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Abstract

In recent decades, the development of novel technologies has intensified due to globalisation, prompting countries to enhance competitiveness through innovation. These technologies have significantly improved global welfare, particularly in sectors like healthcare, where they have facilitated tasks and boosted productivity, for example playing a crucial role in combating the COVID-19 pandemic. However, certain technologies, such as robots, can negatively impact employment by replacing workers and tasks. Additionally, the emergence of artificial intelligence as digital assets not only replaces specific tasks but also introduces complexities that may displace employees who are unable to adapt. While the existing literature extensively explores the heterogeneous effects of these technologies on labour markets, studies of their impact on migrant workers remain scarce. This paper presents pioneering evidence on the effects of various novel technologies on migrant employment in the European Union. The analysis covers 18 EU member states from 2005 to 2019 focusing on the impact of novel innovations, robot adoption, three types of digital assets, and total factor productivity, on migrant employment. The key findings reveal that innovations measured by the number of granted patents increase both the number and proportion of migrant workers relative to the overall workforce. While robots do replace jobs, their impact on native workers surpasses that of migrant workers, resulting in a higher share of migrant workers following robot adoption. Total factor productivity positively influences migrant workers, while the effects of digital assets are heterogeneous. Moreover, the impacts of these technologies on migrant workers vary significantly across different occupation types and educational levels.

Keywords: Robot adoption, digitalisation, novel innovation, migrant workers

JEL classification: O33, F22, D24

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1. Introduction

The continuous advancement of novel technologies, robotisation, and digitalisation has brought about significant transformation in many industries, thereby reshaping the dynamics of the labour market. Especially in the manufacturing sector, the substitution of native workers might shift in favour of robots instead of immigrants, implying that in a destination country robot adoption might become a substitute for immigration. Concurrently, the increasing global mobility of workers has led to a rise in migrant employment across different countries and sectors. Understanding the relationship between migrant jobs and the adoption of these technologies is crucial for comprehending the implications for both migrant workers and the labour market. This paper aims to investigate which specific migrant jobs are associated with the adoption of novel technologies, robotisation, and digitalisation, in the European Union (EU).

The intersection of migration and technological advancement has become a subject of great interest for policymakers, researchers, and industry experts. The ongoing wave of technological innovation has the potential to revolutionise production processes, automate tasks, and enhance overall productivity. These advancements have implications for the demand for different types of labour, including migrant workers. However, the exact nature and extent of the relationship between migrant jobs and the adoption of novel technologies so far has remained less explored. Understanding the implications for migrant workers in the context of technological change is vital for various reasons.

First, migrants often occupy specific niches in the labour market, performing tasks that may be more susceptible to automation or requiring digital skills. Investigating which migrant jobs are linked to the adoption of novel technologies can provide insights into the potential risks and opportunities faced by migrant workers in an increasingly automated and digitised economy. Second, technological advancements can affect employment opportunities for both native and migrant workers. Analysing the relationship between technology adoption and migrant jobs allows us to assess the potential labour market outcomes and identify possible disparities. This knowledge can guide policymakers in formulating effective strategies to mitigate negative consequences and promote inclusive growth in the face of technological change. Third, understanding the implications of technology adoption for migrant employment patterns contributes to the broader discourse on migration and integration. The labour market experiences of migrant workers are intricately linked to their social integration, economic well-being, and overall social cohesion in host societies. By examining the relationship between migrant jobs and the adoption of novel technologies, we can gain insights into the opportunities and challenges faced by migrants in their pursuit of meaningful employment and social integration.

While the literature on technology adoption, automation, and digitalisation is extensive (e.g.: Frey and Osborne, 2013; Autor, Levy and Mournane, 2003; Goos and Manning, 2007; Arntz, Gregory and Zierahn, 2019; Ghodsi et al., 2020; Acemoglu and Restrepo, 2021), there is a noticeable gap when it comes to examining the specific relationship between migrant jobs and the adoption of novel technologies. Although numerous studies have explored the labour market impacts of automation and digitalisation, few have explicitly focused on the intersection with migrant employment. In addressing this gap, we have built upon and synthesised findings from a comprehensive literature review of relevant peer-reviewed academic papers. This review encompasses studies that investigate the impact of technology adoption on employment, wages, and skill requirements. While these studies provide valuable insights into the broader labour market effects of technological change, they often overlook the specific dynamics of migrant employment.

To begin with, Borjas and Freeman (2019) conducted a study in the United States, focusing on the impact of robot adoption on employment at the state-sector level. Their research provides valuable insights into the labour market effects of automation. However, the robot data used in earlier studies on the US does not vary across US states, but only across sectors. Our study expands upon previous studies by considering variations in all variables across sectors and countries within the EU, providing a more comprehensive analysis of the relationship between technology adoption and migrant employment. Basso et al. (2020) utilised a similar specification to examine the relationship between technology change and employment and highlighted the importance of sector-specific analysis and the need to account for country-sector variations. Building upon this foundation, our research extends their analysis to specifically explore the link between technology adoption and migrant jobs, filling an important research gap.

The literature exploring the labour market outcomes of technological change points to routine-biased technological change (RBTC) (Autor, Levy and Mournane, 2003; Goose and Manning, 2007). RBTC refers to a decline in the demand for middle-skilled workers, as routine and codifiable tasks are replaced through robot adoption and automation. Conversely, high-skilled workers, who are complementary to novel technologies, and low-skilled workers performing tasks that are hard to automate and require face-to-face interaction (e.g. cleaners, hairdressers, waiters, babysitters etc.), benefit from these changes. The increasing demand for these low-skilled, non-tradable services can be attributed to the income elasticity effect.

Several studies point out that technological change has been attracting particularly immigrants employed in manual-service occupations, while also further showing that it has been attenuating or eliminating polarisation for native workers (Basso, Peri and Rahman, 2020), i.e., that employment growth at the lower end of skill distribution is affected by low-skilled immigration (Mandelman and Zlate, 2022). Additionally, the literature exploring the impact of immigrants on natives often shows that when immigrants enter the labour market, natives are more likely to move to occupations requiring higher skill levels (e.g., Cattaneo, Fiorio and Peri, 2015).

On the other hand, Cerna and Czaika (2015) draw attention to global competition for high-skilled migrant workers, where the EU has also introduced several policies and directives to enhance its attractiveness to highly skilled migrants, alongside its individual nation states which retain the authority to determine volumes and regulate the immigration of workers. Attracting such workers has been particularly important for developed European countries facing labour and skill shortages, as well as ageing societies leading to an impediment to growth. Moreover, studies suggest that automation-induced reshoring (return of previously offshored production) is positively correlated with the employment and wages of high-skilled workers (Krenz, Prettner and Strulik, 2021). Consequently, further increases in the demand for high-skilled workers within these developed economies can be expected. Therefore, one could understand that the share of migrants in EU countries is increasing, and the literature mentioned here points to this. Moreover, migrant workers often take low-skilled jobs, with some papers also stressing the importance for immigrants with higher skills due to labour shortages. Thus, in this paper we analyse whether or not labour market outcomes are the same for migrants and natives, and whether or not migrants are being displaced by emerging technologies in routine and low-skill jobs.

Therefore, the purpose of this study is to explore whether the effects of new technology adoption have been the same for migrant workers, i.e., has technological change brought the same changes in the demand for migrant workers as in overall labour market trends in these developed EU economies. Additionally, we seek to understand whether there are variations among EU and non-EU migrants, given the different barriers to migration these migrant groups face. These effects are analysed further separately by occupation and educational level to examine if any differences exist. This allows us to indicate the existence of brain waste, i.e. under-placement/over-education of migrant workers, which has so far been shown to be especially prominent in the case of immigrant workers from less developed countries (Matto, Neagu and Ozden, 2008; Beckhusen et al., 2013; Visintin, Tijdens and Klaveren, 2015).

Doing so, we examine the relationship between the adoption of new technologies, such as patent grants that are granted only to novel innovations, robotisation, and digitalisation, and the presence of migrant workers in industries and countries across the EU during the period 2005-2019. Moreover, the paper also explains the impact of these technologies on total employment, the number of migrant workers, and the share of migrant workers in total employment in a sector in one country. Furthermore, empirical results are also provided on these variables according to the occupation of workers in the one-digit International Standard Classification of Occupations (ISCO) classes and according to the International Standard Classification of Education (ISCED) levels of education. In addition to the factors that affect labour demand, we employ a restrictive set of high-dimensional fixed effects which account for the business cycles of each country and the inherent and initial conditions of each sector in a country. By incorporating these fixed effects, we can isolate the relationship between changes in country-sector technologies in robotics, digitalisation, and innovation and the corresponding changes in the stocks of migrant workers over time. In summary, this study fills an existing gap in the literature by examining the relationship between migrant jobs and the adoption of novel technologies, robotisation, and digitalisation.

The organisation of the rest of the paper is as follows: in the next section we provide an extensive survey of the existing literature. Section three presents the methodology and sources of data. Section four presents the data and stylised facts. Section five presents and discusses the estimation results. And section six offers concluding remarks.

2. Literature review

Migration is as old as the history of humankind, but it was a relatively slow and rather limited process until the onset of the first industrial revolution, which marked the beginning of mass migration, and continued until the outbreak of World War I (Ferrie and Hatton, 2015). Throughout the history of industrial revolutions, labour-market related factors such as job availability and wages have been the primary drivers of migration. As a result, migrants have been attracted to the centres of industry and commerce with high economic growth (Grigg, 1977; Greenwood, 2019; De Haas, Castels and Miller, 2020). Demographic changes are also often pointed out as having an important role in the migration process (Hatton and Williamson, 1992). Besides the effects on labour markets which affect the push and pull factors driving migration, technological advancements have also reduced information and transportation costs which have been important obstacles to migration (Lee, 1966). Adverse effects stemmed from migration policies which were largely introduced at the end of the 18th century due to, among other reasons, economists who pointed out that "immigrants crowd out native workers and fuel rising inequality in labour scarce economies" (Timmer and Williamson, 1998). Given the scale of international migration during the First and Second Industrial Revolutions, migrant workers played an important role in the countries that were adopting new technologies, especially since they were often more likely to accept lower wages and poorer working conditions than native workers (Hirschman and Mogford, 2009; Ferrie and Hatton, 2015).

Based on this historical evidence it is necessary to explore labour market developments during the adoption of new technologies in order to understand their potential impact on migration. Adoption of technologies embedded in the Third and Fourth Industrial Revolutions has been transforming the labour markets in the last decades, especially in developed economies. Information and communication technologies (ICT), as well as robots, automation and artificial intelligence have been an important source of widespread concern over the future of work, especially following the high estimates of jobs at risk of computerisation by Frey and Osborne (2013) and others who followed their (occupational) approach to estimating the susceptibility of jobs. Thus "technological unemployment" was brought to the centre of labour market debates. A set of early studies exploring the changes in occupational structure set out the characteristics of skill-biased technological change (SBTC) (Katz and Murphy, 1992), while later on rapid improvements in computing power enabled the automation of routine jobs leading to a decline in the demand for middle-skilled medium-wage workers, i.e. routine-biased technological change (RBTC) (Autor, Levy and Mournane, 2003; Goos and Manning, 2007; Arntz, Gregory and Zierahn, 2019).

Thus new technologies are expected to benefit primarily highly skilled workers, while the demand increase at the lower end (for low-skill manual workers) is due to income elasticity effects, as rising incomes along with technological change leads to increased demand for these manual service occupations such as cleaners, hairdressers, waiters, etc. (Goos and Manning, 2007). Also, in case of robot adoption workers are expected to shift from downstream to upstream (robot-producing) sectors (Barbieri et al., 2020). Vast number of papers explore the effects of novel technologies on employment and labour share displacement while some of them also explore the effects on wages, and the results are ambiguous (e.g., Acemoglu and Restrepo, 2021; Dauth et al., 2021; Dottori, 2021; Acemoglu and Restrepo, 2020; Borjas and Freeman;

2019; Aghion, Antonin and Bunel, 2019; Chiacchio, Petropoulos and Pichler, 2018). Also, results have differed when the effects of different technologies were estimated (e.g., Jestl, 2022). Several important factors are expected to further shape the outcomes of new technology adoption, including the level of complementarity of labour to new technologies, elasticity of the labour supply, demand elasticity of the products produced and income elasticity of demand (Autor, 2015). Given concerns regarding job displacement by robots, they might also serve as a substitute for immigration.

Parallely, determinants of international migration and its effects on labour markets and growth have also been explored extensively in recent decades. The increasing social and political relevance of migration since the 1950s has led to the formulation of different theories and conceptual frameworks at different levels of aggregation (micro-, mezzo- and macro- level theories), striving to provide an answer to the question: "why do people migrate?" (see Arango, 2000 and Massey et al., 1993). Neoclassical theory, stressing the importance of wage and employment condition differentials between countries, as well as migration costs, have attracted the most interest in the literature, accompanied by the push-pull factors and gravity models which were often used in estimations of determinants of migration flows. Another prominent theory the "New Economics of Labour Migration" (Stark and Bloom, 1985) has analysed migration as a family- rather than an individual decision. While most of these analyses focused on micro-level individual decisions, they were primarily led by macro-level structural determinants (Arango, 2000). Ignoring structural factors can be said to be one of the prominent critiques of the micro-level approaches (De Haas, 2011). On the other side, the fragmented historical-structural approach focused on labour demand in geographical places of capital accumulation and social disruption (Abreu, 2010), while the dual labour market theory and the world systems theory focused more on macro-level challenges. Some of the studies also call for the analysis of international migration more in relation to broader global processes and socio-economic changes (Kurekova, 2011). Thus, striving to provide an in-depth understanding of the drivers and effects of migration is seen as important, as it can provide valuable knowledge with which to create adequate migration policies, thus enabling growth.

In the majority of research conducted on novel technology effects and migration determinants, the relationship between immigrant workers and novel technologies has not been explored or mentioned. At the same time, recent data show that almost 70% of total international migrants are labour migrants who mostly reside in advanced economies where they make up almost 20% of the labour force (ILO, 2019), indicating the importance of understanding this nexus. Despite this, the literature exploring this nexus is very limited. The topic is particularly relevant for the EU, which has been facing labour market tightness. A study by Grieveson, Leitner and Stehrer (2019) projects that by 2030 the EU will suffer from serious labour shortages across all member states. So, while the labour supply in western Europe has adjusted so far thanks to the inflow of labour from the East, the demographic tipping point across the whole EU is expected to become the next pressing challenge for European policy makers. This leads to questions about how to maintain economic growth amidst these challenges, including looming labour market shortages, the demographic tipping point, a slowdown in east-west migration and rising demand for high-skilled labour due to automation.

Docquier et al. (2019) point out that the labour force of each industrial country is being shaped by three forces: ageing, education and migration. Besides the aforementioned new technologies, globalisation (which is also affected by technological progress in transportation and communications) through increased offshoring, primarily motivated by differences in factor prices, and trade, can be stressed as another important factor shaping labour market outcomes, together with government policies (De Canio, 2016). Moreover, in the past the debate was on choosing between immigration and offshoring, the latter of which was also often pointed out to negatively affect middle-skilled occupations. This is because immigration and trade can be viewed as substitutes, as countries can respond in both ways to the relative lack of labour as a factor of production. The effects of the globalisation process through labour flows, capital flows and trade ultimately produce the same results, helping to equalise economic opportunities across markets and reduce income differentials, which are often seen as the main motivator to migrate (Borjas, 1999).

Furthermore, Krenz, Prettner and Strulik (2021) suggest that automation-induced reshoring (from low-wage to high wage countries) of previous offshore production is positively associated with the density of robots, and the employment and wages of high-skilled workers. But they find no significant association between reshoring and labour market outcomes for low-skilled workers. If this trend continues it can worsen labour shortages and further increase the demand for high-skilled workers. Therefore, to address labour market shortages and stimulate economic growth these economies can choose to fill these gaps through further immigration and/or investment in novel automation technologies. Besides automation and immigration, Grieveson, Leitner and Stehrer (2019) outline activity rates and fertility increases as possible solutions to this challenge, but they stress that none of these strategies alone is sufficient given the current demographic trends. Additionally, automation may threaten jobs in emerging economies as their labour cost advantage erodes, as pointed out in a study by Carbonero, Ernst and Weber (2020) which estimates that the negative effect of robots on employment was much lower for developed countries than for emerging economies in the period from 2005 to 2014. This could act as an additional push factor and contribute to rising emigration from emerging economies.

Given these developments, the Fourth Industrial Revolution can have an important impact on highly skilled and low skilled manual workers, and some papers point to the trend of upskilling of locals. Basso, Peri and Rahman (2020) show that technological progress measured by the number of personal computers in the US in the period from 1980 to 2010 has been an important determinant of immigration, as US immigration increased in zones where computer adoption was higher, especially strongly for low-skilled migrants (manual and service jobs). Therefore, given the technological change which has decreased the demand for workers in routine-based occupations, they show that immigrants have increasingly obtained manual-service occupations. With that in mind, Peri (2016) stresses the significant variety and differentiation between kinds of tasks that immigrants and natives are more likely to perform, and native workers can shift their choices in response to immigration.

Landesmann and Leitner (2022) also stress that offshoring, technological change, and migration can have complex (multi-directional) impacts on the employment of native workers, especially when one considers different occupational groups. Basso, Peri and Rahman (2020) argue that technological progress without migration would generate even higher polarisation, as adoption of new technology combined with low-skilled migration attenuates the polarisation among natives by shifting them to more high-skilled jobs and higher paid production occupations. Mandelman and Zlate (2022) also show that natives react to immigration by investing in training and upgrading so that employment polarisation does not exist among native workers, as the lower end of the distribution pertains mostly to immigrant workers. Also, elasticity of labour demand determines the extent of immigration effects on native wages in the short run (Peri, 2016).

Borjas and Freeman (2019) point out that the decision to purchase robots and immigration decisions on location are likely to be influenced by labour market conditions. Their study of the impact of robot adoption on employment at the state-industry level in the US, showed that adoption of additional robots reduces employment and wages by more than adding immigrants. Another stream of literature points out a lower adoption of robots in the case of a higher share of foreign-born population (especially if they are low-skilled) as it can diminish incentives to mechanise production (e.g., Liu and Portes, 2021). Also, Mann and Pozzoli (2022) in the case of Denmark find that an increase in the share of non-western migrants decreases the probability of robot adoption. In this regard relative factor prices are considered an important determinant. On the other side, the study shows that the average value of an imported robot is positively correlated with immigrant workers' average wages in Denmark.

Moreover, there is a stream of literature that explores the connection between automation anxiety and immigration sentiment in society, important to consider in this regard. Gamez-Djokic and Waytz (2020) argue that automation anxiety, due to the aforementioned changes in the labour market, may be linked with increased anti-immigration sentiment in the US and Europe, resulting in support for restrictive immigration policies and more discriminatory behaviour toward immigrants in the context of potential layoffs. Additionally, Wu (2022) points out that low-skilled workers in the US tend to blame globalisation (immigrants and workers abroad) for their economic problems such as underemployment, wage stagnation, growing inequality and the disappearance of well-paid factory jobs, rather than new technologies. This might also be due to populist political discourse. Furthermore, negative social externalities that can result from immigration may provide an additional explanation, whereas these are less likely to be produced by automation (Webster and Ivanov, 2020).

Given the outlined gap in the literature, this paper aims to explore whether the adoption of robots and other novel technologies has so far been a complement or a substitute to migrant workers in EU economies. This topic is especially important for the EU, characterised by shrinking working-age populations and ageing, both of which may imperil economic growth prospects. It thus strives to provide adequate policies to address both migration and novel technologies adoption. To the authors' knowledge this is the first study which aims to explore the effects of robot adoption/digitalisation/novel technologies on immigrant workers empirically. Thus, it provides a deeper understanding of this nexus in the recent period, characterised by important technological changes, with the goal of enabling the shaping of further public policy.

3. Methodology and data sources

We analyse the relationship between the adoption of new technologies, such as patent grants, robotisation, digitalisation, and the presence of migrant workers in industries and countries across the European Union during the period 2005-2019. To control for other factors affecting labour demand, we use a methodology based on the model used by Borjas and Freeman (2019) in their study of the impact of robot adoption on employment at the state-sector level in the US. However, our methodology is augmented by exploiting variations in all variables, including International Federation of Robotics (IFR) data on robots, across sectors and countries. Additionally, we use a restrictive set of high-dimensional fixed effects to control for the business cycles of each country δ_{ct} and the inherent and initial conditions of each sector in a country δ_{ci}. This approach enables us to examine how changes in country-sector technologies in different fields of robotics, digitalisation, and innovation are related to changes in the stocks of migrant workers in each country-sector over time. This type of estimation equation has been used in other studies, such as Basso et al. (2020). The specification for the econometric analysis is as follows:

$$y_{ict+1} = exp^{\{\alpha_0+\beta_1 P_{ict}+\beta_2 s_{ict}+\beta_3 D_{ict}^{IT}+\beta_4 D_{ict}^{CT}+\beta_5 D_{ict}^{SD}+\beta_6 X_{ict}+\delta_{ct}+\delta_{ct}+\varepsilon_{ict+1}\}} \quad (1)$$

Where y_{ict+1} is either the dependent variable that is one of the following: total employment l_{ict+1}, the number of migrant labourers M_{ict+1}, or the share of migrant (non-native) labour in total labour $m_{ict+1} = {M_{ict+1}}/{l_{ict+1}}$ in industry i in country c in year $t+1$; P_{ict} is the inverse hyperbolic sine (arcsine) transformation of the total number of patents granted to firms active in country c in sector i in year t divided by a thousand employees in that sector-country-year; s_{ict} is the arcsine transformation of robot intensity that is calculated as the stock of robots installed per thousand employees in the given country-sector-year combination; D_{ict}s are proxies for digitalisation, where D_{ict}^{IT} is the arcsine transformation of the computing equipment capital in thousands of employees of the given country-sector-year combination, D_{ict}^{CT} is the arcsine transformation of the share of communications equipment capital in thousand employees of the given country-sector-year combination, and D_{ict}^{SD} is the arcsine transformation of the share of computer software and databases capital in thousands of employees of the given country-sector-year combination. X_{ict} is the matrix of all other control country-sector-year variables such as total factor productivity TFP_{ict}, labour productivity y_{ict}, capital stocks K_{ict} relative to thousands of employees, average wages w_{ict} calculated as the total labour cost divided by the number of employed persons, and gross value added VA_{ict} in arcsine transformations to control for the size of the sector in a country. δ_{ct}, δ_{ci} are respectively the country-year and country-industry fixed effects, and ε_{ict+1} is the error term.

We include numerous sets of dependent variables in separate specifications. In the main benchmark specification, we are interested in whether the development of technologies affects non-native workers differently than native workers. Therefore, the dependent variable in the benchmark model is the share of workers in sector i in year $t+1$ that are born in countries other than the reporting EU country c relative to the number of all workers in that country-sector-year combination m_{ict+1}. Then, the share of migrants will be separated into two categories of migrants born in other EU member states relative to the total number of employees m_{ict+1}^{EU}, and the share of those born in countries outside the EU27 relative to the total number of workers m_{ict+1}^{nonEU}. As we are interested in disparities in the impact of technologies on native and non-native workers, estimations are also run on equation (1) with the total number of employees as the dependent variable. As robustness checks, the total number of migrants rather than their shares in total labour will be used in additional specifications. Therefore, the total number of workers in sector i in year $t+1$ who are born in the country other than the reporting EU country c is used, which shows the number of non-native workers M_{ict+1}. Furthermore, M_{ict+1}^{EU} is the total number of migrant workers from other EU27 and M_{ict+1}^{nonEU} is the total number of migrant workers from outside the EU27. The estimation results for these seven dependent variables will be presented as the benchmark specifications in Table 1. More importantly, the analysis will explore deeper levels by studying the impact of technology adoption on employment by occupation, and level of education.

As the data on employment are obtained from the Labour Force Survey (LFS), we can distinguish between the occupation of migrant workers based on nine occupations classified by International Standard Classification of Occupations (ISCO) in separate specifications. These occupation groups and their ISCO codes are as follows: 1. Legislators, senior officials and managers (skill levels 3 and 4)[1]; 2. Professionals (skill level 4); 3. Technicians and associate professionals (skill level 3); 4. Clerks (skill level 2); 5. Service workers and shop and market sales workers (skill level 2); 6. Skilled agricultural and fishery workers (skill level 2); 7. Craft and related trades workers (skill level 2); 8. Plant and machine operators and assemblers (skill level 2); 9. Elementary occupations (skill level 2). Therefore, the share of migrant workers in occupation τ of all employees in the same occupation in country c in sector s in year $t+1$ is identified as $m_{ict+1}^{ISCO,\tau}$. Separate estimations will also be run on employees according to their level of education based on the International Standard Classification of Education (ISCED). The three education groups are as follows: High (ISCED 5-8) that is for tertiary education; Medium (ISCED 3-4) for secondary and post-secondary education; Low (ISCED 0-2) for primary and lower education. Therefore, the share of migrant workers with level of education φ of all employees with the same level of education in country c in sector s in year $t+1$ is identified as $m_{ict+1}^{ISCED,\varphi}$.

The estimation of the model takes into account that the dependent variables may include zero values and that the distribution of the share of migrant workers is skewed around zero. To address this, the Poisson pseudo-maximum likelihood (PPML) estimation technique is used, following the gravity literature (Yotov et al., 2016; Santos Silva and Tenreyro, 2006; and Correia et al., 2019a, b). This technique is also robust against heteroscedasticity in the error term ε_{ict+1}. The reason for using the inverse hyperbolic sine transformation $arcsinh(x) = \ln\left(x + \sqrt{x^2+1}\right)$ of the explanatory variables x, instead of their natural logarithm $\ln(x)$, is because these variables include zero values (Mullahy and Norton, 2022). As Bellemare and Wichman (2020) show, the hyperbolic sine transformation of variables in the estimation yields asymptotically similar marginal effects to that of the natural logarithm. Additionally, all control variables are in constant 2015 US dollars.

It is important to note that some of the explanatory variables may be strongly correlated with each other. For instance, robots may affect productivity or wages. However, the main purpose of the analysis is to estimate the number of non-native workers in each sector and country against the adoption of different types of technologies, controlling for other factors. Thus, excluding those variables may introduce an endogeneity bias due to the omitted variable bias. However, robustness checks are conducted by excluding each variable from the main specification. Another source of endogeneity may be the dual causality between the dependent variable and independent variables, or the simultaneity bias. This

[1] A detailed list of ISCO classes and skill levels can be found here: https://ilostat.ilo.org/resources/concepts-and-definitions/classification-occupation/

reverse causality is controlled for by using the one-period lag of all independent variables or one year forward of the dependent variable. The reason for using TFP in the estimation of equation (1) is to capture all-other technological factors that could be related to the managerial skills, innovation, experience, and competitiveness of each sector in each country. TFP_{ict} for each country-sector-year is estimated as the Solow residual of output as a function of its factors of production that are labour, capital, and material inputs. A more detailed discussion of the estimation of TFP and several methods used in the analysis is provided in the appendix.

4. Data and stylised facts

This section outlines the main data sources used in the study and presents some stylised facts related to the explanatory and exploratory variables, including the share of migrant workers in the total number of workers, a range of technological change proxies (number of granted patents, robot intensity, the share of computing, communication and software capital in total capital, and output-weighted TFP) and a set of control variables that encompass capital stock, average wages and gross value added.

4.1. DATA SOURCES

The main source of the data on migrant labour is the Labour Force Survey (LFS) provided by Eurostat. Two rounds of LFS data are harmonised and compiled together for the period 2006-2019. LFS data include information on native employees as well as non-native employees. Non-natives are classified in two categories. One category is for those born in EU member states other than the reporting country, and the other category is for employees born outside the EU. Employees are also categorised based on their one-digit aggregate NACE sector of activity, one-digit aggregate occupations based on ISCO, and also according to their level of education according to ISCED.

The second source of data is the data on industrial robots obtained from the International Federation of Robotics (IFR). This data includes the number of installed robots in each two-digit NACE sector for all countries in the world each year, in addition to the stock number of operational robots. These data are aggregated to the sectors that match the more aggregate sectors in the LFS data. The third source of data on all other variables is the most recent version of the EU KLEMS compiled by Bontadini et al. (2023)[2]. Here the data are reported in national currencies in chain-linked volumes, using the exchange rate to US dollars in 2015.

The number of patents is compiled from Amadeus data provided by Bureau van Dijk. Amadeus, and links the patents to the firms that own them. Therefore, using the core industry activity of those firms, the data on granted patents are aggregated to the two-digit NACE sectors and the countries in which the owning firms reside. The date of patent publication is thus used to identify the year in the patent data.

4.2. DESCRIPTIVE STATISTICS

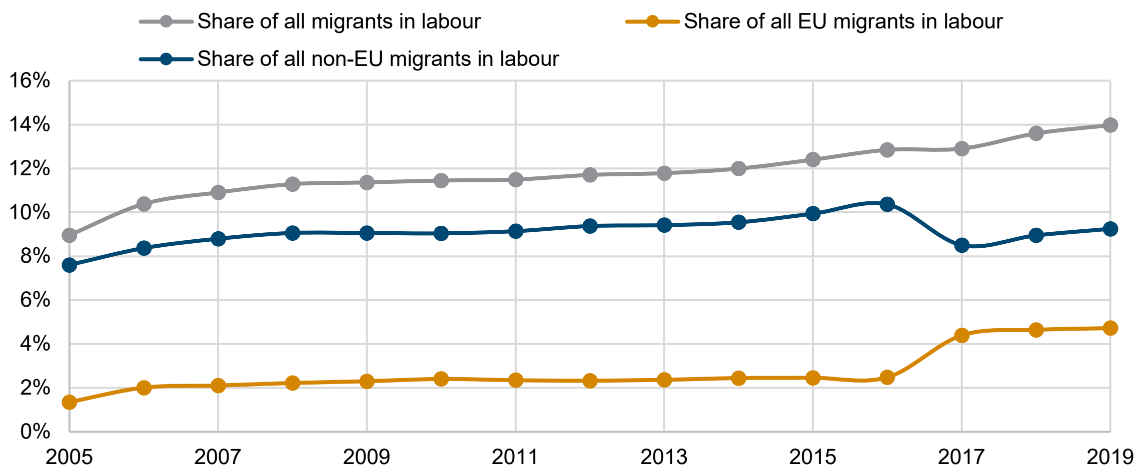
As outlined above, the remaining part of this section provides a descriptive analysis of the variables used in the study, including the share of non-native workers, a range of technological change proxies and a set of control variables. We examine overall trends in the analysed sample, as well as average values of variables by country and by sector of activity.

2 https://euklems-intanprod-llee.luiss.it/

4.2.1. Trends over time

Figure 1 presents the evolution of the share of migrant workers in total workers in selected EU countries from 2005 to 2019, based on data from Eurostat's LFS. The share of all migrant workers increased gradually from 9% in 2005 to 14% in 2019, representing growth of over 50% during the period. Non-EU migrant workers accounted for a substantially larger share of the total number of workers compared to their EU counterparts. The non-EU migrant workers' share remained relatively stagnant and increased by 2 percentage points over the period, peaking at 10% in 2016, before declining by 1.5 percentage points in 2017, and then resuming a growth trend onwards. In contrast, the EU migrant workers' share underwent a more substantial change, more than tripling from only 1.4% in 2005 to 4.7% in 2019. This increase can be attributed to the accession of the new EU member states, which led to a reduction in barriers to migration of their inhabitants. Although the EU migrant workers' share grew slowly until 2016, their share in the total number of workers rose by almost 2 percentage points in 2017, followed by a continuation of the gradual upward trend. Therefore, the decline in the share of non-EU migrant workers in 2017 was offset by the increase in EU migrant workers, resulting in a continuing expansion in the share of migrant workers to all workers until the end of the analysed period.

Figure 1 / Development of share of migrant workers to all workers in selected EU countries, 2005-2019

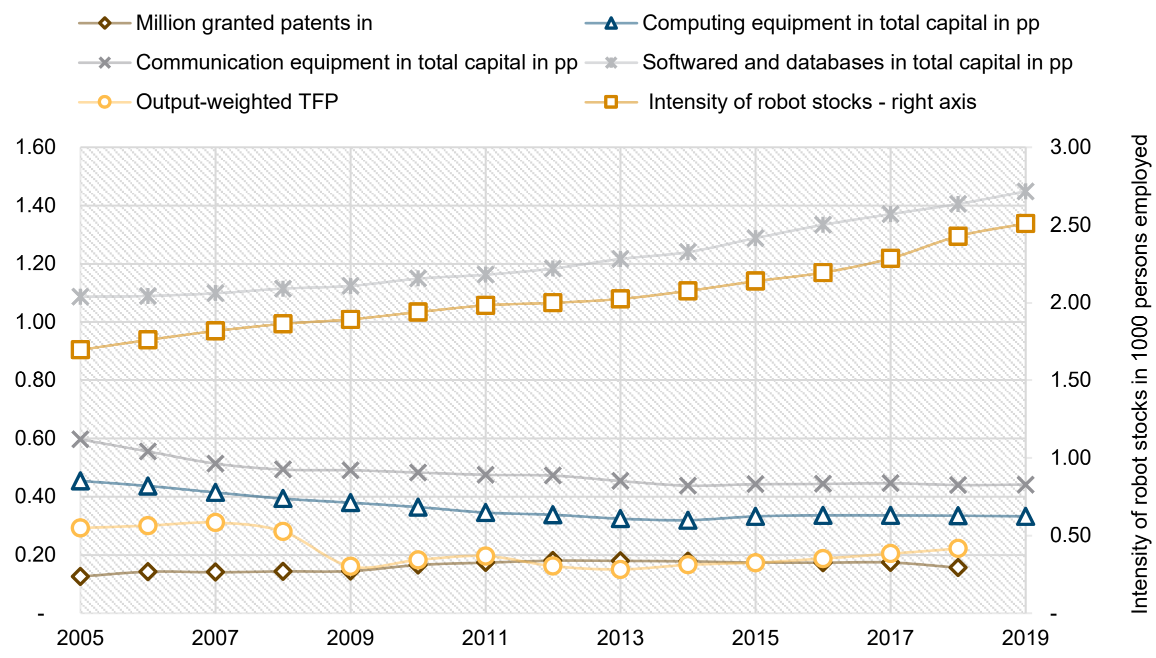


Source: LFS, Eurostat, authors' elaboration.

Figure 2 provides an overview of the technological change proxies included in the study over the analysed period, with the intensity of robot stock per 1000 persons employed shown on the right y-axis, while all other variables are displayed on the left y-axis. The intensity of robot stock per 1000 persons employed increased steadily from 1.7 to 2.5 robots per 1000 persons employed in 2019. The increase of approximately 50% shows the growing trends in the adoption of robots, possibly due to various incentives, from a decrease in their price to an increase in functionality, enabling them to successfully undertake routine jobs previously done by workers. In contrast, the number of granted patents increased steadily until peaking in 2012 at 0.18 million, while following that decreasing to 0.16 million in 2018, indicating a declining level of patent activity in this period.

Throughout the analysed period the share of software and databases in total capital consistently exceeded the shares of computing and communication equipment. This gap widened over the period, as the share of software and databases in total capital continually rose, while the shares of both computing and communication equipment in total capital decreased and showed rather similar trends to each other. Specifically, the share of software and databases increased from 1.1% to 1.5%, while the share of computing equipment decreased from 0.5% to 0.3% and the share of communication equipment decreased from 0.6% to 0.4%. Thus, the share of intangible ICT assets rose in comparison to tangible ICT assets and amounted to almost double the share of tangible assets in total capital in 2019. The output-weighted TFP, calculated according to the methodology of Ackerberg et al. (2015), fluctuated across the analysed period. It peaked in 2007 before the onset of the financial crisis and then reached the bottom during the recession in 2009. It then gradually increased over time.

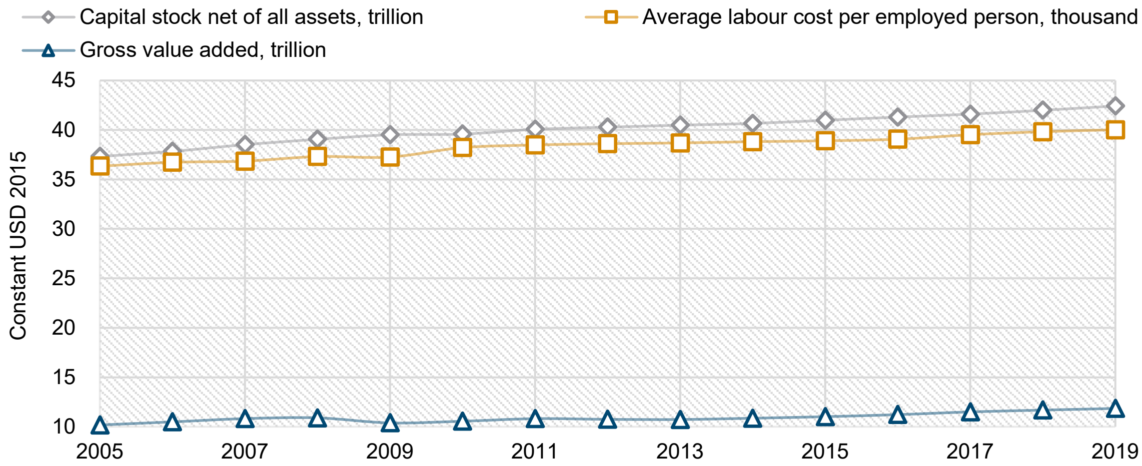
Figure 2 / Development of technological measures in selected EU countries, 2005-2019



Source: Amadeus, Orbis, EU KLEMS, authors' elaboration.

Figure 3 shows the overall trends in the control variables in selected EU countries over the analysed period, all expressed in constant 2015 US dollars. Capital stock, which is primarily attributed to non-ICT capital, rose by approximately 14% over the period, gradually increasing from USD 37.3 trillion in 2005 to a peak of USD 42.4 trillion in 2019. Similarly, gross value added increased by approximately 16%, from USD 10.2 trillion in 2005 to USD 11.9 trillion in 2019. The average labour cost per employed person also followed an increasing trend, rising by a slightly lower proportion of 10%, from USD 36,337 to USD 40,015. This indicates a decrease in the labour share which could be linked to technological change, and can increase labour productivity and wages, but at the same time decrease the share of labour. Also, migrant workers can affect wages as they impact the labour supply.

Figure 3 / Development of control variables in selected EU countries, 2005-2019

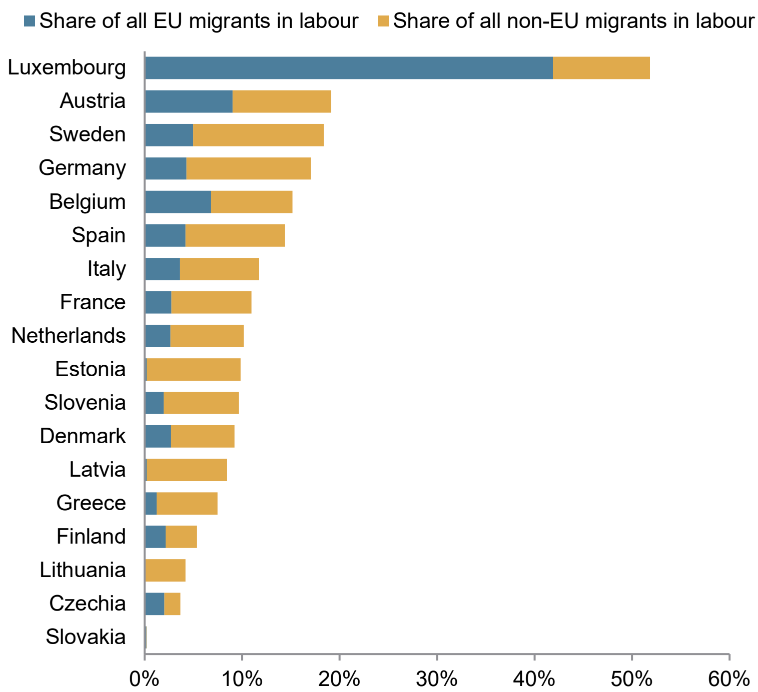


Source: EU KLEMS, authors' elaboration.

4.2.2. Country-level analysis

The following three figures (Figure 4, 5 and 6) present averages of the exploratory and explanatory variables across the selected EU countries in the period from 2015 to 2019. These figures are complemented by the summary statistics Table A13 available in the appendix.

Figure 4 / Share of migrant workers to total employees in selected EU countries averaged over the period 2015-2019



Source: EU LFS authors' elaboration.

Figure 4 shows the substantial variation in the share of migrant workers to total employees across countries, with notable differences also observed in the proportion of EU and non-EU migrant workers. Luxembourg had the highest average share of migrant workers overall, reaching 52%, which was more than twice as high as that of any other analysed country. It was followed by Austria (19%) and Sweden (18%). In contrast, the lowest shares were noted in Slovakia, where it was less than 1%, and in Czechia and Lithuania where it was approximately 4%.

Apart from Luxembourg, which had a larger share of migrant workers from EU countries than from non-EU countries, and Austria which had similar shares, all other countries exhibited larger proportions of non-EU to EU migrant workers. Luxembourg had the largest share of EU migrant workers, comprising an average of 42% of its total workers. This can be attributed to its hosting of several EU institutions and the large share of the financial sector, along with its high wages and central European location, which make it an attractive destination especially for highly skilled workers from neighbouring countries and beyond. Austria followed with 9%, and Belgium with 7% of EU migrant workers' share in the total number of employees. On the other hand, the Baltic states (Lithuania, Estonia and Latvia), as well as Slovakia had the lowest shares, all of them having less than 1% of EU migrant workers in the total number of employees. The highest shares of non-EU migrant workers in labour are observed in Sweden and Germany, at around 13%, followed by Spain and Austria with approximately 10%. The Baltic states and Greece also had a high proportion of non-EU migrant workers to EU-migrant workers, which could be explained by their geo-location and historical ties to neighbouring non-EU countries.

The average distribution of migrant workers across occupations in each country during the specified period is presented in Figure A1 in the appendix. The analysis reveals diverse patterns, with some countries exhibiting a relatively dispersed distribution of migrant workers across various occupations (e.g., Austria, France and Germany), while in other countries migrants were more concentrated in certain occupations. Nevertheless, certain common characteristics can be observed. On average, the largest proportion of migrant workers was employed as Service workers and shop and market sales workers (ISCO 5), ranging from over 30% in countries like Greece, Finland and Spain, to the lowest shares, somewhat larger than 10%, in Lithuania, Luxembourg and Slovenia. Conversely, the lowest share of migrant workers across all countries was found in the category of Skilled agricultural and fishery workers (ISCO 6).

Interestingly, a significant proportion of migrant workers across countries were employed as Professionals (ISCO 2), which refers to high-skill jobs. Luxembourg had the highest share of migrants in these occupations with 46% of migrant workers employed there, followed by Lithuania and Denmark with shares of 28% respectively. Conversely, the lowest shares in this occupational group were observed in southern EU economies. A relatively low proportion of migrants was employed as Legislators, senior officials, and managers (ISCO 1), with Belgium and France having the highest proportion of total migrant workers in these occupations, which was still below 10%, while in some countries it was close to zero. Migrants also displayed relatively high employment shares across certain middle and low-skilled occupations, again with significant variations across countries.

Figure A2 in the appendix shows the extent to which these migrant workers on average contributed to overall employment across occupations in the destination countries during the same period. The highest shares of migrant workers in overall employment can be found in occupations requiring lower skill levels such as Service workers and shop and market sales workers (ISCO 5), Craft and related trades workers (ISCO 7), Plant and machine operators and assemblers (ISCO 8) and particularly in Elementary occupations (ISCO 9), where the share of migrant workers in Luxembourg amounted to 75%, in Germany 42% and in Austria 41% of total workers. These countries also had a higher than average proportion of migrants in Craft and related trades workers (ISCO 7) and Plant and machine operators (ISCO 8).

In terms of occupations that require higher skill levels, the shares of migrant workers in total employment across countries were mostly in single digits. However, there were some notable exceptions. For Legislators, senior officials and managers (ISCO 1), an important outlier is Luxembourg with 83% of immigrant workers in total employment in this category. Furthermore, only Belgium and Germany also had double-digit shares of migrant workers in this occupation group (13% and 12% respectively), while in some countries this share was close to 0% (Greece, Finland and Denmark). In the case of Professionals (ISCO 2), a somewhat larger share of migrant workers in overall employment can be observed. Once again, Luxembourg emerges as an outlier with 57% of migrant workers' share in total workers within this occupational group, followed by Sweden and Austria, with shares of 16% and 15% respectively. The lowest shares of migrant workers in these occupations are found in Greece, Lithuania and Slovenia. The share of migrants out of total workers employed as Technicians and associate professionals (ISCO 3) also varied significantly across countries, from more than 30% in Luxembourg to nearly 0% in Lithuania.

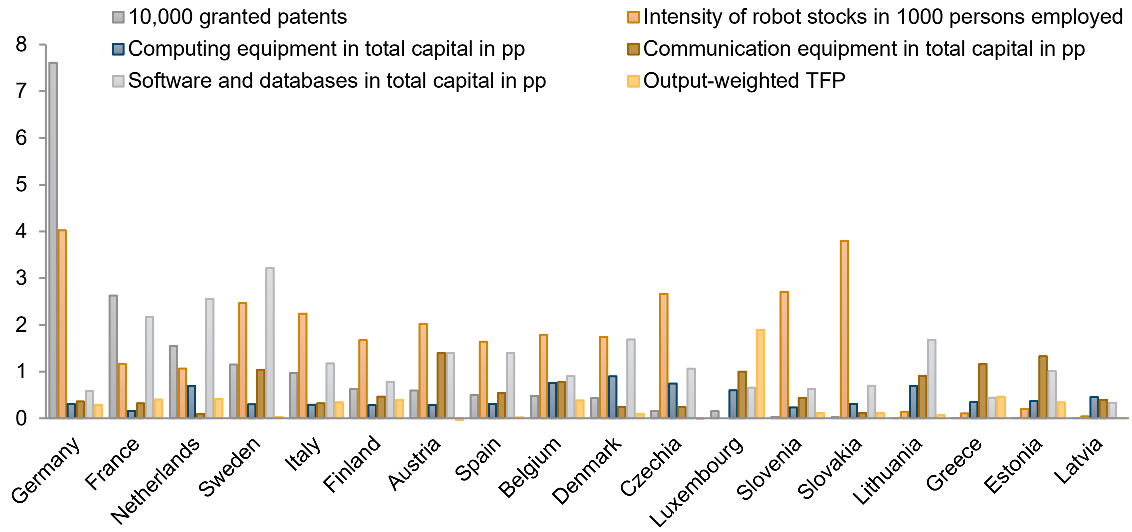
Figure A3 in the appendix presents the distribution of migrant workers across countries based on their levels of education averaged over the period from 2015 to 2019. The distribution of migrants based on their educational attainment also exhibited significant variations across countries. While some countries attracted migrants with diverse educational backgrounds, such as Spain, others displayed varying proportions of migrants across different educational levels. In most countries, the lowest share of migrant workers had low-levels of education, particularly in the new EU member states. Low-educated migrant workers constituted the largest educational group of migrant workers only in Italy, where they accounted for 45% of total migrant workers. A relatively high share of low-educated migrants in total migrant workers was also found in Greece (38%) and Spain (37%), which might be attributed to their geographic location and proximity to less developed countries (where a significant share of their migrants originate) with lower average educational levels compared to EU countries. Interestingly, nearly all migrant workers in Slovakia had a medium level of education, and in Austria and Germany the largest proportion of migrant workers (nearly 50%) also had medium-educated migrant workers. Moreover, a high proportion of medium-educated migrant workers was also found across the new EU member states. Luxembourg, on the contrary, had the lowest share of medium-educated migrant workers.

As expected, given the occupational distribution of migrant workers, Luxembourg had the highest proportion of highly educated among its migrant worker population (55%), followed by Denmark, Sweden, and Estonia. When compared to the occupational distribution of migrant workers it is important to note that the proportion of highly educated migrant workers in most of the countries exceeds the proportion of migrant workers employed in high-skill occupations, indicating overeducation of a part of the migrant workers. The lowest shares of highly educated migrant workers were found in Italy, Greece and Slovenia, as expected given these countries' relatively higher shares of migrants working in less skill intensive occupational groups.

Figure A4 in the appendix complements previous insights by providing an overview of the proportion of migrant workers to total workers within their respective educational groups, i.e., the share of migrants in the total number of employees within each educational level. Consistent with the previous data, these proportions also varied across countries. The share of migrant workers among low-educated employees was the highest in Luxembourg, Germany, Sweden and Austria. Similarly, the share of migrant workers among highly educated employees was the highest in the same countries, although with smaller overall proportions, except in Luxembourg, where migrant workers' share of highly educated workers exceeded that of migrant workers share of low-educated workers.

Figure 5 presents an overview of technological change proxies in the analysed EU countries, averaged over the period 2015-2019. Germany had the highest number of granted patents owned by its firms, with an average of 76,117, more than double the number in France, which had an average of 26,280 granted patents. The Netherlands followed with 15,457 and Sweden with 11,521 granted patents. In contrast, all other countries had fewer than 10.000 patents on average. As expected, smaller economies including the Baltic states, Slovakia, Slovenia and Greece had particularly low numbers of granted patents, less than 100 per year.

Figure 5 / Technological measures in selected EU countries averaged over the period 2015-2019



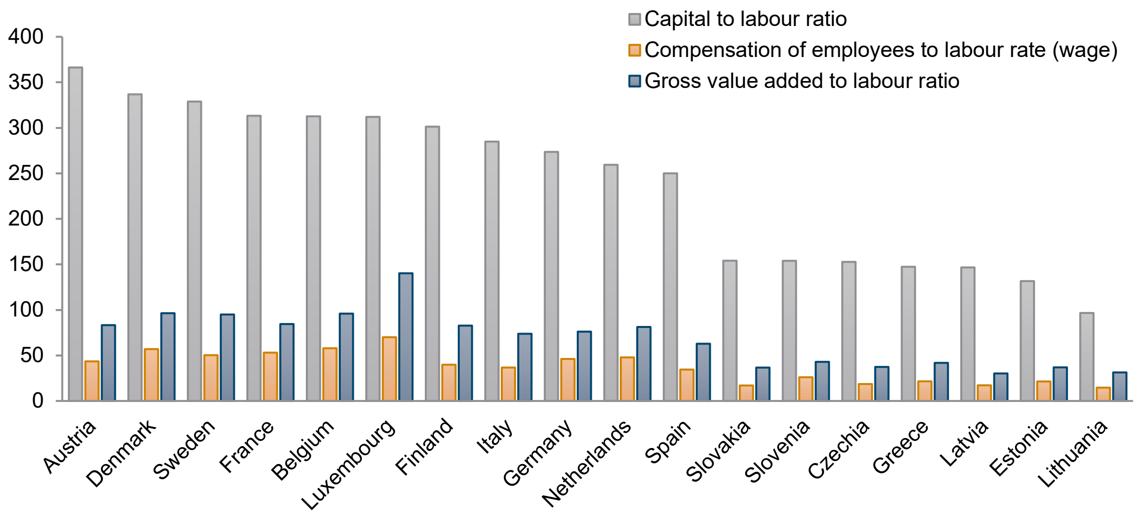
Source: EU KLEMS, authors' elaboration.

Robot adoption is presented as a relative measure to 1000 persons employed. Germany had the highest intensity of robot stock, with 4 robots per 1000 persons employed, followed by Slovakia with 3.8 and Czechia with 2.7 robots per 1000 persons employed. Interestingly, these two Visegrad economies, which have a low share of migrant workers in total employment, have recognised the potential of utilising robots in their industries. This may also be linked to their economic structure as both countries have a relatively high share of manufacturing industry in their GDP compared to other countries in the analysis, and the manufacturing industry has the highest intensity of robot adoption.

The shares of ICT capital variables in total capital stock varied across countries, especially for non-tangible ICT capital. The average share of computing equipment in total capital ranged from 0.9% in Denmark to 0.2% in France. The share of communication equipment ranged from 1.4% in Austria to 0.1% in the Netherlands, and the share of software capital ranged from 3.2% in Sweden to 0.3% in

Latvia. Interestingly, although Germany had the highest intensity of robot adoption and the largest number of patents granted, it showed relatively low shares of ICT capital in total capital. Average output weighted TFP varied from 1.89 in Luxembourg to -0.04 in Austria. Luxembourg's value was followed by Greece with 0.46 and the Netherlands and France with 0.41. Besides Austria only Czechia noted a negative value of -0.01, while in Latvia it was 0.

Figure 6 / Control variables in selected EU countries averaged over the period 2015-2019, USD '000



Source: EU KLEMS, authors' elaboration.

Figure 6 provides an overview of average values of control variables in the set of analysed countries, expressed in current US dollars. The capital to labour ratio varied significantly among the analysed countries. Austria recorded the highest ratio, surpassing USD 350,000 of capital per worker, followed by Denmark and Sweden. In contrast, the Baltic states and Greece demonstrated the lowest values of this ratio, all below USD 150,000 US dollars of capital per worker. The other new EU member states in the sample showed only a slightly higher value of capital to labour ratio.

Average wages also varied considerably across the analysed countries. The highest average wages were noted in Luxembourg, reaching USD 70,000, followed by Belgium and Denmark with nearly USD 60,000. On the other hand, Lithuania had the lowest average wage level amounting to only USD 15,000, while Slovakia, Latvia, and Czechia reported only slightly higher wages. As expected, old EU member states experienced higher labour costs, with relatively lower values in the southern EU countries (Italy, Spain and Greece). The new EU member states had comparatively lower labour costs. Therefore, as expected, more developed economies with a higher relative abundance of capital had higher wages compared to less developed ones with a lower abundance of capital.

Similar variations can be seen in the gross value added (GVA) to labour ratio, with Luxembourg having the highest ratio of USD 140,000 of GVA per worker, followed by Denmark and Belgium with USD 96,000 of GVA per worker. New EU member states and Greece had lower values, with Latvia having the smallest GVA per worker at USD 30,000.

4.2.3. Sectoral analysis

As shown in Table A8 in the appendix, in the period from 2006 to 2019, sector I (hotel and restaurant) had the largest share of migrant workers in total workers across sectors, averaging 25.9%. This can be attributed to the sector's labour-intensive nature and its demand for low-skilled manual labour. Sector F (construction) followed with an average of 16.7% of immigrant workers in total workers, and sector D (manufacturing) with 12.9%. This is expected due to their demand for low-skilled routine workers and the relatively lower wages these sectors provide, making them less attractive to native workers across developed economies. Additionally, this might be linked to the lower educational attainment of migrant workers and/or down-skilling to manual and routine jobs that they may be overqualified for, due to possible undervaluation of degrees earned in their home countries, in order to enable them to stay in these countries. Conversely, sector 0 (public administration) had the lowest share of migrant workers in total workers with 4.8%, followed by sector C (mining) with 5.5% and sector E (utilities) with 5.8%.

Non-EU migrant workers represented a higher proportion of total workers than EU migrant workers in all sectors, accounting for more than 65% of migrant workers in all sectors. Sector I (hotel and restaurants) and D (manufacturing) had almost 80% of migrant workers coming from non-EU countries. Thus, sector I (hotel restaurant) had the largest share of non-EU migrant workers in total workers amounting to more than 20%, followed by sectors C (construction) and D (manufacturing) with approximately half that share. Similarly, the share of EU migrant workers in total workers was the highest in sector I (hotel and restaurant) and sector F (construction) with a share of 5.3% respectively, followed by sector A (agriculture) with 3.5%. Following the data on overall migrant workers, the lowest shares of both EU and non-EU migrant workers were noted in sectors O (public administration), E (utilities) C (mining) and K (financial and insurance).

The number of granted patents varied significantly across sectors, with the manufacturing industry having the highest number of patents granted, averaging 106,582 patents per year, which was expected given the nature of this sector and its potential for technological improvements. Sectors M, N, P, H and J (all other services), had a joint number of granted patents that was less than 40% of the yearly number of patents granted in the manufacturing industry. Sector G (wholesale trade) followed, with less than 10% of the same number. Additionally, only sectors K (financial and insurance) and F (construction) had more than a thousand granted patents on average per year. On the other hand, sector O (public administration) had the lowest average number of patents, with only 30 patents granted per year. The sector with the highest share of migrant workers (sector I- hotel restaurant) had a very low average of 76 patents per year.

The average share of computing capital in the total was the highest in sector K (financial and insurance), where it amounted to 2.3%. Among all other sectors, it ranged from 0.1% in sector A (agriculture) to 1.3% in sector G (wholesale trade). The share of communication capital in the total was also the lowest on average in sector A (agriculture), while it was the highest in sector R (other community social and personal service) where it amounted to 1.2%, followed by sector I (hotel restaurant) and sector K (financial and insurance), each with 1.1%. The highest share of software capital on average was in sector K (financial and insurance industry) amounting to 7.8%, while it was the lowest in sector A (agriculture) at 0.1%. Among other sectors it ranged from 3.6% in sector G (wholesale trade) and 0.6% in sector C (mining). Output-weighted TFP varied from 1.53 in sector F (construction) to -0.99 in sectors M, N, P, H and J jointly (all other services). Sectors O (public administration), C (mining), A (agriculture) and E (utilities) also had negative values on average.

Capital stock was the highest in the jointly presented data of sectors M, N, P, H and J (all other services), while it was lowest in sector C (mining). Sector O (public administration) also had relatively high levels of capital stock, as did sector D (manufacturing). Average labour costs in terms of the real wage of each employed person, varied significantly across sectors, ranging from a high of USD 73,725 in sector K (finance and insurance) to USD 9,074 in sector A (agriculture). It is interesting to note that most of the sectors with the highest labour costs were those with fewer immigrant workers, while sector I (restaurant hotels) which had the largest share of immigrant workers, had the second lowest average labour cost, amounting to USD 22,379. Gross value added was the highest in the jointly presented data of sectors M, N, P, H and J (all other services), followed by sector D (manufacturing) and sector G (wholesale trade), while it was the lowest in sector C (mining) on average. Sectors A (agriculture), E (utilities) and I (hotel restaurant) also had relatively low gross value added on average.

5. Estimation results

The hypothesis of this paper focuses on the impact of technological advancements on the labour market outcomes of migrants compared to natives. The analysis presented here aims to analyse whether the labour market outcomes for migrants are similar to those of natives or if migrants are being displaced by emerging technologies in routine and low-skill jobs. The first sub-section below discusses the results in terms of impact on total employment, total number of migrant workers and their share in total employment in each sector in a country, while migrants' origin distinguishes between intra-EU and extra-EU migrants. The second sub-section goes deeper into the skills and occupations of workers. The third sub-section presents the results according to the level of education of workers in sectors of countries.

5.1. ESTIMATIONS OF TOTAL NUMBER OF MIGRANT WORKERS

Table 1 displays the PPML estimation results of equation (1) for total employees, total migrant workers, and their share in total employment by their origin during the period 2005-2019. The three left columns present the share of migrant workers in each sector-country-year combination as the dependent variable, while the next three columns to their right present the total number of migrant workers in each sector-country-year combination as the dependent variable, and the right column presents the total workers l_{ict+1} in sector i in country c in year t. To investigate whether the correlation between the technological explanatory variables causes any significant change in their coefficients in the benchmark specification on the share of migrant workers, Table A1 in the appendix adds these variables one by one to the main control variables without including others in different columns. The results remain consistent with the baseline specification, while the magnitudes of coefficients change.

The technological measures have varying effects on workers across specifications. Novel innovations, measured as the share of granted patents owned by firms in a sector of a country relative to the total number of employees P_{ict}, have positive and statistically significant coefficients in the models estimating the share of migrant workers in the total workforce. However, they have a strong negative impact on total employment and the total number of intra-EU migrant workers. This suggests that novel innovations significantly reduce the number of employees. However, they reduce the number of migrant workers less than they reduce the number of native workers, which contributes to the share of migrant workers in the sample of countries.

Table 1 / PPML estimation results of migrant workers by their origin during the period 2005-2019

Dependent variables	m_{ict+1}	m^{EU}_{ict+1}	m^{nonEU}_{ict+1}	M_{ict+1}	M^{EU}_{ict+1}	M^{nonEU}_{ict+1}	l_{ict+1}
P_{ict}	0.12***	0.099***	0.20***	-0.013	-0.15***	-0.0015	-0.097***
	(0.027)	(0.030)	(0.069)	(0.040)	(0.037)	(0.047)	(0.017)
s_{ict}	0.075***	-0.0035	0.10***	-0.099***	-0.031	-0.099***	-0.031***
	(0.027)	(0.032)	(0.033)	(0.025)	(0.023)	(0.028)	(0.0076)
D^{IT}_{ict}	-0.014	-0.096**	0.038	0.089**	-0.037	0.091*	0.061***
	(0.029)	(0.041)	(0.043)	(0.044)	(0.036)	(0.047)	(0.016)
D^{CT}_{ict}	-0.073*	0.038	-0.15**	0.038	0.077***	-0.010	-0.039**
	(0.041)	(0.054)	(0.059)	(0.032)	(0.028)	(0.037)	(0.019)
D^{SD}_{ict}	0.12***	0.11***	0.089	-0.099**	0.029	-0.12***	-0.050***
	(0.035)	(0.036)	(0.061)	(0.039)	(0.034)	(0.044)	(0.019)
$\mathrm{TFP}^{ACF,GO,II}_{ict}$	0.20***	0.097	0.28***	0.33***	0.15**	0.33***	0.15***
	(0.067)	(0.074)	(0.097)	(0.077)	(0.070)	(0.087)	(0.040)
K_{ict}	-0.0013***	0.00042	-0.0017***	-0.0013***	-0.0011***	-0.0017***	-0.00051***
	(0.00031)	(0.00044)	(0.00037)	(0.00035)	(0.00030)	(0.00036)	(0.00015)
w_{ict}	-0.42***	-0.18	-0.55***	-0.64***	-0.52***	-0.58***	-0.45***
	(0.097)	(0.13)	(0.12)	(0.082)	(0.11)	(0.083)	(0.034)
VA_{ict}	0.10*	0.092	0.11	0.66***	0.61***	0.67***	0.48***
	(0.057)	(0.082)	(0.082)	(0.071)	(0.078)	(0.075)	(0.037)
Constant	1.55	-1.26	2.10	4.86***	2.79***	4.04***	6.81***
	(1.02)	(1.17)	(1.31)	(0.79)	(1.03)	(0.90)	(0.39)
Observations	2721	2109	2663	2721	2109	2663	2721
Pseudo R-squared	0.149	0.249	0.094	0.972	0.915	0.971	0.993
AIC	1477.2	639.6	1108.9	16089.7	9437.1	14231.7	27130.0
BIC	1536.3	696.1	1167.7	16148.7	9493.7	14290.6	27189.1

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.

Another interesting result regards the adoption of robots, measured as the intensity of robot stocks per thousand employees in a sector of a country s_{ict}. According to the estimations at the employee level, robots replace workers. In fact, a 1% increase in the intensity of robots to employees in a sector of the sample would result in a reduction of the total number of employees by 0.031%, the total number of migrant workers by 0.099%, and the total number of non-EU migrant workers by 0.099%. However, the effect of robot adoption on the share of migrant workers is positive. This suggests that while robots replace jobs, they primarily replace the jobs of native workers rather than those of migrant workers. That is why a 1% increase in robot stock intensity in a sector of a country in the sample is associated with a 0.075% increase in the share of migrant workers and a 0.1% increase in the share of non-EU migrant workers. It is interesting to note that robot adoption has no statistically significant impact on intra-EU migrant workers, which could suggest that their mobility across EU countries is better than that of natives or non-EU migrants.

Diverse effects are observed on the proxy variables for digitalisation. The intensity of computing equipment capital per thousand employees D^{IT}_{ict} has a strong positive impact on the total number of workers, the total number of migrant workers, and, to a lesser extent, the total number of non-EU migrant workers. While the adoption of digital technologies does not significantly affect the number of intra-EU migrant workers, it reduces their share in the total number of employees. The intensity of communication equipment capital per thousand employees in a sector of a country D^{CT}_{ict} has a negative coefficient for the specification with the total number of employees as the dependent variable, which is statistically significant at the 5% level. However, the adoption of these communication assets increases the number of intra-EU migrant workers while not affecting their share in the total number of employees. Adoption of these digital assets, however, reduces the share of migrant workers and the share of extra-EU migrant workers in the total workforce. The intensity of software and database capital per thousand employees D_{ict}^{SD} also has a negative coefficient for the specification with the total number of employees as the dependent variable, which is statistically significant at the 1% level. Adoption of these digital assets also reduces the number of migrant workers, especially those born outside the EU. However, they increase the share of migrant workers, particularly intra-EU migrant workers, relative to the total workforce. This could indicate that intra-EU migrant workers might be better trained and educated with the software and digital skills needed to work with these digital assets.

Coefficients of TFP are positive and statistically significant at the 1-5% level in all specifications presented in Table 1, except for the model estimating the share of intra-EU migrant workers. This indicates that all other forms of technology, know-how, or managerial skills, measured as the Solow residual, also have a positive impact on migrant workers. As mentioned above, the TFP used in the baseline specification is calculated using real gross output and follows the methodology of Ackerberg et al. (2015), while controlling for the number of patents and robot intensity. However, other types of productivity measured in different ways are also used in robustness specifications estimating m_{ict}, the results of which are presented in Table A2 in the appendix. It can be observed that when productivity is measured using real gross output, positive coefficients are obtained from the estimations. However, when productivity is measured using real value added, the coefficients become negative. One major reason for this is that value added is included as a control variable measuring the scale of the sector in a country. Therefore, the TFP calculated using value added is heavily correlated with that variable, while the one from gross output might still have some residual values beyond value added, which mainly come from the intermediate inputs of production. Therefore, the TFP estimated using gross output is used in the estimations. Nevertheless, the choice of productivity does not affect the coefficients of other variables, and the results on other variables remain consistent with the baseline specification.

The capital stock to labour ratio has a negative and significant impact on the number of workers across all specifications, except for the share of intra-EU migrant workers relative to total workers, which has a statistically insignificant coefficient. Wages, measured as total labour costs relative to the total number of employees, have a negative impact on the number of workers and share of migrant workers across almost all specifications, which might indicate a negative slope of the labour demand function. However, wages do not affect the share of intra-EU migrant workers in the total number of employees in a statistically significant manner. This could indicate that average wages affect intra-EU migrant employees to a similar extent as they affect all employees. However, wages affect extra-EU migrants more than they affect all employees, leading to a statistically significant negative coefficient of wages in the third column to the left. This may suggest that extra-EU migrants do not get the high-paid jobs compared to native workers. Real gross value added has a significant and positive effect on the total number of workers and migrant workers, while it does not have a strong and significant impact on the share of migrant workers relative to all workers.

The results of the estimations with contemporaneous variables are presented in Table A3 in the appendix. These results are consistent with the benchmark results presented in Table 1 using lagged explanatory variables.

5.2. ESTIMATION RESULTS OF MIGRANT WORKERS BY OCCUPATION

In this subsection, the results of the estimation of total employees and the share of migrant workers among total employees, categorised by their ISCO occupations, are presented. Table 2 presents the results of total employment for each occupation within a sector in a country as the dependent variable in equation (1). Table 3 presents the share of migrant workers out of total workers by occupation within each sector and country as the dependent variable. Table 4 presents the results of the share of intra-EU migrant workers out of total employment for each occupation within each sector and country as the dependent variable. Table 5 presents the results of the share of extra-EU migrant workers out of total employment for each occupation within a sector in a country as the dependent variable. The results of the total number of migrant workers in each occupation within a sector in a country are presented in Tables A4 through A6 in the appendix.

Role of innovation as measured by granted patents

According to the results in Table 2, total employment in six out of nine occupations is negatively affected by novel innovations, measured as granted patents, in each sector of a country. However, the total employment of Legislators, senior officials, and managers (ISCO 1, with skill levels 3 and 4), Service workers and shop and market sales workers (ISCO 5, with skill levels 2), and Skilled agricultural and fishery workers (ISCO 6, with skill level 2) shows a positive correlation with novel innovations. The number of migrant workers in these occupations is also positively affected by novel innovations, as indicated by the results in Table A4 in the appendix. Novel innovations only affect the share of intra-EU migrants working as Skilled agricultural and fishery workers positively and in a statistically significant manner. Table 3 reveals that granted patents have a positive impact on the share of migrant workers out of total workers in the Craft and related trades workers category (ISCO 7, with skill level 2). Therefore, while novel innovations reduce the number of native workers and migrant workers in these occupations, the reduction is greater for native workers. This pattern is also observed for intra-EU migrant workers, according to Table 4, suggesting that the mobility of skilled workers in these occupations makes them more resilient to innovative shocks, enabling them to retain their jobs better than native workers. However, according to the results in Table 5, novel innovations increase the share of extra-EU migrants working as Service workers and shop and market sales workers (ISCO 5, with skill level 2). While the number of workers in these professions generally increases due to novel innovations, the number of extra-EU migrants working in these professions increases even more than that of native workers, resulting in a statistically significant positive coefficient in Table 5 at the 5% level.

The share of migrants working as Legislators, senior officials, and managers (ISCO 1), especially those born in other EU member states, is negatively affected by novel innovations. This suggests that their employment is adversely impacted to a greater extent compared to native workers.

Table 2 / PPML estimation results of total number of workers by ISCO occupations during the period 2005-2019

Dependent variable:	l_{ict}	$l_{ict+1}^{ISCO,1}$	$l_{ict+1}^{ISCO,2}$	$l_{ict+1}^{ISCO,3}$	$l_{ict+1}^{ISCO,4}$	$l_{ict+1}^{ISCO,5}$	$l_{ict+1}^{ISCO,6}$	$l_{ict+1}^{ISCO,7}$	$l_{ict+1}^{ISCO,8}$	$l_{ict+1}^{ISCO,9}$
P_{ict}	-0.097***	0.42***	-0.30***	-0.28***	-0.12***	0.16**	1.03**	-0.11***	-0.33***	-0.59***
	(0.017)	(0.077)	(0.043)	(0.049)	(0.027)	(0.067)	(0.47)	(0.030)	(0.044)	(0.092)
s_{ict}	-0.031***	0.13***	0.072***	0.21***	0.091***	-0.12***	-0.86***	-0.050***	-0.097***	0.15***
	(0.0076)	(0.024)	(0.019)	(0.023)	(0.014)	(0.039)	(0.19)	(0.010)	(0.015)	(0.041)
D_{ict}^{IT}	0.061***	0.15***	0.15***	-0.066*	0.16***	-0.0096	-0.81	-0.0096	-0.018	0.38***
	(0.016)	(0.046)	(0.030)	(0.036)	(0.018)	(0.037)	(0.55)	(0.039)	(0.040)	(0.066)
D_{ict}^{CT}	-0.039**	-0.21***	-0.018	-0.070*	-0.052***	0.15***	0.94	0.081***	0.035	-0.13**
	(0.019)	(0.057)	(0.022)	(0.037)	(0.020)	(0.040)	(0.60)	(0.029)	(0.024)	(0.052)
D_{ict}^{SD}	-0.050***	0.066	-0.077***	-0.12***	-0.11***	0.14***	1.05***	-0.17***	0.091***	-0.63***
	(0.019)	(0.054)	(0.022)	(0.035)	(0.021)	(0.031)	(0.27)	(0.021)	(0.028)	(0.058)
$\mathrm{TFP}_{ict}^{ACF,GO,II}$	0.15***	0.39***	-0.091	0.064	0.17***	-0.20***	-1.76**	0.32***	0.32***	0.96***
	(0.040)	(0.14)	(0.066)	(0.072)	(0.055)	(0.066)	(0.77)	(0.047)	(0.075)	(0.13)
K_{ict}	-0.00051***	0.0024***	-0.000093	0.0016***	0.00041**	-0.0052***	-0.020***	-0.00015	-0.00047**	0.00097*
	(0.00015)	(0.00039)	(0.00020)	(0.00027)	(0.00017)	(0.00047)	(0.0031)	(0.00019)	(0.00021)	(0.00050)
w_{ict}	-0.45***	-1.49***	-0.20**	-0.55***	-0.58***	0.72***	-0.86*	-0.11**	-0.70***	-0.56***
	(0.034)	(0.15)	(0.095)	(0.11)	(0.064)	(0.090)	(0.44)	(0.046)	(0.078)	(0.11)
VA_{ict}	0.48***	0.34***	0.50***	0.27***	0.14***	-0.38***	-0.78	0.40***	0.71***	0.47***
	(0.037)	(0.12)	(0.079)	(0.083)	(0.049)	(0.094)	(0.59)	(0.046)	(0.054)	(0.11)
Constant	6.81***	15.3***	2.39**	8.55***	10.2***	3.64***	25.8***	2.93***	4.76***	5.85***
	(0.39)	(1.32)	(1.12)	(1.27)	(0.64)	(0.84)	(7.23)	(0.45)	(0.80)	(1.48)
Observations	2721	1626	2178	2072	1661	1921	286	1768	1766	2524
Pseudo R-squared	0.993	0.918	0.976	0.969	0.966	0.967	0.957	0.982	0.969	0.919
AIC	27130.0	16773.2	20337.6	24675.4	13350.1	21175.4	2697.2	14221.2	13706.3	28278.3
BIC	27189.1	16827.1	20394.5	24731.8	13404.3	21231.0	2733.8	14276.0	13761.1	28336.6

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.
ISCO occupations: 1. Legislators, senior officials and managers; 2. Professionals; 3. Technicians and associate professionals; 4. Clerks; 5. Service workers and shop and market sales workers; 6. Skilled agricultural and fishery workers; 7. Craft and related trades workers; 8. Plant and machine operators and assemblers; 9. Elementary occupations.

Table 3 / PPML estimation results of share of migrant workers by ISCO occupations in total number of employees during the period 2005-2019

Dependent variable:	m_{ict}	$m_{ict+1}^{ISCO,1}$	$m_{ict+1}^{ISCO,2}$	$m_{ict+1}^{ISCO,3}$	$m_{ict+1}^{ISCO,4}$	$m_{ict+1}^{ISCO,5}$	$m_{ict+1}^{ISCO,6}$	$m_{ict+1}^{ISCO,7}$	$m_{ict+1}^{ISCO,8}$	$m_{ict+1}^{ISCO,9}$
P_{ict}	0.12***	-0.22**	-0.30***	-0.41***	0.14	0.20	-2.06	0.46***	-0.19**	-0.21***
	(0.027)	(0.10)	(0.079)	(0.098)	(0.14)	(0.16)	(1.58)	(0.11)	(0.088)	(0.078)
s_{ict}	0.075***	0.094	0.072	0.099*	-0.082	0.90***	-0.31	-0.28***	-0.23***	0.066*
	(0.027)	(0.074)	(0.065)	(0.056)	(0.092)	(0.14)	(0.83)	(0.053)	(0.056)	(0.037)
D_{ict}^{IT}	-0.014	0.24**	0.00069	0.12	0.087	-0.30***	0.21	0.28**	-0.21*	0.071
	(0.029)	(0.094)	(0.085)	(0.11)	(0.12)	(0.11)	(0.95)	(0.12)	(0.12)	(0.070)
D_{ict}^{CT}	-0.073*	0.073	0.15**	-0.15	-0.016	0.45***	-2.47**	-0.22**	0.026	-0.029
	(0.041)	(0.15)	(0.075)	(0.18)	(0.15)	(0.12)	(1.16)	(0.097)	(0.064)	(0.036)
D_{ict}^{SD}	0.12***	-0.30***	-0.027	-0.19**	-0.33***	0.30***	-0.39	-0.089	0.15*	-0.13**
	(0.035)	(0.099)	(0.059)	(0.094)	(0.12)	(0.087)	(0.62)	(0.083)	(0.080)	(0.064)
$\mathrm{TFP}_{ict}^{ACF,GO,II}$	0.20***	0.0022	0.18	0.96***	0.97	-0.89***	0.78	-0.42**	0.41**	0.29**
	(0.067)	(0.29)	(0.20)	(0.28)	(0.60)	(0.17)	(2.22)	(0.20)	(0.18)	(0.11)
K_{ict}	-0.0013***	0.0048***	0.0025***	0.00040	0.000068	0.00055	0.017**	-0.0046***	-0.00016	-0.00025
	(0.00031)	(0.0011)	(0.00083)	(0.00090)	(0.00094)	(0.0015)	(0.0072)	(0.00088)	(0.00071)	(0.00053)
w_{ict}	-0.42***	0.036	0.73***	0.041	0.28	-0.79***	-2.36	-0.035	-0.83***	-0.16
	(0.097)	(0.33)	(0.22)	(0.26)	(0.43)	(0.20)	(1.54)	(0.21)	(0.26)	(0.11)
VA_{ict}	0.10*	0.83***	-0.41**	-0.70***	-0.18	1.07***	2.04	0.48***	0.51***	-0.12
	(0.057)	(0.30)	(0.20)	(0.26)	(0.54)	(0.22)	(1.48)	(0.16)	(0.18)	(0.082)
Constant	1.55	-11.0***	-5.75***	4.37	-3.53	-4.42**	-3.93	-5.30**	1.73	1.72
	(1.02)	(3.18)	(2.22)	(3.02)	(3.29)	(2.20)	(26.5)	(2.07)	(2.26)	(1.25)
Observations	2721	1538	2092	2019	1648	1891	272	1719	1671	2426
Pseudo R-squared	0.149	0.233	0.207	0.158	0.131	0.177	0.304	0.187	0.213	0.203
AIC	1477.2	631.4	900.6	813.5	602.6	939.5	130.1	917.2	912.4	1812.6
BIC	1536.3	684.8	957.1	869.6	656.7	995.0	166.2	971.7	966.6	1870.6

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.
ISCO occupations: 1. Legislators, senior officials and managers; 2. Professionals; 3. Technicians and associate professionals; 4. Clerks; 5. Service workers and shop and market sales workers; 6. Skilled agricultural and fishery workers; 7. Craft and related trades workers; 8. Plant and machine operators and assemblers; 9. Elementary occupations.

Table 4 / PPML estimation results of share of intra-EU migrant workers by ISCO occupations in total number of employees during the period 2005-2019

Dependent variable:	m_{ict}	$m_{ict+1}^{EU,ISCO,1}$	$m_{ict+1}^{EU,ISCO,2}$	$m_{ict+1}^{EU,ISCO,3}$	$m_{ict+1}^{EU,ISCO,4}$	$m_{ict+1}^{EU,ISCO,5}$	$m_{ict+1}^{EU,ISCO,6}$	$m_{ict+1}^{EU,ISCO,7}$	$m_{ict+1}^{EU,ISCO,8}$	$m_{ict+1}^{EU,ISCO,9}$
P_{ict}	0.099***	-0.25**	-0.28***	-0.45***	0.13	0.24	-15.9***	0.29**	0.080	-0.032
	(0.030)	(0.11)	(0.100)	(0.12)	(0.17)	(0.21)	(4.38)	(0.14)	(0.081)	(0.11)
s_{ict}	-0.0035	0.072	-0.040	-0.089	-0.40**	1.61***	-8.02**	-0.41***	-0.55***	-0.34***
	(0.032)	(0.11)	(0.098)	(0.095)	(0.17)	(0.42)	(3.75)	(0.061)	(0.093)	(0.11)
D_{ict}^{IT}	-0.096**	0.16	0.053	0.20	-0.022	-0.31	0.65	0.24	0.050	0.085
	(0.041)	(0.14)	(0.13)	(0.18)	(0.23)	(0.24)	(4.18)	(0.15)	(0.096)	(0.098)
D_{ict}^{CT}	0.038	0.12	0.17*	0.037	-0.034	0.32	6.09	-0.23**	0.087	-0.042
	(0.054)	(0.21)	(0.098)	(0.25)	(0.22)	(0.27)	(3.88)	(0.10)	(0.087)	(0.060)
D_{ict}^{SD}	0.11***	-0.26*	-0.14	-0.41***	-0.37*	-0.14	2.45	0.091	0.12**	-0.032
	(0.036)	(0.16)	(0.087)	(0.13)	(0.22)	(0.22)	(2.40)	(0.085)	(0.059)	(0.13)
$\mathrm{TFP}_{ict}^{ACF,GO,II}$	0.097	-0.45	0.25	1.76***	1.91*	-0.51	2.38	0.34	-0.024	0.79***
	(0.074)	(0.52)	(0.31)	(0.44)	(1.14)	(0.32)	(4.42)	(0.31)	(0.18)	(0.23)
K_{ict}	0.00042	0.0059**	0.0062***	0.0033*	0.0011	-0.0035	0.077***	-0.0029**	0.0012	0.0022***
	(0.00044)	(0.0028)	(0.0014)	(0.0020)	(0.0024)	(0.0046)	(0.027)	(0.0013)	(0.00097)	(0.00069)
w_{ict}	-0.18	0.57	0.59*	0.79*	1.28*	-0.88**	6.69	0.74**	-0.36	-0.47*
	(0.13)	(0.72)	(0.31)	(0.47)	(0.71)	(0.45)	(6.60)	(0.29)	(0.30)	(0.24)
VA_{ict}	0.092	1.09**	-0.51*	-1.41***	-1.04	1.75***	0.83	0.23	0.063	0.098
	(0.082)	(0.52)	(0.27)	(0.43)	(0.93)	(0.43)	(3.89)	(0.20)	(0.17)	(0.15)
Constant	-1.26	-18.2**	-4.64	1.54	-6.93	-7.55*	-116.3**	-11.5***	1.56	2.12
	(1.17)	(7.78)	(3.64)	(5.90)	(7.80)	(4.48)	(58.2)	(2.49)	(2.79)	(2.26)
Observations	2109	931	1637	1514	1112	1326	120	1059	970	1435
Pseudo R-squared	0.249	0.374	0.317	0.286	0.226	0.298	0.310	0.297	0.399	0.389
AIC	639.6	274.4	484.1	385.2	252.8	358.6	49.6	351.3	329.2	613.8
BIC	696.1	322.7	538.1	438.5	302.9	410.5	77.5	401.0	378.0	666.5

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.
ISCO occupations: 1. Legislators, senior officials and managers; 2. Professionals; 3. Technicians and associate professionals; 4. Clerks; 5. Service workers and shop and market sales workers; 6. Skilled agricultural and fishery workers; 7. Craft and related trades workers; 8. Plant and machine operators and assemblers; 9. Elementary occupations.

Table 5 / PPML estimation results of share of extra-EU migrant workers by ISCO occupations in total number of employees during the period 2005-2019

Dependent variable:	m_{ict}	$m_{ict+1}^{nEU,ISCO,1}$	$m_{ict+1}^{nEU,ISCO,2}$	$m_{ict+1}^{nEU,ISCO,3}$	$m_{ict+1}^{nEU,ISCO,4}$	$m_{ict+1}^{nEU,ISCO,5}$	$m_{ict+1}^{nEU,ISCO,6}$	$m_{ict+1}^{nEU,ISCO,7}$	$m_{ict+1}^{nEU,ISCO,8}$	$m_{ict+1}^{nEU,ISCO,9}$
$\boldsymbol{P_{ict}}$	0.20***	0.33	-0.54***	-0.19*	0.22	0.40**	1.08	0.22	-0.73***	-0.44***
	(0.069)	(0.32)	(0.16)	(0.11)	(0.15)	(0.16)	(1.40)	(0.20)	(0.18)	(0.12)
$\boldsymbol{s_{ict}}$	0.10***	0.19**	0.19***	0.26***	0.085	0.72***	0.93	-0.16**	-0.038	0.18***
	(0.033)	(0.091)	(0.070)	(0.052)	(0.059)	(0.13)	(0.65)	(0.075)	(0.067)	(0.046)
$\boldsymbol{D_{ict}^{IT}}$	0.038	0.28	0.20	0.092	0.18	-0.29***	-1.40	0.37*	-0.30	0.11
	(0.043)	(0.19)	(0.12)	(0.11)	(0.13)	(0.099)	(1.12)	(0.19)	(0.26)	(0.11)
$\boldsymbol{D_{ict}^{CT}}$	-0.15**	0.036	0.36***	-0.22*	0.15	0.58***	-0.77	-0.21	0.13	-0.022
	(0.059)	(0.27)	(0.14)	(0.13)	(0.13)	(0.11)	(1.31)	(0.14)	(0.10)	(0.055)
$\boldsymbol{D_{ict}^{SD}}$	0.089	-0.32**	0.089	0.057	-0.35***	0.54***	-0.30	-0.25*	-0.092	-0.15*
	(0.061)	(0.13)	(0.099)	(0.11)	(0.13)	(0.098)	(0.66)	(0.13)	(0.14)	(0.078)
$\mathbf{TFP}_{ict}^{ACF,GO,II}$	0.28***	0.32	0.032	-0.0031	0.42*	-0.99***	2.16	-1.09***	0.20	-0.14
	(0.097)	(0.45)	(0.26)	(0.18)	(0.25)	(0.21)	(2.40)	(0.27)	(0.33)	(0.16)
$\boldsymbol{K_{ict}}$	-0.0017***	0.0039***	-0.00093	-0.00059	0.000044	-0.000077	0.017**	-0.0053***	-0.0014	-0.0018**
	(0.00037)	(0.0014)	(0.0012)	(0.00073)	(0.00087)	(0.0014)	(0.0078)	(0.00096)	(0.0011)	(0.00076)
$\boldsymbol{w_{ict}}$	-0.55***	-0.56	1.03***	-1.03***	-0.51	-0.69***	-2.19	-0.24	-1.03***	-0.16
	(0.12)	(0.50)	(0.33)	(0.28)	(0.33)	(0.23)	(1.48)	(0.26)	(0.36)	(0.13)
$\boldsymbol{VA_{ict}}$	0.11	0.76*	-0.44	0.49**	0.50	0.32	0.62	0.93***	1.08***	-0.027
	(0.082)	(0.39)	(0.33)	(0.24)	(0.31)	(0.20)	(1.63)	(0.21)	(0.33)	(0.11)
Constant	2.10	-5.61	-8.59***	2.52	-3.22	0.62	9.77	-7.91***	-2.51	0.89
	(1.31)	(3.91)	(2.86)	(2.56)	(3.11)	(2.15)	(25.9)	(2.92)	(4.06)	(1.65)
Observations	2663	1319	1857	1733	1371	1794	251	1596	1525	2263
Pseudo R-squared	0.094	0.144	0.111	0.095	0.092	0.121	0.265	0.152	0.141	0.146
AIC	1108.9	433.1	555.7	531.8	426.5	734.0	113.0	689.4	684.1	1448.1
BIC	1167.7	485.0	611.0	586.3	478.7	788.9	148.3	743.2	737.4	1505.3

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.
ISCO occupations: 1. Legislators, senior officials and managers; 2. Professionals; 3. Technicians and associate professionals; 4. Clerks; 5. Service workers and shop and market sales workers; 6. Skilled agricultural and fishery workers; 7. Craft and related trades workers; 8. Plant and machine operators and assemblers; 9. Elementary occupations.

Table 6 / PPML estimation results of total employment by level of education during the period 2005-2019

Dependent variables	l_{ict+1}^{L}	l_{ict+1}^{M}	l_{ict+1}^{H}
P_{ict}	-0.28***	-0.19***	-0.24***
	(0.034)	(0.021)	(0.024)
s_{ict}	-0.031***	0.017**	0.0088
	(0.012)	(0.0068)	(0.011)
D_{ict}^{IT}	0.015	0.032*	0.061***
	(0.026)	(0.018)	(0.016)
D_{ict}^{CT}	0.014	-0.040***	-0.021
	(0.025)	(0.015)	(0.018)
D_{ict}^{SD}	-0.13***	-0.18***	-0.053***
	(0.021)	(0.016)	(0.019)
$\mathrm{TFP}_{ict}^{ACF,GO,II}$	0.30***	0.16***	0.091**
	(0.050)	(0.037)	(0.042)
K_{ict}	-0.00060***	-0.00017	-0.000015
	(0.00020)	(0.00015)	(0.00016)
w_{ict}	-0.51***	-0.39***	0.012
	(0.048)	(0.035)	(0.050)
VA_{ict}	0.37***	0.46***	0.086*
	(0.045)	(0.043)	(0.047)
Constant	7.40***	5.77***	5.57***
	(0.54)	(0.38)	(0.60)
Observations	2571	3284	2913
Pseudo R-squared	0.977	0.986	0.982
AIC	22885.7	31203.9	25993.4
BIC	22944.3	31264.9	26053.2

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.

Table 7 / PPML estimation results of share of migrant workers by ISCED level of education from different origins in total number of employees, 2005-2019

Dependent variable:	m_{ict}	$m_{ict+1}^{ISCED,L}$	$m_{ict+1}^{ISCED,M}$	$m_{ict+1}^{ISCED,H}$	$m_{ict+1}^{EU,ISCED,L}$	$m_{ict+1}^{EU,ISCED,M}$	$m_{ict+1}^{EU,ISCED,H}$	$m_{ict+1}^{nEU,ISCED,L}$	$m_{ict+1}^{nEU,ISCED,M}$	$m_{ict+1}^{nEU,ISCED,H}$
P_{ict}	0.12***	-0.082	0.073	-0.18*	-0.035	0.14	-0.19*	-0.26**	-0.12	0.040
	(0.027)	(0.12)	(0.078)	(0.090)	(0.20)	(0.090)	(0.11)	(0.12)	(0.10)	(0.11)
s_{ict}	0.075***	-0.17***	-0.085**	0.095**	-0.26***	-0.32***	-0.050	-0.046	0.051	0.16***
	(0.027)	(0.034)	(0.035)	(0.048)	(0.060)	(0.051)	(0.071)	(0.041)	(0.035)	(0.056)
D_{ict}^{IT}	-0.014	-0.050	0.070	0.053	0.0075	0.019	0.085	-0.030	0.14*	-0.072
	(0.029)	(0.070)	(0.056)	(0.068)	(0.092)	(0.077)	(0.098)	(0.097)	(0.076)	(0.072)
D_{ict}^{CT}	-0.073*	-0.037	-0.098*	-0.17***	-0.00070	0.061	-0.12	-0.017	-0.098	-0.059
	(0.041)	(0.040)	(0.054)	(0.059)	(0.067)	(0.075)	(0.079)	(0.054)	(0.061)	(0.072)
D_{ict}^{SD}	0.12***	0.083	0.19***	-0.094*	-0.035	0.12	-0.14**	0.11*	0.17***	-0.15*
	(0.035)	(0.051)	(0.059)	(0.052)	(0.090)	(0.084)	(0.071)	(0.061)	(0.057)	(0.084)
$\mathrm{TFP}_{ict}^{ACF,GO,II}$	0.20***	-0.052	0.028	0.38**	0.78***	0.25	0.22	-0.72***	-0.18	0.51***
	(0.067)	(0.13)	(0.12)	(0.16)	(0.23)	(0.20)	(0.27)	(0.19)	(0.15)	(0.17)
K_{ict}	-0.0013***	-0.0012**	-0.0014**	0.0013*	0.0024***	0.0022***	0.0030***	-0.0028***	-0.0037***	0.00068
	(0.00031)	(0.00053)	(0.00060)	(0.00068)	(0.00080)	(0.00076)	(0.00094)	(0.00076)	(0.00068)	(0.00080)
w_{ict}	-0.42***	0.24*	-0.26**	0.17	-0.077	0.21	0.76***	0.27*	-0.41***	-0.40**
	(0.097)	(0.14)	(0.13)	(0.15)	(0.27)	(0.21)	(0.26)	(0.14)	(0.15)	(0.20)
VA_{ict}	0.10*	0.17	0.66***	-0.24*	-0.059	0.79***	-0.44**	0.51***	0.60***	0.0016
	(0.057)	(0.12)	(0.10)	(0.13)	(0.17)	(0.17)	(0.20)	(0.16)	(0.10)	(0.17)
Constant	1.55	-5.21***	-5.53***	-1.20	-1.06	-12.0***	-6.10**	-8.91***	-3.86**	1.45
	(1.02)	(1.53)	(1.39)	(1.45)	(2.30)	(2.27)	(2.74)	(2.09)	(1.58)	(1.76)
Observations	2721	2524	3264	2816	1675	2363	2078	2322	2995	2578
Pseudo R-squared	0.149	0.175	0.172	0.200	0.331	0.257	0.297	0.137	0.121	0.131
AIC	1477.2	1650.2	1484.9	1413.1	588.4	666.3	667.8	1272.6	1049.3	978.1
BIC	1536.3	1708.6	1545.8	1472.6	642.7	724.0	724.2	1330.1	1109.3	1036.6

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.

The share of migrants working as Professionals (ISCO 2, with skill level 4) from both types of origins is also negatively affected by novel innovations. It is important to note that professional occupations encompass a range of roles, including scientists, researchers, engineers, and specialists who are typically inventors of patents. However, these professions also include lawyers, judges, musicians, actors, and artists who are not involved in patent innovation. This suggests that a more detailed analysis of the two- to four-digit occupation classes is needed to draw accurate conclusions. Nevertheless, the results indicate that a higher intensity of granted patents per thousand employees leads to lower employment levels for these professionals, on average. According to Tables 3, 4, and 5, the reduction in employment for these professionals is more pronounced for migrant workers than for native workers.

The share of migrants working as Technicians and associate professionals (ISCO 3, with skill level 3) is also negatively affected by novel innovations. While the number of employees working as Clerks (ISCO 4, with skill level 2) is reduced by novel innovations, the share of migrant workers out of total workers is not affected. Additionally, the number of migrants working as Clerks is not impacted by novel innovations.

Novel innovations reduce the number of employees and migrants working as Plant and machine operators and assemblers (ISCO 8, with skill level 2), as well as those in Elementary occupations (ISCO 9, with skill level 2). They also decrease the share of migrant workers, particularly extra-EU migrants, working in these occupations. This suggests that the reduction in the number of migrant workers due to novel innovations is greater than that of native workers.

Role of robot adoption

As shown in Table 2, the adoption of robots has a heterogeneous impact on the total number of employees across different occupations. While the number of employees in 'high-level' occupations (ISCO 1, ISCO 2, ISCO 3) and lower-level occupations (ISCO 4 and ISCO 9) increases due to robotisation, the total number of employees is reduced overall. This trend is also observed for the number of migrant workers from both types of origin, as presented in the appendix.

According to Table 3, the share of migrant workers, relative to total employees, in occupations such as Legislators, senior officials, and managers (ISCO 1), Professionals (ISCO 2), Clerks (ISCO 4), and Skilled agricultural and fishery workers (ISCO 6) is not significantly affected by the adoption of robots. This suggests that the impact of robotisation is similar for both migrant and native workers in these occupations. However, the share of migrants working as Technicians and associate professionals (ISCO 3), Service workers and shop and market sales workers (ISCO 5), and Elementary occupations (ISCO 9) is positively affected by the adoption of robots. On the other hand, the share of migrants working as Craft and related trades workers (ISCO 7) and Plant and machine operators and assemblers (ISCO 8) is negatively affected by robotisation.

According to Table 4, the adoption of robots increases the share of intra-EU migrants working as Service workers and shop and market sales workers (ISCO 5) in a statistically significant manner. However, the share of intra-EU migrants working as Clerks (ISCO 4), Skilled agricultural and fishery workers (ISCO 6), Craft and related trades workers (ISCO 7), Plant and machine operators and assemblers (ISCO 8), and Elementary occupations (ISCO 9) is negatively affected by the adoption of robots.

According to Table 5, the intensity of robots per thousand employees is positively correlated with the share of extra-EU migrants working in several occupations: Legislators, senior officials, and managers (ISCO 1), Professionals (ISCO 2), Technicians and associate professionals (ISCO 3), Service workers and shop and market sales workers (ISCO 5), and Elementary occupations (ISCO 9). The adoption of robots reduces the share of extra-EU migrants working only as Craft and related trades workers (ISCO 7) in a statistically significant manner.

Role of computing equipment

According to Table 2, the intensity of computing equipment capital per thousand employees has a positive effect on total employment in high-skill jobs. The adoption of these digital assets increases the number of employees in high-skilled occupations such as Legislators, senior officials, and managers (ISCO 1) and Professionals (ISCO 2). Additionally, they also increase medium-skilled employment in the category of Clerks (ISCO 4) and low-skilled employment in Elementary occupations (ISCO 9). However, they have a weak statistically significant negative impact on the total number of Technicians and associate professionals.

As shown in Table 3, these digital assets increase the share of migrants working as Legislators, senior officials, and managers (ISCO 1), as well as Craft and related trades workers (ISCO 7). However, they reduce the share of migrants working as Service workers and shop and market sales workers (ISCO 5), and Plant and machine operators and assemblers (ISCO 8). The results in Table 4 show that these assets have no impact on the share of intra-EU migrant workers relative to total workers. However, the results in Table 5 indicate that the adoption of these digital assets would also decrease the share of extra-EU migrants working as Service workers and shop and market sales workers (ISCO 5), and Plant and machine operators and assemblers (ISCO 8), while other occupations remain unaffected.

Role of communication equipment

According to Table 2, the intensity of communication equipment capital per thousand employees increases the number of workers in Service workers and shop and market sales workers (ISCO 5) as well as Craft and related trades workers (ISCO 7). However, it reduces the number of employees in the categories Legislators, senior officials, and managers (ISCO 1), Technicians and associate professionals (ISCO 3), and Elementary occupations (ISCO 9).

According to Table 3, the intensity of these digital assets per thousand employees increases the share of migrants in the total employee population working as Professionals (ISCO 2) and Service workers and shop and market sales workers (ISCO 5). However, it reduces the share of migrant workers to total employees working as Skilled agricultural and fishery workers (ISCO 6) and Craft and related trades workers (ISCO 7).

As shown in Table 4, these digital assets increase the share of intra-EU migrants relative to total employees working as Professionals (ISCO 2), while they reduce the share of intra-EU migrants relative to total employees working as Craft and related trades workers (ISCO 7).

According to Table 5, these digital assets increase the share of extra-EU migrants working as Professionals (ISCO 2) and Service workers and shop and market sales workers (ISCO 5). However, they decrease the share of extra-EU migrants working as Technicians and associate professionals (ISCO 3).

Role of software and databases

As shown in Table 2, the intensity of software and databases per thousand employees reduces the number of workers in five occupations (Professionals, Technicians and associate professionals, Clerks, Craft and related trades workers, and Elementary occupations), while it increases the number of workers in three occupations (Service workers and shop and market sales workers, Skilled agricultural and fishery workers, Plant and machine operators and assemblers).

According to Table 3, the adoption of these digital assets decreases the share of migrants relative to total employees working in four occupations (Legislators, senior officials, and managers, Technicians and associate professionals, Clerks, and Elementary occupations), while it increases the share of migrant workers relative to total employees in only two occupations (Service workers and shop and market sales workers, and Plant and machine operators and assemblers).

According to Table 4, the intensity of software and databases per thousand employees reduces the share of intra-EU migrants relative to total employees working as Legislators, senior officials and managers (ISCO 1), Technicians and associate professionals (ISCO 3), and Clerks (ISCO 4). However, they reduce the share of intra-EU migrants relative to total employees working as Plant and machine operators and assemblers (ISCO 8).

According to Table 5, these digital assets decrease the share of extra-EU migrants relative to total employees working as Legislators, senior officials and managers (ISCO 1), and Clerks (ISCO 4), Craft and related trades workers (ISCO 7), and Elementary occupations (ISCO 9). However, they increase the share of these migrants working as Service workers and shop and market sales workers (ISCO 5).

Summary

In summary, it can be observed that automation and digitalisation have a similar impact on EU migrants in high-skilled occupations (Legislators, senior officials and managers or Professionals) as they do on native workers, as indicated by coefficients that are not statistically significant in Table 4. However, they affect extra-EU high-skilled migrants differently. Robotisation increases the share of extra-EU migrant workers relative to total employees in these high-skilled occupations. However, novel innovations measured as granted patents would reduce the share of migrant workers in high-skilled occupations, and this effect is more statistically significant for intra-EU migrants. The impact of robotisation and other technologies is more pronounced for intra-EU migrants in low-skilled occupations. The share of extra-EU migrants working in Service workers and shop and market sales workers (ISCO 5 with skill level 2) is the one that is affected differently by various technologies. Their share in other low-skilled occupations is also influenced differently by certain technologies.

5.3. ESTIMATION RESULTS OF MIGRANT WORKERS BY LEVEL OF EDUCATION

In this subsection, the results of the estimation of total employees and the share of migrant workers out of total employees, categorised by their level of education, are presented. Table 6 presents the results of the estimation of equation (1) on the total employment in each sector and country based on the level of education. Table 7 then presents the share of migrant workers relative to total employment with different levels of education and the two types of EU and non-EU origin.

Role of novel innovations

According to Table 6, novel innovations have a negative impact on total employment within a sector of a country across all three levels of education. Specifically, a 1% increase in the intensity of granted patents per thousand employees in a sector leads to a 0.28% reduction in employment for low-educated individuals with primary and lower education, a 0.19% reduction for medium-educated individuals with secondary and post-secondary education, and a 0.24% reduction for highly educated individuals with tertiary education. Additionally, Table 7 reveals that novel innovations also decrease the share of highly educated migrants, primarily due to a reduction in the share of highly educated intra-EU migrants. This indicates that while these innovations decrease the number of employees across all education levels, the reduction is more significant for highly educated intra-EU migrants compared to native workers. Furthermore, the share of low-educated extra-EU migrants is also decreased by the intensity of patents per thousand employees.

Role of robot adoption

According to Table 6, the adoption of industrial robots in a sector of the economy has a positive impact on the number of employees with secondary and post-secondary education, which aligns with the positive impact observed on high-skilled occupations in Table 2. However, there is no statistically significant impact on the employment of highly educated employees. On the other hand, there is a significant negative impact on the number of employees with primary and lower education. This provides evidence that robots tend to replace jobs held by individuals with lower levels of education, while simultaneously increasing job opportunities for those with middle-level education. However, there is no discernible impact on the employment of highly educated employees.

As noted above for the results of Table 1, the share of migrants and in particular the share of non-EU migrants increases with the adoption of robots. According to Table 7, one can observe that this positive impact stems from the strong positive impact of robotisation on the share of highly educated extra-EU migrant workers relative to total workers with tertiary education. In fact, a 1% increase in the intensity of industrial robots per thousand employees in a sector of a country would increase the share of intra-EU migrants relative to total workers with tertiary education by 0.16%, which is statistically significant at the 1% level. It is important to note that according to Table A7 in the appendix, the number of migrant workers with tertiary education from both types of origin is significantly increased by the adoption of robots, although the total employment of highly educated workers is unaffected according to Table 6. This suggests that robotisation welcomes highly educated migrants while it replaces the jobs of migrants with low and medium levels of education.

Role of computing equipment

According to Table 6, the intensity of computing equipment per thousand employees has a statistically significant impact on increasing the number of employees with secondary and post-secondary education, as well as tertiary education. However, as shown in Table 7, there is no statistically significant difference in the impact of these digital assets between native workers and migrant workers. The only significant effect observed is an increase in the share of extra-EU migrant workers relative to total workers with tertiary education, which is statistically significant at the 10% level.

Role of communication equipment

According to Table 6, the intensity of communication equipment per thousand employees has a negative impact on the number of medium-educated employees with secondary and post-secondary education, while it does not significantly affect the employment of other levels of education. As shown in Table 7, the adoption of these technologies leads to a reduction in the share of medium and highly educated migrant workers with secondary and post-secondary education, as well as tertiary education. However, the impact of these digital assets on the share of migrant workers based on their origin and level of education is statistically insignificant.

Role of software and databases

Table 6 shows that the intensity of software and database assets per thousand employees has a strong negative impact on the number of employees with all three levels of education. However, these assets increase the share of medium-educated migrant workers, which stems from the strong positive impact on the share of extra-EU migrant workers with secondary and post-secondary education. Adoption of these technologies decreases the share of highly educated migrant workers, which stems from the strong positive impact on the share of intra-EU migrant workers with tertiary education, while the positive impact on the share of extra-EU migrant workers with tertiary education is statistically significant only at the 10% level.

6. Summary and concluding remarks

The development of novel technologies in the past decades has intensified with the globalisation process, which has pushed countries to enhance their competitiveness through innovation. Many of these new technologies have had a significant impact on improving the welfare of global society, such as facilitating tasks and enhancing productivity in essential sectors like healthcare, where it has played a crucial role in combating the COVID-19 pandemic. However, some of these technologies, like the adoption of robots, can have adverse effects on the job market by replacing workers and tasks. Other technologies, such as the emergence of artificial intelligence (AI) in the form of digital assets, not only replace certain tasks but also introduce complexities to the performed tasks, which can lead to displacement of employees who are unable to adapt to these technologies. While the recent literature extensively analyses the heterogeneous effects of these novel technologies on labour market dynamics, there is a lack of studies examining their impact on migrant workers. This paper presents pioneering evidence on the effects of various forms of these novel technologies on the employment of migrant workers in the European Union. The analysis is conducted at the aggregate sector-level for 18 EU member states from 2005 to 2019, using data on migrant workers compiled from Labour Force Surveys provided by Eurostat. The paper focuses on novel innovations measured by granted patents, robot adoption, three types of digital assets, and total factor productivity, accounting for these factors and other production factors.

The econometric analysis is performed on multiple samples of workers and migrant workers based on their origin, distinguishing between migrants born in other EU countries and those born outside the EU. Additionally, estimations are carried out based on workers' and migrants' occupations and levels of education. The main findings indicate that novel innovations, measured by the number of granted patents owned by firms in each sector-country combination, increase the share of migrant workers relative to the total workforce, while reducing the total number of workers and migrant workers. While robots do replace jobs, they affect the employment of native workers more than non-EU migrant workers, resulting in an increased share of non-EU migrant workers due to robot adoption. Total factor productivity has a positive impact on migrant workers, while the effects of digital assets are varied. Furthermore, the impacts of these technologies on migrant workers differ significantly across different occupation types and education levels. Overall, this study aims to highlight important aspects of the relationship between technology, migration, and labour markets.

However, it is important to emphasise that technological change and automation are not inevitable forces but rather choices made by humans. The notion that automation is a solution to labour shortages is extensively discussed in relation to attracting investment and gaining support in the business and policy arenas. However, many industries face shortages due to restrictions on immigration rather than a lack of available workers. Barriers to migration often create labour scarcity, compelling businesses to invest in technology to replace workers instead of allowing people to move to where their skills are needed. Moreover, restrictions on migration have substantial impacts on wages and economic productivity as they contribute to labour shortages. These barriers to migration create significant wage differentials between workers in different countries. Additionally, allowing more skilled workers to migrate can lead to changes in innovation patterns. As argued by Pritchett (2023), the current approach of favouring machines over people may be a mistake. It should be emphasised that technology is not always the most suitable solution for certain tasks, such as personal care, cooking, and truck driving. Barriers to labour mobility can distort the trajectory of technological change, prompting businesses to invest in unnecessary and inefficient automation, as demonstrated by Pritchett (2023). For example, the elimination of the Bracero Program in the United States, which allowed seasonal migration of agricultural guest workers from Mexico, resulted in increased reliance on machines and technological advancements in the agricultural sector. The false sense of necessity created by barriers to migration leads to inefficient inventions and wasted resources.

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Appendix

DISCUSSION OF MEASUREMENT OF LABOUR PRODUCTIVITY AND TFP

Since equation (1) estimates the share of migrant workers against patents and robot intensity in addition to TFP, the Solow residual is estimated net of these variables to analyse how other forms of technologies could affect migration. Therefore, the TFP estimation of output controls for granted patents and robot intensity is estimated following the methodology proposed by Ackerberg et al. (2015, ACF) that controls for the functional dependence of variables estimated in the production function. Therefore, real gross output (in constant 2015 USD) Y_{ict} is used as the dependent variable of the production function that is estimated by this approach against labour L_{ict}, while state variables are real capital stocks K_{ict}, robot to labour intensity s_{ict}, and granted patents P_{ict}, and the proxy variable for unobserved time-varying productivity is real costs on intermediate input II_{ict}. The estimated TFP using this approach is used in the benchmark models as $\mathrm{TFP}_{ict}^{ACF,GO,II}$, while robustness specifications include labour productivity in terms of gross output relative to labour y_{ict}^{GO}, labour productivity in terms of value added relative to labour y_{ict}^{VA}, and TFP estimated using six other methodologies as follows:

1. $\mathrm{TFP}_{ict}^{ACF,GO,I}$ estimated using real gross output following the ACF methodology but including real investment I_{ict} or gross fixed capital formation (GFCF) as the proxy variable for unobserved time-varying productivity following Olley and Pakes (1996) instead of intermediate input II_{ict} following ACF.

2. $\mathrm{TFP}_{ict}^{ACF,VA,II}$ estimated using real value added VA_{ict} following the ACF methodology but including intermediate input II_{ict} as the proxy variable.

3. $\mathrm{TFP}_{ict}^{ACF,VA,I}$ estimated using real value added VA_{ict} following the ACF methodology but including real investment I_{ict} as the proxy variable instead of intermediate input II_{ict}.

4. $\mathrm{TFP}_{ict}^{TLP,GO}$ estimated as the residual of the trans-log production of real gross output Y_{ict} of a sector-country-year combination as a function of capital stocks K_{ict}, number of employees L_{ict}, intermediate inputs II_{ict}, intensity of robots to employees s_{ict}, and the number of granted patents P_{ict}.

5. $\mathrm{TFP}_{ict}^{TLP,VA}$ estimated as the residual of the trans-log production of value added VA_{ict} of a sector-country-year combination as a function of capital stocks K_{ict}, number of employees L_{ict}, intermediate inputs II_{ict}, intensity of robots to employees s_{ict}, and the number of granted patents P_{ict}.

6. $\mathrm{TFP}_{ict}^{W,GO,I}$ estimated using real gross output augmenting the generalised method of moments (GMM) methodology proposed by Wooldridge (2009) where the first lag and second lag of granted patents P_{ict}, and first lag of intensity of robots to employees s_{ict} are included as exogenous variables in addition to the standard variables in his approach; and the second lag of robot intensity in addition to the second lag of intermediate input II_{ict} and first lag of number of employees L_{ict} are considered as exogenous instruments variables, while intermediate input II_{ict} and number of employees L_{ict} are the endogenous variables in his GMM.

Table A1 / PPML estimation results of share of migrant workers in total number of employees during the period 2005-2019, stepwise addition of technological variables

Dependent variables: m_{ict+1}	M1	M2	M3	M4	M5	M6	M7	M8
P_{ict}	0.12***							0.11***
	(0.027)							(0.026)
s_{ict}	0.075***						0.10***	
	(0.027)						(0.027)	
D_{ict}^{IT}	-0.014					-0.015		
	(0.029)					(0.029)		
D_{ict}^{CT}	-0.073*				-0.051			
	(0.041)				(0.040)			
D_{ict}^{SD}	0.12***			0.11***				
	(0.035)			(0.034)				
$\mathrm{TFP}_{ict}^{ACF,GO,II}$	0.20***		0.20***					
	(0.067)		(0.069)					
K_{ict}	-0.0013***	-0.0013***	-0.0011***	-0.0015***	-0.0012***	-0.0013***	-0.0013***	-0.0013***
	(0.00031)	(0.00031)	(0.00032)	(0.00031)	(0.00030)	(0.00031)	(0.00030)	(0.00030)
w_{ict}	-0.42***	-0.36***	-0.38***	-0.38***	-0.36***	-0.36***	-0.40***	-0.37***
	(0.097)	(0.091)	(0.091)	(0.092)	(0.090)	(0.094)	(0.095)	(0.090)
VA_{ict}	0.10*	0.14**	0.074	0.14**	0.14***	0.15***	0.16***	0.16***
	(0.057)	(0.056)	(0.057)	(0.054)	(0.055)	(0.056)	(0.056)	(0.055)
Constant	1.55	0.74	1.43	0.93	0.71	0.69	1.03	0.56
	(1.02)	(0.93)	(0.96)	(0.95)	(0.92)	(0.97)	(0.96)	(0.93)
Observations	2721	2721	2721	2721	2721	2721	2721	2721
Pseudo R-squared	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149
AIC	1477.2	1465.6	1467.5	1467.5	1467.6	1467.6	1467.6	1467.5
BIC	1536.3	1489.2	1497.1	1497.1	1497.1	1497.2	1497.1	1497.0

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.

Table A2 / PPML estimation results of share of migrant workers in total number of employees during the period 2005-2019, including different measures on productivity

Dependent variable:	m_{ict+1}								
Productivity variables:	$\mathrm{TFP}_{ict}^{ACF,GO,II}$	$\mathrm{TFP}_{ict}^{ACF,GO,I}$	$\mathrm{TFP}_{ict}^{ACF,VA,II}$	$\mathrm{TFP}_{ict}^{ACF,VA,I}$	$\mathrm{TFP}_{ict}^{TLP,GO}$	$\mathrm{TFP}_{ict}^{TLP,VA}$	$\mathrm{TFP}_{ict}^{W,GO,I}$	y_{ict}^{GO}	y_{ict}^{VA}
P_{ict}	0.12***	0.12***	0.11***	0.12***	0.11***	0.10***	0.11***	0.096***	0.11***
	(0.027)	(0.027)	(0.030)	(0.030)	(0.027)	(0.027)	(0.028)	(0.028)	(0.028)
s_{ict}	0.075***	0.084***	0.081***	0.064**	0.070**	0.11***	0.074***	0.074***	0.092***
	(0.027)	(0.026)	(0.027)	(0.027)	(0.028)	(0.031)	(0.027)	(0.027)	(0.029)
D_{ict}^{IT}	-0.014	-0.020	-0.032	-0.043	-0.015	-0.031	-0.018	-0.021	-0.027
	(0.029)	(0.028)	(0.030)	(0.028)	(0.029)	(0.029)	(0.029)	(0.028)	(0.028)
D_{ict}^{CT}	-0.073*	-0.072*	-0.070	-0.061	-0.068	-0.076*	-0.073*	-0.078*	-0.069*
	(0.041)	(0.042)	(0.043)	(0.042)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
D_{ict}^{SD}	0.12***	0.13***	0.12***	0.12***	0.14***	0.11***	0.12***	0.11***	0.12***
	(0.035)	(0.035)	(0.036)	(0.036)	(0.035)	(0.037)	(0.035)	(0.035)	(0.035)
$\mathrm{productivity}_{ict}$	0.20***	0.25	-0.66	-2.06**	0.20***	-0.13	0.14***	0.18***	-0.11
	(0.067)	(0.21)	(1.03)	(0.91)	(0.065)	(0.090)	(0.056)	(0.060)	(0.12)
K_{ict}	-0.0013***	-0.0015***	-0.0015***	-0.0014***	-0.0015***	-0.0015***	-0.0015***	-0.0016***	-0.0014***
	(0.00031)	(0.00029)	(0.00030)	(0.00029)	(0.00029)	(0.00029)	(0.00029)	(0.00030)	(0.00031)
w_{ict}	-0.42***	-0.41***	-0.38***	-0.26**	-0.38***	-0.41***	-0.41***	-0.47***	-0.36***
	(0.097)	(0.097)	(0.11)	(0.10)	(0.10)	(0.096)	(0.097)	(0.096)	(0.11)
VA_{ict}	0.10*	0.15**	0.14**	0.043	0.13**	0.21***	0.13**	0.12**	0.21***
	(0.057)	(0.059)	(0.072)	(0.081)	(0.056)	(0.060)	(0.056)	(0.055)	(0.065)
Constant	1.55	0.71	-2.14	-8.43**	0.69	0.63	1.03	1.11	0.36
	(1.02)	(1.04)	(4.81)	(4.02)	(1.01)	(0.99)	(1.00)	(1.00)	(1.04)
Observations	2721	2721	2722	2722	2721	2722	2721	2721	2722
Pseudo R-squared	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149
AIC	1477.2	1477.3	1477.6	1477.5	1477.2	1477.6	1477.2	1477.2	1477.6
BIC	1536.3	1536.4	1536.7	1536.6	1536.3	1536.7	1536.3	1536.3	1536.7

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.

Table A3 / PPML estimation results of migrant workers by their origin during the period 2005-2019, contemporaneous variables

Dependent variables:	m_{ict}	m_{ict}^{EU}	m_{ict}^{nonEU}	M_{ict}	M_{ict}^{EU}	M_{ict}^{nonEU}	l_{ict}
P_{ict}	0.11***	0.088**	0.21***	-0.060	-0.17***	-0.053	-0.13***
	(0.032)	(0.035)	(0.074)	(0.044)	(0.043)	(0.050)	(0.019)
s_{ict}	0.073**	-0.013	0.10***	-0.10***	-0.026	-0.10***	-0.030***
	(0.032)	(0.038)	(0.039)	(0.028)	(0.027)	(0.033)	(0.0088)
D_{ict}^{IT}	-0.013	-0.069	0.024	0.055	-0.020	0.052	0.069***
	(0.029)	(0.043)	(0.044)	(0.045)	(0.039)	(0.046)	(0.017)
D_{ict}^{CT}	-0.054	0.050	-0.11*	0.011	0.069**	-0.030	-0.044**
	(0.041)	(0.058)	(0.061)	(0.033)	(0.031)	(0.037)	(0.019)
D_{ict}^{SD}	0.13***	0.067*	0.14**	-0.090**	-0.0030	-0.11**	-0.053***
	(0.035)	(0.036)	(0.057)	(0.040)	(0.035)	(0.044)	(0.019)
$\mathrm{TFP}_{ict}^{ACF,GO,II}$	0.23***	0.18**	0.27***	0.15**	-0.053	0.17**	0.067**
	(0.070)	(0.073)	(0.10)	(0.062)	(0.072)	(0.067)	(0.034)
K_{ict}	-0.0013***	0.00072	-0.0019***	-0.0018***	-0.0015***	-0.0023***	-0.00073***
	(0.00030)	(0.00045)	(0.00037)	(0.00038)	(0.00034)	(0.00037)	(0.00016)
w_{ict}	-0.42***	-0.16	-0.55***	-0.71***	-0.63***	-0.64***	-0.49***
	(0.10)	(0.13)	(0.13)	(0.095)	(0.13)	(0.093)	(0.037)
VA_{ict}	0.13**	0.055	0.16*	0.72***	0.65***	0.74***	0.51***
	(0.061)	(0.089)	(0.084)	(0.075)	(0.086)	(0.078)	(0.039)
Constant	1.26	-1.15	1.52	5.11***	3.59***	4.18***	7.02***
	(1.02)	(1.21)	(1.36)	(0.78)	(1.18)	(0.90)	(0.40)
Observations	2532	1948	2478	2532	1948	2478	2532
Pseudo R-squared	0.149	0.250	0.095	0.972	0.908	0.972	0.993
AIC	1368.4	589.9	1027.6	14782.0	8679.9	13059.8	24962.2
BIC	1426.8	645.6	1085.8	14840.3	8735.6	13118.0	25020.5

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.

Table A4 / PPML estimation results of the number of migrant workers by ISCO occupations during the period 2005-2019

Dependent variable:	M_{ict}	$M_{ict+1}^{ISCO,1}$	$M_{ict+1}^{ISCO,2}$	$M_{ict+1}^{ISCO,3}$	$M_{ict+1}^{ISCO,4}$	$M_{ict+1}^{ISCO,5}$	$M_{ict+1}^{ISCO,6}$	$M_{ict+1}^{ISCO,7}$	$M_{ict+1}^{ISCO,8}$	$M_{ict+1}^{ISCO,9}$
P_{ict}	-0.013	0.98***	-0.29***	-0.35***	0.034	0.57***	4.08***	-0.084	-0.88***	-0.77***
	(0.040)	(0.17)	(0.081)	(0.082)	(0.089)	(0.12)	(0.89)	(0.076)	(0.12)	(0.15)
s_{ict}	-0.099***	0.34***	0.20***	0.46***	0.22***	0.17	-1.95*	-0.32***	-0.32***	0.42***
	(0.025)	(0.084)	(0.052)	(0.050)	(0.053)	(0.12)	(1.04)	(0.031)	(0.043)	(0.064)
D_{ict}^{IT}	0.089**	0.48***	0.17**	-0.020	0.26***	-0.18**	-1.47*	0.63***	-0.27**	0.71***
	(0.044)	(0.16)	(0.069)	(0.083)	(0.082)	(0.083)	(0.87)	(0.13)	(0.11)	(0.15)
D_{ict}^{CT}	0.038	-0.15	0.0066	-0.24**	0.16	0.50***	1.11	0.23***	0.044	-0.19**
	(0.032)	(0.15)	(0.061)	(0.11)	(0.10)	(0.071)	(0.80)	(0.065)	(0.065)	(0.079)
D_{ict}^{SD}	-0.099**	-0.090	-0.15***	-0.054	-0.32***	0.52***	1.76***	-0.28***	-0.064	-1.11***
	(0.039)	(0.11)	(0.046)	(0.090)	(0.089)	(0.073)	(0.56)	(0.062)	(0.074)	(0.10)
$\mathrm{TFP}_{ict}^{ACF,GO,II}$	0.33***	0.18	-0.14	-0.60***	-0.32*	-0.65***	1.15	-0.037	0.68***	1.03***
	(0.077)	(0.32)	(0.13)	(0.13)	(0.17)	(0.12)	(1.18)	(0.15)	(0.18)	(0.20)
K_{ict}	-0.0013***	0.0036***	-0.00028	-0.00029	-0.0012**	-0.0084***	-0.024***	-0.0013**	-0.0011*	-0.000091
	(0.00035)	(0.00100)	(0.00046)	(0.00050)	(0.00049)	(0.0014)	(0.0039)	(0.00060)	(0.00058)	(0.00084)
w_{ict}	-0.64***	-2.64***	0.37*	-1.11***	-0.87***	0.62***	-3.53***	-0.21*	-1.33***	-0.81***
	(0.082)	(0.36)	(0.22)	(0.21)	(0.20)	(0.17)	(0.69)	(0.11)	(0.21)	(0.17)
VA_{ict}	0.66***	1.13***	0.25	0.83***	1.02***	-0.050	-0.68	0.90***	1.58***	0.58***
	(0.071)	(0.31)	(0.19)	(0.16)	(0.16)	(0.15)	(1.15)	(0.10)	(0.18)	(0.16)
Constant	4.86***	15.8***	-2.57	6.06***	0.47	-0.83	50.5***	-3.11**	0.79	6.53***
	(0.79)	(2.98)	(2.05)	(2.32)	(1.84)	(1.58)	(13.6)	(1.33)	(2.45)	(2.13)
Observations	2721	1629	2178	2077	1661	1922	286	1768	1767	2528
Pseudo R-squared	0.972	0.816	0.914	0.901	0.863	0.932	0.848	0.952	0.931	0.891
AIC	16089.7	6386.7	8743.0	9435.1	6746.4	9285.3	877.8	8112.4	6732.4	14262.4
BIC	16148.7	6440.6	8799.9	9491.4	6800.6	9341.0	914.4	8167.1	6787.2	14320.8

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.
ISCO occupations: 1. Legislators, senior officials and managers; 2. Professionals; 3. Technicians and associate professionals; 4. Clerks; 5. Service workers and shop and market sales workers; 6. Skilled agricultural and fishery workers; 7. Craft and related trades workers; 8. Plant and machine operators and assemblers; 9. Elementary occupations.

Table A5 / PPML estimation results of the number of intra-EU migrant workers by ISCO occupations during the period 2005-2019

Dependent variable:	M_{ict}	$M_{ict+1}^{EU,ISCO,1}$	$M_{ict+1}^{EU,ISCO,2}$	$M_{ict+1}^{EU,ISCO,3}$	$M_{ict+1}^{EU,ISCO,4}$	$M_{ict+1}^{EU,ISCO,5}$	$M_{ict+1}^{EU,ISCO,6}$	$M_{ict+1}^{EU,ISCO,7}$	$M_{ict+1}^{EU,ISCO,8}$	$M_{ict+1}^{EU,ISCO,9}$
P_{ict}	-0.15***	0.96***	-0.43***	-0.33***	-0.41**	0.41***	-5.75**	-0.14	-1.38***	-1.28***
	(0.037)	(0.25)	(0.092)	(0.11)	(0.20)	(0.14)	(2.81)	(0.13)	(0.21)	(0.29)
s_{ict}	-0.031	0.23**	0.12*	0.30***	0.15	1.39***	-13.1*	-0.31***	-0.37***	0.23*
	(0.023)	(0.12)	(0.066)	(0.077)	(0.11)	(0.51)	(6.72)	(0.039)	(0.085)	(0.12)
D_{ict}^{IT}	-0.037	-0.39*	0.092	0.13	0.072	-0.53***	-4.38	0.32***	0.25	0.20
	(0.036)	(0.21)	(0.093)	(0.11)	(0.12)	(0.12)	(3.36)	(0.11)	(0.23)	(0.19)
D_{ict}^{CT}	0.077***	0.20	0.019	-0.17	-0.19	0.99***	2.76	-0.27***	0.020	-0.14
	(0.028)	(0.18)	(0.087)	(0.12)	(0.14)	(0.098)	(1.73)	(0.10)	(0.13)	(0.13)
D_{ict}^{SD}	0.029	-0.16	-0.52***	0.13	-0.080	0.33***	1.91	0.020	-0.025	-1.16***
	(0.034)	(0.16)	(0.079)	(0.10)	(0.13)	(0.089)	(1.36)	(0.075)	(0.11)	(0.15)
$\mathrm{TFP}_{ict}^{ACF,GO,II}$	0.15**	-0.045	0.40**	-0.34	0.15	-0.34**	-0.43	0.11	1.14***	1.67***
	(0.070)	(0.53)	(0.19)	(0.23)	(0.26)	(0.15)	(2.85)	(0.22)	(0.32)	(0.32)
K_{ict}	-0.0011***	0.00070	0.0060***	-0.00017	-0.00032	-0.011***	0.010	-0.00074	0.0031**	0.0033***
	(0.00030)	(0.0020)	(0.00094)	(0.0013)	(0.0012)	(0.0022)	(0.016)	(0.00073)	(0.0013)	(0.0012)
w_{ict}	-0.52***	-1.35**	0.51	-0.48	-1.21***	-0.50**	-0.53	0.25	-2.13***	-1.02***
	(0.11)	(0.56)	(0.32)	(0.30)	(0.40)	(0.20)	(1.37)	(0.23)	(0.37)	(0.31)
VA_{ict}	0.61***	0.45	-0.020	-0.55*	-0.37	1.11***	2.66	0.75***	1.14***	0.65**
	(0.078)	(0.45)	(0.25)	(0.28)	(0.37)	(0.20)	(1.78)	(0.13)	(0.24)	(0.26)
Constant	2.79***	10.0**	-3.27	13.7***	19.5***	-3.77**	-24.4	-7.12***	11.7***	6.03*
	(1.03)	(4.78)	(3.15)	(3.95)	(4.79)	(1.91)	(18.6)	(2.13)	(3.82)	(3.55)
Observations	2109	1007	1695	1560	1125	1334	121	1066	989	1505
Pseudo R-squared	0.915	0.570	0.791	0.726	0.638	0.818	0.739	0.895	0.820	0.741
AIC	9437.1	2748.5	4950.4	4753.6	3019.9	4329.5	293.2	3647.5	2734.2	5225.7
BIC	9493.7	2797.7	5004.8	4807.1	3070.1	4381.4	321.1	3697.3	2783.2	5278.9

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.
ISCO occupations: 1. Legislators, senior officials and managers; 2. Professionals; 3. Technicians and associate professionals; 4. Clerks; 5. Service workers and shop and market sales workers; 6. Skilled agricultural and fishery workers; 7. Craft and related trades workers; 8. Plant and machine operators and assemblers; 9. Elementary occupations.

Table A6 / PPML estimation results of the number of extra-EU migrant workers by ISCO occupations during the period 2005-2019

Dependent variable:	M_{ict}	$M_{ict+1}^{nEU,ISCO,1}$	$M_{ict+1}^{nEU,ISCO,2}$	$M_{ict+1}^{nEU,ISCO,3}$	$M_{ict+1}^{nEU,ISCO,4}$	$M_{ict+1}^{nEU,ISCO,5}$	$M_{ict+1}^{nEU,ISCO,6}$	$M_{ict+1}^{nEU,ISCO,7}$	$M_{ict+1}^{nEU,ISCO,8}$	$M_{ict+1}^{nEU,ISCO,9}$
P_{ict}	-0.0015	0.94***	-0.28***	-0.34***	0.090	0.64***	4.08***	-0.066	-0.77***	-0.70***
	(0.047)	(0.20)	(0.11)	(0.098)	(0.100)	(0.14)	(0.96)	(0.083)	(0.12)	(0.14)
s_{ict}	-0.099***	0.50***	0.23***	0.48***	0.23***	0.049	-0.97	-0.28***	-0.31***	0.41***
	(0.028)	(0.100)	(0.059)	(0.057)	(0.056)	(0.13)	(0.69)	(0.036)	(0.044)	(0.059)
D_{ict}^{IT}	0.091*	0.84***	0.26***	-0.034	0.31***	-0.12	-1.78**	0.51***	-0.23*	0.72***
	(0.047)	(0.19)	(0.083)	(0.097)	(0.10)	(0.092)	(0.86)	(0.13)	(0.12)	(0.14)
D_{ict}^{CT}	-0.010	-0.47**	-0.11	-0.26**	0.16	0.37***	0.49	0.19**	0.049	-0.20***
	(0.037)	(0.19)	(0.080)	(0.13)	(0.12)	(0.076)	(0.81)	(0.075)	(0.068)	(0.073)
D_{ict}^{SD}	-0.12***	-0.016	-0.0013	-0.055	-0.34***	0.58***	1.86***	-0.30***	-0.13	-1.04***
	(0.044)	(0.12)	(0.055)	(0.11)	(0.11)	(0.082)	(0.58)	(0.067)	(0.081)	(0.10)
$\mathrm{TFP}_{ict}^{ACF,GO,II}$	0.33***	0.18	-0.27*	-0.57***	-0.30	-0.78***	1.20	-0.22	0.69***	0.93***
	(0.087)	(0.37)	(0.14)	(0.14)	(0.20)	(0.14)	(1.34)	(0.15)	(0.19)	(0.19)
K_{ict}	-0.0017***	0.0039***	-0.0012***	-0.00064	-0.0016***	-0.0088***	-0.027***	-0.0024***	-0.0017***	-0.0012
	(0.00036)	(0.0012)	(0.00045)	(0.00053)	(0.00053)	(0.0015)	(0.0042)	(0.00056)	(0.00062)	(0.00079)
w_{ict}	-0.58***	-2.82***	0.33	-1.20***	-0.91***	0.85***	-3.85***	-0.22**	-1.14***	-0.79***
	(0.083)	(0.42)	(0.26)	(0.23)	(0.22)	(0.19)	(0.90)	(0.11)	(0.23)	(0.16)
VA_{ict}	0.67***	1.24***	0.39*	1.13***	1.17***	-0.30*	-0.45	0.92***	1.65***	0.54***
	(0.075)	(0.37)	(0.21)	(0.17)	(0.17)	(0.16)	(1.64)	(0.11)	(0.18)	(0.15)
Constant	4.04***	16.1***	-3.94*	3.26	-1.06	-0.45	52.4***	-3.13**	-2.16	6.90***
	(0.90)	(3.43)	(2.25)	(2.32)	(1.82)	(1.78)	(17.5)	(1.41)	(2.62)	(2.19)
Observations	2663	1338	1900	1746	1371	1819	262	1643	1602	2307
Pseudo R-squared	0.971	0.814	0.914	0.903	0.857	0.927	0.823	0.948	0.927	0.890
AIC	14231.7	5212.8	7002.7	7707.0	5837.6	8261.8	787.7	6983.5	5920.4	12009.9
BIC	14290.6	5264.8	7058.2	7761.6	5889.9	8316.9	823.4	7037.5	5974.2	12067.3

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.
ISCO occupations: 1. Legislators, senior officials and managers; 2. Professionals; 3. Technicians and associate professionals; 4. Clerks; 5. Service workers and shop and market sales workers; 6. Skilled agricultural and fishery workers; 7. Craft and related trades workers; 8. Plant and machine operators and assemblers; 9. Elementary occupations.

Table A7 / PPML estimation results of the number of migrant workers by ISCED levels of education from different origins, 2005-2019

Dependent variable:	M_{ict}	$M_{ict+1}^{ISCED,L}$	$M_{ict+1}^{ISCED,M}$	$M_{ict+1}^{ISCED,H}$	$M_{ict+1}^{EU,ISCED,L}$	$M_{ict+1}^{EU,ISCED,M}$	$M_{ict+1}^{EU,ISCED,H}$	$M_{ict+1}^{nEU,ISCED,L}$	$M_{ict+1}^{nEU,ISCED,M}$	$M_{ict+1}^{nEU,ISCED,H}$
P_{ict}	-0.013	-0.57***	-0.18***	-0.23***	-0.90***	-0.37***	-0.38***	-0.51***	-0.16***	-0.16**
	(0.040)	(0.068)	(0.052)	(0.056)	(0.12)	(0.075)	(0.067)	(0.070)	(0.057)	(0.072)
s_{ict}	-0.099***	-0.14***	-0.059**	0.13***	-0.24***	-0.14***	0.13***	-0.096***	-0.010	0.11**
	(0.025)	(0.031)	(0.024)	(0.035)	(0.047)	(0.035)	(0.047)	(0.032)	(0.025)	(0.044)
D_{ict}^{IT}	0.089**	0.27***	0.23***	0.11*	0.16	0.23***	0.069	0.26***	0.21***	0.10
	(0.044)	(0.082)	(0.051)	(0.056)	(0.10)	(0.067)	(0.063)	(0.083)	(0.053)	(0.067)
D_{ict}^{CT}	0.038	-0.10**	-0.063*	0.00035	-0.16**	-0.034	-0.081	-0.11**	-0.11***	0.0034
	(0.032)	(0.046)	(0.035)	(0.054)	(0.065)	(0.048)	(0.060)	(0.047)	(0.038)	(0.067)
D_{ict}^{SD}	-0.099**	-0.19***	-0.22***	-0.16***	-0.12*	-0.080	-0.42***	-0.17***	-0.24***	-0.083
	(0.039)	(0.041)	(0.039)	(0.051)	(0.067)	(0.060)	(0.066)	(0.042)	(0.043)	(0.058)
$\mathrm{TFP}_{ict}^{ACF,GO,II}$	0.33***	0.23**	0.057	0.15	0.58***	0.0083	0.74***	0.13	0.057	0.050
	(0.077)	(0.10)	(0.084)	(0.098)	(0.16)	(0.11)	(0.17)	(0.10)	(0.089)	(0.097)
K_{ict}	-0.0013***	-0.0021***	-0.0018***	-0.00021	0.00026	-0.0018***	0.0028***	-0.0030***	-0.0022***	-0.00065
	(0.00035)	(0.00046)	(0.00039)	(0.00039)	(0.00062)	(0.00053)	(0.00068)	(0.00046)	(0.00038)	(0.00040)
w_{ict}	-0.64***	-0.25**	-0.63***	0.018	0.27	-0.26	0.23	-0.34***	-0.64***	-0.083
	(0.082)	(0.11)	(0.099)	(0.12)	(0.20)	(0.17)	(0.17)	(0.11)	(0.11)	(0.13)
VA_{ict}	0.66***	0.68***	0.92***	0.31***	0.49***	0.74***	0.40***	0.72***	0.97***	0.42***
	(0.071)	(0.082)	(0.070)	(0.098)	(0.14)	(0.10)	(0.15)	(0.085)	(0.073)	(0.11)
Constant	4.86***	0.050	1.21	0.82	-4.85**	-1.72	-3.82*	0.56	0.71	0.33
	(0.79)	(1.10)	(0.92)	(1.23)	(1.90)	(1.61)	(2.01)	(1.11)	(1.04)	(1.33)
Observations	2721	2572	3285	2914	1711	2364	2143	2346	3013	2629
Pseudo R-squared	0.972	0.938	0.952	0.927	0.828	0.846	0.811	0.934	0.953	0.923
AIC	16089.7	14120.9	16120.2	13911.5	6545.9	9189.4	7675.9	12335.1	13703.7	11717.5
BIC	16148.7	14179.4	16181.2	13971.3	6600.3	9247.1	7732.6	12392.7	13763.8	11776.3

Robust standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.
These estimations include country-time δ_{ct} and country-sector δ_{ci} fixed effects.

Table A8 / Summary statistics of the main variables across sectors in the sample of estimations, averaged over the period 2006-2019

Sectors	Sector Description	Share of all migrants in labour	Share of all EU migrants in labour	Share of all non-EU migrants in labour	Number of granted patents	Share of Computing capital in total	Share of communication capital in total	Share of software capital in total	Output-weighted TFP ACF	Capital stock net of all assets constant USD 2015 mn	Average labour cost in terms of real wage of each employed person USD	GVA constant USD 2015 mn	Intensity of stock robots in 1000 employment
A	Agriculture	10.7%	3.5%	7.2%	317	0.1%	0.1%	0.1%	-0.24	655,442	9,074	133,173	0.11
C	Mining	5.5%	1.7%	3.8%	374	0.2%	0.5%	0.6%	-0.34	97,953	50,342	18,469	0.35
D	Manufacturing	12.9%	2.7%	10.2%	106,582	0.5%	0.8%	2.7%	0.91	2,987,316	47,887	1,822,579	13.76
E	Utilities	5.8%	1.3%	4.5%	669	0.2%	0.6%	0.9%	-0.04	1,556,537	60,720	296,872	0.08
F	Construction	16.7%	5.3%	11.5%	1,115	0.3%	0.3%	0.9%	1.53	824,624	33,312	604,109	0.08
G	Wholesale trade	11.4%	2.4%	9.0%	10,082	1.3%	1.0%	3.8%	0.97	1,111,148	29,432	1,209,928	
I	Hotel Restaurant	25.9%	5.3%	20.6%	76	0.5%	1.1%	0.7%	1.07	384,864	22,379	323,847	
K	Financial and Insurance	6.2%	1.8%	4.4%	4,845	2.3%	1.1%	7.8%	1.10	635,463	73,725	558,945	
MtN&P&H&J	All other services	11.1%	2.5%	8.6%	38,403	0.2%	0.4%	0.9%	-0.99	26,425,073	40,191	4,087,237	0.07
O	Public Admin	4.8%	1.2%	3.6%	30	0.4%	0.3%	0.8%	-0.41	3,821,782	52,866	737,881	
Q	Health and social work	11.0%	2.5%	8.4%	512	0.8%	0.8%	1.2%	0.59	1,122,683	35,667	822,883	
R	Other community social and personal service	12.6%	3.1%	9.5%	670	0.8%	1.2%	1.7%	0.33	681,212	26,706	351,305	0.11

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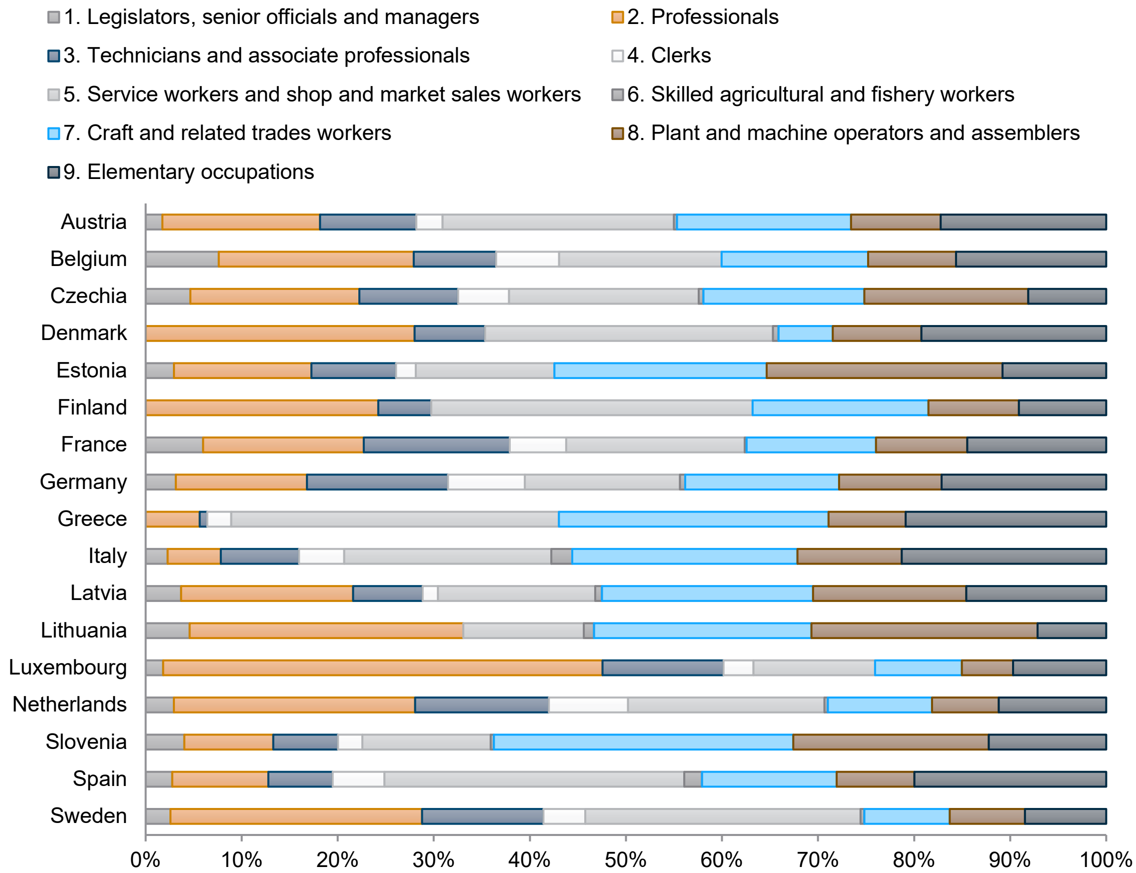
Table A9 / Summary statistics of the main variables across countries in the sample of estimations, averaged over the period 2006-2019

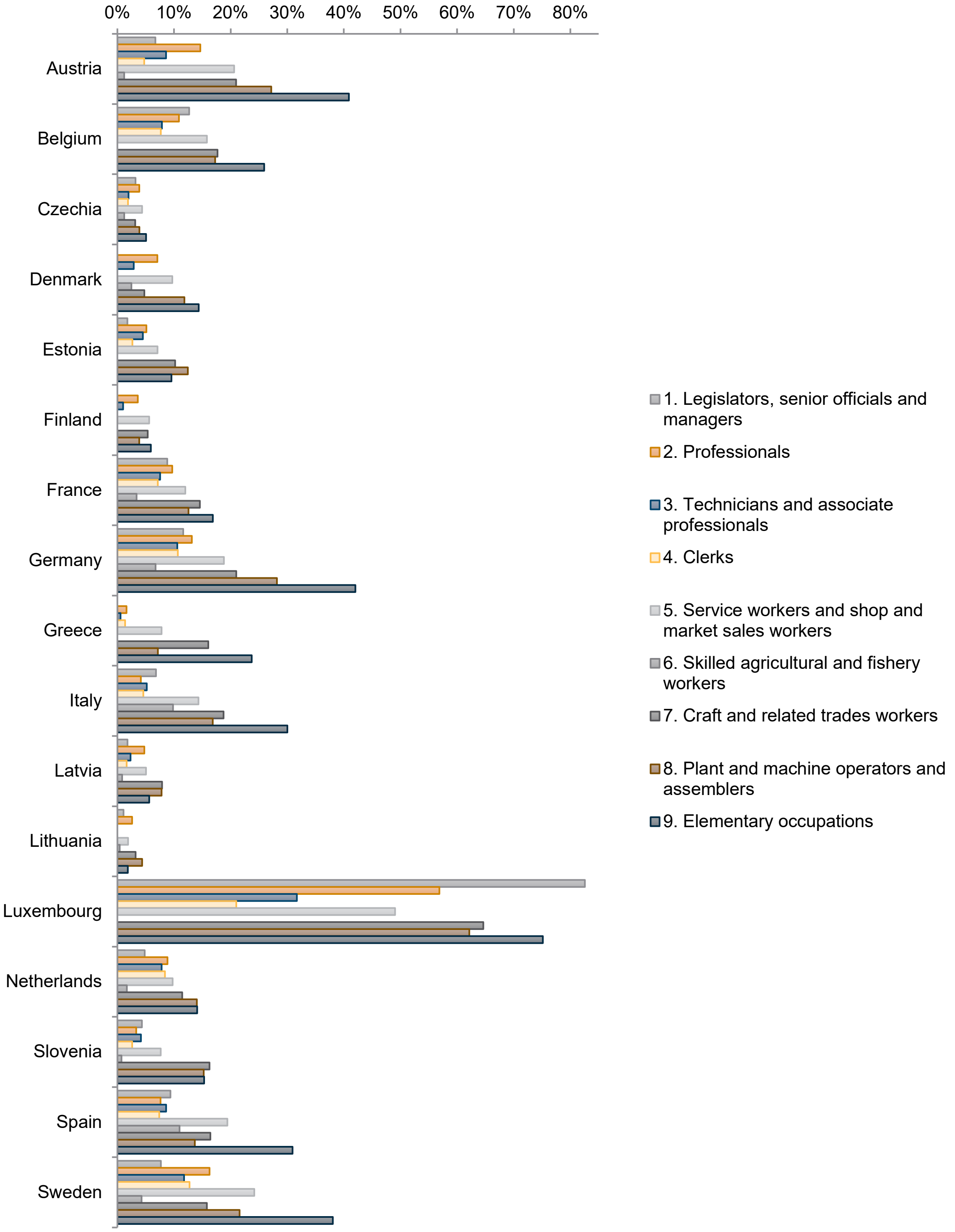
ISO	Country	Share of all migrants in labour	Share of all EU migrants in labour	Share of all non-EU migrants in labour	Number of granted patents	Share of Computing capital in total	Share of communication capital in total	Share of software capital in total	Output-weighted TFP ACF	Capital stock net of all assets constant USD 2015 mn	Average labour cost in terms of real wage of each employed person	GVA constant USD 2015 mn
AT	Austria	19%	9%	10%	5,964	0.3%	1.4%	1.4%	-0.04	1,656,166	47,514	381,469
BE	Belgium	15%	7%	8%	4,839	0.8%	0.8%	0.9%	0.39	1,528,733	55,894	468,897
CZ	Czechia	4%	2%	2%	1,554	0.7%	0.2%	1.1%	-0.01	30,689	660	7,385
DE	Germany	17%	4%	13%	76,117	0.3%	0.4%	0.6%	0.28	12,253,134	46,454	3,479,784
DK	Denmark	9%	3%	7%	4,306	0.9%	0.2%	1.7%	0.09	136,589	8,309	39,653
EE	Estonia	10%	0%	10%	78	0.4%	1.3%	1.0%	0.34	86,487	20,769	24,018
ES	Spain	14%	4%	10%	5,025	0.3%	0.5%	1.4%	0.02	4,934,878	33,429	1,260,471
FI	Finland	5%	2%	3%	6,315	0.3%	0.5%	0.8%	0.40	721,993	48,671	206,227
FR	France	11%	3%	8%	26,280	0.2%	0.3%	2.2%	0.41	8,920,397	53,327	2,455,628
EL	Greece	7%	1%	6%	102	0.3%	1.2%	0.4%	0.46	645,683	19,679	183,738
IT	Italy	12%	4%	8%	9,731	0.3%	0.3%	1.2%	0.34	7,183,267	34,293	1,855,868
LT	Lithuania	4%	0%	4%	109	0.7%	0.9%	1.7%	0.07	135,989	15,821	43,425
LU	Luxembourg	52%	42%	10%	1,539	0.6%	1.0%	0.7%	1.89	138,460	78,972	63,100
LV	Latvia	8%	0%	8%	63	0.5%	0.4%	0.3%	0.00	131,904	16,878	27,892
NL	Netherlands	10%	3%	8%	15,457	0.7%	0.1%	2.6%	0.41	2,533,288	46,229	787,005
SE	Sweden	18%	5%	13%	11,521	0.3%	1.0%	3.2%	0.04	186,011	5,987	55,276
SI	Slovenia	10%	2%	8%	340	0.2%	0.4%	0.6%	0.12	158,953	25,804	44,846

Figure A1 / Distribution of migrant workers in each country across occupations, 2015-2019



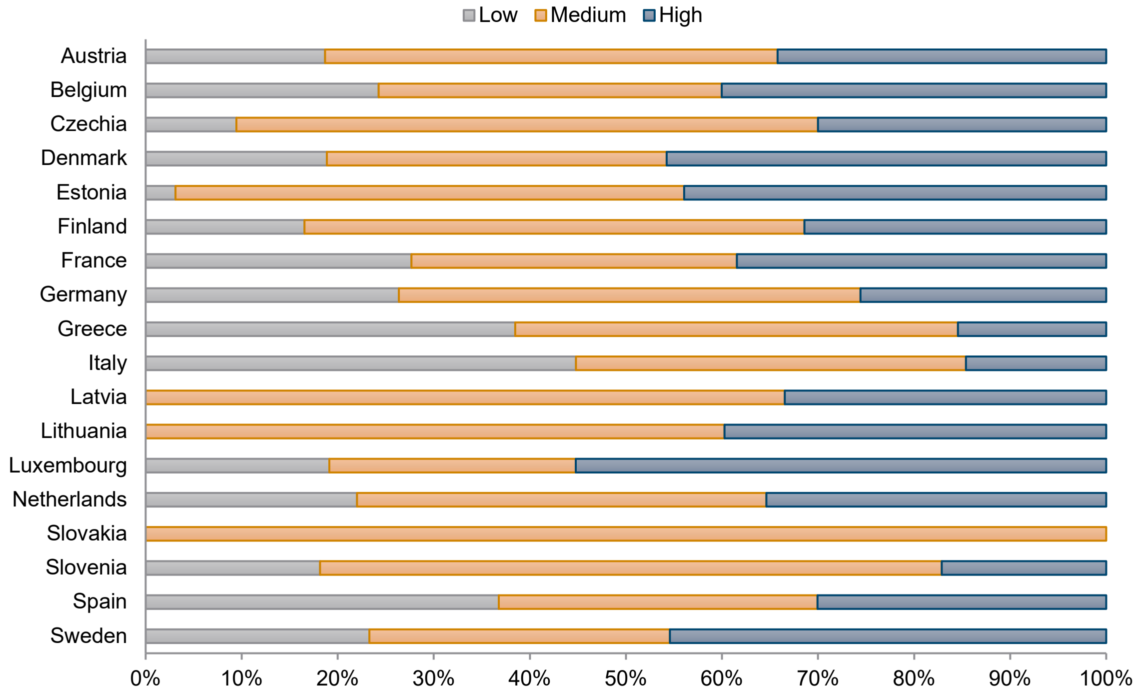
Source: LFS, authors' calculations.

Figure A2 / Average share of migrants per total employees in each occupation across countries, 2015-2019



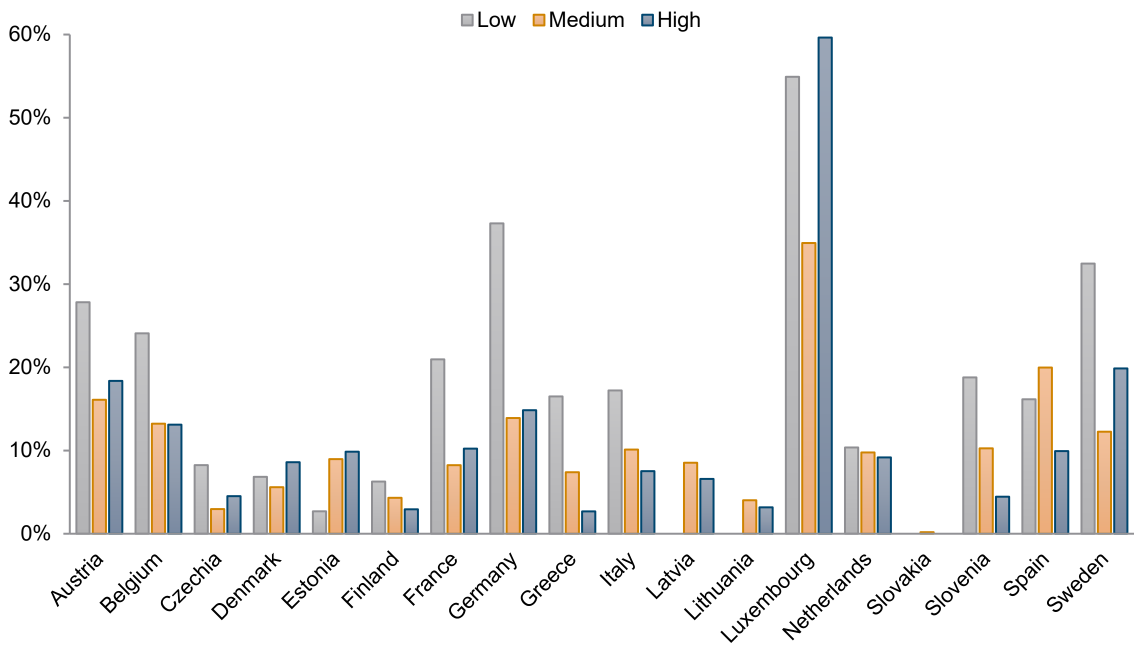
Source: LFS, authors' calculations.

Figure A3 / Distribution of migrant workers in each country across levels of education, 2015-2019



Source: LFS, authors' calculations.

Figure A4 / Average share of migrants per total employees within each level of education across countries, 2015-2019



Source: LFS, authors' calculations.

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