assuming that the prices of goods remain unchanged, a cost decrease in offshoring produces an increase in unskilled activities offshored to developing countries. This, in turn, causes a rise in profits and sector expansion for those industries that heavily employ unskilled labor, pushing up the sector's demand, productivity and wages, while leaving demand unchanged in industries relying on skilled labor. Therefore, through this channel, the skill-premium decreases.[1]

The evolution of the new patterns of globalization has been embodied by Gereffi and Korzeniewicz (1994) in the concept of GVCs. According to Amador and Di Mauro (2015), GVCs describe "the full range of activities undertaken to bring a product or service from its conception to its end use and how these activities are distributed over geographic space and across international borders". The role of geographically dispersed production stimulated many studies to assess the impact of GVC participation on earnings and wages (e.g., Baumgarten et al. 2013; Hummels et al. 2014; Parteka and Wolszczak-Derlacz 2015). In a recent contribution, Wang et al. (2021) develop a model suggesting that GVC participation is associated with higher profitability, which in turn leads to demands for higher wages (based upon a fair wage assumption). Given the higher bargaining power of skilled workers, GVC participation would increase the skill-premium. However, little has been done to quantify the effects of GVC participation on inequality. For instance, Lopez Gonzales (2015) measure backward GVC participation using the foreign value-added share of a country's gross exports and find that increased GVC participation is associated with a narrowing wage gap between skilled and unskilled labor in both developed and emerging economies—a finding in line with the theoretical predictions by Grossman and Rossi-Hansberg (2008). Conversely, as pointed out by Timmer et al. (2014), the expansion of emerging economies resulted in an increased global supply of low-skilled workers, consequently exerting downward pressure on the relative wages of less-skilled labor in developed countries.

Finally, a relevant role in affecting labor market outcomes is played by institutions and regulations (for a survey of studies on the effects of labor market institutions on living standards, productivity and social cohesion, see Betcherman 2012), such as measures of employment protection legislation (EPL). Existing studies find mixed evidence on the effect of labor market protection on labor market outcomes. A number of studies have demonstrated a significant and substantial effect of strong labor market protections in mitigating wage differentials, as shown, for example, by Koeniger et al. (2007) for a sample of 11 OECD countries over the period 1973–1998. Conversely, using data for a sample of 20 OECD countries spanning the years 1973–2011 and

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[1] Glass and Saggi (2001) argue that outsourcing produces two offsetting effects. Outsourcing from developed to developing countries provides firms in developed countries with access to low-wage labor in the south. On the one hand, this increases competition for low-skilled labor in developed countries, reducing demand for low-skilled labor in developed countries. On the other hand, access to low-skilled and low-wage labor in developing countries increases profits for firms in developed countries, which can create incentives for innovation, and which ultimately can offset the negative effects of outsourcing on low-skilled labor in developed countries.

indicators for regular and temporary contracts, Sparrman and Rossvoll (2015) find that the two indicators of labor market restrictions have opposite impacts on wage inequality, with EPL for temporary contracts shrinking the wage gaps and EPL for regular contracts intensifying them.

In summary, existing work on the relationship between technology and labor markets, often focuses on one particular dimension of technology (e.g., robots) or uses a broad definition (e.g., patents), thus neglecting the various types of technology and how they may impact upon labor markets in different ways. Moreover, the review of the literature suggests that there is relatively little evidence linking the various types of technology to relative wages specifically. In what follows, therefore, we build upon and extend existing work linking technology to labor markets, empirically examining the relationship between relative wages and different aspects of both tangible and intangible technologies, as well as different globalization measures and labor market regulations on determining wage differentials dynamics.

3 Data sources and variables construction

The empirical analysis relies on annual panel data for 17 mostly developed European economies and 5 industries—classified according to the one-digit-level NACE Rev. 2 (ISIC Rev. 4)—spanning the period 2008–2017.[2]

Data are collected and integrated from various sources. The main dataset is the EU KLEMS (2019) database, which provides information on skill composition, employment, labor compensation, hours worked, real fixed capital assets and value added by country-industry-year. The EU KLEMS dataset combines information on the shares of labor compensation and hours worked for three different worker types, which are distinguished on the basis of their educational attainment: university graduates; secondary and post-secondary education; and primary and lower secondary education.[3] Such a decomposition allows for a multifaceted investigation of the dynamics of skill-premia, analyzing whether workers are affected differently by tangible and intangible technologies, as well as by globalization and labor market regulations.

Relative wages are calculated as the ratio of the higher to the lower-educated hourly wage, along the three dimensions (i.e., high- to medium-skilled workers, w_h/w_m; high- to low-skilled workers, w_h/w_l; and medium- to low-skilled workers, w_m/w_l).[4] Relative skill supplies (i.e., the quantity effect), included in the models as controls, are measured by the ratios of hours worked in each analyzed category—namely the ratio of high-skilled to medium-skilled hours worked (H/M), the ratio of high-skilled

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[2] The set of countries and industries—reported in Tables 6 and 7 of the Appendix—as well as time periods included in the analysis are dictated by data availability.

[3] Although the EU KLEMS (2019) data are mostly available at the two-digit level and from 1995 onward, information on labor inputs cover the period 2008–2017 only and are provided according to the ISCED (2012) classification and NACE Rev. 2 (ISIC Rev. 4) one-digit industries. Throughout the analysis, we refer to high-skilled as workers with a university degree; medium-skilled as workers who obtained upper secondary or post-secondary education, but not tertiary education; low-skilled as workers with primary and lower secondary education. Whenever the terms "less-skilled" or "lower-skilled" are used, we refer to medium- and low-skilled workers as an aggregate.

[4] Further details about the variables' construction are reported in the Appendix A.

to low-skilled hours worked (H/L), and the ratio of medium-skilled to low-skilled hours worked (M/L). It is important to note that the data we have are limited to information on employment by education level rather than by specific skill sets or tasks that workers undertake. While this serves as a valuable proxy for examining labor aspects discussed in recent task-based literature, it needs to be kept in mind that this mapping from education to tasks and activities is not perfect.

As for capital inputs, based on Haskel and Westlake (2018), the EU KLEMS database groups asset types into tangibles and intangibles. Specifically, the tangible category includes ICT net of Software & Databases (i.e., hardware) and non-ICT (comprising, among others, transport equipment and total non-residential investments) capital stocks. The intangible assets contain S&DB and R&D capital stocks.[5] All capital intensity variables are taken as a ratio to total hours worked (in millions of hours).[6]

The second source of data is the International Federation of Robotics (IFR) for the stock of industrial robots by country-industry-year. IFR data are broken down by industrial branches and classified according to ISIC Rev. 4, which makes them highly compatible with EU KLEMS. However, due to limitations in the number of industries covered, the merger with EU KLEMS is possible only for the sectors reported in Table 7 of the Appendix.[7] In the benchmark analysis, the robot density variable (R) is computed as the number of industrial robots[8] per million hours worked, rather than the number of persons engaged, on the grounds that workers in different countries/industries may vary in the quantity of hours worked (Graetz and Michaels 2018). As observed by Blanas et al. (2020) and Jungmittag et al. (2019), robots are widely deployed in heavy industries, as a form of automation that links machinery (non-ICT capital) and software. Nonetheless, because of the tangible nature of robots, the inclusion of robot density in the analysis is aimed at isolating potential independent effects on the skill-premia and, following Graetz and Michaels (2018) and de Vries et al. (2020), assessing the robot high-skill complementarity or "hollowing-out" of middle-skilled workers hypotheses.

In the second stage of our analysis, we examine the role played by globalization, and in particular overall trade openness and participation in GVCs, in strengthening or mitigating the wage premia. For this purpose, we use data from the Trade in Value Added (TiVA) database (OECD, 2022) to measure the extent of trade openness at the country-industry level. By aggregating information at the one-digit level, the overall measure of international trade ($GLOB$) is calculated as the sum of intermediate imports and total (i.e., intermediate plus final) gross exports expressed as a share of real gross value added. According to Epifani and Gancia (2008) and Michaels et al. (2014),

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[5] For details, see Stehrer et al. (2019).

[6] As shown in Sect. 4, the empirical investigation relies on a technology in intensive form.

[7] Although it would be possible to cover the "Electricity, gas, steam; water supply, sewerage, waste management" sector (D_E), information on hours worked, which are essential for constructing the robot density variable, is missing for Japan. A dedicated part of the analysis is based on this country (see Sect. 6). Therefore, in order to compare the results obtained from different estimation techniques, the aforementioned sector is excluded from the sample. However, including the D_E sector, the baseline estimates are qualitatively consistent with those reported in the text and are available upon request.

[8] As illustrated in Appendix A, the robot stock variable is obtained applying the perpetual inventory method, using a depreciation rate of 10%.

we would expect either high-skill-oriented or a polarization of the wage distribution, as a result of higher trade openness. Thus, whether $GLOB$ affects the skill-premia positively or negatively, for the three dimensions of wage inequality, is an empirical question.

From the same source we gather information to account for participation in GVCs. Specifically, we collect data on domestic value added embodied in foreign final demand (FFD_DVA) and foreign value added embodied in domestic final demand (DFD_FVA). These two indicators can be interpreted, respectively, as "exports of value-added" and "imports of value added"—capturing forward and backward linkages in GVCs, respectively. The (total) $GVCs$ participation indicator is computed as the sum of FFD_DVA and $DFDA\_FVA$ expressed as a ratio to real gross value added. The inclusion of GVC variables, in the third stage of the analysis, has the goal of detecting whether and how a diverse form of engagement in trade (i.e., other than $GLOB$) impacts upon different kinds of workers.
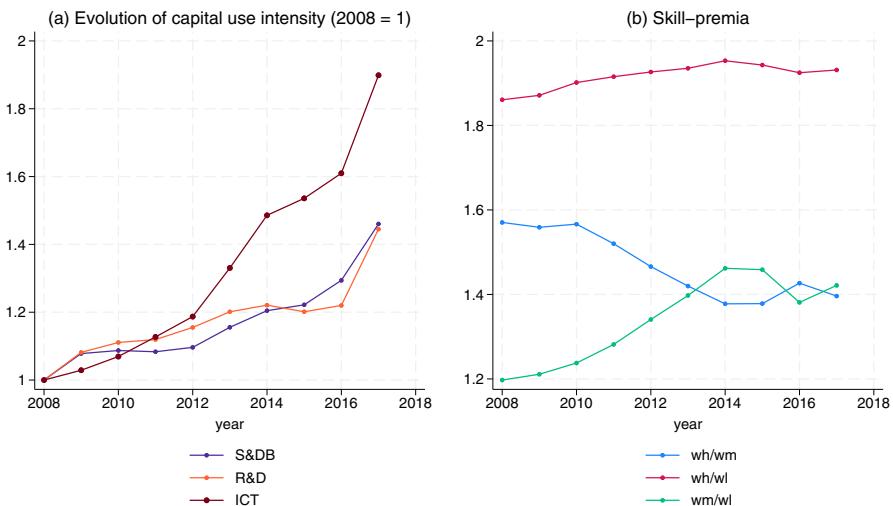
Finally, from the OECD we employ data on Employment Protection Legislation (EPL) in the third stage of the study, where the impact of labor market institutions on the skill-premia is assessed. Borrowing from IMF (2016) and Hantzsche et al. (2018), and making use of information from the Eurostat Labour Force Survey (EU-LFS, 2020) database, we construct two sector-specific indices of EPL for permanent and temporary workers, EPL_PERM and EPL_TEMP. By including the sector-specific measures for EPL in the models, we test the hypothesis that the recent findings of a negative relationship between EPL and skill-premia (e.g., Koeniger et al. 2007) are confirmed when the extent of labor market regulations are proxied by two separate, sector-specific indicators, one for each group of workers. As an additional check, we also consider an overall sectoral EPL index ($SECT\_EPL$), given by the sum of EPL_PERM and EPL_TEMP.

Real price variables are expressed in PPP adjusted 2005 international dollars, with the PPP conversion factors taken from Inklaar and Timmer (2014). The benchmark sample consists of 751 observations. Summary statistics, by country and industry, for the levels of the variables included in the empirical analysis are reported in Tables 8, 9, 10 and 11 of the Appendix, respectively.

3.1 Descriptive evidence

In Figs. 1 and 2, we document the evolution of the capital intensity technologies (ICT (net of $S\&DB$), $S\&DB$ and $R\&D$), the skill-premia (w_h/w_m; w_h/w_l; w_m/w_l), and robot density (R) from 2008 to 2017. To maintain the relative importance of the industries across time within each country, all the averages are calculated by first computing the within-country means across all sectors, weighted by the 2008 share of each industry's employment, and then subsequently using the unweighted averages across countries. Such an approach means that observed developments in the skill-premia do not reflect wage developments due to a changing composition of economic activity over time.

Panel (a) of Fig. 1 shows the patterns of the capital intensity technologies. By including $R\&D$ among the intangible capital stocks, the EU KLEMS (2019) database

Fig. 1 Developments in the intensity of technology use and the skill-premia, 2008–2017. *Sources*: Authors' calculations based on EU KLEMS (2019)
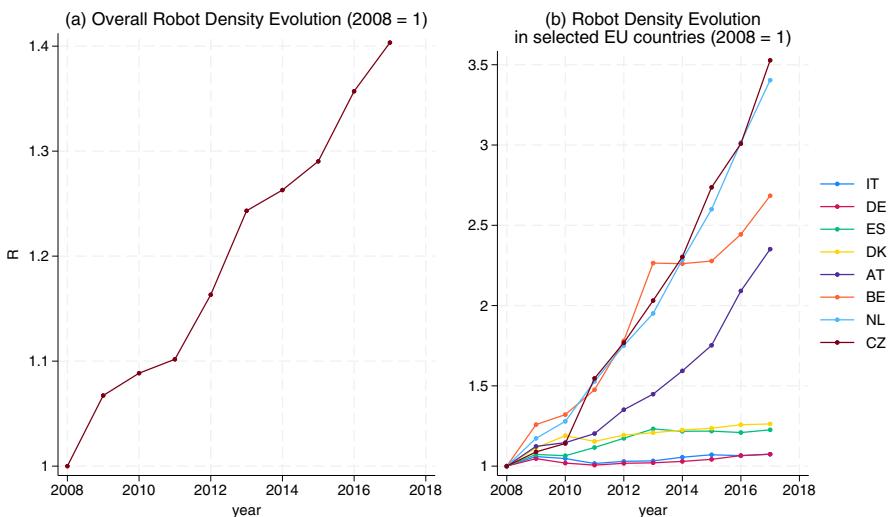
allows us to expand and update some of the previous descriptive findings in the literature (e.g., Blanas et al. 2020), albeit for a smaller number of industries. In particular, the important contribution of $R\&D$ and $S\&DB$ capital stocks can be observed, with their shares increasing by about 45% from 2008 to 2017. Although constituting a lower share compared to the $R\&D$ capital intensity, ICT (net of $S\&DB$) experienced even more sustained growth over the same period, with an increase of approximately 90%.

Panel (b) of Fig. 1 reports the skill-premia evolution. The wage premium between high- and low-skilled workers (w_h/w_l) increased somewhat over the period, while the wage gap between high- and medium-skilled workers (w_h/w_m) showed a more marked decline.[9] Conversely, the increase of about 16% in wage dispersion between medium- and low-skilled workers (w_m/w_l) appears in line with the recent findings of European Union (2019, 2015).

With respect to the behavior of wage differentials within countries and industries during the analyzed period,[10] it can be noticed that although the vast majority of countries experienced a slight decline in w_h/w_m (more pronounced in the education sector), Finland, and Sweden showed a rising trend. As for w_h/w_l, the data reveals a rather fragmented evolution: decreasing in some countries (e.g., Italy, Netherlands and Estonia), increasing in others (e.g., Austria, Germany and Sweden, with higher peaks in construction and mining and quarrying industries) and stagnant in yet others (e.g., Czech Republic, Germany and Slovenia). Ultimately, the growth trend in w_m/w_l, as shown in the Panel (b) of Fig. 1, occurred for all industries and with more remarkable increases in Austria and Germany.

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[9] Similarly, IMF (2017) documents a stagnating or shrinking wage dispersion in European economies from 2006 to 2014.

[10] Graphs representing the evolution of wage gaps for a subsample of European economies, as well as for the covered industries, are reported in Figs. 4 and 5 in the Appendix to this paper.

Fig. 2 Developments in the robot density, 2008–2017. *Sources*: Authors' calculations based on IFR, 2019

Development in robot density (R) followed a clear path of growth, as illustrated in Fig. 2. In Panel (a), the evolution of the overall robot density suggests a growth of about 40% over the years 2008–2017 but, as highlighted in Panel (b) of Fig. 2, there exist dramatic differences between countries. In fact, while some economies—such as Italy and Germany—recorded a modest growth,[11] this is not the case for other countries, most notably Czech Republic, Netherlands, Belgium and Austria, where robot density more than doubled or tripled within 10 years.

The trends in both overall trade openness ($GLOB$) and GVC participation have shown fluctuating dynamics during the examined decade, as depicted in Fig. 6 of Appendix. Following an initial decline after the 2008 financial crisis, there was a rebound in the early 2010s, and a subsequent period of further, slight decline until 2016 (see WTO, 2021, for details). Lastly, Fig. 7 in the Appendix illustrates the temporal evolution of sector-specific EPL measures for both permanent and temporary workers. It is noteworthy that the stringency of EPL_PERM has decreased over time in all industries analyzed. This pattern aligns with the European Commission's (2013) objective of rebalancing protection policies with respect to temporary workers (EPL_TEMP).

In essence, the presented descriptive evidence sheds some additional light on the relevant issues posed by the current wave of automation and digital technologies, which are fueling many concerns about the future of human work (e.g., Frey and Osborne 2017; Berg et al. 2018). It has been observed that all the technologies under investigation, whether tangibles or intangibles, have exhibited significant growth rates within a mere 10-year timeframe. Regarding robotization, it is worth emphasizing that even in smaller European economies, a substantial investment process in this

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[11] It should be nevertheless acknowledged that Italy and Germany started investing strongly in industrial robots long before, representing, along with Sweden, the three European countries with the highest robot density (see IFR, 2019).

automated technology has occurred. Ultimately, this trend is even more evident for intangibles (S&DB and R&D), which were included in other forms of capital prior to the release of EU KLEMS (2019).

4 Theoretical and empirical frameworks

To set the underlying rationale of our empirical investigation, we rely on the contributions of Acemoglu and Autor (2011) and Blanas et al. (2020), proposing a simple theoretical framework analyzing the effects of both tangible (including robots) and intangible assets on relative wages.

Let us assume that output per-worker, y, is obtained by an intensive production function, f, combining multiple factors[12]:

$$y = \mathbf{A} \, f(\mathbf{K}, h, m, l), \tag{1}$$

where $\mathbf{A}$ is a vector of efficiency parameters, $\mathbf{K} = \{R, S\&DB, ICT, R\&D, N\_ICT\}$ indicates a vector of capital per-worker inputs and h, m and l denote high-, medium- and low-skilled labor inputs, respectively.

We consider that labor markets are competitive and inelastically supply h, m and l to firms. Each skill group is required to perform a set of (non-mismatching) tasks, $z = (z_h, z_m, z_l)$, and is paid its marginal product (i.e., w_h, w_m and w_l). We also assume that initially there is no automation ($\mathbf{K} = \mathbf{0}$) that can replace for labor in performing tasks. First-order conditions of profit-maximizing and price-taking firms imply that the relative wages can be expressed as a function, g, of relative supplies and allocation of tasks to skill groups in which these exhibit a comparative advantage. For instance, the skill-premium between high- and medium-skilled workers is given by:

$$\frac{\partial f / \partial h}{\partial f / \partial m} = \frac{w_h}{w_m} = g(z_h, z_m, \theta_{hm}), \tag{2}$$

where $\theta_{hm} = \frac{h}{m}$ represents the relative supply of high- to medium-skilled workers, while z_h and z_m denote tasks allocated to h and m, respectively. The relative wages of medium- to low-skilled workers and high- to low-skilled workers, w_m/w_l and w_h/w_l, are obtained analogously as in Eq. (2).

Once we allow for automation replacing tasks ($\mathbf{K} \neq \mathbf{0}$) previously performed by labor, according to the job and wage polarization framework proposed by Autor et al. (2003), medium-skilled workers—typically employed in intermediate routine or codifiable tasks—should be the group affected the most by the current wave of innovations, such as robots and digital (intangible) technologies. As a result, we can first expect that w_h/w_m increases and w_m/w_l decreases. As for the w_h/w_l, the direction of the impact of technological progress is an empirical question, depending on whether m are closer substitutes for h or l.

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[12] To keep the model tractable, due to the large number of factors involved in the effective empirical analysis, we do not assume any explicit functional form.

Additionally, some specific types of technological progress may reveal peculiar, strong complementarities or substitutability with a particular skill group. The extent of these will depend on the relative importance of the specific channels through which capital impacts on different types of labor. These channels include a productivity effects, which operates via both labor-augmenting and capital-augmenting technological change, a substitution effect involving certain tasks of distinct labor types being undertaken by different forms of capital, and an effect linked to the emergence of new tasks associated with specific forms of capital that can increase the demand for particular types of labor (Acemoglu and Restrepo 2019). In light of this, the polarization of the wage distribution, as in the scenario of robots replacing middle-skilled workers, is only one possible outcome. Such an eventuality thus motivates our intention of dealing with a variety of tangible and intangible technologies in a comprehensive setting, with the objective of discovering their potential differential impact on wage premia dynamics along the three possible dimensions.

To this end, and building upon the outlined theoretical framework and empirical works of, among others, Goldin and Katz (2009), Michaels et al. (2014), Glitz and Wissmann (2021), and Graetz and Michaels (2018), the estimated (system of) three equations (in logarithmic form) accounting for the evolution of skill-premia can be explicitly formulated as follows:

$$\ln\left(\frac{w_i}{w_j}\right)_{cst} = \alpha_{n,c} + \beta_{n,s} + \gamma_{n,t} + \delta_{n,k} \ln \mathbf{K}_{cst} + \eta_{n,x} \ln \mathbf{X}_{cst} + \epsilon_{n,cst}, \quad (3)$$

where $c = 1, ..., C$, $s = 1, ..., S$ and $t = 1, ..., T$, indicate, respectively, country, industry and time; $\alpha_{n,c}$, $\beta_{n,s}$ and $\gamma_{n,t}$ (with $n = \{1, 2, 3\}$) are country, industry and time fixed effects, respectively, to control for cross-country and cross-industry unobserved heterogeneity, and to capture time varying unobserved factors, such as global shocks. The dependent variable is the skill-premium, w_i/w_j (with $i = \{h, m\}$ and $j = \{m, l\}$)—namely w_h/w_m, w_h/w_l and w_m/w_l; $\mathbf{K}$ is a vector of the main explanatory variables, including R[13] and the EU KLEMS capital intensity variables, i.e., ICT, $R\&D$ and $S\&DB$, with δ being the vector of coefficients of interest; $\mathbf{X}$ denotes the vector of control variables, including non-ICT capital intensity (N_ICT)[14] and relative supplies of labor $(h/m; h/l; m/l)$; and ϵ_n are well behaved error terms (with $n = \{1, 2, 3\}$).

The three skill-premium relationships in Eq. (3) are both individually and simultaneously estimated using Ordinary Least Squares (OLS) and SUR techniques (Zellner 1962), respectively. The latter may prove to be more reliable and efficient than OLS, for example, if all relations are influenced by common factors, which can induce a correlation of the error terms across the equations. According to Goldin and Katz (2009)

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[13] To deal with the zero values in the series of stock of robots, which are reflected in the absence of robot density, we make use of the inverse hyperbolic sine transformation (see, for instance, Burbidge et al. 1988; Pence 2006; Bellemare and Wichman 2020), defined as $\ln\left(R_{cst} + (R_{cst}^2 + 1)^{1/2}\right)$. Similarly, as in Artuc et al. (2018), estimations are also carried out using $\ln(1 + R_{cst})$. The results are qualitatively comparable and available upon request.

[14] Differently from what is reported in Eq. (1), we include N_ICT in the controls as we consider the other components of capital as proxies for tangible and intangible automation technologies.

and Glitz and Wissmann (2021), identification of the model given by Eq. (3) relies on the assumption that the relative skill supplies are inelastic in the short-run (i.e., predetermined), stemming from past investment decisions in education and training. Therefore, under such an assumption, the wage premia and relative skill supplies are not jointly determined.[15] In Sect. 6, we further discuss additional endogeneity concerns, such as those related to productivity shocks—reflected in wages—that may impact upon technology adoption. From a cross-industry perspective, however, these issues should be less concerning, due to the lower substitutability and/or mobility of inputs across sectors (e.g., Battisti et al. 2022). In any case, we do not claim any causal effect at this stage, as our intent is to highlight the statistical link between the different indicators of capital and technology and relative wages.

5 Basic results and discussion

This section presents and discusses the baseline estimates of the study, where the focus is placed upon the role played by tangible and intangible technologies. Table 1 reports the OLS and SUR results, in Panels I–II and Panel III, respectively, for the three wage premium equations described in the previous section: high- to medium-skilled workers (w_h/w_m), in Column (a); high- to low-skilled workers (w_h/w_l), in Column (b); medium- to low-skilled workers (w_m/w_l), in Column (c). Initially, in Panels I and II of Table 1, we present the results of the specification in Eq. (3), estimated by OLS, and evaluate whether the outcomes are sensitive to the inclusion of additional control variables in the models (i.e., non-ICT capital intensity and relative supplies), whereas in Panel III, the SUR estimation allows us to control for correlation of the disturbances across equations. In this respect, the Breusch–Pagan test strongly rejects the null hypothesis of contemporaneously independent disturbances across the equations—providing support for the adoption of SUR estimates against OLS.

Turning to our main variables of interest, in all cases the estimated coefficients on the technology-skill complementarity effect of robot density (R)—our first measure of tangible technologies—are in line with our expectations and suggest that they widen the skill-premia of high-skilled with respect to both medium- and low-skilled workers (see Columns (a) and (b)), results in line with those of Graetz and Michaels (2018), Blanas et al. (2020) and Dauth et al. (2021). Such an outcome may reflect a complementary relationship between robot density (R) and high-skilled workers or a substitution effect with respect to low- and medium-skilled workers. In elasticity terms, all else being equal, a 1% increase in R is linked, on average, to a growing wage gap of 0.08% and 0.03%, for w_h/w_m and w_h/w_l, respectively. Moreover, as shown in Column (c) of Table 1, we detect a negative correlation between robot density and w_m/w_l. In particular, a 1% increase in robot density is linked, on average, to a declining w_m/w_l of approximately 0.05%. This finding, combined with the coefficients presented in Column (a), suggests that robots are associated with a polarization of the wage distribution, disproportionately affecting medium-skilled workers. Such results

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[15] In any case, to mitigate potential endogeneity concerns stemming from this channel, we re-estimated our benchmark specification, as detailed in Sect. 6, both by excluding and lagging the relative supplies by one period. The central results of the analysis remain unchanged and are reported in Table 14 of the Appendix.

are in line with both predictions and empirical findings by Acemoglu and Autor (2011), Acemoglu and Restrepo (2018) and de Vries et al. (2020), who highlight a severe decline in the employment share of routine manual task-intensive jobs.

Focusing on the role of $R\&D$ capital—the first proxy for intangible technologies—we observe coefficients in Columns (a) and (c) of Table 1 consistent with a polarizing effect. This is shown by the positive coefficient of $R\&D$ on w_h/w_m and the negative coefficient on w_m/w_l. At the same time, the evidence is somewhat weak with the coefficient on w_m/w_l being insignificant and that on w_h/w_m being only marginally significant.

Results on the intangible part of ICT—i.e., $S\&DB$—present a consistent pattern across the different specification and indicate that intangible ICT is associated with falling relative wages for low-skilled workers. This is true with respect to both high-skilled and medium-skilled wages, with the coefficients being consistently significant. In this case, *ceteris paribus*, a 1% increase in the intensity of $S\&DB$ use is associated, on average, with an increase in w_h/w_l and w_m/w_l, on average across panels, of around 0.035% and 0.025%, respectively.

On the contrary, the tangible component of ICT capital—i.e., hardware—appears to improve, to a greater extent, the wages of lower-educated workers, relative to high-skilled workers, as shown in Columns (a) and (b) of Table 1. Such results may be due to the role of ICT as a general-purpose technology,[16] as well the fact that such technology has reached maturity and become pervasive across European economies, facilitating the adaptability and skill upgrading opportunities even for middle- and low-skilled workers. In turn, this relative enhancement in productivity may translate into an improvement in wage differentials *vis-à-vis* high-skilled labor (e.g., Aghion and Commander 1999; Conceição and Galbraith 2012; Acemoglu and Restrepo 2020, 2018).

Overall, our findings suggest that considering relative wages along three dimensions and disentangling the roles played by different kinds of technological advances in a systematic and comprehensive analytical framework, can favor a better understanding of the dynamics of wage dispersion within the labor market induced by tangible and intangible automation technologies. In particular, the evidence so far indicates that different technologies do not affect wage differentials in the same way, being characterized by specific complementarities and/or substitutabilities with respect to different types of workers.[17]

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[16] See, for instance, Bresnahan and Trajtenberg (1995) and Helpman (1998).

[17] Identifying the major causes of these differences is far from straightforward given the different and competing mechanisms at work. A partial approach is to compare results from the regression model when including and excluding an indicator of relative labor productivity in the model. By controlling for this component, the model identifies the effects of the particular technologies for a given level of relative productivity, with the results thus providing an estimate of the impact of channels other than labor productivity on relative wages. The difference between the conditional and unconditional results can thus provide an estimate of the productivity effect. This method has a number of shortcomings, including that it is not possible to identify the different productivity channels that exist. Adopting such an approach, however, leads to the conclusion that the productivity effect is often relatively small. Exceptions do exist, however, such as large productivity effects that raise the wages of high-educated relative to medium-educated workers in the case of robots and $S\&DB$, while in the case of $R\&D$ the productivity effect serves to reduce the wage

Table 1 Regression results of relationship between tangible and intangible investments and relative wages

Dep. Var.	Panel I			Panel II			Panel III		
	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l
R	0.062***	0.023**	−0.039***	0.076***	0.036***	−0.047***	0.078***	0.031***	−0.047***
	(0.011)	(0.009)	(0.010)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)
ICT	−0.063***	−0.047***	0.016*	−0.053***	−0.046***	0.007	−0.053***	−0.046***	0.007
	(0.010)	(0.010)	(0.008)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)
R&D	0.012**	0.006	−0.005	0.011*	0.001	−0.007	0.010*	0.003	−0.007
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)
S&DB	0.014	0.036***	0.021**	0.007	0.032***	0.027***	0.007	0.033***	0.027***
	(0.012)	(0.012)	(0.010)	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs	751	751	751	751	751	751	751	751	751
R-squared	0.635	0.709	0.668	0.642	0.711	0.673	0.642	0.710	0.672
Breusch-Pagan (chi-squared)								563.543	

OLS with robust standard errors—Panels I and II—and Seemingly Unrelated Regressions (SUR)—Panel III—with small-sample adjustment for computing the covariance matrix for the equation residuals. All the variables are scaled on total hours worked (in millions) and expressed in logarithms. The estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. Year-, country- and industry-fixed effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses

However, several factors can lead to biased results when using OLS and SUR to estimate Eq. (3). The subsequent section highlights some of these issues and explores an alternative instrumental variable (IV) approach to deal with some of these factors.

6 Instrumental variable approach

In our framework, endogeneity bias could arise due to reverse (or bidirectional) causality, with relative wages potentially influencing the direction of technological progress. If there exists a bidirectional causal relationship, OLS/SUR can result in biased estimates. For example, technological advancements, including heightened automation, may lead to increased productivity and higher (relative) wages for skilled workers. These, in turn, might incentivize firms to invest in new skilled labor technologies, which may (or may not) impact on the wages of low- and medium-skilled workers.[18] Additionally, omitted variables, such as market competition, government policies, tax incentives or financial market conditions, can affect both technology adoption and wage differentials, introducing a bias in the estimates. Hence, reverse causality and omitted variable bias pose a risk to the credibility of OLS/SUR-based estimates in establishing a proper causal relationship (i.e., from technology to relative wages).

To mitigate the aforementioned concerns, we employ a two-stage least squares (2SLS) strategy. The first-stage equation can be formulated as follows:

$$\ln R_{cst} = \rho_{n,r} \ln R_{Jst} + \eta_{n,z} \ln \mathbf{Z}_{cst} + \mu_{n,cst}, \tag{4}$$

where $\mathbf{Z}$ indicates the vector of other capital intensity variables (i.e., ICT, $R\&D$ and $S\&DB$), fixed effects and controls outlined in Eq. (3), while R_J denotes robot penetration in Japan in sector s and year t, which is used as an IV for R.

Subsequently, the second-stage equation can be expressed as:

$$\ln \left(\frac{w_i}{w_j} \right)_{cst} = \phi_{n,r} \ln \hat{R}_{cst} + \eta_{n,z} \ln \mathbf{Z}_{cst} + \epsilon_{n,cst}, \tag{5}$$

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footnote 17 continued

gap between high- and medium-educated workers. For reasons of brevity, these additional estimates are not reported here, but are available from the authors upon request.

[18] In the spirit of Acemoglu and Restrepo (2019), the automation level increases as the relative cost of labor to robots rises. The condition for automation is given by:

$$a_i \leq \phi_i \left(\frac{w_i}{PR} \right),$$

where $\phi_i(\cdot) > 0$, a_i represents the automation level of the i-th job, and PR is the robot price. For instance, the impact of robot density (R) on the wage rate can be expressed as follows:

$$\frac{\partial w_i}{\partial R} = \left(\frac{\partial w_i}{\partial R} \right)_{|a_i} + \left(\frac{\partial w_i}{\partial a_i} \right) \left(\frac{\partial a_i}{\partial R} \right) \geq 0,$$

where $\left(\frac{\partial w_i}{\partial R} \right)_{|a_i} > 0$, $\frac{\partial w_i}{\partial a_i} < 0$, and $\frac{\partial a_i}{\partial R} > 0$. As pointed out by Graetz and Michaels (2018), while robots can contribute to an upward shift in wage rates, the concurrent automation tends to attenuate this increase.

where $\hat{R}_J$ represents the predicted variable from Eq. (4) and the other explanatory variables remain the same as in Eq. (3).

R_J can be considered a reliable IV for R only if the exclusion restriction holds, i.e., automation in Japan is likely to influence European relative wages only through the impact on its robotization process. However, this assumption deserves more scrutiny. In general, robotization in Japan may prove to be a suitable instrumental variable for robotization in Europe for several reasons. First, this country is known for its advanced robotics industry and is a global leader in industrial robots production (e.g., Nof 1999; Gasparetto and Scalera 2019). Further, according to IFR, 2019, Japan is more advanced in robotic technologies compared to our sampled economies. Second, Japan has a long history of adopting and implementing industrial automation, with a high density of robots used in manufacturing processes (Mandfield 1989). Therefore, this suggests that the use of robots is an important factor driving productivity and efficiency improvements in this country, which can be applicable to European industries undergoing robotization. Third, Japan is also the largest exporter of industrial robots in the world, providing 45% of the global supply IFR (2022). Such a market influence implies that the adoption of industrial robots in Europe may be affected by trends and advancements originating from Japan.

Building upon these considerations, using robot density in Japan (R_J) as an instrumental variable for their European counterparts (R) can provide a relevant and appropriate approximation of the impact of robotization within these industries. In terms of excludability, Japanese robot density is not directly related to the European skill-premia. In other words, this implies that the effect of industrial robots in Japan on European labor market outcomes (including wage differentials) operates only through their influence on the level of robotization. Quantitatively, we expect R_J to be positively associated with R in the first-stage equation (i.e., Eq. (4)), reflecting the technological catch-up process in automation pursued by the European countries in our sample. Therefore, by using Japanese robot density, we isolate the exogenous source of variation originating from a country at the forefront of robotization (a similar approach is adopted by Acemoglu and Restrepo 2020, who make use of robot penetration trends in five advanced European countries ahead of the USA in robotics.).

Results from 2SLS estimates of the three skill-premium relationships in Eqs. (4)-(5) are reported in Table 2.[19] The table includes two sets of results, both excluding (Panel I) and including (Panel II) additional control variables in the model. In both cases, as expected, the first-stage coefficient on Japanese robot density (R_J) is positive and strongly significant. In terms of magnitude, this implies that, *ceteris paribus*, a 1% increase in R_J is associated with an increment in the range of $0.34-0.43\%$ in European robot density (R).[20] Moreover, the F-test statistic from the first-stage regression provides strong evidence against the hypothesis of weak instruments.

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[19] As in Blanas et al. (2020) and Almeida and Neves Sequeira (2023) our findings on ICT $R\&D$ and $S\&DB$ should capture conditional correlations, differently from R, where we aim at identifying a causal effect. In any case, instrumenting each alternative capital measure (i.e., ICT $R\&D$ and $S\&DB$) with its Japanese counterpart confirms our key results, which are available upon request. In addition, it is not possible to perform this set of regressions using SUR.

[20] To address the potential sensitivity of our findings to the choice of the IV, we employ an alternative measure known as "replaceable hours" (RH), inspired by the work of Graetz and Michaels (2018). This indicator captures the proportion of hours worked within each industry in 1980 that were subsequently

The second-stage estimates substantially confirm the core findings, as discussed in the previous section, with the exception of the coefficient associated with R in Column (b), which loses its statistical significance for the relationship involving w_h/w_l. Furthermore, the 2SLS regressions reveal that the coefficients estimated through OLS/SUR were upward (downward) biased for the relationship between R and w_h/w_m (w_m/w_l). In fact, upon comparing the outcomes of Columns (a) and (c) of Table 2 (Panel II) with the counterparts of Table 1 (Panels II and III), the 2SLS estimated coefficients suggest that a 1% increase in R is associated, on average, with an increment in w_h/w_m of about 0.065% and a decline in w_m/w_l of approximately 0.07%. In other words, medium-skilled workers experienced similar relative losses compared to both high- and low-skilled labor.

By and large, the outcomes of our IV regressions allow us, on the one hand, to mitigate endogeneity problems characterizing the relationship involving robotization and relative wages and, on the other hand, substantiate the hypothesis that investments in tangibles and intangibles technologies are likely to produce a variety of effects on the three dimensions of wage inequality. Particularly, we observe that not all types of technology considered impact relative wages in the same way. For example, in line with the predictions of Haskel and Westlake (2018), intangibles have a detrimental effect (although the evidence is rather weak in the case of $R\&D$) on the relative wages of lower-skilled workers, while 'tangible' automation—as proxied by robots— is associated with a polarization of the wage distribution, as conjectured, *inter alia*, by Acemoglu and Autor (2011).

6.1 Digging deeper: insights from instrumental variable quantile regressions

Devoting particular attention to the relationship between robotization and relative wages, existing models, such as Acemoglu and Restrepo (2020), highlight that there is a range of tasks that workers undertake and that are potentially at risk of robotization. This observation implies that different worker skill types will undertake a specific range of tasks, each being compensated differently. It is relevant, therefore, to ask whether there exist heterogeneous effects of robotization on relative wages at different points of the (conditional) wage distributions (i.e., the influence of robotization, conditional on the set of explanatory variables, may exhibit a different relationship at higher wage gaps than lower ones). The heterogeneous effects of robotization on the skill-premium distributions could be driven by the differing job tasks—and related compensation—within worker types, as well as industry characteristics, differences in the intensity of automation adoption and labor market conditions. Conversely, a stable

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footnote 20 continued

performed by occupations susceptible to robot replacement. The data for such a second IV is sourced from Graetz and Michaels (2018), who make use of information on robot applications from the IFR, as well as US Census occupational classifications and data on hours worked by occupation and industry. By focusing on specific task categories, such as welding and painting, within occupations, RH accounts for variations in the types of tasks performed by robots across industries. As argued by Graetz and Michaels (2018), this strategy is grounded in the assumption that firms are more likely to adopt robots when the share of tasks suitable for automation exceeds a certain threshold. The 2SLS regressions results based on this different IV largely confirm the key findings of the analysis, as shown in Table 12 of Appendix.

Table 2 2SLS regression results: tangible and intangible investments and relative wages

Dep. Var.	Panel I			Panel II		
	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l
R	0.048***	−0.008	−0.056***	0.065***	−0.026	−0.069***
	(0.015)	(0.014)	(0.016)	(0.021)	(0.026)	(0.015)
ICT	−0.058***	−0.036***	0.021**	−0.051***	−0.037***	0.013
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
R&D	0.012**	0.008	−0.004	0.012*	0.011	−0.007
	(0.005)	(0.005)	(0.005)	(0.007)	(0.009)	(0.005)
S&DB	0.020*	0.049***	0.028***	0.011	0.056***	0.037***
	(0.012)	(0.013)	(0.010)	(0.013)	(0.014)	(0.011)
First-stage coefficient (R_J)	0.423***			0.377***	0.348***	0.413***
	(0.019)			(0.026)	(0.028)	(0.019)
R-squared	0.862			0.864	0.865	0.863
F-test	460.9			192.5	144.8	426.0
Controls	✓			✓	✓	✓
Obs	751	751	751	751	751	751

2SLS regressions using R_J as IV for R in the first-stage equation. All the variables are scaled on total hours worked (in millions) and expressed in logarithms. The estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. Year-, country- and industry-fixed effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses
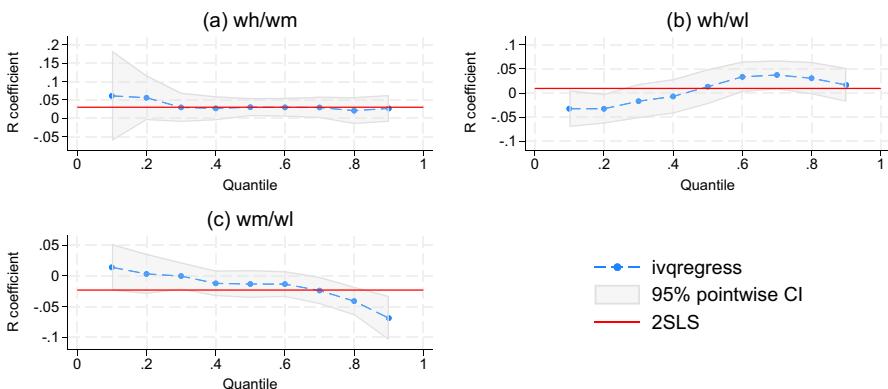
interplay would imply that robots affect relative wages similarly at different points of the conditional distribution, reflecting a more homogenized influence of this type of automation on the workforce. To address this, we make use of instrumental variable quantile regression (IVQR) techniques, which are capable of dealing with endogenous variables, as discussed above. Specifically, we rely on the inverse quantile regression (IQR) method, developed by Chernozhukov and Hansen (2006), and perform IVQRs of Eqs. (4)-(5).[21]

Figure 3 graphically illustrates the results obtained for different deciles of the conditional distributions of our dependent variables.[22] In the case of the skill-premium involving high- and medium-skilled workers (w_h/w_m), Panel (a) documents that the relationship with R remains relatively stable—and largely overlapping with the positive coefficient of the 2SLS estimate—and being statistically significant between the 4th and 7th decile. Such a positive and stable interplay across different levels of the conditional distribution may be due, for example, to the so-called "displacement and reinstatement effects" of automation outlined by Acemoglu and Restrepo (2019). On the one hand, robotization replaces tasks commonly performed by medium-skilled labor, resulting in an exacerbation of the wage differential. On the other hand, new tasks, in which medium-skilled workers have a comparative advantage, are subsequently created, thus contributing to a recovery of productivity and wages for medium-skilled workers. In addition, both worker types might experience skill-specific changes in their roles and tasks in response to robotization, leading to the overall stability of the R effect. These processes, combined with specific labor market dynamics and institutional factors—which are a typical feature of our sampled European economies—may in turn lead to a positive but stationary w_h/w_m (i.e., preventing a more substantial exacerbation of wage inequality induced by robots).

Interestingly, Panel (b) of Fig. 3 depicts a nonlinear relationship between robotization and w_h/w_l. As argued by Acemoglu and Autor (2011), the impact of automation on the relative wage of high- to low-skilled labor is somehow ambiguous. In fact, at the lower deciles of the conditional distribution (1st and 2nd), a negative association can be observed. The coefficient then begins to increase, shifting from negative to positive, and becoming statistically significant from the 6th decile. Various potential explanations for this pattern exist. One possible interpretation for such non-linearity could be the changing nature of tasks and skill requirements in response to robotization. For relatively low-wage gaps (conditional on the set of explanatory variables), in fact, low-skilled workers seem to experience relative gains from robotization compared to high-skilled labor. In the early stages, these workers might be required to collaborate more closely with robots, utilizing their expertise in handling intricate tasks that require human involvement. This collaboration can lead, in turn, to skill enhancement and contribute to increased productivity and wages. Furthermore, at low w_h/w_l, there might

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[21] The routine for this estimator is provided by the Stata package *ivqregress* However, it does not support the use of weights in regressions. As a result, the 2SLS point estimates proposed as a reference do not exactly match those in Table 2. Nonetheless, the differences are only slight and the detailed estimates available upon request.

[22] As a robustness check, we also considered the smoothed estimating equations (SEE) estimator, proposed by Kaplan and Sun (2017). The outcomes are substantially in line with those of Fig. 3 and are reported in Fig. 8 of the Appendix.

Fig. 3 IQR-IVQRs results—Robot density and relative wages, by decile

be a scarcity of low-skilled labor, leading to increased competition and subsequently upward pressure on their wages as employers seek to retain or attract these workers. However, at higher levels of the conditional wage gap distribution, the nature of complementarity shifts toward high-skilled workers, who possess the necessary expertise to work alongside advanced automation. In this case, robots might free up space for complex tasks that require a combination of cognitive, technical, and decision-making skills. High-skilled workers, equipped with these multi-dimensional abilities, could eventually benefit from this kind of technological advancement, resulting in an increasing wage premium. An alternative argument would involve the substitutability of low- and high-skilled workers with medium-skilled workers. The direction of the impact of R on w_h/w_l depends on whether medium-skilled workers are better substitutes for high- or low-skilled labor (Acemoglu and Autor 2011). As automation increases, the range of tasks in which high-skilled workers have a comparative advantage expands, contrary to that of medium-skilled workers, who are more likely to be displaced by machines. If medium-skilled workers are close substitutes for low-skilled workers, robots may trigger a reallocation of the former toward low-skilled occupations, leading to an upward pressure on w_h/w_l.

Finally, Panel (c) of Fig. 3 displays the IQR-IVQRs results for the relationship between w_m/w_l and R. Also in this case, a nonlinear relationship is detected, although being not statistically significant until the 7th decile, with the impact on w_m/w_l transitioning from positive to negative along the conditional distribution. Mirroring what has been observed for the relationship involving w_h/w_l, in Panel (b) of Fig. 3, on the basis of a higher (albeit weak) level of complementarity with medium-skilled workers, compared to low-skilled, at relatively low-wage differential. However, as we move further up the conditional wage gap distribution, robots are increasingly likely to compete with medium-skilled workers, undertaking routine and/or manual tasks, as opposed to low-skilled workers toward the bottom of the (conditional wage) distribution, that are engaged in non-routine manual tasks, with this complementarity (or lower substitutability) effect shifting wages in favor of low-skilled workers at higher levels of the conditional distribution—leading to an improvement in the wage differential for low-

skilled labor. In any case, R significantly enters in the w_m/w_l equation with a negative coefficient, aligning more closely with the theoretical implications of Acemoglu and Autor (2011) about a polarization of the wage distribution as a result of robotization. Furthermore, sufficiently high levels of w_m/w_l could signal that specific labor market regulations are relatively favoring medium-skilled workers (for instance, being paid more than their marginal product) compared to low-skilled labor. This might make robots, in the form of middle-skilled labor-saving technology, more attractive to employers, leading to a compression of the relative wage of medium- to low-skilled workers. (e.g., Alesina et al. 2018).

The outcomes of this quantile analysis confirm the complexity and heterogeneity of the relationship between robotization and relative wages. In particular, the impact of robots is shown to be substantially multifaceted. It does not translate into a substantial increase in the wage gap between high- and medium-skilled workers (w_h/w_m), being relatively stable across the conditional distribution. By contrast, our findings reveal nonlinear patterns for the relationships between the ratios of high- to low-skilled and medium- to low-skilled workers wages (w_h/w_l and w_m/w_l, respectively), suggesting that the influence of robotization changes with varying levels of the conditional wage gaps distributions.

7 Robustness checks and additional determinants

In this section, we consider extensions, which also serve as robustness checks, to the benchmark analysis described above. Specifically, the first extension, reported in Sect. 7.1 takes into account the cost of robots in our study. The second extension, presented in 7.2, involves the inclusion of globalization, while Sect. 7.3 further incorporates variables capturing sector-specific proxies for labor market regulations. Through this analysis we are interested in examining whether the inclusion of these additional drivers of the skill-premia impact—in terms of robust correlations—upon the estimated relationships between the different technologies and wage premia described in the previous section.

7.1 The cost of robots

The results observed in Table 2 have highlighted how robots are associated with a polarization of the wage distribution. As with any innovation diffusion process, a reduction in the adoption cost for this type of automation could incentivize firms to make substantial investments aimed at modernizing their production technology (e.g., Mansfield 1961; Stokey 2021). On this point, Fig. 9 of the Appendix shows that the global average unit price of robots, expressed in thousands of current US dollars, has recorded a decline of approximately 40% over the period under investigation.[23] Such an occurrence, along with the already observed dramatic growth of the robot

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[23] As documented by Jurkat et al. (2022) and Battisti et al. (2021), from 2006 onward IFR provides a single global average price for industrial robots, in current value terms. This is estimated relying on the total market value obtained from robot producers and national robot federations. Subsequently, this number is divided by the amount of robot deliveries for a specific year. For comparison, see also

density (R), may have potentially further affected employment patterns and wage structures, particularly for workers engaged in tasks susceptible to automation (Graetz and Michaels 2018). While our analysis already accounts for the effect on labor markets of robot prices that works through increased robot density, prices could potentially have additional effects. For example, it may be that as robot prices decline, the cost of replacing certain types of labor has fallen, potentially exerting downward pressure on wages. This would be the case if robots act like a reserve army that leads to relatively lower wages for certain types of workers (e.g., medium-educated workers) without necessarily displacing them. In addition, the widespread availability of cheaper robots could create a perception of "job insecurity," potentially leading workers to accept lower wages or be less likely to negotiate for raises, fearing easier replacement (Nam 2019; Brougham and Haar 2020). Relatedly, as pointed out by Arnoud (2018), the possibility of job automation can exert impact on wages even in the absence of adoption of the automation technology. For example, if robots become a more accessible and affordable substitute for workers, employers might have more bargaining power in wage negotiations. The "fear of automation," in turn, may result in lower wages for the most exposed workers. These arguments motivate us to examine whether the price of robots may have influenced the dynamics of relative wages, independently of the channel operating through robots demand (i.e., captured by R). To achieve this, we firstly assume that the downward trend in the average robot prices observed globally has also occurred within the European context. Subsequently, we adopt an imputation procedure for the countries and industries in our sample as follows: i) prices are PPP-adjusted 2005 international dollar, and ii) expressed in constant values using the "other machinery equipment" capital deflator.[24] Finally, the robot prices (RP) variable is employed as an additional regressor to augment the specification of Eqs. (4)–(5).

Table 3 reports the results of the corresponding 2SLS estimates. As can be observed, our main findings on tangible and intangible assets remain substantially unchanged with the inclusion of this additional control in the models, and are highly comparable to those presented in Table 2. Furthermore, while the RP estimated coefficient is not statistically significant for the w_h/w_l equation in Column (b), it turns out to be strongly significant for the relative wage equations in Columns (a) and (c). In particular, whether it is the baseline or full model specification (Panel I or II), the robot prices associated coefficient enters with a negative (positive) sign for the w_h/w_m (w_m/w_l) equation. This implies that, *ceteris paribus*, a unit increase in the RP is correlated, on average, with a decrease (increase) of 0.1% in w_h/w_m (w_m/w_l). This is not unexpected, as intermediate skilled workers, whose tasks are particularly prone to automation, would experience (relative) benefits from an increase in the price of robots. However, the combined dynamics of a rise in robot density (R) and a decline in the observed robot prices (RP) would give rise to a sort of "reinforcing effect," further disadvantaging

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Footnote 23 continued

Fernandez-Macias et al. (2021). To create Fig. 9, a smoothing transformation was applied to the robot prices, as IFR does not permit the disclosure of data externally.

[24] Following the guidelines of the International Standard Industrial Classification of all Economic Activities (ISIC Rev. 4), robots are categorized under "general-purpose machinery". More specifically, they fall under the subcategories of "lifting and handling equipment" and "other special-purpose machinery." As such, these classifications are encompassed within the broader category of machinery (i.e., non-ICT capital).

medium-skilled occupations as a result of these two factors. Indeed, being engaged in tasks characterized by mostly manual and/or routine content, these workers compete significantly with robots (Goos et al. 2009; de Vries et al. 2020).

7.2 Globalization

In the second extension of our investigation, the contribution of different forms of trade engagement in determining the dynamics of the skill-premia is taken into consideration. Trade is supposed to produce effects on wage dispersion through the relative prices of skilled- and unskilled-intensive goods (e.g., Wood 1995). For this purpose, we further augment the models proposed in Sect. 4 by including two alternative indices of globalization: (i) a measure of general trade openness ($GLOB$), calculated as the ratio of imports plus exports to real gross value added, and (ii) an indicator capturing $GVCs$ participation, computed as the sum of DFD_FVA and FFD_DVA to real gross value added. 2SLS results from including these indicators alongside tangibles and intangibles are shown in Table 4.

As for the main findings uncovered in Sect. 6, it can be noticed that the technology variables turn out to be robust to the inclusion of further controls in the models, with the only exception of $S\&DB$, in Column (a) of Panel I, which is statistically insignificant.

Turning to the contribution of globalization as an additional driver of the skill-premia dynamics, the estimates suggest that higher trade openness ($GLOB$) is associated with an increase of wage premia for the relationships between high- to medium-skilled and medium- to low-skilled labor. Our findings confirm the conclusions of Helpman (2016), who pointed out that globalization affects the relative wages of various types of workers to different extents. This can be seen by the positive and significant coefficients on $GLOB$ in Columns (a) and (c) of Panel I in Table 4. Specifically, *ceteris paribus*, a unit increase in $GLOB$ is associated with increments in w_h/w_l and w_m/w_l of 0.5% and 1.1%, respectively. In the context of the relationship between high- and medium-skilled workers, this result can be attributed to the (high-)skill-biased effect of trade openness (Epifani and Gancia 2008), which promotes increased specialization and efficiency gains. Consequently, the heightened demand for skilled workers contributes to an upward pressure on their relative wages compared to medium-skilled workers. Likewise, an increase in w_m/w_l is consistent with a medium-skill-biased effect of trade openness, to the extent that the nature of traded goods and services relatively favors middle-educated workers, while low-skilled labor may be more involved in production activities that are more exposed to foreign competition.

With respect to the effects provided by GVC participation, in Columns (a) and (b) of Panel II in Table 4, we find evidence of a strong positive association between GVC integration and both w_h/w_m and w_h/w_l, indicating a greater benefit for high-skilled labor, relative to both medium- and low-skilled workers. In terms of magnitude, a unit increase in GVC leads to growing w_h/w_m and w_h/w_l of 1% and 0.6%, respectively. Such an outcome is in line with the theory of Wang et al. (2021) and empirical findings by Dollar et al. (2017), which suggest that the growth of $GVCs$ participation in devel-

Table 3 2SLS regression results: the cost of robots

Dep. Var.	Panel I			Panel II		
	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l
R	0.042***	−0.006	−0.047***	0.060***	−0.027	−0.056***
	(0.014)	(0.014)	(0.016)	(0.020)	(0.026)	(0.016)
ICT	−0.054***	−0.038***	0.016*	−0.051***	−0.036***	0.012
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
R&D	0.014***	0.007	−0.007	0.012*	0.012	−0.008*
	(0.005)	(0.005)	(0.005)	(0.007)	(0.009)	(0.005)
S&DB	0.022*	0.048***	0.026***	0.014	0.055***	0.031***
	(0.012)	(0.013)	(0.010)	(0.013)	(0.014)	(0.010)
RP	−0.001***	0.000	0.001***	−0.001***	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Controls				✓	✓	✓
Obs	751	751	751	751	751	751
F-test	468.5			191.9	141.6	421.4

2SLS regressions using R_I as IV for R in the first-stage equation. All the capital intensity variables are scaled on total hours worked (in millions) and expressed in logarithms. The estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. Year-, country- and industry-fixed effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Table 4 2SLS regression results with globalization variables

Dep. Var.	Panel I			Panel II		
	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l
R	0.055***	−0.029	−0.096***	0.062***	−0.027	−0.068***
	(0.019)	(0.024)	(0.019)	(0.021)	(0.026)	(0.015)
ICT	−0.050***	−0.036***	0.015	−0.051***	−0.037***	0.013
	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
R&D	0.013*	0.012	−0.005	0.013*	0.011	−0.007
	(0.007)	(0.009)	(0.005)	(0.007)	(0.009)	(0.005)
S&DB	0.013	0.056***	0.042***	0.011	0.055***	0.037***
	(0.012)	(0.014)	(0.011)	(0.013)	(0.014)	(0.011)
GLOB	0.005**	0.001	0.011**			
	(0.002)	(0.002)	(0.005)			
GVCs				0.010***	0.006**	−0.003
				(0.003)	(0.003)	(0.002)
Controls	✓	✓	✓	✓	✓	✓
Observations	751	751	751	751	751	751
F-test	227.9	176.0	286.9	198.9	148.3	453.3

2SLS regressions using R_J as IV for R in the first-stage equation. All the capital intensity variables are scaled on total hours worked (in millions) and expressed in logarithms. The estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. Year-, country- and industry-fixed effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

oped countries primarily benefits individuals with higher skills, thereby exacerbating wage inequality.

The analysis carried out up to this point reveals that tangible and intangible technologies, along with globalization, proves to be crucial in shaping wage differentials within the labor market.

7.3 Labor market regulations

In the last stage of our study, we deal with the supplemental influence of labor market regulations on wage dispersion, starting from the assumption that such regulations are likely to be effective at attenuating inequalities especially in European countries (e.g., Koeniger et al. 2007). To this end, we augment the models with the sector-specific measures of EPL outlined in Sect. 3.

Table 5 reports the 2SLS estimated results of these further extended specifications.[25] As expected, stricter employment protection rules, as proxied by the two sector-specific EPL measures for permanent and temporary employees (EPL_PERM and EPL_TEMP), in both panels, have strongly negative effects on the skill-premia, particularly benefiting low-skilled workers (Columns (a) and (b)). In fact, *ceteris paribus*, all else constant, a unit increase in EPL_PERM and EPL_TEMP, are associated, on average, with a declining skill-premia of between 0.3% and 0.5%. In both cases, the effects tend to be largest for w_h/w_l. It is also worth noting that these effects are not significant for w_m/w_l, suggesting that only the wages of high-skilled (relative to both medium- and low-skilled) workers tend to fall.

As for the outcomes discussed in Sects. 6 and 7.2, it can be noticed that the contribution of the two measures of globalization in exacerbating wage disparities is substantially confirmed and technology variables turn out to be robust to the inclusion of further controls in the models. However, as for the impact of the intensity of $R\&D$ capital, this second set of extended 2SLS regressions reveal statistical significance for the skill-premium relationships involving high- to low-skilled (Column (b) of both panels) and medium- to low-skilled workers (in Column (c) of Panel II), in contrast to what we have previously detected in Tables 1, 2 and 4. In fact, the estimates in Columns (a) and (c) of Panel II in Table 5 now reflect and complement those reported by Michaels et al. (2014) and Breemersch et al. (2019), who observe polarizing effects of $R\&D$ related process innovations that impact upon middle-skilled labor negatively. For this specific relationship, all else being equal, a 1% increase in the $R\&D$ share is accompanied, on average, by an increase in w_h/w_m of about 0.02% and a reduction in w_m/w_l of approximately 0.01%, respectively. Results in Column (b) of Table 5 further suggest that $R\&D$ capital benefits high-skilled relative to low-skilled workers. When compared to the results presented earlier, these specific outcomes should be taken with caution due to the reduced sample size (663 *vis-à-vis* 751 observations in the benchmark dataset).

The extended analysis reported in these sub-sections supports and reinforces the view that a systematic and comprehensive investigation of the core drivers of skill-

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[25] For readability reasons, the estimated results obtained using the overall sectoral EPL measure ($SECT\_EPL$) are presented in Table 13 of Appendix.

Table 5 2SLS regression results with globalization and labor market regulations variables

Dep. Var.	Panel I			Panel II		
	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l
R	0.048***	−0.011	−0.065***	0.064***	−0.017	−0.037**
	(0.017)	(0.018)	(0.020)	(0.020)	(0.022)	(0.014)
ICT	−0.044***	−0.029***	0.014	−0.047***	−0.028**	0.012
	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)
R&D	0.019***	0.019**	−0.007	0.018**	0.020**	−0.009**
	(0.007)	(0.008)	(0.004)	(0.007)	(0.008)	(0.004)
S&DB	−0.003	0.023*	0.022**	−0.005	0.023*	0.018*
	(0.014)	(0.013)	(0.011)	(0.014)	(0.013)	(0.011)
GLOB	0.013***	0.001	0.011*			
	(0.005)	(0.005)	(0.006)			
GVCs				0.032***	0.017***	−0.004
				(0.006)	(0.006)	(0.006)
EPL_PERM	−0.003***	−0.004***	−0.001	−0.003***	−0.004***	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EPL_TEMP	−0.003***	−0.005***	−0.001	−0.003***	−0.005***	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	✓	✓	✓	✓	✓	Y
Obs	663	663	663	663	663	663
F-test	322.7	254.4	265.5	244.5	173.2	568.0

2SLS regressions using R_J as IV for R in the first-stage equation. All the capital intensity variables are scaled on total hours worked (in millions) and expressed in logarithms. The estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. Year-, country- and industry-fixed effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

premia requires a multifaceted approach. By breaking down technologies into tangible and intangible categories, and including two distinct measures of trade engagement (i.e., general trade openness and GVC participation), the empirical evidence shows that both tangibles and intangibles, as well as globalization are likely to produce different—and sometime offsetting—effects on the wage differential dynamics. Our findings point to a crucial role played by intangible technologies in either increasing the wage gap or producing polarizing effects, as in the case of $S\&DB$ and $R\&D$, respectively. As for the impact of tangible technologies, robotization (R) turns out to be robust in creating a polarization of the wage distribution. On the contrary, ICT (net of $S\&DB$) is found to lower the high-skill-premium, favoring both middle- and low-skilled workers.

Turning to the consequences of globalization on the skill-premia, the overall indicator of trade openness ($GLOB$) mainly identifies high- and medium-skill-biased patterns, while GVC participation is associated with widening wage inequality at the expense of lower-educated workers. Finally, as expected, stricter labor market regulations are typically linked to a decline in wage differentials, primarily benefiting less-skilled labor.

8 Conclusions and policy recommendations

The growing concerns about the issues of artificial intelligence, robotics, automation and digital innovation on the future of people's working lives, supplemented by the well-known puzzling influence of global trade and offshoring, has recently led many researchers to question and investigate the real effectiveness and magnitude of the impact exerted by these powerful economic forces within the labor market, especially in developed countries. The results of several studies have strengthened such concerns, leading to calls for policies directed at protecting jobs and industries from new and/or foreign threats. By contrast, other scholars reject such a pessimistic view, claiming that many of the fears are clearly unfounded.

In this paper, we contribute to the ongoing debate by studying the effects of automation technologies, as well as different forms of international trade engagement and labor market institutions, on the wage premia, relying on the technology-skill complementarity and polarization approaches. The empirical analysis is performed using annual data for a panel of 17 mostly advanced European economies and 5 industries over the period 2008–2017. According to the recent literature, new technologies are split into tangibles and intangibles, globalization is considered through the overall trade openness and GVC participation channels, while the impact of labor market institutions on wage disparities is evaluated by making use of sector-specific measures of Employment Protection Legislation. In order to detect potential specific effects of the main determinants of wage gaps for different worker types, we break down relative wages in three categories (high- to medium-skilled, high- to low-skilled and medium- to low-skilled labor) and simultaneously estimate a system of equations employing SUR techniques to take into account correlation of the error terms across equations. However, to mitigate endogeneity concerns, an instrumental variable approach is mainly used throughout the empirical investigation.

The core results of our analysis can be summarized as follows. First, intangible technologies, as proxied by Software & Databases and R&D capital intensity, exhibit low-skill substitutability and a polarization of the wage distribution, respectively. Second, we find that robotization is associated with a polarization of the wage distribution, producing heterogeneous effects on the relative wage distributions as well. Third, through channels such as "job insecurity" and "the fear of automation," which could potentially alter the bargaining power of employers, the decline in robot prices exerts additional pressure on the relative wages of medium-skilled workers. Fourth, the role of globalization on the dynamics of the wage differentials depends upon the specific measure considered. Greater trade openness appears to be characterized by both high- and medium-skill-biased patterns, while higher participation in GVCs predominantly harms lower-skilled labor. Finally, employment protection rules prove to be effective in mitigating medium- and low-skilled wage differentials.

From a policy perspective, the main challenge is represented by the effects of intangible technologies and robotization. As our findings suggest, high-skilled workers typically benefit from technological progress (consistent with the extensive existing empirical literature on this topic). This implies, in terms of policy implications, that the strong substitutability we observe between low-skilled workers and Software & Databases (and, albeit to a lesser extent, between medium-skilled labor and R&D) related process innovations, as well as the "hollowing effect" of robotization call for the adoption of institutional measures and actions aimed at investing in education and skills training for less-skilled workers, particularly given that intangible technologies and robots are likely to pervade the workplace even more in the future. Overall, policymakers will need to play a crucial role in ensuring that the economic benefits stemming from new technologies will not be focused on a small elite and further research should be devoted to understanding the exact mechanisms by which rising automation might lead to new job opportunities or destruction.

Furthermore, our findings point to harmful effects of trade openness and GVC participation upon lower-skilled labor. Blanchard and Willmann (2016) suggest that subsidizing human capital investments and/or providing temporary wage top-ups for these particular categories of workers may be a relevant policy.

In essence, our empirical investigation indicates that the influence of tangible and intangible technologies can either be positive or negative in affecting the dynamics of the skill-premia, with the effects depending on the specific dimensions, characteristics and economic mechanisms underlying them. Such a conclusion suggests that there may exist a third way, which lies between the technological optimists and pessimists, whereby the different dimensions of technology (and globalization) affect workers in varied ways.

Appendix

A Additional details on variables construction

This appendix provides further information about the construction of variables used throughout the empirical analysis.

Relative wages: The skill-premium between high-skilled and middle-skilled workers (w_h/w_m) is obtained as follows:

$$\frac{w_h}{w_m} = \frac{\left(\frac{\omega_h LAB}{H}\right)}{\left(\frac{\omega_m LAB}{M}\right)} \tag{A1}$$

where w_h and w_m represent the hourly wages of high- and medium-skilled workers, respectively, $\omega_h LAB$ and $\omega_m LAB$ indicate the total labor compensation of high- and medium-skilled workers, respectively, and H and M are the total hours worked by high- and medium-skilled workers, respectively. The ratios of high- to low-skilled (w_h/w_l) and medium- to low-skilled (w_m/w_l) wages are computed analogously to equation (A1).

Robot density: According to the ISO 8373 definition, an industrial robot is "an automatically, 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, 2019). The IFR database contains information on the estimated operational stock of industrial robots and deliveries of robots for each country-industry-year. The operational stock of robots is constructed by assuming that robots operate for 12 years, on average, without losing economic value and leaving service precisely after the 12th year. Graetz and Michaels (2018) and Artuc et al. (2018), *inter alia*, argue that the assumption of no capital depreciation may be unrealistic. Therefore, the series of operational stock of robots, R^S, is computed by applying the perpetual inventory method on robot deliveries, R^D, to each country, industry and year in the sample, assuming a depreciation rate, δ, of 10%,[26] according to the following formula:

$$R^S_{cst} = R^D_{cst} + (1 - \delta) R^S_{cst-1} \tag{A2}$$

where c, s and t stand for, respectively, country, industry and time.

Sector-specific EPL indicators: The country-level EPL[27] indicators are multiplied by the shares of permanent and temporary workers for each country-industry-year. For instance, the EPL index for permanent workers (EPL_PERM) in country c, industry i and year t is computed according to the following formula:

$$EPL^{Perm}_{cst} = \left(\frac{EPL^{Perm}_{cst}}{E^{Temp}_{cst} + E^{Perm}_{cst}}\right) EPL^{Perm}_{ct}, \tag{A3}$$
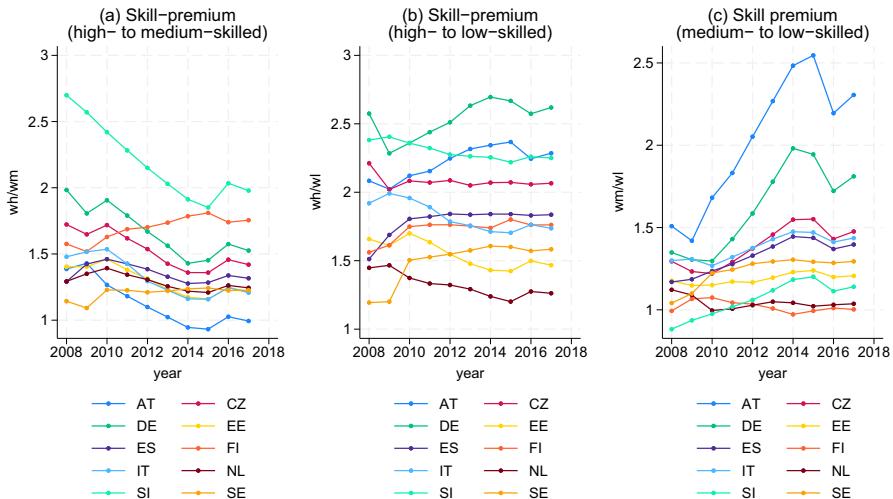
where E^{Temp}_{cst} and E^{Perm}_{cst} represent temporary and permanent employees in country c, industry i and year t, respectively, provided by Eurostat Labour Force Survey (EU-

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[26] As in Graetz and Michaels (2018) and Artuc et al. (2018), the constructed series is initialized using the IFR measure of operational stock of robots for the first year (2008), for each country and industry in the sample. Nonetheless, the two series exhibit a correlation coefficient of about 0.99, by making the results of the analysis qualitatively similar. These are not reported for reasons of space, but available upon request.

[27] The time period covered by EPL indicators ends in 2014. By assuming that labor market institutions are only slowly time varying, observations from 2015 to 2017 of EPLs are forecasted to gain useful information in the sample. Specifically, we employ uniformly weighted moving average using 4 lagged terms, 5 forward terms and the current observation in the filter.
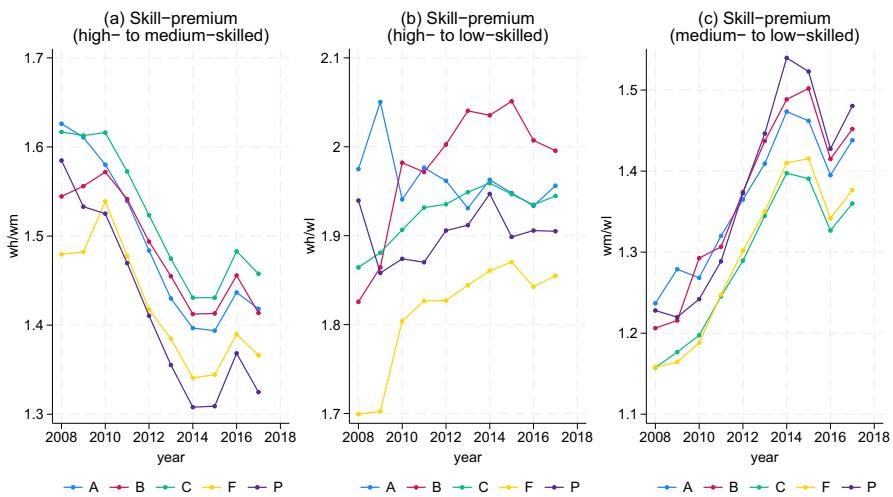
LFS).[28] The sector-specific EPL indicator for temporary workers (EPL_TEMP), EPL_{cst}^{Temp}, is calculated analogously to equation (A3), multiplying the share of temporary employees by EPL_{ct}^{Perm}.

B Additional tables and figures
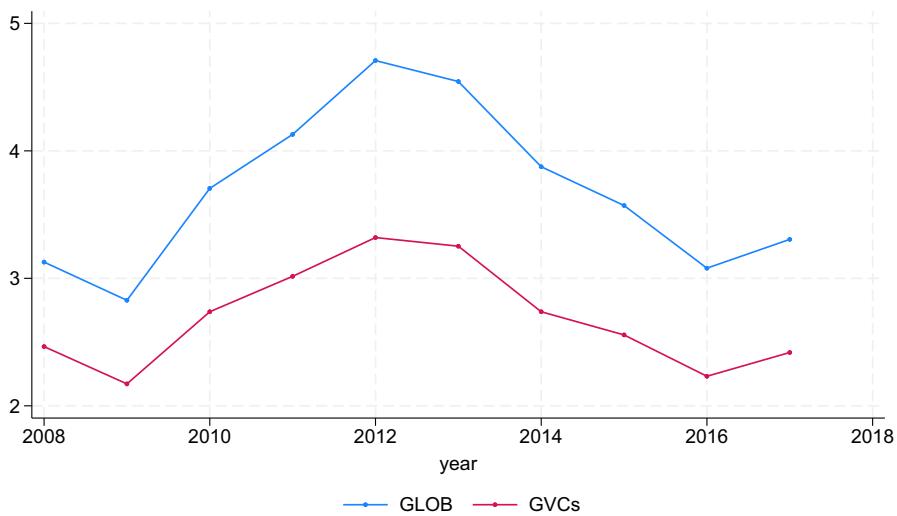
Fig. 4 Developments in the skill-premium, by country. *Notes*: Skill-premium evolution for a subsample of European countries. The figure reports mean values over the period 2008–2017 using 2008 sectoral employments weights to aggregate to the country level

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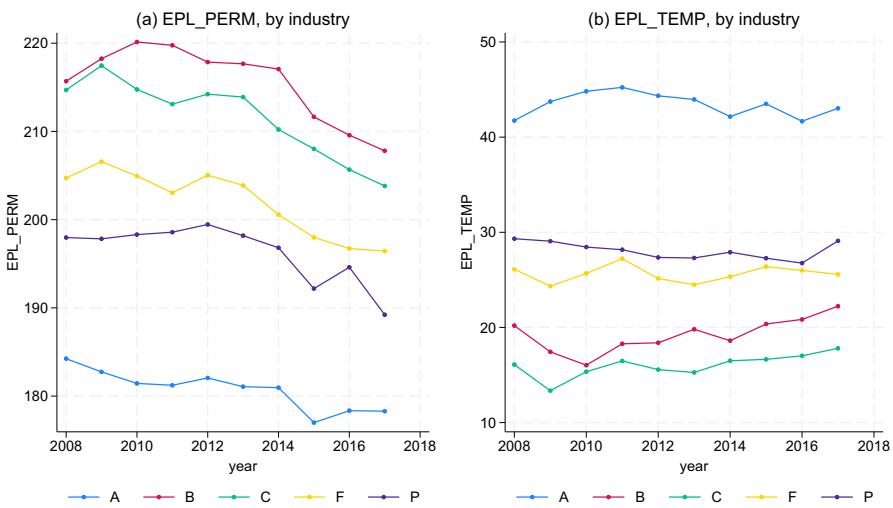
[28] Missing observations in the series of temporary employees are filled through linear interpolation.
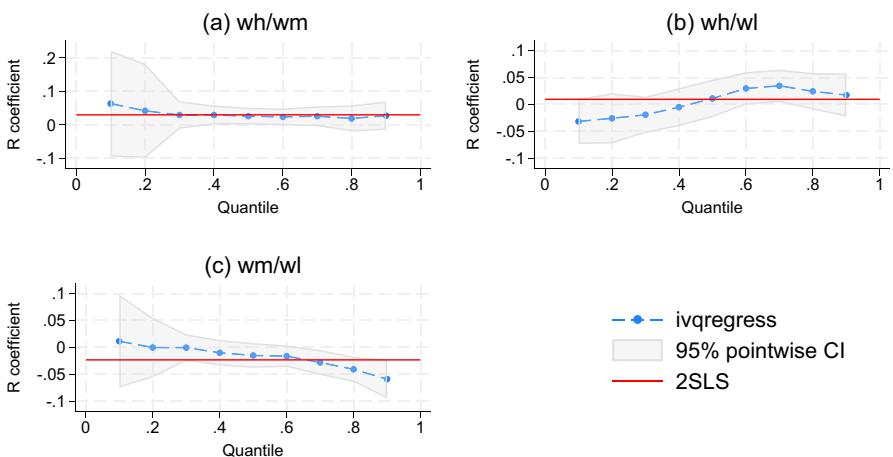
Fig. 5 Developments in the skill-premium, by industry. *Notes*: Skill-premium evolution within European industries (NACE Rev. 2). The figure reports mean values over the period 2008–2017 using 2008 sectoral employments weights to aggregate to the country level
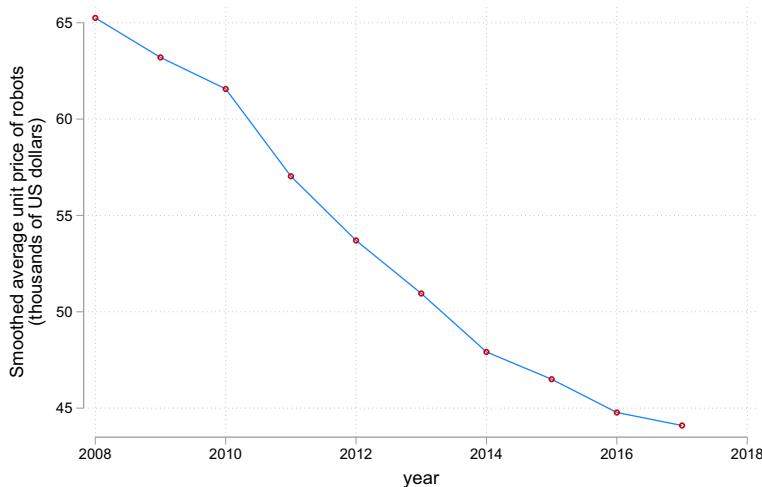
Fig. 6 Developments in overall trade openness and GVC participation, 2008–2017. *Notes*: Evolution of overall trade openness ($GLOB$) and GVC participation. The figure reports log mean values over the period 2008–2017 using 2008 sectoral employments weights to aggregate to the country level

Fig. 7 Developments in EPLs for permanent and temporary employees, by industry. *Notes*: Evolution of EPLs for permanent and temporary employees within European industries (NACE Rev. 2). The figure reports mean values over the period 2008–2017

Fig. 8 IVQRs-SEE results—Robot-density and relative wages, by decile

Fig. 9 Evolution of the global average unit price of robots, 2008–2017

Table 6 List of countries

ISO-3166 code	Country
AT	Austria
BE	Belgium
CZ	Czech Republic
DE	Germany
DK	Denmark
EE	Estonia
ES	Spain
FI	Finland
FR	France
GB	Germany
GR	Greece
IT	Italy
LT	Lithuania
NL	Netherlands
SE	Sweden
SI	Slovenia
SK	Slovak Republic

Table 7 List of industries

NACE code	Industry Description
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Total Manufacturing
F	Construction
P	Education

Source: EU KLEMS (2019). Industry codes are NACE Rev. 2 (ISIC Rev. 4)

Table 8 Summary statistics: levels averaged by country

Country	w_h/w_m	w_h/w_l	w_m/w_l	R	ICT	S&DB	R&D	N_ICT	H/M	H/L	M/L
AT	1.184	2.284	1.985	1.872	1.218	2.148	18.714	91.908	.62	3.079	4.09
BE	1.521	1.601	1.05	2.268	1.241	1.46	19.592	102.854	2.165	3.963	1.83
CZ	1.655	2.07	1.273	1.377	1.343	.338	2.969	59.747	.292	4.72	15.064
DE	1.532	2.615	1.765	7.591	1.276	1.564	20.982	60.813	.679	3.76	4.756
DK	1.223	1.661	1.378	3.522	4.337	2.407	23.181	116.975	1.032	2.395	2.137
EE	1.353	1.615	1.201	.037	1.698	.142	.452	31.699	.768	6.555	6.014
ES	1.346	1.73	1.287	2.499	2.495	.653	5.644	69.368	2.902	2.432	.531
FI	1.67	1.682	1.009	3.241	3.385	1.687	21.517	71.34	.98	5.727	4.03
FR	1.494	1.772	1.197	2.735	1.526	3.991	13.333	43.116	1.097	2.87	2.335
GB	1.57	1.966	1.251	1.088	.759	1.427	4.035	78.089	.813	1.297	1.497
GR	1.356	1.947	1.458	.057	.953	.195	1.86	30.574	1.659	5.375	1.356
IT	1.371	1.752	1.291	3.605	.751	1.15	4.642	62.104	.355	1.258	1.622
LT	2.025	3.069	1.525	.011	.746	2	2	29.884	.752	10.339	10.823
NL	1.229	1.19	.993	1.228	1.767	3.284	15.255	98.443	1.231	3.723	1.893
SE	1.185	1.441	1.214	3.876	4.134	2.362	24.934	63.945	.896	4.292	4.14
SI	2.191	2.305	1.066	1.165	.452	.35	4.012	52.693	.516	2.91	4.14
SK	1.35	1.9	1.454	1.546	.702	.288	1.458	65.967	.35	5.376	20.346
Unweighted mean	1.468	1.916	1.338	1.055	2.402	1.508	7.496	155.389	0.995	4.117	4.755

w_h/w_m: ratio of high- to medium-skilled wages; w_h/w_l: ratio of high- to low-skilled wages; w_m/w_l: ratio of medium- to low-skilled wages; R: Robot Density; ICT: ratio of real ICT capital stock net of Software & Databases to total hours worked; $R\&D$: ratio of $R\&D$ capital stock to total hours worked; $S\&DB$: ratio of Software & Databases capital stock to total hours worked; N_ICT: ratio of non-ICT capital stock to total hours worked; H/M: relative supply of high- to medium-skilled; H/L: relative supply of high- to low-skilled; M/L: relative supply of medium- to low-skilled. The table reports mean values over the period 2008–2017 using 2008 sectoral employments weights to aggregate to the country level

Table 9 Summary statistics: levels averaged by industry

Country	w_h/w_m	w_h/w_l	w_m/w_l	R	ICT	S&DB	R&D	N_ICT	H/M	H/L	M/L
A	1.557	2.118	1.42	.048	1.224	.271	.485	104.331	.232	.481	2.408
B	1.48	1.976	1.368	.284	5.104	2.293	3.763	360.646	.433	1.44	5.928
C	1.538	1.947	1.29	4.876	2.599	2.564	19.417	80.437	.412	1.428	5.544
F	1.411	1.786	1.283	.039	.516	.34	.196	32.657	.3	.943	4.715
P	1.409	1.875	1.357	.124	1.121	1.077	10.34	45.924	3.506	15.412	5.838

w_h/w_m: ratio of high- to medium-skilled wages; w_h/w_l: ratio of high- to low-skilled wages; w_m/w_l: ratio of medium- to low-skilled wages; R: Robot Density; ICT: ratio of real ICT capital stock net of Software & Databases to total hours worked; $R\&D$: ratio of $R\&D$ capital stock to total hours worked; $S\&DB$: ratio of Software & Databases capital stock to total hours worked; N_ICT: ratio of non-ICT capital stock to total hours worked; H/M: relative supply of high- to medium-skilled; H/L: relative supply of high- to low-skilled; M/L: relative supply of medium- to low-skilled. The table reports mean values over the period 2008–2017 using 2008 sectoral employments weights to aggregate to the country level

Table 10 Summary statistics: levels averaged by country

Country	GLOB	GVCS	SECT_EPL	EPL_PERM	EPL_TEMP
AT	1.516	.78	225.489	211.307	14.182
BE	2.037	.917	198.988	175.801	23.187
CZ	2.291	.899	285.043	273.944	11.098
DE	1.315	.703	246.151	232.419	13.731
DK	1.266	.677	209.985	196.557	13.428
EE	2.144	.921	199.085	187.866	11.219
ES	1.152	.6	237.061	151.357	85.704
FI	1.227	.634	208.695	188.079	20.616
FR	1.151	.6	260.71	197.447	63.263
GB	.846	.504	114.098	111.768	2.33
GR	1.048	.636	236.955	191.934	45.02
IT	1.093	.548	261.058	226.947	34.111
LT	1.417	.752	244.739	231.849	12.89
NL	1.454	.659	252.005	236.783	15.221
SE	1.197	.617	238.983	229.145	9.838
SI	1.954	.951	240.026	211.598	28.428
SK	3.054	1.04	197.956	188.265	9.6914
Unweighted mean	3.687	2.690	226.815	199.378	27.437

GLOB: sum of imports plus export to real gross value added; GVCS: sum of real domestic value added embodied in foreign final demand plus foreign value added embodied in domestic final demand to real gross value added; EPL_PERM: EPL permanent employees; EPL_TEMP: EPL temporary employees; SECT_EPL: sum of EPL_PERM and EPL_TEMP. The table reports means weighted by 2008 share of each country's employment

Table 11 Summary statistics: levels averaged by industry

Industry	GLOB	GVCS	SECT_EPL	EPL_PERM	EPL_TEMP
A	.877	.88	229.55	179.149	50.4
B	9.037	7.5	241.611	225.706	15.905
C	3.027	1.189	229.803	214.199	15.604
F	.036	.125	225.77	197.452	28.318
P	.06	.089	219.062	191.534	27.528

GLOB: sum of imports plus export to real gross value added; GVCS: sum of real domestic value added embodied in foreign final demand plus foreign value added embodied in domestic final demand to real gross value added; EPL_PERM: EPL permanent employees; EPL_TEMP: EPL temporary employees; SECT_EPL: sum of EPL_PERM and EPL_TEMP. The table reports means weighted by 2008 share of each country's employment

Table 12 Robustness checks 2SLS regression results: tangible and intangible investments and relative wages

Dep. Var.	Panel I			Panel II		
	(a)	(b)	(c)	(a)	(b)	(c)
	w_h/w_m	w_h/w_l	w_m/w_l	w_h/w_m	w_h/w_l	w_m/w_l
R	0.057***	−0.012	−0.069***	0.068***	−0.032	−0.073***
	(0.015)	(0.015)	(0.014)	(0.018)	(0.021)	(0.014)
ICT	−0.061***	−0.035***	0.026***	−0.052***	−0.036***	0.014
	(0.011)	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)
R&D	0.012**	0.008*	−0.004	0.012*	0.012*	−0.006
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.005)
S&DB	0.016	0.050***	0.034***	0.010	0.058***	0.039***
	(0.013)	(0.013)	(0.010)	(0.013)	(0.013)	(0.010)
First-stage coefficient (RH)	9.943***			10.124***	10.189***	9.715***
	(0.364)			(0.488)	(0.514)	(0.362)
R-squared	0.869			0.881	0.881	0.881
F-test	732.6			418.4	379.8	709.2
Controls				✓	✓	✓
Obs	751	751	751	751	751	751

2SLS regressions using RH as IV for R in the first-stage equation. All the variables are scaled on total hours worked (in millions) and expressed in logarithms. The estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. Year-, country- and industry-fixed effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Table 13 2SLS regression results with labor market regulations and globalization variables

Dep. Var.	Panel I			Panel II		
	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l
R	0.048***	−0.010	−0.062***	0.064***	−0.016	−0.036**
	(0.017)	(0.018)	(0.019)	(0.020)	(0.022)	(0.014)
ICT	−0.042***	−0.025**	0.016*	−0.046***	−0.025**	0.014
	(0.010)	(0.010)	(0.009)	(0.010)	(0.011)	(0.009)
R&D	0.019***	0.019**	−0.008*	0.018**	0.020**	−0.009**
	(0.007)	(0.008)	(0.004)	(0.007)	(0.008)	(0.004)
S&DB	−0.002	0.024*	0.023**	−0.005	0.024*	0.019*
	(0.013)	(0.013)	(0.011)	(0.014)	(0.013)	(0.011)
SECT_EPL	−0.003***	−0.004***	−0.001	−0.003***	−0.004***	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GLOB	0.014***	0.001	0.010*			
	(0.005)	(0.005)	(0.005)			
GVCs				0.032***	0.018***	−0.003
				(0.006)	(0.006)	(0.006)
Controls	✓	✓	✓	✓	✓	✓
Obs	663	663	663	663	663	663
F-test	318.3	250.3	285.6	241.3	170.7	561.4

2SLS regressions using R_J as IV for R in the first-stage equation. All the variables are scaled on total hours worked (in millions) and expressed in logarithms. The estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. Year-, country- and industry-fixed effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Table 14 Sensitivity analysis 2SLS regression results: checks on relative supplies

Dep. Var.	Panel I			Panel II		
	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l	(a) w_h/w_m	(b) w_h/w_l	(c) w_m/w_l
R	0.059***	−0.011	−0.070***	0.077***	−0.009	−0.070***
	(0.015)	(0.015)	(0.016)	(0.021)	(0.026)	(0.016)
ICT	−0.051***	−0.038***	0.013	−0.056***	−0.038***	0.016
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
R&D	0.014***	0.008	−0.006	0.012	0.008	−0.009*
	(0.005)	(0.005)	(0.005)	(0.007)	(0.009)	(0.005)
S&DB	0.013	0.050***	0.037***	0.003	0.047***	0.039***
	(0.012)	(0.013)	(0.011)	(0.013)	(0.014)	(0.011)
First-stage coefficient (R_J)	0.412***			0.383***	0.350***	0.419***
	0.020			(0.029)	(0.031)	(0.021)
R-squared	0.863			0.872	0.874	0.871
F-test	415.8			174.5	130.5	388.8
Relative supplies	N	N	N	$t-1$	$t-1$	$t-1$
Other controls	✓	✓	✓	✓	✓	✓
Obs	751	751	751	672	672	672

2SLS regressions using R_J as IV for R in the first-stage equation. All the variables are scaled on total hours worked (in millions) and expressed in logarithms. In Panel I, relative supplies are excluded from the estimated models. In Panel II, relative supplies are lagged one period. The estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. Year-, country- and industry-fixed effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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