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Automation, Globalisation and Relative Wages: An Empirical Analysis of Winners and Losers

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Abstract

In this paper, we study the effects of advances in robotics, tangible and intangible technologies, and trade openness and global value chain participation on relative wages, relying upon the skill-biased technical change and polarisation of the labour force frameworks. The empirical analysis is carried out using a panel dataset comprising 18 mostly advanced European economies and 6 industries, with annual observations spanning the period 2008-2017. Our findings suggest that intangible technologies – especially software & databases – significantly increase the wage premium for high relative to lower-skilled labour. Additionally, the tangible component of ICT primarily benefits lower-skilled workers, whereas R&D and trade openness produce polarising effects. The results are robust to the inclusion of sector-specific labour market regulations variables in the models.

Keywords: Robots, Intangibles, Automation, ICT, Globalisation, Wage Differentials

JEL Classifications: C01, F16, F63, J31, O11, O33, O43

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1. Introduction

We are witnessing an increasingly intense debate centred 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 labour markets (see, for instance, Acemoglu and Restrepo, 2018a, 2019; Hemous and Olsen, 2018; Nakamura and Zeira, 2018), the empirical evidence is far from conclusive. For instance, in a panel of 17 advanced economies, Graetz and Michaels (2018) observe a positive correlation between the use of industrial robots and growth in both employment and total factor productivity, but also a decline in the employment share of low-skilled workers. On the contrary, Acemoglu and Restrepo (2020) show that robots had a negative impact on employment and wages within the US.

By focussing on robots, these studies capture only the 'tangible' or 'embodied' part of technical change (e.g., Greenwood *et al.*, 1997, Hercowitz, 1998), with employment, productivity and wages being affected by investment in new machinery. In recent years, 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 labour-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, for instance, Blanas *et al.* (2019) provide evidence in support of the hypothesis that software displaced medium- and low-

skilled workers, whereas Michaels *et al.* (2014) point out a polarising, negative impact of R&D on the share of the wage bill captured by medium-skilled labour. 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 overall outcome, therefore, 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, either enhancing or mitigating their relative importance in the production process.

Relatedly, the existing empirical studies in this field are typically focused on the impact of automation technologies, neglecting the potentially relevant role played by trade and particularly participation in Global Value Chains (GVCs) in determining labour market outcomes. 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 labour demand, wages and productivity (e.g., Wood, 1995; Michaels *et al.*, 2014; Lopez Gonzales *et al.*, 2015).

Finally, the contributions of labour market institutions in affecting wage differentials deserves scrutiny, with such institutions producing significant effects on living standards, productivity and social cohesion, especially in European economies (e.g., Betcherman, 2012; Koeniger *et al.* 2017).

Building on these considerations and the mixed empirical evidence on the role played by automation technologies and globalisation, we fill the gaps in the literature by investigating the effects of both advances in robotics, tangible and intangible technologies, trade, and labour market institutions on relative wages, relying on the skill-biased technical change and polarisation frameworks (e.g., Autor *et al.*, 2006; Goos and Manning, 2007; Goldin and Katz, 2009; Goos *et al.*, 2009; Acemoglu and Autor, 2011).

In terms of data, the research carried out in this paper relies on a panel of 18 mostly advanced European economies and 6 industries, using annual data over the years 2008-2017. In performing the empirical investigation, we exploit the new 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 as different, independent proxies for tangible and intangible technologies, respectively. To disentangle the effects of the abovementioned drivers on relative wages, we simultaneously estimate a system of wage premium equations by making use of seemingly unrelated regressions to deal with correlations in the error terms across equations. Thereby, this study fits into different strands of the literature: from the skill-biased technical change and polarisation frameworks to the impact of automation technologies, international trade and institutions on labour market outcomes.

One of the main messages of this paper is that breaking down technology into tangible and intangible components allows for a clearer understanding of how technological changes impacts the skill-premia. For instance, intangible technologies, such as Software & Databases, produce greater advantages to well-educated labour. By contrast, less-qualified workers seem to be able to benefit more from the tangible component of ICT. The analysis also highlights the role played by international trade and labour market institutions in the dynamics of wage differentials.

The paper is structured as follows: Section 2 reviews the relevant literature; Section 3 describes the data employed in the analysis; Section 4 illustrates the empirical framework and the estimation strategy; Sections 5 and 6 present and comment the results; Section 7 concludes with a discussion of policy implications and recommendations.

2. Related Literature

The empirical literature aimed at investigating the role of (automation) technology, globalisation and institutions in affecting labour market outcomes constitutes a large and growing body of research. Since the seminal work by Griliches (1969) on capital-skill complementarity, many scholars have examined the potentially biased effects of technology on the demand for, the

productivity of, and consequently the wages of well-educated 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 polarisation 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 as fundamental drivers of changes in employment, in the skill composition of labour demand and in wages, the focus has mostly been placed on computerisation, ICT, R&D expenditure and patents (e.g., Berman *et al.*, 1994; Morrison and Siegel, 2001; Chennells and Van Reenen, 2002; Michaels *et al.*, 2014; Breemersch *et al.*, 2017; Mann and Püttnam, 2018). 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 labour 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 labour 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 because 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.* (2019), analysing 402 German labour 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.* (2020) find that the adoption of an additional robot is associated, on average, with the employment of five additional workers.

Most of the technologies so far discussed, such as computerisation, 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 characterised 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 their triggering of a "competitive process of investments in continuous product improvement". 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.* (2019) 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.

In addition to technological advances, the many dimensions of globalisation are thought to play an important role in affecting wage 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 labour. In this respect, Wood (1995) analysed the labour-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 liberalisation 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 US, 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 a polarising and skill-biased effects of international trade, respectively. Goos *et al.* (2014) also find evidence to suggest that offshoring can lead to job polarisation.

In reconsidering the traditional HOS trade-based approach, which has attracted considerable criticism (e.g., Berman *et al.*, 1998; Godlberg and Pavcnick, 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-Hasenberg (2008) offer a different explanation: by assuming that the prices of goods remain unchanged, a cost decrease in offshoring produces an increase of unskilled activities offshored to developing countries. This, in turn, causes a rise in profits and sector expansion for those industries that heavily employ unskilled labour, pushing up its demand, productivity and wage, while leaving that of skilled labour unchanged. Therefore, through this channel, the skill-premium decreases. 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 labour in the South. On the one hand, this increases

competition for low-skilled labour in developed countries, reducing demand for low-skilled labour in developed countries. On the other hand, access to low-skilled and low-wage labour 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 labour in developed countries.

The evolution of the new patterns of globalisation 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), although little has been done to quantify the effects of GVC participation on inequality. For instance, Lopez-Gonzales *et al.* (2015) measure backward GVCs 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 labour in both developed and emerging economies – a finding in line with the theoretical predictions by Grossman and Rossi-Hasenberg (2008).

Overall, Helpman (2016) states that globalisation has contributed to the dynamics of relative wages and inequality, but only to a modest extent if evaluated against other factors. Among these other factors, a prominent position pertains to labour market institutions (for a survey of studies on the effects of labour market institutions on living standards, productivity and social cohesion, see Betcherman, 2012), such as measures of employment protection legislation (EPL). Existing contributions find mixed evidence on the effect of labour market protection on labour market outcomes. Several studies have demonstrated a significant and substantial effect of strong labour 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 indicators for regular and temporary contracts, Sparrman and Rossvoll (2015) find that the two indicators of labour market restrictions have opposite impacts on wage inequality, with EPL for temporary contracts shrinking the wage gaps and EPL for regular contracts intensifying them.

3. Data and descriptive statistics

The empirical analysis relies on annual panel data for 18 mostly developed European economies and 6 industries spanning the period 2008-2017[1]. The countries included in the sample are: Austria, Belgium, Czech Republic, Denmark, Germany, Estonia, Finland, France, Greece, Italy, Lithuania, Netherlands, Spain, Sweden, Slovenia, Slovak Republic, the United Kingdom and Japan.[2] Industries are classified according to the one-digit-level NACE Rev. 2 (ISIC Rev. 4) codes and reported in Table 1.

Table 1: List of Sectors

NACE code	Industry Description
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Total Manufacturing
D-E	Electricity, gas, steam; water supply, sewerage, waste management
F	Construction
P	Education

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

Data are collected and integrated from various sources. The main dataset is the EU KLEMS (2019) database, which provides information on skill composition, employment, labour compensation, hours worked, real fixed capital assets and value added by country-industry-year.

The EU KLEMS dataset combines information on the shares of labour compensation and hours worked for three different workers types, which are distinguished on the basis of their

[1] The set of countries, industries and time periods included in the analysis are dictated by data availability.
[2] Due to data constraints, we include as many countries as possible in the analysis. Removing Japan from the sample does not alter the main outcomes of the study, which are available upon request.

educational attainment: university graduates; secondary and post-secondary education; and primary and lower secondary education. [3] Such a decomposition allows a multifaceted investigation of the dynamics of skill-premia, analysing whether workers are affected differently by tangible and intangible technologies, as well as by globalisation and labour 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, high- to medium-skilled workers and medium- to low-skilled workers). For instance, the skill-premium between high-skilled and middle-skilled workers (SP HS/MS) is obtained as follows:

$$SP\frac{HS}{MS} = \frac{w_{hs}}{w_{ms}} = \frac{\left(\frac{\omega_{hs}LAB}{H_{hs}}\right)}{\left(\frac{\omega_{ms}LAB}{H_{ms}}\right)} \tag{1}$$

where w_{hs} and w_{ms} represent the hourly wages of high- and medium-skilled workers respectively, $\omega_{hs}LAB$ and $\omega_{ms}LAB$ indicate the total labour compensation of high- and medium-skilled workers, respectively, and H_{hs} and H_{ms} are the total hours worked by high- and medium-skilled workers, respectively. The ratios of high- to low-skilled (SP HS/LS) and medium- to low-skilled (SP MS/LS) wages are computed analogously. Relative skill supplies (i.e., the quantity effect) are measured by the ratios of hours worked in each analysed category – namely, the ratio of high-skilled hours worked to medium-skilled hours worked (H/M), the ratio of high-skilled hours worked to low-skilled hours worked (H/L), and the ratio of medium-skilled hours worked to low-skilled hours worked (M/L). The inclusion of relative skill supplies in the models is aimed at assessing whether there is a negative association between relative supply and the wage premia, as suggested by Katz and Murphy (1992), Card and Lemieux (2001) and Glitz and Wissmann (2017), amongst others.

[3] Although the EU KLEMS (2019) data are mostly available at the two-digit level and from 1995 onwards, information on labour inputs only cover the period 2008-2017 and are provided according to the ISCED (2011) 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.

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 Software & Databases (S&DB) and R&D capital stocks.[4] Following Michaels *et al.* (2014) and Blanas *et al.* (2019), all capital intensity variables are taken as a ratio to real gross value added. In this context, the crucial empirical questions, according to Haskel and Westlake (2018), are whether intangibles may produce either skill-biased or polarising effects and whether the tangible component of ICT, by contrast, may negatively affect wage dispersion (e.g., Acemoglu and Restrepo, 2018b, 2020).

The second source of data is the International Federation of Robotics (IFR) for the stock of industrial robots by country-industry-year. 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). IFR data are broken down by industrial branches and classified according to ISIC Rev. 4, which makes them highly compatible with EU KLEMS. Nonetheless, due to limitations in the number of industries covered, the merger with EU KLEMS is possible only for the sectors reported in Table 1. The 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 is computed by applying the perpetual inventory method on robot deliveries to each country, industry and

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

year in the sample, assuming a depreciation rate of 10%.[5] The robot density variable (ROB) is computed as robot stocks per million hours worked, rather than numbers of person 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.* (2019) and Jungmittag and Pesole (2019), robots are widely deployed in heavy industries, as a form of automation that links machineries (non-ICT capital) and software. Nonetheless, because of its tangible nature, the inclusion of robot density in the analysis is aimed at isolating potential independent effects on the skill-premia. Following Graetz and Michaels (2018), the inclusion of robot density in the model, as a distinct proxy for tangible technology, has the objective to test the skill-biased technical change hypothesis.

In the second stage of our analysis we examine the role played by globalisation, and in particular trade openness and participation in GVCs, in strengthening or mitigating the wage premia. For this purpose, we use data from the World Input-Output Database (WIOD) by Timmer *et al.* (2015) to measure the extent of trade openness at the country-industry level.[6] 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) exports expressed as a share of real gross value added. According to Epifani and Gancia (2008) and Michaels *et al.* (2014), we would expect either skill-biased or polarising effects of trade openness. Thus, whether GLOB affects the skill-premia positively or negatively, for the three dimensions of wage inequality, is an empirical question.

OECD represents an additional source of data to account for participation in GVCs. Specifically, we rely on the Trade in Value Added (TiVA) database[7], collecting information on domestic value

[5] As in Graetz and Michaels (2018) and Artuc *et al.* (2018), the constructed series is initialised 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.

[6] These data are available up to 2014.

[7] The 2018 OECD update of the TiVA database encompasses the years 2005 to 2015.

added embodied in foreign final demand (FFD_DVA) and foreign value added embodied in domestic final demand (DVD_FVA). These two indicators can be interpreted, respectively, as "exports of value-added" and "imports of value added" – capturing upstream and downstream participation in GVCs, respectively – and are expressed as a share of real gross value added. The inclusion of participation in GVCs variables, in the second stage of the analysis, has the goal of detecting whether and how a different form of engagement in trade produces skill-biased effects along the two channels of imports and exports of value added. In a recent contribution, Wang *et al.* (2018) develop a model suggesting that downstream participation in GVCs is associated with higher wage inequality. In their model, 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, the model suggests that GVC participation increases the skill premium. Franssen (2015) finds some evidence using WIOD data that upstream GVC participation is also associated with a higher skill premium.

From OECD we also employ data on Employment Protection Legislation (EPL) in the third stage of the study, where the impact of labour market institutions on the skill-premia is assessed. Borrowing from IMF (2016) and Hantzsche *et al.* (2018), we construct two sector-specific measures of EPL for permanent and temporary workers.[8] In particular, the country-level EPL 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:

$$EPL_{cit}^{Perm} = \left(\frac{E_{cit}^{Perm}}{E_{cit}^{Temp} + E_{cit}^{Perm}}\right) EPL_{ct}^{Perm} \tag{2}$$

[8] The time period covered by EPL indicators ends in 2014. By assuming that labour 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.

where E_{cit}^{Temp} and E_{cit}^{Perm} represent temporary and permanent employees in country c, industry i and year t, respectively, provided by Eurostat Labour Force Survey (EU-LFS).[9] The sector-specific EPL indicator for temporary workers (EPL_TEMP), EPL_{cit}^{Temp}, is calculated analogously to equation (2), multiplying the share of temporary employees by EPL_{ct}^{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 labour market regulations are proxied by two separate, sector-specific indicators, one for each group of workers.

Real price variables are expressed in PPP adjusted 2005 international dollars, with the PPP conversion factors from Inklaar and Timmer (2014). The benchmark sample consists of 955 observations. Summary statistics, by country and industry, for the levels of the variables included in the empirical analysis are reported in tables A1 and A2 of the Appendix, respectively.

In figures 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 (SP HS/MS; SP HS/LS; SP MS/LS), the non-ICT capital intensity and robot density (ROB) 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 Figure 1 shows the patterns of the capital-intensity technologies. By including R&D among the intangible capital stocks, the new EU KLEMS (2019) database release allows us to expand and update some of the previous descriptive findings in the literature (e.g., Blanas *et al.*, 2019), albeit for a smaller number of industries. In particular, the important contribution of R&D

[9] Missing observations in the series of temporary employees are filled through linear interpolation.

capital stock can be observed, with its share increasing from 10% in 2008, to almost 14% in 2017. The shares of ICT (net of S&DB) and S&DB exhibit more modest growth over the same period: from 4.5% to 5.5% for ICT and from 2.2% to about 2.9% for S&DB. Although ICT and S&DB constitute lower shares compared to the R&D capital intensity, we must emphasise the fact that the investments in these specific assets grew by about 30% over the ten years under investigation.

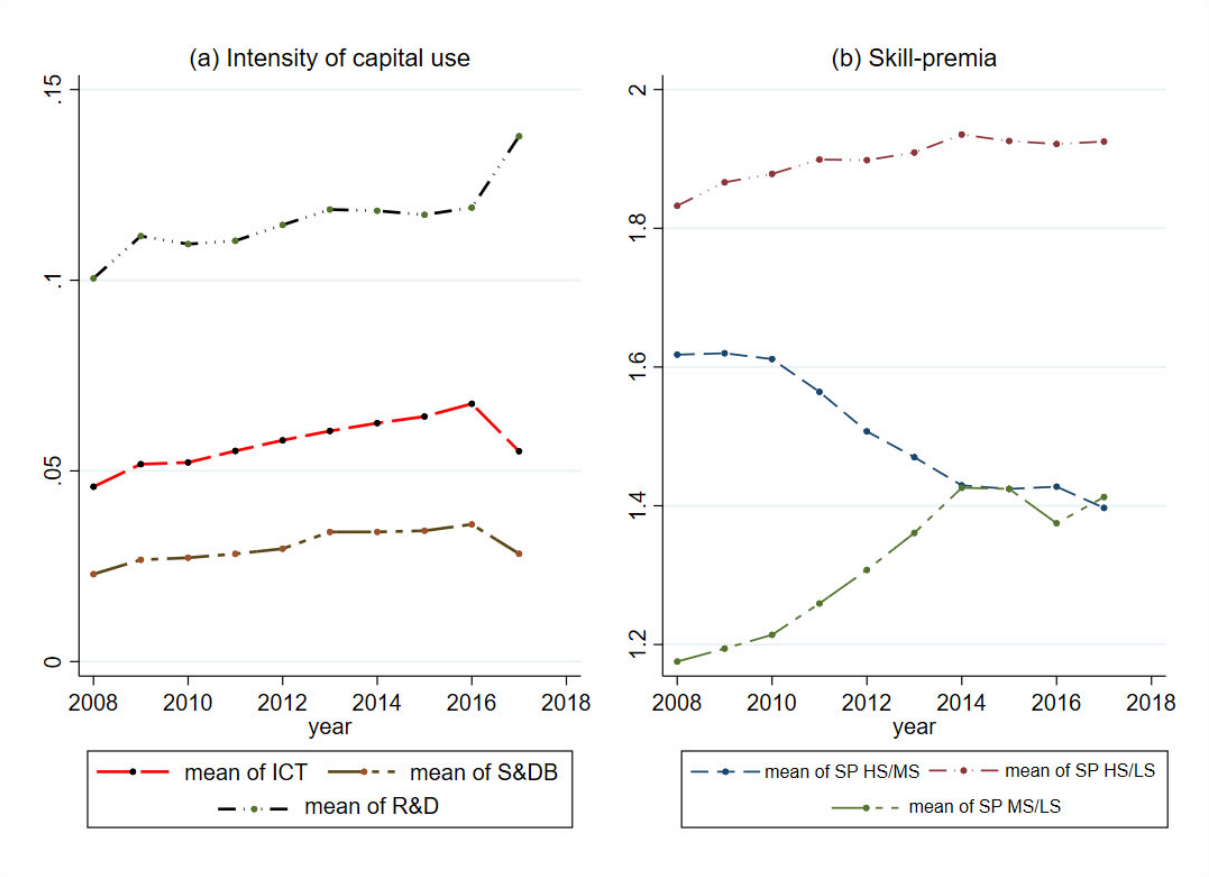
Panel (b) of Figure 1 reports the skill-premia evolution. The wage premium between high- and low-skilled workers (SP HS/LS) increased somewhat over the period, while the wage gap between high- and medium-skilled workers (SP HS/MS) showed a more marked decline.[10] Conversely, the increase in the wage dispersion between medium- and low-skilled workers (SP MS/LS) appears in line with the recent findings of EU (2015, 2019).

With respect to the behaviour of wage dispersion within countries during the analysed period[11], it can be noticed that although the vast majority of countries experienced a slight decline in the skill-premium between high- and medium-skilled workers, Finland, Spain and Slovenia showed a rising trend. As for the wage gap between high- and low-skilled workers, a stagnant evolution prevailed. Ultimately, the growth trend in the skill-premium between medium- and low-skilled labour, as shown in the Panel (b) of Figure 1, was mainly driven by Austria, Germany and Slovenia.

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

[11] Graphs representing the evolution of wage gaps for a subsample of European economies are reported in figures A1-A3 in the appendix to this paper.

Figure 1: Developments in the Intensity of Technology Use and the Skill-Premia



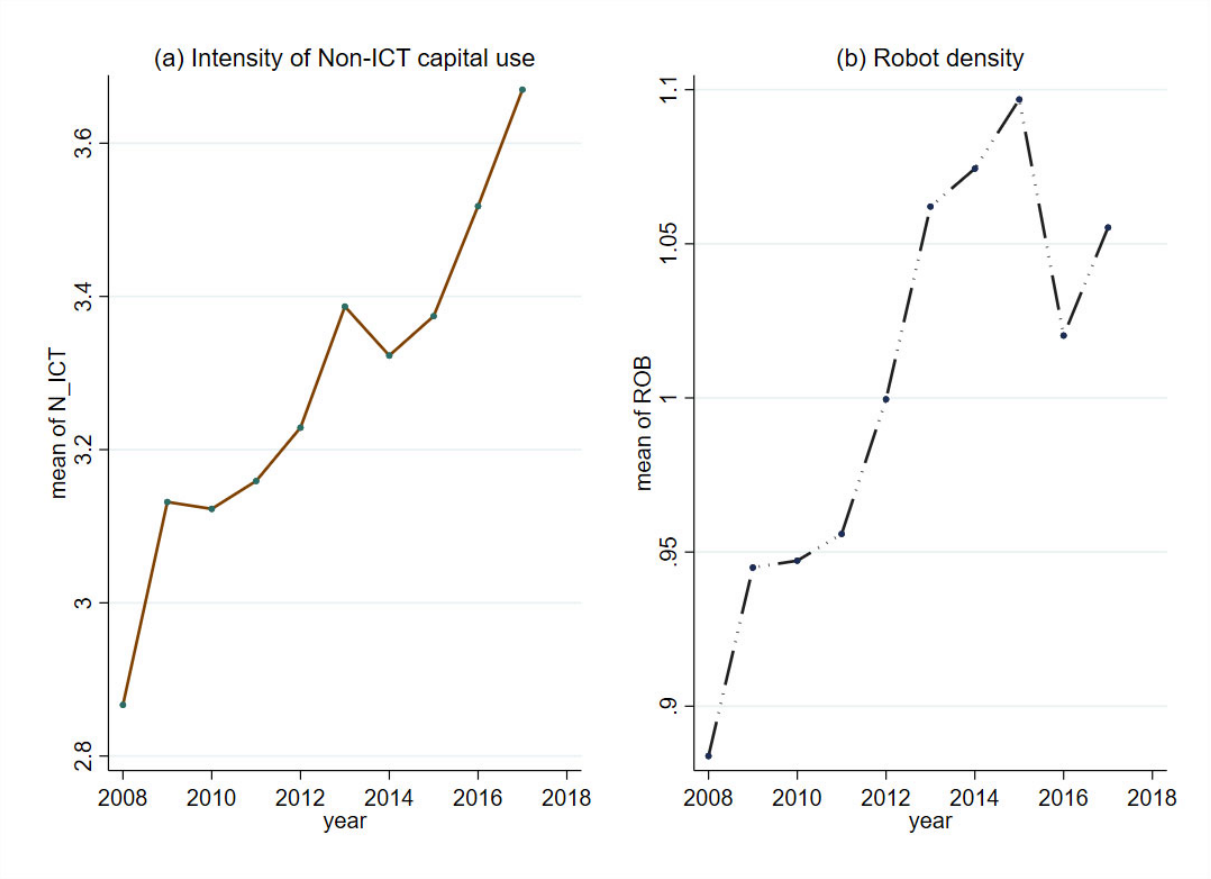
Sources: Authors' calculation based on EU KLEMS (2019)

Developments in the intensity of use of non-ICT capital and robot density (ROB) show strong rising trends, as illustrated in Figure 2. In Panel (a) of Figure 2, the evolution of non-ICT capital intensity (N_ICT) seems to extend the descriptive evidence by Blanas *et al.* (2019), which highlights an increase of "Traditional Capital" starting from the 2000s after nearly 20 years of unpredictable patterns.[12] Likewise, robot density – computed as the stock of industrial robots per million hours worked – followed a clear path of growth (albeit with a short-run slowdown between 2015 and 2016), fuelling concerns about the future of human work (e.g., Frey and

[12] As argued by Blanas *et al.* (2019), data on intangible investments, especially software, were not fully captured in earlier EU KLEMS versions, being potentially included in both ICT and non-ICT capital assets. In confirmation of this, McGrattan (2017) provides evidence of a high correlation between investments in non-ICT capital and intangible assets.

Osborne, 2017; Berg *et al.*, 2018). Overall, both non-ICT capital and robot density recorded an increase of about 20% during the period 2008-2017.

Figure 2: Developments in the Intensity of Non-ICT capital Use and Robot Density



Sources: Authors' calculations based on EU KLEMS (2019) and IFR (2019)

4. Empirical models and estimation strategy

Relying on the theoretical contributions described in section 2 and empirical works, amongst others, of Goldin and Katz (2009), Michaels *et al.* (2014), Glitz and Wissmann (2017), Graetz and Michaels (2018) and Blanas *et al.* (2019), the estimated system of three equations accounting for the evolution of skill-premia can be expressed as follows:

$$\begin{cases} ln\left(\frac{w_{hs}}{w_{ms}}\right)_{cit} = \alpha_{1,c} + \beta_{1,i} + \gamma_{1,t} + \delta_{1,r}\, ln(ROB)_{cit} + \delta_{1,k}K'_{cit} + \delta_{1,y} ln\, Y_{cit} + \delta_{hm}\, ln\left(\frac{H}{M}\right)_{cit} + \varepsilon_{1,cit} \\ ln\left(\frac{w_{hs}}{w_{ls}}\right)_{cit} = \alpha_{2,c} + \beta_{2,i} + \gamma_{2,t} + \delta_{2,r}\, ln(ROB)_{cit} + \delta_{2,k}K'_{cit} + \delta_{2,y} ln\, Y_{cit} + \delta_{hl}\, ln\left(\frac{H}{L}\right)_{cit} + \varepsilon_{2,cit} \\ ln\left(\frac{w_{ms}}{w_{ls}}\right)_{cit} = \alpha_{3,c} + \beta_{3,i} + \gamma_{3,t} + \delta_{3,r}\, ln(ROB)_{cit} + \delta_{3,k}K'_{cit} + \delta_{3,y} ln\, Y_{cit} + \delta_{ml}\, ln\left(\frac{M}{L}\right)_{cit} + \varepsilon_{3,cit} \end{cases} \quad (3)$$

where $c = 1, \dots, C$, $i = 1, \dots, I$ and $t = 1, \dots, T$, indicate, respectively, country, industry and time. The dependent variables are the logarithms of the skill-premium between high and middle-skilled workers (SP HS/MS), high and low-skilled workers (SP HS/LS) and medium and low-skilled workers (SP MS/LS), respectively; $a_{j,c}$,, $\beta_{j,i}$ and $\delta_{j,t}$, (with $j = 1, 2, 3$) 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; $ln\ (ROB)$ is the logarithm of robot density[13]; K' is a vector of EU KLEMS capital intensity variables[14] – the shares of real fixed ICT (net of S& DB), R&D, N_ICT and S&DB capital stocks to real gross value added; $ln\, Y$ is the logarithm of real gross value added, included as control for industry-scale effects; $ln\left(\frac{H}{M}\right)$, $ln\left(\frac{H}{L}\right)$ and $ln\left(\frac{M}{L}\right)$ stand for, respectively, the relative supplies of high- to medium, high- to low and medium- to low-skilled workers; and ε_j are well behaved error terms (with $j = 1, 2, 3$).

The three skill-premium equations in (3) are simultaneously estimated using Seemingly Unrelated Regression (SUR) techniques (Zellner, 1962) to control for potential correlation of the error terms across the equations. According to Goldin and Katz (2009) and Glitz and Wissmann

[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 $ln(x_{cit} + (x_{cit}^2 + 1)^{1/2})$. Similarly as in Artuc *et al.* (2018), estimations are also carried out using $ln(1 + x_{cit})$. The results are qualitatively comparable and available upon request.

[14] Following Michaels *et al.* (2014) and Blanas *et al.* (2019), the EU KLEMS share variables are expressed in levels rather than logarithms, due to the near-zero values for some country-industry pairs in our sample: this, in turn, implies large negative values after the logarithmic transformation. The use of log-transformation, rather than levels, for the robot density variable is dictated by the heavy right-skewness distribution and nonlinearities affecting the non-transformed variable. Additionally, as robustness checks, we lagged by one year the main independent variables to attenuate potential simultaneity bias: the estimations of this alternative model specification do not alter the core results of the analysis, which are available upon request.

(2017), identification of the system given by equation (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.

5. Basic results and discussion

This section presents and discusses the estimates for the first stage of the study, where the focus is placed upon the role played by tangible and intangible technologies.

Table 2 reports the SUR results for the three wage premium equations described in the previous section: high- to medium-skilled workers (SP HS/MS), in Column (1); high- to low-skilled workers (SP HS/LS), in Column (2); medium- to low-skilled workers (SP MS/LS), in Column (3). The Breusch-Pagan test strongly rejects the null hypothesis of contemporaneously independent disturbances across the equations – providing support for the adoption of SUR estimates. In terms of our control variables, we find evidence of the negative impact of relative skills supplies on wage premia for all the estimated models, in line, among others, with Krusell *et al.* (2000) and Goldin and Katz (2009). Consistent with some of the findings in Michaels *et al.* (2014), non-ICT capital displays complementarity with medium-skilled workers, as revealed by the negative and positive significant coefficients in columns (1) and (3) respectively.

Turning to our main variables of interest, estimated coefficients on the capital-skill complementarity effect for robot density (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 (1) and (2)), results in line with those of Graetz and Michaels (2018). Such results may reflect a complementary relationship between robot density and high-skilled workers or a substitution effect with respect to low- and medium-skilled workers. In elasticity terms, all else being equal, a one percent increase in robot density is

associated, on average, with a growing wage gap by 0.025 and 0.037 percent, respectively, for high- to medium skilled labour and high- to low-skilled labour.

Likewise, the intangible part of ICT – i.e., S&DB – seems to severely disadvantage less-skilled labour in terms of wage dispersion. In this case, *ceteris paribus*, a one percentage point increase in the intensity of S&DB use is associated, on average, with an increase in the skill-premium between high- to low-skilled workers, high- to low-skilled and medium- to low-skilled workers, of around 0.6, 0.8 and 0.25 percent respectively. On the contrary, the tangible component of the ICT (net of S&DB) capital – i.e., hardware – appears to improve, in particular, the wages of middle-educated workers, relative to high- and low-skilled workers, as shown in columns (1) and (3). Results in Column (2) further suggest that ICT capital benefits low-skilled relative to high-skilled workers. Such results may be due to ICT (net of S&DB), as a General-Purpose Technology[15], reaching maturity and its pervasiveness in advanced economies that has facilitated innovation dynamics in many industries as well as boosting the adaptability, productivity and wages of less-skilled labour (e.g., Aghion and Commander, 1999; Conceição and Galbraith, 2000; Acemoglu and Restrepo, 2020, 2018b).

With regard to the impact of the intensity of R&D expenditure, the second proxy for intangible technology, the estimates in columns (1) and (3) reflect and complement those reported by Michaels *et al.* (2014) and Breemersch *et al.* (2017), who observe polarising effects of R&D related process innovations that impact upon middle-skilled labour negatively. For this specific relationship, all else being equal, a one percentage-point increase in the R&D share is accompanied, on average, by an increase in the skill-premium between high- and medium skilled labour by 0.16 percent and a reduction in the skill-premium between medium- and low-skilled labour by 0.18 percent, respectively.

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

It is important to note that the incidence of the intensity of S&DB capital in exacerbating wage inequalities is economically more relevant than R&D, although the share of S&DB in gross value added as well as its growth rate over the period under investigation are considerably lower. The effect of S&DB on the skill-premium between high- and medium-skilled labour, for example, is about 3.5 times as large as the effect of an increase in R&D. Such an outcome highlights that intangibles are of great importance in driving the dynamics of wage differentials. In this respect, our estimates reveal that S&DB, as a proxy for digitalisation technology, has the potential to boost inequalities to a greater extent than R&D or robot investment (e.g., Balsmeier and Woerter, 2019; Arntz *et al.*, 2019).

Overall, our findings suggest that disentangling the roles played by different kinds of technological advances in a systematic and comprehensive analytical framework, can favour a better understanding of the dynamics of wage dispersion within the labour market induced by tangible and intangible automation technologies.

Table 2: Regression Results of Relationship between Tangible and Intangible Investments and Relative Wages

	(1)	(2)	(3)
Dep. Var: ln(SP)	(HS/MS)	(HS/LS)	(MS/LS)
ln(ROB)	0.025**	0.037***	0.013
	(0.013)	(0.011)	(0.013)
ICT	-0.978***	-0.313**	0.670***
	(0.169)	(0.149)	(0.168)
R&D	0.160***	-0.021	-0.182***
	(0.045)	(0.039)	(0.044)
S&DB	0.572***	0.829***	0.248***
	(0.096)	(0.085)	(0.095)
N_ICT	-0.031***	0.005	0.036***
	(0.005)	(0.004)	(0.005)
ln Y	-0.113***	-0.003	0.108***
	(0.021)	(0.018)	(0.021)
ln(H/M)	-0.034**		
	(0.013)		
ln(H/L)		-0.026**	
		(0.012)	
ln(M/L)			-0.039***
			(0.013)
Obs.		955	
R-squared	0.637	0.731	0.688
Breusch-Pagan (chi-squared)		663.922	
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes

Notes: Seemingly Unrelated Regressions (SUR), with small-sample adjustment for computing the covariance matrix for the equation residuals. All the estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses.

6. Robustness and extensions

In this section we consider extensions to the baseline analysis described above. Specifically, the first extension, reported in sub-section 6.1, involves the inclusion of variables capturing globalisation in our analysis, while sub-section 6.2 further includes sector-specific proxies for labour market regulations. Through this analysis we are interested in both the effects of these sets of variables on the skill-premia and their impacts on the relationships between technologies and the skill-premia described in the previous section.

6.1. Globalisation

In the second stage of our investigation, the supplemental role played by 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-intensive and unskilled-intensive goods (e.g., Wood, 1995). For this purpose, we augment the models proposed in Section 4 by including two alternative indexes of globalisation: 1) an overall measure of trade openness (GLOB), calculated as the ratio of imports plus exports to real gross value added, and 2) indicators of upstream (DFD_FVA) and downstream (FFD_DVA) GVCs participation. Results from including these indicators alongside the technology variables are reported in Table 3.

The extended regressions show that the main findings uncovered in the previous section are generally robust to the inclusion of further control variables – with the only exceptions of ICT (net of S&DB) in columns (2) and (5), which remain negative but are no longer significant, and robot density (ROB) in column (4), which remains positive but is no longer significant.

Turning to the contribution of globalisation as an additional determinant of the skill-premia dynamics, the estimates suggest – similarly to Michaels *et al.* (2014) – that a higher trade openness (GLOB) produces polarising effects, with middle-skilled labour suffering relative to high- and low-skilled labour. This can be seen by the positive and significant coefficient on GLOB in Column (1) and the negative and significant coefficient in Column (3). Specifically, *ceteris paribus*, a one percentage point increase in GLOB is associated with an increase in the wage premium between high- and medium-skilled labour of about 0.05 percent, and to a reduction of the wage premium between medium- and low-skilled labour by about 0.07 percent, respectively. The results further suggest (Column 2) that trade openness produces a decline in the wage gap between high- and low-skilled workers, suggesting that trade openness is in general low-skill-biased for this specific relationship. This outcome is also in line with previous findings by

Spilimbergo *et al.* (1999) and IMF (2002), who highlight a decline of the wage premium between skilled and unskilled workers in countries well-endowed with capital, as a result of a higher participation in trade. Furthermore, the modest incidence of trade openness on relative wages confirms the conclusions by Helpman (2016).

With respect to the effects provided by GVC participation, in columns (4) and (5) we find evidence of a negative association between downstream participation (FFD_DVA) and the skill-premia involving high- to medium-skilled labour as well as high- to low-skilled labour. Such a finding is in line with the theory of Grossman and Rossi-Hasenberg (2008), which suggests that an increase in offshoring of low-skilled tasks to developing countries raises wages for low-skilled labour and reduces the skill-premium.

The analysis carried out up to this point reveals that the international trade, together with technological advances, plays a crucial role in strengthening or mitigating the wage differentials within the labour market. Additionally, by disaggregating wage premia along the three dimensions considered we can better identify potential "winners and losers" – in relative terms – from technology and globalisation. Results suggest that while openness in a general sense has both polarising and low-skill-biased effects, offshoring can diminish the skill-premia in line with existing theoretical results.

Table 3: Regression Results with Globalisation Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var: ln(SP)	(HS/MS)	(HS/LS)	(MS/LS)	(HS/MS)	(HS/LS)	(MS/LS)
ln(ROB)	0.043***	0.028**	-0.013	0.010	0.028**	0.021
	(0.016)	(0.014)	(0.015)	(0.015)	(0.013)	(0.015)
ICT	-0.925***	-0.289	0.641***	-0.792***	-0.225	0.563***
	(0.209)	(0.186)	(0.203)	(0.199)	(0.173)	(0.197)
R&D	0.205***	-0.051	-0.257***	0.167***	-0.049	-0.218***
	(0.052)	(0.046)	(0.050)	(0.050)	(0.044)	(0.050)
S&DB	0.611***	0.960***	0.340***	0.593***	0.881***	0.271**
	(0.118)	(0.105)	(0.114)	(0.108)	(0.095)	(0.107)
N_ICT	-0.035***	0.003	0.037***	-0.034***	0.005	0.037***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln Y	-0.146***	-0.002	0.142***	-0.113***	0.022	0.127***
	(0.024)	(0.021)	(0.024)	(0.026)	(0.022)	(0.026)
ln(H/M)	-0.036**			-0.036**		
	(0.015)			(0.015)		
ln(H/L)		-0.030**			-0.026**	
		(0.013)			(0.013)	
ln(M/L)			-0.043***			-0.048***
			(0.015)			(0.014)
GLOB	0.048***	-0.028***	-0.075***			
	(0.011)	(0.010)	(0.011)			
FFD_DVA				-0.210**	-0.225***	0.017
				(0.095)	(0.085)	(0.096)
DFD_FVA				-0.010	0.006	0.015
				(0.009)	(0.008)	(0.009)
Obs.		703			801	
R-squared	0.646	0.724	0.688	0.634	0.726	0.678
Breusch-Pagan (chi-squared)		487.744			543.750	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Seemingly Unrelated Regressions (SUR), with small-sample adjustment for computing the covariance matrix for the equation residuals. All the estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses.

6.2. Labour Market Regulations

The last stage of our investigation deals with the impact of labour market institutions on wage dispersion, starting from the assumption that these are likely to be effective at attenuating

inequalities especially in the European countries (e.g., Koeniger *et al.*, 2007).[16] To this end, we further augment the models with the sector-specific measures of EPL for permanent (EPL_PERM) and temporary (EPL_TEMP) employees described in Section 3. Table 4 reports the estimated results of the models that consider the roles of technologies, trade and labour market institutions as determinants of the dynamics of wage premia.

As for the main findings uncovered in Section 5 and subsection 6.1, it can be noticed that once we control for the strictness of employment protection law, the coefficients associated with robot density become insignificant for all estimated models. Conversely, the coefficients on ICT (net of S&DB) recover their statistical significance. Coefficients on the R&D are also now found to be sensitive to the choice of proxy for globalisation. Common to both model specifications, the contribution of S&DB turns out to be fully robust in affecting only the wage gaps between high- to medium-skilled and high- to low-skilled labour[17], as indicated in columns (1)-(2) and (4)-(5). Such a specific finding corroborates the view of Haskel and Westlake (2018), according to which managing intangible technologies, such as S&DB, entails the need for specific skills, education and training. As a result, a higher S&DB leads to a higher demand for high-skilled workers and in turn higher wages, which tends to exacerbate the wage premia.

Additionally, when controlling for the strictness of employment protection law, the coefficients associated with the relative supplies of skills (H/M, H/L and M/L) become insignificant for all estimated models. In line with Acemoglu (2003), such a result can be explained on the grounds that European industries, due to the degree of compression in the wage structure over the business-cycle stemming (at least to some extent) from the strict labour market regulations, might

[16] Since the sector-specific EPL indicators are constructed relying upon the shares of permanent and temporary employees, for which data are available only for European countries, Japan is excluded from the estimated sample.

[17] The increased size of the coefficients for the S&DB variables is due to a drop in the observations for some specific country-industry pairs in the sample, for which the sector-specific EPL measures cannot be constructed because of data availability for permanent and/or temporary employees. Specifically, the vast majority of missing observations occur for the "Mining and Quarrying" (B) and the "Electricity, gas, steam; water supply, sewerage, waste management" sectors. This, in turn, would suggest that the impact of S&DB is not as strong for these industries. The outcomes of the regressions performed on the reduced sample size obtained by excluding the EPL variables, as well as the magnitude of the S&DB coefficients, do not differ significantly from those reported in Table 4 - these are available upon request.

be incentivised to adopt technologies that are low-skill-biased. The latter, subsequently, would push-up productivity and wages for medium- and low-skilled workers, as some of our findings seem to point to. This, in turn, implies limits placed on the skill upgrading of the workforce, de-emphasising the role of market forces through the channels of demand for and supply of skills (e.g., Bertola, 1999; Boeri *et al.*, 2012).

Although the evidence for the trade openness variables (GLOB) is confirmed in this further extension of the analysis, as shown in columns (1)-(3), one interestingly finding emerges regarding the impact of GVCs participation. In column (4) of Table 4 the coefficient for the upstream participation (DFD_FVA) becomes positive and statistically significant, a result in line with those of Franssen (2015).

Ultimately, as expected, stricter employment protection rules, as proxied by the sector-specific EPL measures (EPL_PERM and EPL_TEMP), have strongly negative effects on the skill-premia, for all the estimated models. In fact, *ceteris paribus*, a unit increase in EPL_PERM is accompanied, on average, by a reduction in the skill premium of between 0.2 and 0.6 percent, with the effects tending to be largest for the high- to low-skilled wage premium. Similarly, all else equal, a unit increase in EPL_TEMP is associated, on average, to a narrowing of the skill-premium by between 0.3 and 0.9 percent, with the effects again being largest for the high- to low-skilled wage premium.

Table 4: Regression Results with Labour Market Regulations

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var: ln(SP)	(HS/MS)	(HS/LS)	(MS/LS)	(HS/MS)	(HS/LS)	(MS/LS)
ln(ROB)	-0.010	-0.025	-0.015	-0.019	-0.020	-0.001
	(0.017)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)
ICT	-1.264***	-0.544**	0.722***	-1.154***	-0.446**	0.708***
	(0.228)	(0.213)	(0.216)	(0.212)	(0.198)	(0.209)
R&D	0.152***	0.045	-0.108**	0.065	0.028	-0.038
	(0.053)	(0.049)	(0.050)	(0.050)	(0.046)	(0.049)
S&DB	2.335***	2.032***	-0.312	2.028***	1.994***	-0.048
	(0.434)	(0.403)	(0.409)	(0.410)	(0.379)	(0.402)
N_ICT	-0.013**	-0.001	0.011**	-0.008	0.001	0.009*
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln Y	0.094***	0.047*	-0.048*	0.165***	0.073**	-0.093***
	(0.029)	(0.028)	(0.028)	(0.031)	(0.029)	(0.031)
ln(H/M)	0.014			0.011		
	(0.015)			(0.015)		
ln(H/L)		0.013			0.009	
		(0.014)			(0.014)	
ln(M/L)			0.011			0.004
			(0.014)			(0.014)
GLOB	0.032***	-0.028***	-0.060***			
	(0.012)	(0.011)	(0.011)			
FFD_DVA				-0.312***	-0.307***	0.015
				(0.099)	(0.095)	(0.101)
DFD_FVA				0.043*	0.011	-0.032
				(0.023)	(0.021)	(0.022)
EPL_PERM	-0.003***	-0.006***	-0.002***	-0.003***	-0.005***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EPL_TEMP	-0.007***	-0.009***	-0.003*	-0.006***	-0.008***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs		555			637	
R-squared	0.684	0.769	0.703	0.677	0.767	0.693
Breusch-Pagan (chi-squared)		415.484			471.520	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Seemingly Unrelated Regressions (SUR), with small-sample adjustment for computing the covariance matrix for the equation residuals. All the estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses.

To sum up, the extended analysis reported in this section supports and reinforces the view that a systematic and comprehensive investigation of the core drivers of skill-premia requires a multifaceted approach. By breaking down technologies into tangible and intangible categories,

and globalisation into trade openness and GVC participation, the empirical evidence shows that both technology and globalisation 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 polarising effects, as in the case of S&DB and R&D, respectively. As for the impact of tangible technologies, the skill-biased effect of robots turns out to be not fully robust, especially when the contribution of labour market institutions is taken into consideration – such a result appears to be in line with the mixed empirical evidence so far available for the European economies (Reiter, 2019). On the contrary, ICT (net of S&DB) proves to be associated with a lower high-skill premium, in particular for the high- to middle-skilled premium.

Turning to the effects of globalisation on the skill-premia, the overall indicator of trade openness mainly identifies patterns of polarisation, widening wages inequality at the expense of middle-skilled workers. By contrast, downstream GVC participation narrows the skill-premia in favour of less-skilled labour, whereas there is some limited evidence to suggest that upstream GVC participation worsens the wage differential between high- and medium-skilled workers.

7. Conclusion

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 labour market, especially in developed countries. The results of several studies have strengthened such concerns, leading to call 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 would be 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 labour market institutions, on the wage premia, relying on the skill-biased technical change and polarisation approaches. The empirical analysis is performed using annual data for a panel of 18 mostly advanced European economies and 6 industries over the period 2008-2017. According to the recent literature, new technologies are split into tangibles and intangibles, and globalisation into trade openness and GVCs participation, while the impact of labour market institutions on wage disparities is evaluated by making use of sector-specific measures of EPL for permanent and temporary employees. In order to detect potential specific effects of the main determinants of wage gaps for different workers types, we break down the relative wages in three categories (high- to medium-skilled, high- to low-skilled and medium- to low-skilled labour) and simultaneously estimate a system of equations employing SUR techniques to take into account correlation of the error terms across equations.

The core results of our analysis can be summarised as follows. First, intangible technologies, as proxied by Software & Databases and R&D capital intensity, produce skill-biased and polarising effects, respectively. Second, we find only weak evidence of the skill-biased impact of robotisation. Third, the role of globalisation on the dynamics of the wage differentials depends upon the specific measure considered – whether trade openness or GVCs participation. Higher trade openness is mainly associated with a polarisation of the wage distribution, while downstream GVC participation favours lower-skilled labour and upstream participation benefits high-skilled workers. Finally, employment protection rules prove to be effective in mitigating wage differentials.

From a policy perspective, the main challenge is represented by the effects of intangible technologies. As our findings suggest, the strong complementarity between high-skilled workers and S&DB as well as the job polarisation of R&D related innovations call for policymakers to invest in education and skills training for less-skilled workers, particularly given that intangible

technologies are likely to pervade the workplace even more in the future. Additionally, the weak evidence of a skill-biased impact of robotisation should not be underestimated, as the speed of deployment of new and qualitatively improved robots is predicted to rise dramatically in the coming years. Overall, policymakers will need to play a crucial role in ensuring that the economic benefits stemming from new technologies will not be focussed 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 "hollowing-out" effects of trade openness upon middle-skilled labour. Blanchard and Willmann (2012) suggest that subsidising human capital investments and/or providing temporary wage top-ups for this category of workers may be a relevant policy. Conversely, the results on our GVC indicators suggest that an open trade policy, with offshoring low-skilled activities being encouraged, can help reduce skill-premia, although further work looking at the employment level effects of offshoring would be useful.

In essence, our investigation suggests that the influence of automation, tangible and intangible technologies, and international trade 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 implies that there may exist a third way, which lies between the technological optimists and pessimists, whereby the different dimensions of technology (and globalisation) affect workers in varied ways.

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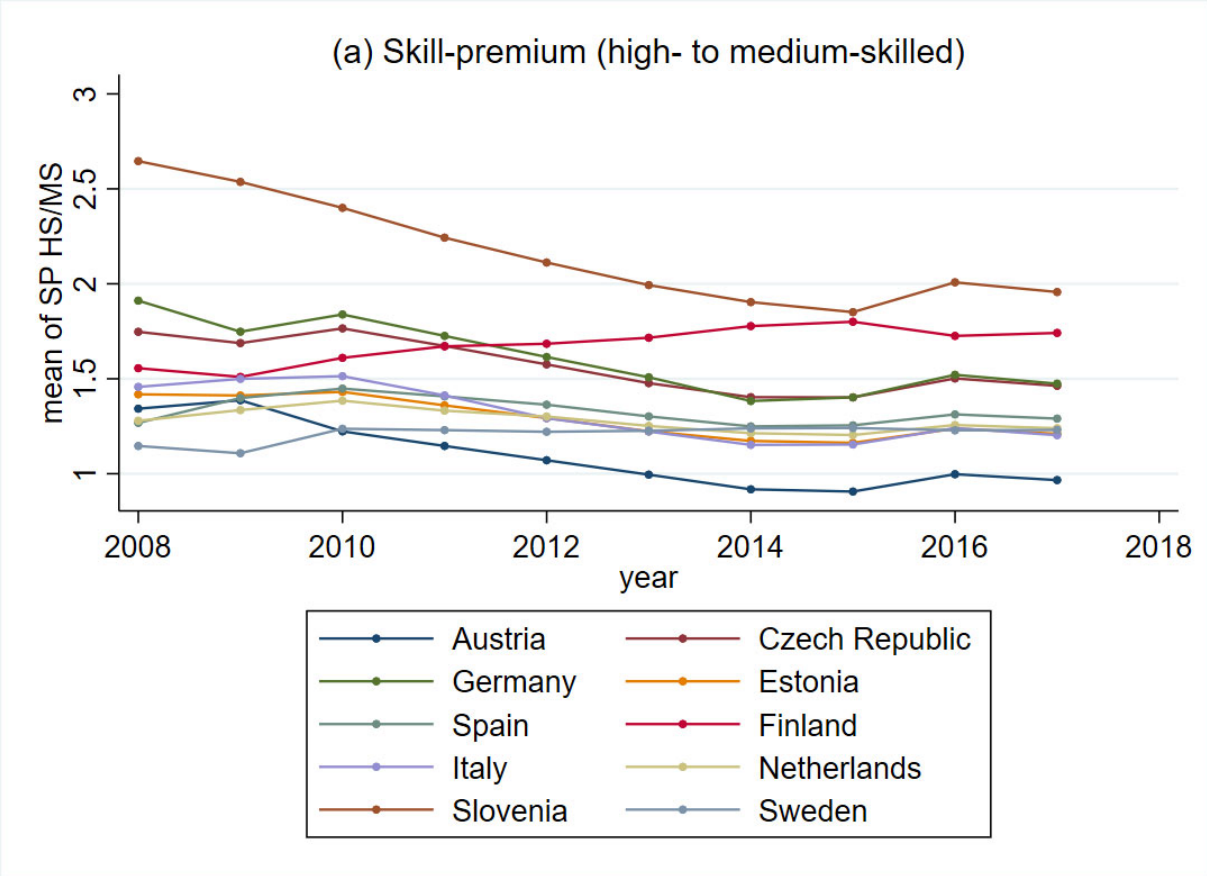
Appendix

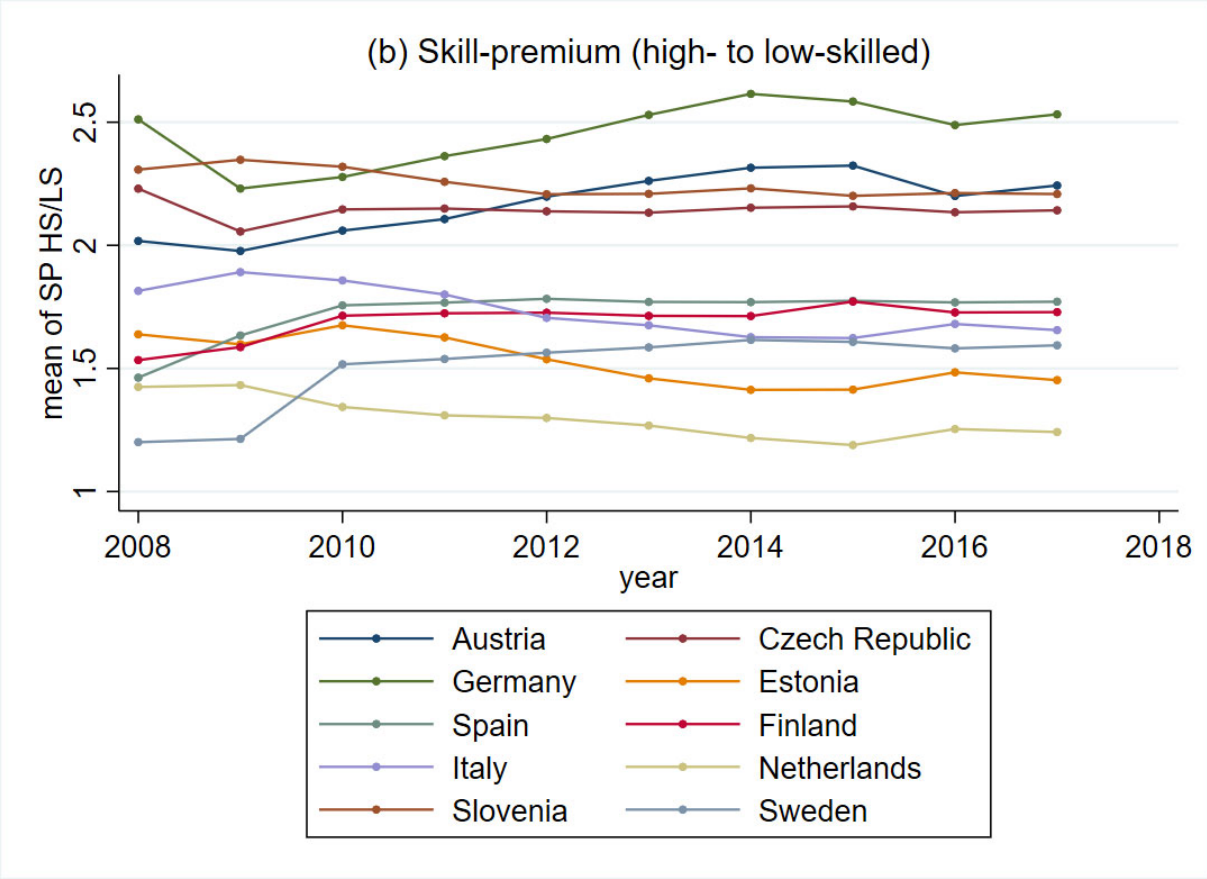
Additional Figures and Tables

Figure A1: Developments in the skill-premium of high- to medium-skilled workers, 2008-2017



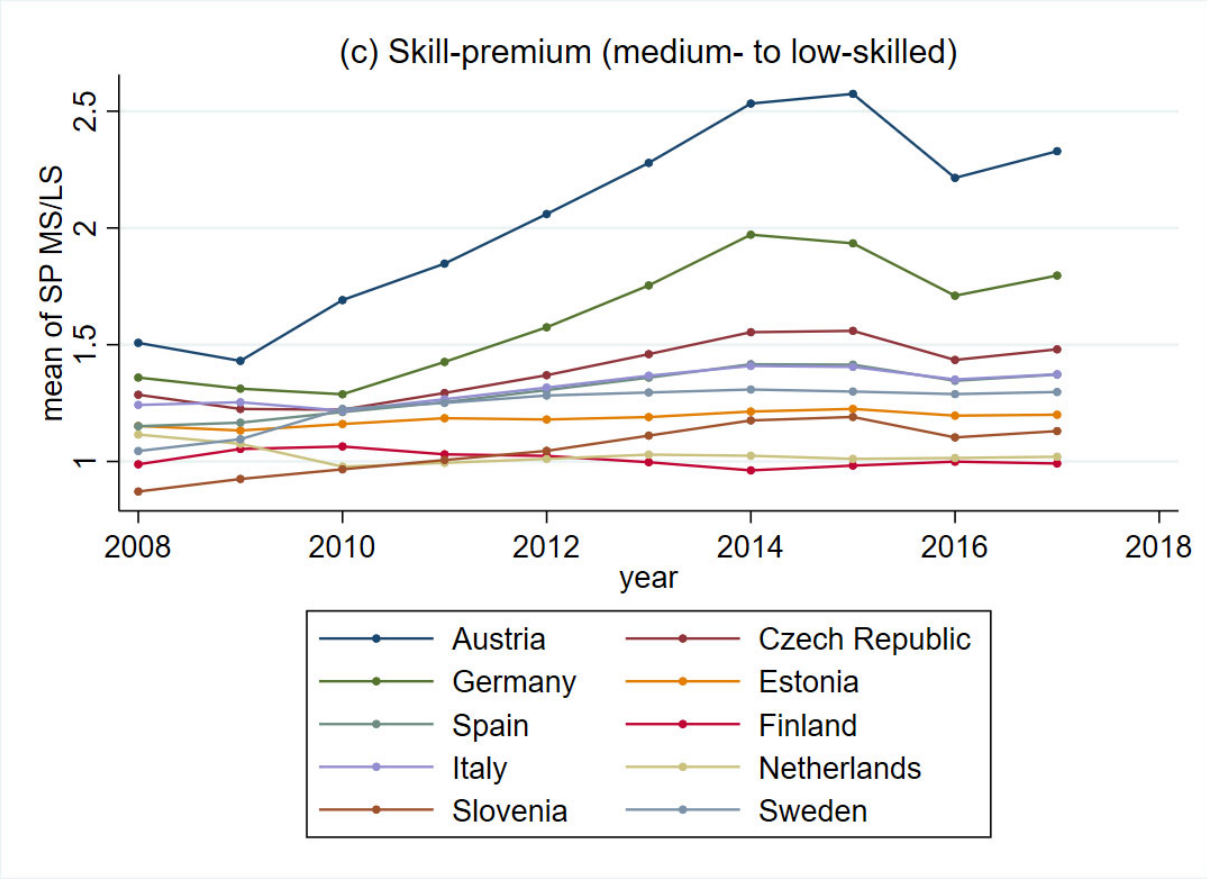
Notes: Skill-premium between high- and medium-skilled workers evolution, for a subsample of European countries. The figure reports mean values over the period 2008-2017 using 2008 sectoral employments weights to aggregate to the country level.

Figure A2: Developments in the skill-premium of high- to low-skilled workers, 2008-2017



Notes: Skill-premium between high- and low-skilled workers 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.

Figure A3: Developments in the skill-premium of medium- to low- skilled workers, 2008-2017



Notes: Skill-premium between medium- and low-skilled workers 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.

Table A1a: Summary Statistics: Levels Averaged by Country

Country	HS/MS	HS/LS	MS/LS	ROB	ICT	R&D	S&DB	N_ICT	Y	RS HS/MS	RS HS/LS	RS MS/LS
Austria	1.176	2.272	1.99	1.81	.02	.283	.034	2.801	44882.34	.613	3.045	4.126
Belgium	1.515	1.596	1.051	2.197	.003	.247	.018	1.617	46955.48	2.131	3.899	1.83
Czech Republic	1.66	2.084	1.278	1.326	.014	.116	.014	2.884	51291.51	.289	4.65	14.978
Denmark	1.525	2.595	1.758	7.312	.012	.305	.025	1.502	508000	.671	3.713	4.785
Estonia	1.224	1.656	1.372	3.431	.011	.377	.033	2.076	22188.34	1.021	2.367	2.137
Finland	1.349	1.609	1.199	.036	.086	.031	.011	2.281	2380.545	.764	6.42	5.957
France	1.343	1.722	1.285	2.44	.044	.123	.018	1.846	122000	2.886	2.406	.534
Germany	1.668	1.678	1.008	3.157	.035	.31	.022	1.519	28000.54	.976	5.646	4.007
Greece	1.492	1.761	1.191	2.642	.019	.178	.06	1.009	178000	1.084	2.833	2.341
Italy	1.567	1.96	1.25	1.054	.005	.08	.031	2.193	139000	.803	1.278	1.494
Japan	1.349	1.934	1.454	.055	.036	.057	.007	1.59	14760.1	1.623	5.242	1.369
Lithuania	1.368	1.738	1.284	3.5	.008	.097	.027	1.911	203000	.352	1.232	1.618
Netherlands	2.17	1.537	.841	8.207	.005	.102	.026	.247	761000	.589	25.435	21.802
Slovak Republic	2.005	3.035	1.522	.011	.026	.164	.164	2.04	5295.929	.742	10.136	10.861
Slovenia	1.229	1.189	.992	1.196	.002	.242	.055	1.579	59905.51	1.22	3.663	1.891
Spain	1.187	1.444	1.215	3.752	.057	.31	.044	1.522	46326.65	.882	4.212	4.13
Sweden	2.185	2.294	1.064	1.124	.004	.121	.012	2.314	6800.225	.516	2.907	4.19
United Kingdom	1.356	1.91	1.455	1.477	.006	.072	.014	3.149	21217.77	.346	5.25	19.887
Unweighted mean	1.492	1.873	1.306	0.97	0.03	0.123	0.032	3.244	55760	0.931	5.361	5.562

Notes: HS/MS: ratio of high to medium skilled wages; HS/LS: ratio of high to low skilled wages; MS/LS: ratio of medium to low skilled wages; ROB: Robot Density; ICT: ratio of real ICT capital stock net of Software & Databases to real gross value added; R&D: ratio of R&D capital stock to real gross value added; S&DB: ratio of Software & Databases capital stock to real gross value added; N_ICT: ratio of real non-ICT capital stock to real gross value added; Y: real gross value added; RS HS/MS: relative supply of high-skilled to medium skilled; RS HS/LS: relative supply of high-skilled to low-skilled; RS MS/LS: relative supply of medium-skilled 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 A1b: Summary Statistics: Levels Averaged by Industry

Industry	HS/MS	HS/LS	MS/LS	ROB	ICT	R&D	S&DB	N_ICT	Y	RS HS/MS	RS HS/LS	RS MS/LS
Agriculture, forestry and fishing	1.77	2.077	1.352	0.05	0.02	0.013	0.009	3.918	18078.5	0.221	0.524	3.899
Mining and quarrying	1.483	1.976	1.365	0.28	0.05	0.05	0.018	3.892	3824.9	0.431	1.444	5.93
Total Manufacturing	1.542	1.926	1.272	5.46	0.03	0.257	0.037	1.446	225000	0.412	1.672	6.036
Electricity, gas, steam; water supply, sewerage, waste management	1.407	1.763	1.28	0.02	0.09	0.034	0.049	7.68	21624.5	0.6	2.286	5.015
Construction	1.418	1.771	1.266	0.04	0.01	0.008	0.013	1.211	44511.2	0.306	1.105	4.97
Education	1.426	1.872	1.344	0.13	0.01	0.324	0.056	1.618	39486.7	3.49	19.911	7.494

Notes: HS/MS: ratio of high to medium skilled wages; HS/LS: ratio of high to low skilled wages; MS/LS: ratio of medium to low skilled wages; ROB: Robot Density; ICT: ratio of real ICT capital stock net of Software & Databases to real gross value added; R&D: ratio of R&D capital stock to real gross value added; S&DB: ratio of Software & Databases capital stock to real gross value added; N_ICT: ratio of real non-ICT capital stock to real gross value added; Y: real gross value added; RS HS/MS: relative supply of high-skilled to medium skilled; RS HS/LS: relative supply of high-skilled to low-skilled; RS MS/LS: relative supply of medium-skilled 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 A2a: Summary Statistics: Levels Averaged by Country

Country	GLOB	FFD_DVA	DFD_FVA	EPL_PERM	EPL_TEMP
Austria	1.553	0.385	0.349	289.883	14.182
Belgium	2.73	0.37	0.444	462.623	23.114
Czech Republic	2.373	0.481	0.382	195.167	10.992
Denmark	1.501	0.357	0.285	259.423	13.428
Estonia	2.213	0.414	0.464	253.257	11.219
Finland	1.396	0.342	0.278	141.057	20.619
France	1.077	0.253	0.339	279.413	62.39
Germany	1.451	0.362	0.295	314.96	13.611
Greece	0.7	0.2	0.375	265.762	44.678
Italy	1.116	0.274	0.259	333.555	33.596
Japan	0.52	0.168	0.263	-	-
Lithuania	1.597	0.312	0.373	272.244	12.89
Netherlands	2.252	0.314	0.232	256.211	15.202
Slovak Republic	2.812	0.499	0.463	333.591	10.395
Slovenia	1.872	0.466	0.438	283.266	28.075
Spain	0.931	0.229	0.288	250.469	84.677
Sweden	1.222	0.32	0.251	219.809	9.812
United Kingdom	0.8	0.201	0.318	265.09	2.304
Unweighted mean	1.092	0.318	1.997	273.569	26.434

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

Table A2b: Summary Statistics: Levels Averaged by Industry

Industry	GLOB	FFD_DVA	DFD_FVA	EPL_PERM	EPL_TEMP
Agriculture, forestry and fishing	0.853	0.369	0.463	234.56	50.4
Mining and quarrying	1.065	0.583	6.516	261.6	15.905
Total Manufacturing	3.051	0.59	0.506	288.83	15.604
Electricity, gas, steam; water supply, sewerage, waste management	0.801	0.257	0.229	291.62	19.551
Construction	0.421	0.059	0.039	271.3	28.318
Education	0.059	0.036	0.036	271.72	27.528

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

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