THE IMPACT OF ROBOTS ON LABOUR MARKET TRANSITIONS IN EUROPE

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Table of contents

Abstract

We study the effects of robot exposure on worker flows in 16 European countries. Overall, we find small negative effects on job separations and small positive effects on job findings. Labour costs are shown to be a major driver of cross-country differences: in countries with lower labour costs, robot exposure had more positive effects on hirings and more negative effects on separations. These effects were particularly pronounced for workers in occupations intensive in routine manual or routine cognitive tasks, but were insignificant in occupations intensive in non-routine cognitive tasks. For young and old workers in countries with lower labour costs, robot exposure had a beneficial effect on transitions. Our results imply that robot adoption increased employment and reduced unemployment in most European countries, mainly through lower job separation rates.

JEL codes

J24, O33, J23

Keywords

robots, technological change, tasks, labour market effects, Europe

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1. Introduction

The use of robots has multiplied during the last two decades. Between 2000 and 2017, robot exposure, as measured by the number of industrial robots per 1,000 workers, has quadrupled in Europe as a whole; and it has doubled in Germany, which deploys the highest number of robots per worker in Europe. In high-income countries, robot adoption has increased GDP, labour productivity, and wages (Graetz and Michaels 2018). But it has also ignited fears, especially among policymakers and the general public, of considerable job losses. However, the international evidence on the employment effects of robot exposure is mixed. It has, for example, been reported that robot adoption has reduced total employment in the US (Acemoglu and Restrepo 2019), but not in Germany, where the decline in manufacturing employment was counterbalanced by an increase in employment in the service sector (Dauth et al. 2021). It also appears that the employment effects of robots may be dependent on the development level: while robot adoption was found to be associated with a decline in employment shares of jobs intensive in routine manual tasks in high-income countries, no such association was identified in emerging or in transition economies (de Vries et al. 2020). The reasons for such cross-country differences, as well the labour market mechanisms behind the aggregate employment effects of automation, remain largely unexplored.

This paper fills this gap by investigating the effects of robot exposure on worker flows in Europe. We focus on worker flows because they are an important determinant of worker welfare, and because they constitute a key mechanism behind changes in employment and unemployment levels. We answer three main research questions: First, what was the effect of rising robot exposure on job separation and job finding rates in Europe, and what role did labour costs play in the observed cross-country differences? Second, how did the effects differ between worker groups? Third, what impact did the effects of robot exposure on worker flows have on employment and unemployment rates, and how did it differ by country?

To answer these questions, we estimate labour market transition probabilities from employment to unemployment (a proxy for job separations and, hence, for job stability) and from unemployment to employment (a proxy for job findings) in 16 European countries. We use individual-level data from the European Union Labour Force Survey (EU-LFS), combined with the data on robot exposure from the International Federation of Robotics (IFR), which are available yearly by country and sector. To quantify the importance of labour costs, we interact them with robot exposure. To account for potential endogeneity in robot adoption, we use a control-function approach; and, as an instrument, the average robot exposure in comparable countries, which has been applied by, e.g., Acemoglu and Restrepo (2019) and Dauth et al. (2021). We control for a range of potential confounders, such as general investment, globalisation and trade, and labour demand shocks.

From a theoretical point of view, labour costs can be expected to play an important role in cross-country differences in the labour market effects of labour-saving technologies, in particular of industrial robots. Labour costs influence the economic incentives of firms, as the higher labour costs are, the more likely the substitution of labour with robots is, all other things being equal. Therefore, robot adoption is likely to have a stronger impact on job separation rates and job finding rates in countries with high labour costs than in countries with lower labour costs. Indeed, much lower labour costs may explain why the effects of robot adoption on routine jobs have been more benign in emerging countries than in high-income countries (de Vries et al. 2020). To account for this mechanism, we interact robot exposure with different proxies of labour costs. Importantly, we use labour costs at the beginning of the observation period, which are plausibly exogenous to the robot adoption during the studied period, and are not affected by feedback effects from robot adoption to labour costs.

To analyse differences between worker groups, we focus on the job tasks performed by workers, as this is a key determinant of the substitutability of human labour by robots. To distinguish between workers performing different job tasks, we use categories proposed by Acemoglu and Autor (2011). We also consider heterogeneity by age as this is another worker characteristic that is very likely to be correlated with the substitutability by robots (Acemoglu and Restrepo 2021; Dauth et al. 2021).

To quantify how the effects of robots on worker flows affect employment and unemployment, we first perform a counterfactual exercise. The results of this exercise show how worker flows would have evolved in the absence of increased robot use, and how employment and unemployment would have evolved as a result. Second, we perform a decomposition exercise originally proposed by Fujita and Ramey (2009) in a business-cycle context. This allows us to decompose how the effects of robots on hirings and separations contribute to changes in employment and unemployment. As we perform this exercise by country, we are able to provide some suggestive evidence on the role of labour market institutions in this context. Labour market institutions are of interest in this context because even shocks that are common at the macro or sectoral level can lead to different labour market outcomes between countries, as shown by Blanchard and Wolfers (2000). Following their insights, we provide evidence for three labour market institutions: employment protection legislation (EPL), trade union coverage, and unemployment benefit replacement rates.

Our paper's findings and contributions to the literature can be summarised as follows. First, we study labour market transitions, and provide evidence of the effects of automation on worker flows in a range of European countries. Up to now, the literature has focused on employment stocks or structures.[1] We find that, on average, robot exposure significantly reduced the likelihood of job separations, and it increased, albeit slightly, the likelihood of job finding. Our results are consistent with country-specific findings on worker flows. For example, Domini et al. (2021) found that automation episodes in French manufacturing firms were associated with a higher hiring rate and a lower separation rate. However, there is no evidence yet on the effects of automation on labour market flows in a cross-country setting.

Second, we identify differences in (initial) labour costs as a driver of cross-country differences in the labour market effects of robot adoption. Previous cross-country studies of employment effects of automation (de Vries et al. 2020; Klenert, Fernandez-Macias, and Anton 2020) did not shed much light on the factors that may explain cross-country differences, as they used broad country categorisations rather than explicitly quantifying the effect of differences in countries' labour costs, as we do here. We find that in countries with initially lower labour costs, robot exposure reduced the likelihood of job separation more strongly.[2] In addition, we observe that the effect of robot exposure on the likelihood of job finding was positive in countries with relatively low initial labour costs, but was negative in countries with the highest initial labour costs in Europe.

[1] Previously, economists have mainly investigated either regional (Acemoglu and Restrepo 2019; Dauth et al. 2021) or worker-level (Domini et al. 2020; Koch, Manuylov, and Smolka 2021) effects of robot exposure in specific countries, or have examined the effects of robotisation in a cross-country setting using industry-level data (Aksoy, Özcan, and Philipp 2021; de Vries et al. 2020; Klenert, Fernandez-Macias, and Anton 2020).

[2] In our sample, the lowest initial labour costs were recorded in the Central Eastern European countries that joined the EU in 2004, such as Poland, Slovakia, and Hungary; while the highest initial labour costs were recorded in the Nordic countries, the German-speaking countries, and Belgium.

Third, our individual-level analysis allows us to provide evidence of heterogeneity in the effects of robot exposure on labour market flows among worker groups in a cross-country setting. This approach stands in contrast to those of previous cross-country studies, which have used industry-level measures of employment. On the one hand, for occupational task groups, we generally find more beneficial effects for routine workers than for non-routine workers. In particular, in most European countries, except for the richest ones, robot exposure increased the likelihood of job finding among workers in routine manual and routine cognitive occupations. It also reduced the likelihood of job separation in countries with the lowest initial labour costs. On the other hand, we find no effect on labour market flows among workers in non-routine cognitive occupations. As we discuss in more detail in the conclusions, these results point to the importance of taking labour costs into account when considering the substitutability with robots of workers performing different job tasks.

We find important differences between workers of different ages. In most countries, except for those with the highest initial labour costs, robot exposure increased the job finding rate of young workers, and thus of most labour market entrants; but robot exposure had no impact on the job finding rate of older workers. At the same time, robot exposure reduced the likelihood of job separation among older workers in countries with low initial labour costs, but it did not affect job separations among young workers. These differences in workers' adjustments to the adoption of robots suggest that there was complementarity between human labour and robots for both older and younger workers, particularly in countries with low labour costs. For older workers, the benefits were in the form of higher job stability; while for younger workers, the benefits were in the form of easier job entries. We also find that for the countries with the highest labour costs, job findings were slightly reduced by robots.

Fourth, we assess the importance of job separations and hirings for the effects of robots on employment and unemployment. Our counterfactual analysis shows that rising robot exposure increased aggregate employment levels in European countries by about 1-2% of the working-age population between 2004 and 2018. While robots and other labour-saving technologies can directly reduce employment as machines replace humans in performing certain tasks (labour-saving effect), the product demand effect – i.e., an increase in activity thanks to a productivity-enhancing technology – and the demand spillover effect – i.e., demand for other sectors' output resulting from higher value added and incomes in the technology-adopting sector – can increase employment. Indeed, Gregory et al. (2021) showed that the latter two effects have been dominant in Europe, leading to an overall positive employment effect of routine-replacing technologies. Our reduced-form estimation results reflect the overall effects. Thus, the balance of all three abovementioned effects and are consistent with the findings of Gregory et al. (2021) for Europe and of Koch et al. (2021) for Spain. Klenert et al. (2020) also studied the overall effect of robot use on employment at the industry level in Europe, and found a positive aggregate effect, and no impact on the employment of low-skilled workers. However, our flow-based approach allows us to quantify the contributions of particular labour market flows to these aggregate effects. We show that lower job separations were the key driving factor behind the positive employment effects of robot adoption in Europe.

Fifth, we provide suggestive evidence on the role of labour market institutions in the cross-country differences in the labour market effects of automation. The existing literature has not focused on institutional factors, but it has hinted that they may play a role in understanding the contrasting findings of country-specific studies (Dauth et al. 2021). We find that in European countries with higher union coverage, in countries with less strict employment protection legislation, and in countries with lower unemployment benefit replacement rates, the contribution of job separations to employment changes driven by rising robot exposure was higher, while the contribution of job findings was lower.

The remainder of the paper is organised as follows. In Section 2, we present our data, particularly the EU-LFS data containing the worker-level information and the data on robots from the International Federation of Robotics (IFR); and we provide descriptive evidence. In Section 3, we discuss measurement issues, the control-function approach for dealing with endogeneity, and the counterfactual analysis and decomposition exercise. In Section 4, we present and discuss our results. In Section 5, we summarise and conclude the discussion.

2. Data and Descriptive Evidence

2.1. Data Sources and Definitions

Our worker-level dataset is drawn from the European Labour Force Survey (EU-LFS) for the years 1998–2017, a period of rapid robotisation in many industrialised countries. The EU-LFS includes information on all European Union member states. However, due the lack of availability of other data discussed below for certain countries, our sample is limited to 16 countries: Austria, Belgium, the Czech Republic, Denmark, Finland, Germany, Greece, Hungary, Italy, Poland, Portugal, Slovenia, Spain, Sweden, Slovakia, and the United Kingdom.

The EU-LFS provides representative and harmonised information on individuals who are aged 15 years or older and live in a private household. The EU-LFS data are available as repeated cross-sections. The respondents report their labour market status in the month they were surveyed, as well as their status one year earlier. Using this information, we follow Bachmann and Felder (2021) to measure transitions from one year to the next between particular labour market states (employment, unemployment, and non-participation) at an individual level. We classify a person as having made a transition from employment (unemployment) to unemployment (employment) if s/he reported being employed (unemployed) one year before the survey, and being unemployed (employed) in the month of the survey. However, we cannot account for employment transitions within that year. We compare these individuals to their counterparts who were employed (unemployed) in the year before the survey and the month of the survey. We exclude individuals who moved from and into non-participation.

The data on robots come from the International Federation of Robotics (IFR), which provides annual information covering the current stock and the deliveries of industrial robots across countries, by industry and by application (e.g., assembling and disassembling, welding, laser cutting), and accounting for depreciation (IFR, 2017). The data are based on consolidated information collected by nearly all industrial robot suppliers worldwide. The IFR ensures that the data are internationally comparable and have a high degree of reliability. For the Western European countries, we use the data on robots from 1998 to 2016. For the Central and Eastern Europe (CEE) countries, data on robots are only available from 2004 onwards. As the stock of robots in CEE was negligible before 2004, this does not limit our analysis. According to the definition by the International Organization for Standardization (ISO 8373:201), an industrial robot is an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications". Moreover, an industrial robot usually operates in a series of movements in several directions to grasp or move something (ISO, 2012).

Our second major source of industry-level data is the EU KLEMS Growth and Productivity Accounts database, which contains industry-level measures of output, inputs, and productivity. We use data on GDP per capita, gross fixed capital formations in sectors, and gross value added. The data on

GDP per capita are then used to construct GDP growth rates between two consecutive years, and are merged with a lag at the country level. Data on investment (gross fixed capital formation) and gross value added are mapped to occupations, and are merged with the EU-LFS data on the occupational level. We also control for participation in global value chains using data provided by the Research Institute on Global Value Chains (UIBE). In addition, we account for trade flows by using data on exports to all countries from the UN Comtrade database. These data are available at the commodity level, are assigned to industries using a crosswalk available on the webpage of the World Integrated Trade Solutions[3], and are aggregated and merged with the EU-LFS data at the one-digit sector level.

To quantify the exposure of workers to robots, we merge the EU-LFS data with the IFR data described above. To this end, we use harmonised information on the occupation (International Standard Classification of Occupations – ISCO) and the sector (Statistical Classification of Economic Activities in the European Community – NACE) of an individual, applying it to the current and the retrospective information. For the currently unemployed, we assign each individual to an occupation based on the last job s/he performed before becoming jobless.

Merging the worker-level data from the EU-LFS with the industry-level data is not straightforward, as the EU-LFS provides information on the economic sector at the one-digit sector level only.[4] To achieve a more precise mapping of industry-level variables, we apply an occupation-industry matrix calculated using the distribution of two-digit occupations across two-digit sectors in a given country and time. For this purpose, we use data provided by Eurostat via the tailor-made extraction procedure.[5] We follow Ebenstein et al. (2014) and Baumgarten et al. (2013) to transform two-digit industry-level variables (Y_{sct}) into two-digit occupation-specific variables (Y_{oct}) according to:

$$Y_{oct} = \sum_{j=1}^{J} \frac{L_{osct}}{L_{oct}} Y_{sct} \tag{1}$$

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[3] https://wits.worldbank.org/product_concordance.html

[4] For robots, the one-digit sector disaggregation used in the EU-LFS is too broad for the precise measurement of robot adoption, as there are substantial differences in robot exposure between two-digit sectors within a given one-digit sector, particularly in manufacturing (IFR, 2017).

[5] See https://ec.europa.eu/eurostat/documents/1978984/6037342/EULFS-Database-UserGuide.pdf; the service is available through the Eurostat user support at https://ec.europa.eu/eurostat/help/support. The same data and methodology were used by Aghelmaleki et al. (2021).

where L_{osct} denotes the level of employment in occupation o, sector s, country c, and year t. Using this approach, we are able to assign industry-specific information to each worker based on his/her two-digit level occupation. In particular, it allows us to measure how strongly a particular occupation (at the two-digit level) is exposed to robotisation. We also apply this mapping approach to the industry-level data on gross value added and capital investment (EU-KLEMS), and on global value chain participation (data from the Research Institute of Global Value Chains – UIBE GVC). The trade data (Comtrade) are aggregated and merged at the one-digit sector level to attenuate strong fluctuations in exports over the years.

Finally, we classify workers into five groups according to the predominant task of their occupation: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical. We thus follow Fonseca et al. (2018) and Lewandowski et al. (2020). First, we calculate the task content of occupations using the methodology of Acemoglu and Autor (2011), based on the Occupational Information Network (O*NET) data, adapted to the European data by Hardy et al. (2018), who presented methodological details.[6] Second, we allocate occupations to groups according to the task with the highest value. For instance, we classify an occupation as routine manual if the routine manual task intensity of that occupation is higher than the intensities of other task content measures; as routine cognitive if the routine cognitive task intensity is the highest; and so forth. The allocation of occupations to task groups is shown in Tables A3-4 in Appendix A. We keep these allocations constant to ensure comparability and exogeneity to robot adoption across countries.

The descriptive statistics of the final estimation sample are presented in Table A2 in Appendix A.

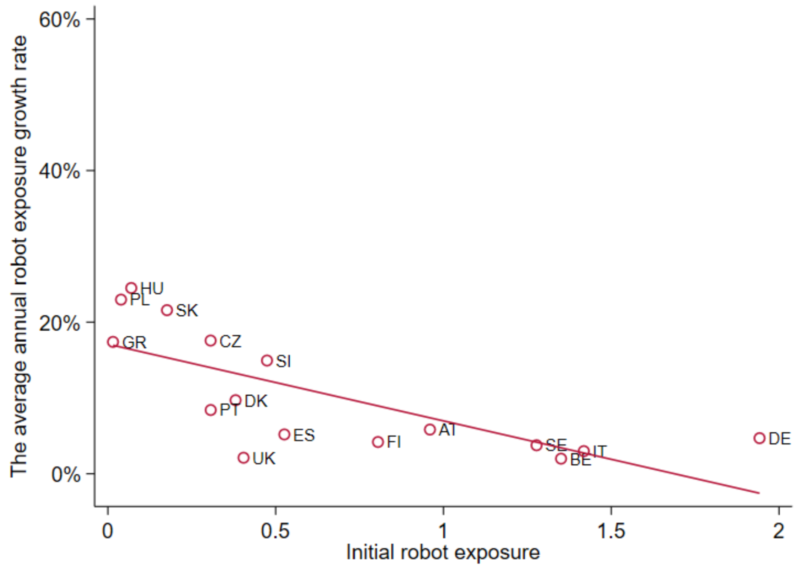
2.2. Descriptive evidence

In the late 1990s and early 2000s (the beginning of our study period), there was significant cross-country variation in robot exposure (Figure 1). It ranged from virtually zero robots per 1,000 workers in Central and Eastern European countries (Hungary, Poland, Slovakia) and in Greece; to

[6] O*NET is a US dataset of occupational descriptors that has been commonly applied to European data (Fonseca, Lima, and Pereira 2018; Goos, Manning, and Salomons 2014; Hardy, Keister, and Lewandowski 2018; Lewandowski et al. 2020), as the differences between occupational demands in the US and in European countries are small (Handel 2012; Lewandowski et al. 2022).

about two robots per 1,000 workers in Western European countries such as Belgium, Italy, and, in particular, Germany.

Figure 1. Initial robot exposure and the average robot exposure growth rate, by country.

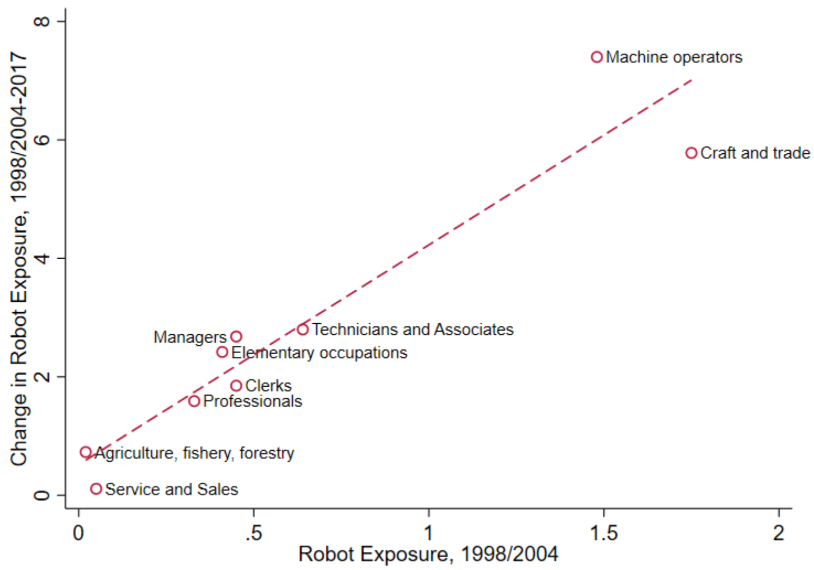


Note: Robot exposure is measured as the number of robots per 1,000 workers. The detailed data on industrial robots start in 1998 for Denmark, Finland, Germany, Italy, Spain, Sweden, and the United Kingdom; in 2003 for Austria; in 2004 for Belgium, the Czech Republic, Hungary, Poland, and Slovakia; and in 2005 for Greece, Portugal, and Slovenia. The robot exposure growth rate refers to the average annual growth rate from the initial date to 2017. – Source: authors' calculations based on the IFR data.

By 2017 (the final year covered by our sample) the countries with the lowest initial level of robot exposure, such as Poland, Hungary, and Slovakia, experienced the highest average growth rate (about 25% per year); while the countries with initially high levels of robot exposure experienced lower growth rates. Overall, the correlation between initial robot exposure and the average robot exposure growth rate over the observation period was strong and negative (-0.73), indicating that there was considerable convergence in robot exposure across European countries.

Robot exposure also differed strongly between occupation groups (Figure 2). Initial robot exposure was by far the highest for machine operators (1.48) and craft and trade workers (1.75). While technicians and associates had a medium initial level of robot exposure (0.64), the level was lowest for service and sales (0.05) and agriculture, fishery, and forestry workers (0.02). In contrast to robot exposure across countries, which converged over time, the exposure across occupations diverged: i.e., it increased in all occupations, but the correlation between initial robot exposure and the average robot exposure growth rate by occupation was strong and positive (0.95). The two occupational groups who initially faced the highest exposure levels also had the highest growth rates of exposure (e.g., machine operators: 7.4; craft and trade workers: 5.8). In the remaining occupations, the growth rate was much lower (e.g., 2.8 for technicians and associates, and 0.11 for service and sales workers).[7]

Figure 2. Initial robot exposure and average robot exposure growth rate, by occupation group.



Note: Robot exposure is measured as the number of robots per 1,000 workers. The detailed data on industrial robots start in 1998 for Denmark, Finland, Germany, Italy, Spain, Sweden, and the United Kingdom; in 2003 for Austria; in 2004 for Belgium, the Czech Republic, Hungary, Poland, and Slovakia; and in 2005 for Greece, Portugal, and Slovenia. The robot exposure growth rate refers to growth from the initial date to 2017. Figures displayed refer to averages by occupation groups across all countries. – Source: authors' calculations based on the EU-LFS and IFR data.

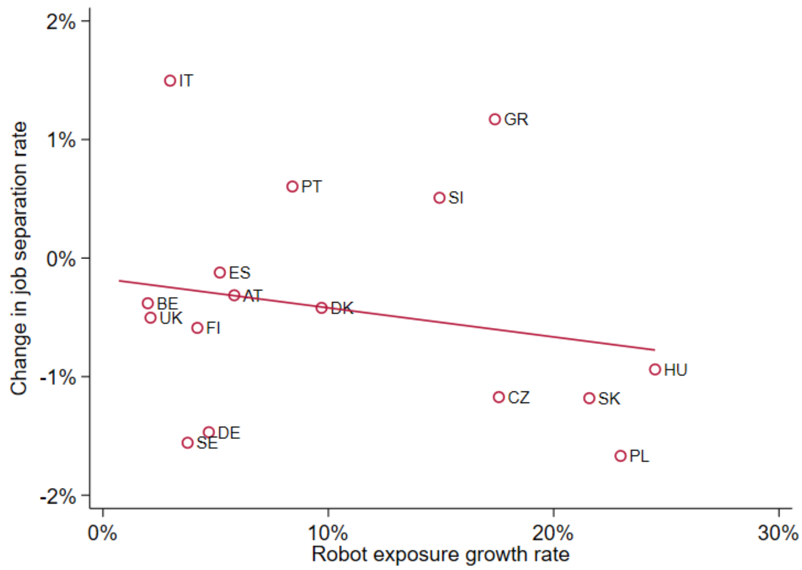
Turning to the labour market variables, we note that job separation and job finding rates are known to display strong variation between countries and over time (Bachmann and Felder 2021). In our sample, the average job separation rate ranged from 1.3% in Sweden to 5.0% in Spain, while the average job finding rate ranged from 30% in Greece to 54% in the UK.[8] At the country level, there

[7] The results for occupational groups, particularly the importance of machine operators and craft and trade workers, are in line with the evidence for the distribution of robots across economic sectors, which is highly concentrated: i.e., about 98.5% of all robots are installed in manufacturing (IFR, 2017). The sector with the second-highest share of robots is education, research and development, which, however, accounts for only 1% of total robot installations. In general, the distribution of robots across economic sectors in Europe has been stable over time.

888 The fluctuations over time are largely driven by cyclical fluctuations (Bachmann and Felder 2021). In several countries in our sample – most importantly in Spain and Portugal – the job separation rates peaked in 2009 due to the Great Recession, and later returned to the pre-crisis levels (see Figure C1 in the appendix). Other countries, such as Austria and Belgium, instead experienced a constant rate; while Germany even had a decreasing rate over the time period investigated. In some countries, such as Greece and Spain, the job finding rates had declined during the Great

was a moderately negative correlation between the changes in the job separation rate and the robot exposure growth rate (-0.22, see Figure 3).[9] Thus, in countries with a stronger increase in robot exposure, job stability has remained rather constant, or it has even improved.

Figure 3. Changes in job separation rates and average robot exposure growth rates.



Note: The changes in the job separation rates are calculated based on the differences between the three-year averages of the last three years and the first three years for which both IFR and LFS data are available. The first three years are 1998-2000 for Denmark, Finland, France, Germany, Italy, Spain, Sweden, and the United Kingdom; 2003, 2004, and 2006 for Austria; 2004-2006 for Belgium, the Czech Republic, Hungary, Poland, and Slovakia; and 2005-2007 for Greece, Portugal, and Slovenia. The last three years are 2015-2017. Source: authors' calculations based on the EU-LFS and IFR data.

Recession. Overall, however, the fluctuations of the job finding rates were less pronounced than those of the job separation rates.

[9] To avoid year-specific fluctuations, we take the average of the transition rates during the first three years and the last three years for which the data are available. Then we take the difference.

Figure 4. Changes in job finding rates and average robot exposure growth rates.

Note: The changes in the job finding rates are calculated based on the differences between the three-year averages of the last three years and the first three years for which both IFR and LFS data are available. The first three years are: 1998-2000 for Denmark, Finland, France, Germany, Italy, Spain, Sweden, and the United Kingdom; 2003, 2004, and 2006 for Austria; 2004-2006 for Belgium, the Czech Republic, Hungary, Poland, and Slovakia; and 2005-2007 for Greece, Portugal, and Slovenia. The last three years are 2015-2017. Source: authors' calculations based on the EU-LFS and IFR data.

There is also a positive correlation between the changes in the job finding rates and the robot exposure growth rates (0.37, see Figure 4), which means that in countries with a stronger increase in robot exposure, the chances of finding a job improved more. These patterns are partly driven by different country clusters. First, a cluster of CEE countries recorded high robot exposure growth rates and a relatively strong reduction of job separation rates, as well as increases in job finding rates. Second, a cluster of countries with robot exposure growth rates, such as France and several Southern European countries, recorded increases in job separation rates and declines in job finding rates.

Thus, overall, the descriptive statistics show a positive association between the growth in robot exposure and favourable labour market developments: i.e., lower job separation rates and higher job finding rates. In the following, we will investigate whether robots have a causal effect on labour market transitions using within-country, between-sector differences in robot exposure and instrumental variables.

3. Methodology

Here, we outline our estimation framework and causal approach, and explain the methodology of post-estimation analyses to quantify their economic significance.

3.1. Estimation framework and instruments

We focus on two key labour market yearly flows: (1) job separations (being employed in year $t-1$ and unemployed in year t) and (2) job findings (being unemployed in year $t-1$ and employed in year t).[10] Our outcome variables are indicator variables equal to one if a given flow occurs, and equal to zero if it does not.

Following Graetz and Michaels (2018) and Acemoglu and Restrepo (2019), we calculate robot exposure as the number of robots per thousand workers at the two-digit sector level, ($\mathrm{R}_{\mathrm{c,s,t}}$):

$$R_{c,s,t} = \frac{ROB_{c,s,t}}{EMP_{c,s,t}} \tag{2}$$

Where $ROB_{c,s,t}$ is the total stock of industrial robots, and $EMP_{c,s,t}$ is employment (in thousands of workers) in sector s, country c, and year t. We use this definition and the sector-occupation mapping (see equation (1)) to map robot exposure to individual workers (for details, see *Technical details* in Appendix C).

To estimate the causal effects of robot adoption, we instrument robot exposure.[11] We generalise the "technology frontier" instrument previously applied by Acemoglu and Restrepo (2019) and Dauth et al. (2021). We instrument the robot exposure in sector s, country c, and year t with the average robot exposure in advanced economies.[12] For each of the 11 Western European countries in our sample, we use average robot exposure from other countries. This average robot exposure is computed from the 10 European countries for which we have robot data, omitting the country

[10] We have to exclude workers transitioning from employment into inactivity and from inactivity into unemployment because the EU-LFS data do not include information about the last occupation or sector of employment of inactive individuals.

[11] Robot exposure could be endogenous to labour market outcomes if, for instance, firms invest in industrial robots in response to worker shortages, and thus to increases in the relative price of labour with respect to capital.

[12] To calculate the value of the instrument, we take the average of robot exposure in the following countries: Austria, Belgium, Denmark, Finland, Germany, Greece, Italy, Portugal, Spain, Sweden, France, the Netherlands, Norway, and the United Kingdom.

for which the instrument is computed.[13] For each of five Eastern European countries in our sample, we instrument robot exposure with the average robot exposure in the 11 Western European countries for which we have robot data available.

Importantly, we use employment levels from 1995 – i.e., before our study period – as denominators to calculate instruments $I_{c,s,t}$. This ensures that changes in the instrument over time result only from changes in the number of robots, and are independent of changes in employment (which could be endogenous to robot exposure).

Instrumented robot exposure is thus given by the formula:

$$I^{1}_{c,s,t} = \frac{\sum_{c \neq k,k}^{C} \sum_{s}^{S} \frac{ROB_{k,s,t}}{EMP^{1995}_{k,s,t}}}{C}, where\ C = \begin{cases} 14\ if\ c\ \in E \\ 13\ if\ c\ \in W \end{cases} \tag{3}$$

where $ROB_{k,s,t}$ is the total stock of industrial robots, $EMP^{1995}_{k,s,t}$ is employment level in thousands in country k, sector s and year 1995, $|C|$ is the number of countries in a particular group.

As a baseline model, we estimate probit regressions of the following form:

$$Pr(flow = 1|X)_{i,o,s,c,r,t} = \beta_1 R_{o,c,t-1} + \beta_2 L_c + \beta_3 \mathbf{X} + \beta_4 \mathbf{M} + \rho_s + \delta_t + \epsilon_{i,o,s,c,r,t} \tag{4}$$

whereby Pr $(flow)_{i,o,s,c,r,t}$ is the likelihood of a given flow $= \{eu, ue\}$ predicted by the model. Flow $eu(ue)$ indicates that a person made a transition from employment (unemployment) in year t-1 to unemployment (employment) in year t.

Our main variable of interest is R_{oct-1} – robot exposure in occupation o, country c, and year $t-1$.[14] In all regressions, we account for individual characteristics ($\mathbf{X}$) such as gender, age, education,

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[13] Note that we have more countries available for calculating the robot exposure than we can analyse in our estimation sample using our worker-level data. Our sample includes five Eastern European countries (E): the Czech Republic, Hungary, Poland, Slovenia, and Slovakia; and 11 Western European countries (W): Austria, Belgium, Denmark, Finland, Germany, Greece, Italy, Portugal, Spain, Sweden, and the United Kingdom. For instance, the instrument for Austria is calculated as the average of the robot exposure in Belgium, Denmark, Finland, Germany, Greece, Italy, Portugal, Spain, Sweden, and the United Kingdom. The instrument for each Eastern European country is calculated as the average across all 11 Western European countries.

[14] For those employed in year $t-1$ and in year t, we assign robot exposure based on the occupation performed in t, but using the value of robot exposure in year $t-1$. For those employed in year $t-1$ and unemployed in year t, we assign robot exposure based on the last occupation performed before becoming jobless, using the value of robot exposure in $(t-1)$. For those unemployed in year $t-1$ and in year t, we assign robot exposure based on the last occupation performed before become jobless, using the value of robot exposure in year $t-1$. For those unemployed in year $t-1$ and employed in year t, we assign robot exposure based on the occupation performed in t, but using the value of robot exposure in year $t-1$.

and native or migrant worker status. We also add time (δ_t), and industry group $\left(\rho_j\right)$ fixed effects. For industries, we follow Dauth et al. (2021) and consider manufacturing and six industry groups outside of manufacturing: agriculture and mining, utilities, construction, general services, business services, and public services & education. As the robot exposure data is merged with the LFS data at the country-occupation level, the variance used for identification is the within-industry, between-occupations and between-country variance in robot exposure.[15]

To control for the macroeconomic conditions, we include several macro indicators ($\mathbf{M}$): lagged GDP growth, sectoral gross value added, the ratio of investments to the gross capital formation (see Stehrer et al., 2019), trade flows, and changes in labour demand at the regional level (NUTS2). In addition, we account for the effects of globalisation using sector-specific measures of participation in global value chains proposed by Wang et al. (2017).

Importantly, we allow the effect of robots to vary between countries at different development levels. To this end, we use two measures of the initial conditions of a country (L_c): labour costs in 2004, in our main specification[16]; and GDP per capita in 2004 as a robustness check. We interact these measures with robot exposure. Therefore, the main specification of our model is an augmented version of equation (4) and reads as follows:

$$Pr(flow = 1|X)_{i,o,s,c,r,t} = \beta_1 R_{o,c,t-1} + \beta_2 R_{o,c,t-1} * L_c + \beta_3 R_{o,c,t-1} * L_c^2 + \\ + \beta_4 L_c + \beta_5 L_c^2 + \beta_6 \mathbf{X} + \beta_7 \mathbf{M} + \rho_s + \delta_t + \epsilon_{i,o,s,c,r,t} \tag{5}$$

where all variables are the same as in equation (4), and in addition, we interact country-specific labour costs in 2004, L_c with robot exposure (R_{oct-1}). We transform labour costs (and GDP in the robustness check) into relative values by taking the log of and deducting the value of Slovenia, which is the richest country amongst the Central Eastern European (CEE) EU member states in our sample. We use data from 2004 because the Eurostat data on labour costs in CEE countries are available only from 2004 onwards. As the data on robots in these countries are also available from 2004 onwards, the variables to control for the initial conditions capture differences in the first year for which all key data are available. Table A1 in Appendix A provides an overview of the relative labour costs and GDP per capita in 2004 across countries.

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[15] We have also estimated models without industry fixed effects, and obtained results in line with our baseline results presented in the paper. These additional results are available upon request.

[16] Five out of the six Central and Eastern Europe in our sample joined the EU in 2004.

3.2. The control function approach

To account for potential endogeneity, we use an IV specification implemented as a control function approach (Aghelmaleki, Bachmann, and Stiebale 2021) with instrumental variables described in the previous section. This approach is more efficient than the standard instrumental variable approach when working with several instruments, and allows for the estimation of marginal effects when using interaction terms.[17]

The control function method we use is a limited information maximum likelihood approach, and follows a two-step procedure. In the first step, all exogenous variables – including the instruments – are regressed on the endogenous variable. In the case of N endogenous variables, we estimate N first-stage regressions. In the second step, residuals obtained from the first stage are included as control variables in the original equation to eliminate endogeneity (Wooldridge 2015). Applying this method to our baseline specification, all exogenous variables including the instrument are regressed on our robot exposure variable in the first stage. For the second stage, we predict the residual of the first stage, and include this as an additional regressor in equations (3) and (4). This approach allows us to isolate the changes in exposure driven by technological progress, and, at the same time, to remove occupation-specific shocks that affect robot adoption and the probability of making a transition out of or into a certain occupation.

3.3. Counterfactual analysis

To assess the economic impact of increasing robot exposure on labour market flows, we perform a counterfactual historical analysis. In the counterfactual scenario, in each country and sector, we keep robot exposure constant from 2004 onwards. This means that new robot installations would have only compensated for the depreciation of robot stock and the aggregate changes in the labour force.

In the first step, we use estimated coefficients (equation 4) and actual values of all variables to calculate the predicted job separation (EU) and job finding (UE) likelihoods. In the second step, we use the same coefficients and the counterfactual values of robot exposure to calculate the counterfactual flows likelihoods. In the third step, we use the predicted and the counterfactual flow

[17] See Petrin and Train (2010) for a discussion of the control function approach for non-linear (including discrete choice) models, and Bachmann et al. (2014) for an application to labour market transitions.

likelihoods to recursively calculate the predicted and counterfactual levels of employment and unemployment for each country until 2017. We use the actual levels of employment and unemployment in 2004 as the starting point. In the fourth step, we calculate the effect of robot exposure on the labour market as a relative difference between the counterfactual and the predicted scenarios for each country and year.

In the fifth step, we analyse to what extent the overall effect of robot exposure on the labour market is driven by the impacts on job separation (EU) and job finding (UE) channels. To this end, we use the counterfactual likelihoods of job separation and the predicted likelihoods of job finding to calculate values of employment conditional on counterfactual job separations; and, vice versa, for employment conditional on counterfactual job findings. For each of these simulations, we calculate a relative difference between a given simulation and a predicted scenario. Finally, we use a covariance-based decomposition, originally proposed by Fujita and Ramey (2009), to quantify the contributions of job separation and job finding channels to the overall effect of rising robot exposure on labour market flows. Methodological details and formulas are included in Appendix A.

4. Econometric results

In this section, we present our econometric results, first for all workers, then for workers belonging to different task and age groups. This is followed by the counterfactual analysis, which assesses the economic significance of the impact of robot exposure on workers flows, employment, and unemployment; and the decomposition analysis, which quantifies the contributions of job findings and job separations to the changes in employment and unemployment.

4.1. The impact of robots on labour market transitions in Europe and the role of labour costs

We start by investigating the causal effects of robot exposure on job separations using our baseline specification, Equation 4. We report the coefficients of interest (Table 1), followed by the marginal effects of robot exposure (Figure 5), which allow for an interpretation of the effect sizes.

In the probit estimation without instruments, we find no significant effect of robot exposure on the likelihood of job separation (Table 1, column 1).[18] However, the IV results using the control function approach reveal a significant and negative effect (column 2 of Table 1): i.e., robot exposure reduces the job separation rate, which implies an increase in job stability.[19]

Accounting for interactions between robot exposure and countries' initial labour costs (equation 5), we find a noticeable heterogeneity in the size of this effect between countries with higher and lower labour costs (columns 3 and 4 of Table 1). In Slovenia, the country in our sample with an average initial level of labour costs, the estimated effect was negative. The estimated interaction term between robot exposure and countries' initial levels of labour costs suggests a non-monotonic and nonlinear relationship between job separation likelihood and robot exposure (columns 3 and 4, respectively).

Table 1. The effect of robot exposure on the likelihood of job separation

	(1) Probit	**(2) CF**	**(3) Probit**	**(4) CF**
A: All Sectors				
Robot Exposure	-0.001	-0.007***	0.002	-0.008***
	[0.001]	[0.001]	[0.002]	[0.002]
Robot Exposure X Labour Costs			0.009***	0.005*
			[0.002]	[0.002]
Robot Exposure X (Labour Costs)^2			-0.011***	-0.001
			[0.003]	[0.003]
Labour Costs	-0.104***	-0.097***	-0.114***	-0.103***
	[0.009]	[0.009]	[0.009]	[0.010]
(Labour Costs)^2	-0.033**	-0.031**	-0.019	-0.035**
	[0.011]	[0.011]	[0.011]	[0.012]
No. of Observations	11.8 M	11.8 M	11.8 M	11.8 M
F-statistic for weak identification		17.0 M		3.3 M
B: Manufacturing				
Robot Exposure	-0.001	-0.009***	0.001	-0.011***
	[0.001]	[0.002]	[0.001]	[0.003]
Robot Exposure X Labour Costs			0.008***	0.007**
			[0.002]	[0.002]
Robot Exposure X (Labour Costs)^2			-0.009***	-0.001
			[0.002]	[0.003]
Labour Costs	-0.123***	-0.085***	-0.151***	-0.124***
	[0.014]	[0.016]	[0.014]	[0.017]
(Labour Costs)^2	0.009	0.024	0.043*	0.007
	[0.014]	[0.014]	[0.017]	[0.019]
No. of Observations	11.8 M	11.8 M	11.8 M	11.8 M
Kleibergen-Paap F-statistic for weak identification		6.3 M		1.0 M

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Year and industry group fixed effects included. Individual-

[18] The detailed results of the full specification are included in Tables B1 (for job separations) and B2 (for job findings) in the appendix.

[19] The results of the first stage of the estimation are contained in Table B1 in the appendix. The Kleibergen-Paap F-statistic shows that the instrument is strong, meaning that it is a good predictor of actual robot exposure.

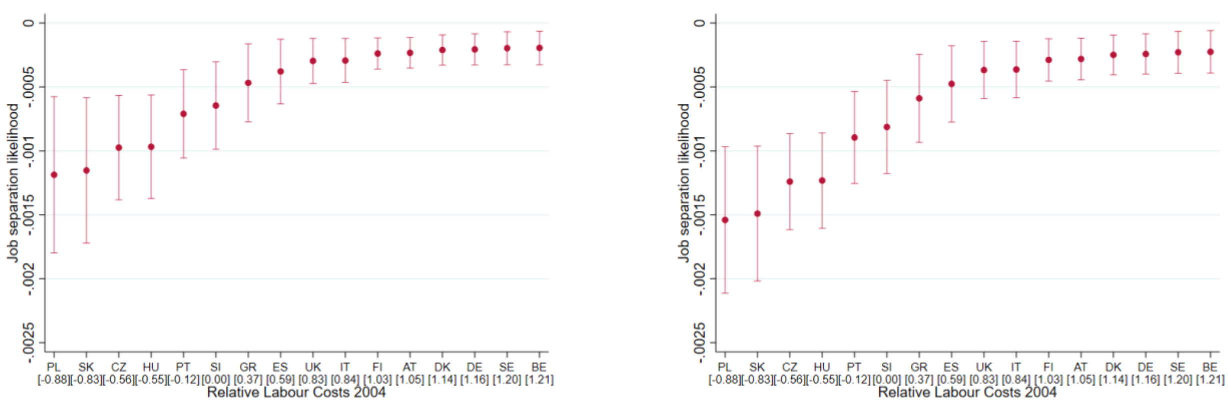
level controls: age group, education group, gender, and native/non-native status. Aggregate-level controls: global value chain participation, global value-added, the ratio of investment added to global value-added, GDP growth, labour demand shocks, and growth in exports. For CF, robot exposure is instrumented using robot exposure in the Western European countries in the sample. For the full specification, see Table B1 in Appendix B. *** p<0.01, ** p<0.05, * p<0.1. Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

The importance of initial labour costs becomes obvious when presenting the marginal effects of robot exposure on job separations by country.[20] We do so for our preferred specification, including the interaction of robots with labour costs, and display the results in Figure 5, where we have ordered countries according to their initial labour costs. The negative effect of robot exposure on job separations was much more pronounced for countries with lower labour costs (Figure 5). In particular, in the country with the average level of initial labour costs – Slovenia – the marginal effect of robot exposure amounted to a 0.07 pp reduction in the likelihood of job separation (the average job separation rate in our sample was 4 pp). In countries that had labour cost levels in 2004 that were at least double the level in Slovenia – i.e., the level of labour costs in Germany – the effect of robot exposure was close to zero (-0.002 pp). By contrast, in the countries with the lowest labour costs in our sample, such as Poland and Slovakia, the effects were much stronger: i.e., the negative marginal effect of robot exposure on the likelihood of job separation was twice as large (0.12 pp) in these countries as it was in Slovenia.

Figure 5. Marginal effects of robot exposure on the likelihood of job separation.

A: All Sectors B: Manufacturing

Interaction with labour cost



Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment, based on regressions presented in Table 1 columns (2) and (4). Robot exposure is instrumented using the average robot exposure in the Western European countries in the sample. Countries on the X-axis are ranked according to the initial labour cost (in parentheses). Figure B1 in the appendix presents the marginal effects with the

[20] We use the estimated quadratic fit pertaining to the initial labour costs (Table 1). For the sake of presentation, we use the values of labour costs recorded in particular countries to calculate the marginal effects of robot exposure conditional on them; and for the figures, we rank countries according to the value of their initial labour costs. Figure B1 in the appendix presents the marginal effects with the linear labour costs scale on the x-axis.

linear labour costs scale on the x-axis. Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

To quantify the economic importance of these effects, we use the estimated marginal effects to assess the contribution of increasing robot exposure to the likelihood of a job separation between the early 2000s (average for 2000-2002) and the mid-2010s (average for 2014-2017). The effects were quantitatively relevant. For instance, in Germany, an increase in robot density by 5.5 units (between 2004 and 2017) was associated with a reduction of the likelihood by 0.11 pp In Germany, the probability of job separation decreased by 1.4 pp over the same period; thus, the change associated with the increase in robot density amounted to 8% of the observed change. In some CEE countries, such as Slovakia, which experienced one of the greatest increases in robot exposure in the EU (by 11.4 units), the effects attributed to this factor were even more pronounced, as they amounted to 50% to the recorded change in job separations. A systematic assessment of the contributions of robot exposure to the evolution of labour market flows in all countries in our sample follows in subsection 4.3.

As a robustness check, we re-estimate our models on the subsample of workers in manufacturing; i.e., the sector with the highest robot usage. This yields very similar results to those of our analysis for the total economy (Table 1, Panel B; Figure 5, Panel B). Furthermore, we re-estimate our models using the level of GDP per capita in 2004 instead of the 2004 labour cost index as a control for the cross-country differences in the initial development level. Results are presented in Table D1 and Figure D3 in Appendix D, and confirm the findings from our baseline specification.

Next, we study the effect of robot exposure on the likelihood of job finding in European countries. Again, we start with the baseline specification (equation 4). We find that, on average, this effect was positive but very small and significant only at the 10% level (Table 2, column 2).[21] However, as for job separations, we find important heterogeneity between more and less developed countries. Once we account for the initial labour costs, we find that the effect of robot exposure on the likelihood of finding a job was significant and positive at the average level of initial labour costs (column 4 of Table 2). The coefficients on interactions between robot exposure and initial labour costs (level and squared) suggest a non-linear relationship.

[21] Again, the instrument is strong, as indicated by the Kleibergen-Paap F-statistic (see Table B2 in the appendix).

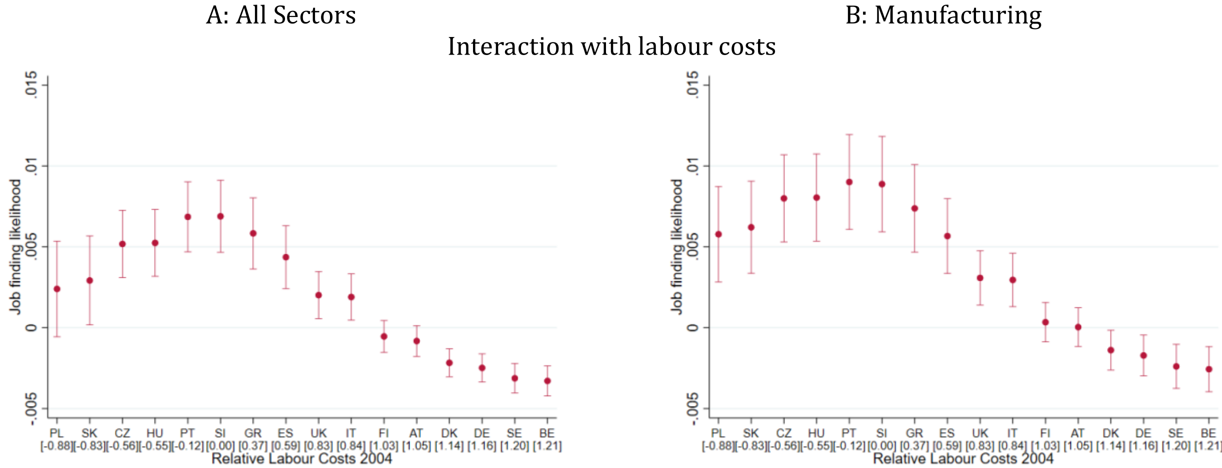
Table 2. Effect of robot exposure on the likelihood of job finding

	(1) Probit	(2) CF	(3) Probit	(4) CF
A: All Sectors				
Robot Exposure	-0.001	0.003*	0.013***	0.019***
	[0.001]	[0.002]	[0.002]	[0.003]
Robot Exposure X Labour Costs			-0.006***	-0.002
			[0.002]	[0.003]
Robot Exposure X (Labour Costs)^2			-0.008***	-0.018***
			[0.002]	[0.004]
Labour Costs	0.061**	0.054**	0.063**	0.057**
	[0.019]	[0.019]	[0.020]	[0.020]
(Labour Costs)^2	0.081***	0.078***	0.099***	0.113***
	[0.022]	[0.023]	[0.023]	[0.024]
No. of Observations	1.3 M	1.3 M	1.3 M	1.3 M
Kleibergen-Paap F-statistic for weak identification		18.3 M		3.6 M
B: Manufacturing				
Robot Exposure	0.003**	0.010***	0.017***	0.026***
	(0.001)	(0.002)	(0.003)	(0.004)
Robot Exposure X Labour Costs			-0.006***	-0.006**
			(0.002)	(0.003)
Robot Exposure X (Labour Costs)^2			-0.010***	-0.018***
			(0.003)	(0.004)
Labour Costs	0.058**	0.027	0.080***	0.075***
	(0.024)	(0.026)	(0.026)	(0.027)
(Labour Costs)^2	0.005	-0.011	0.063*	0.097***
	(0.031)	(0.031)	(0.035)	(0.036)
No. of Observations	1.3 M	1.3 M	1.3 M	1.3 M
Kleibergen-Paap F-statistic for weak identification		6.0 M		1.1 M

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Year and industry group fixed effects are included. Individual-level controls: age group, education group, gender, and native/non-native status. Aggregate-level controls: global value chain participation, global value-added, the ratio of investment added to global value-added, GDP growth, labour demand shocks, and growth in exports. For CF, robot exposure is instrumented using robot exposure in the Western European countries in the sample. For the full specification, see Table B2 in Appendix B. *** p<0.01, ** p<0.05, * p<0.1. Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

The marginal effects plotted by country reveal an inverse U-shape relation between labour costs and the effect of robot exposure on job finding (Figure 6): the positive effect was the largest in the countries with a medium level of labour costs, such as Portugal, Slovenia, and Greece (about 7 pp); but was close to zero or insignificant in the countries with the lowest initial labour costs in our sample, i.e., Poland and Slovakia. In the countries with the highest labour costs, i.e., Denmark, Germany, Sweden, and Belgium, the estimated effect on the likelihood of job finding was even negative (about 3 pp).

Figure 6. Marginal effects of robot exposure on the likelihood of job finding.



Note: The figures show the marginal effects of robot exposure on the probability of transitioning from unemployment to employment, based on regressions presented in Table 2. The robot exposure is instrumented using robot exposure in the Western European countries in the sample. Countries on the X-axis are displayed in ascending order of initial labour cost (in parentheses). Figure B1 in the appendix presents the marginal effects with the linear labour costs scale on the x-axis. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

We use the estimated effects to quantify the economic effects of increasing robot exposure. Hungary is an example of a CEE country that had low labour costs in 2004, and that recorded substantial increases in robot exposure (by 5.8 units). According to our model, this translates into an almost 3 pp increase in the likelihood of finding a job, which is equivalent to 33% of the recorded increase in the job finding probability over this period. However, according to our estimates, in some of the most developed countries, the growth of robot exposure reduced the likelihood of finding a job. For instance, in Sweden, an increase in robot exposure by 11 units reduced this likelihood by 3.4 pp., which is equivalent to 53% of the recorded reduction in this likelihood.

Combined with the effects on job separations, the effects on job findings suggest different net effects on employment in various groups of countries. In the less developed Central Eastern European countries, the effect of robot exposure on employment was likely positive because of the reduced likelihood of job separation and the increased or insignificant likelihood of job finding. However, in the most developed countries, the net effect was ambiguous because of the reduced likelihood of job separation and the reduced likelihood of job finding, which had negative effects on labour market dynamics and turnover. We formalise the analysis of the aggregate consequences of robot exposure via labour market flows in subsection 4.3.

As a robustness check, we again re-estimate our model for a subsample of manufacturing workers. The results are very similar to those for all workers (Table 2, Panel B, and Figure 6, Panel B).

Moreover, a further robustness check using the initial GDP level instead of labour costs yields very similar results (Table D2 and Figure D4 in the appendix).

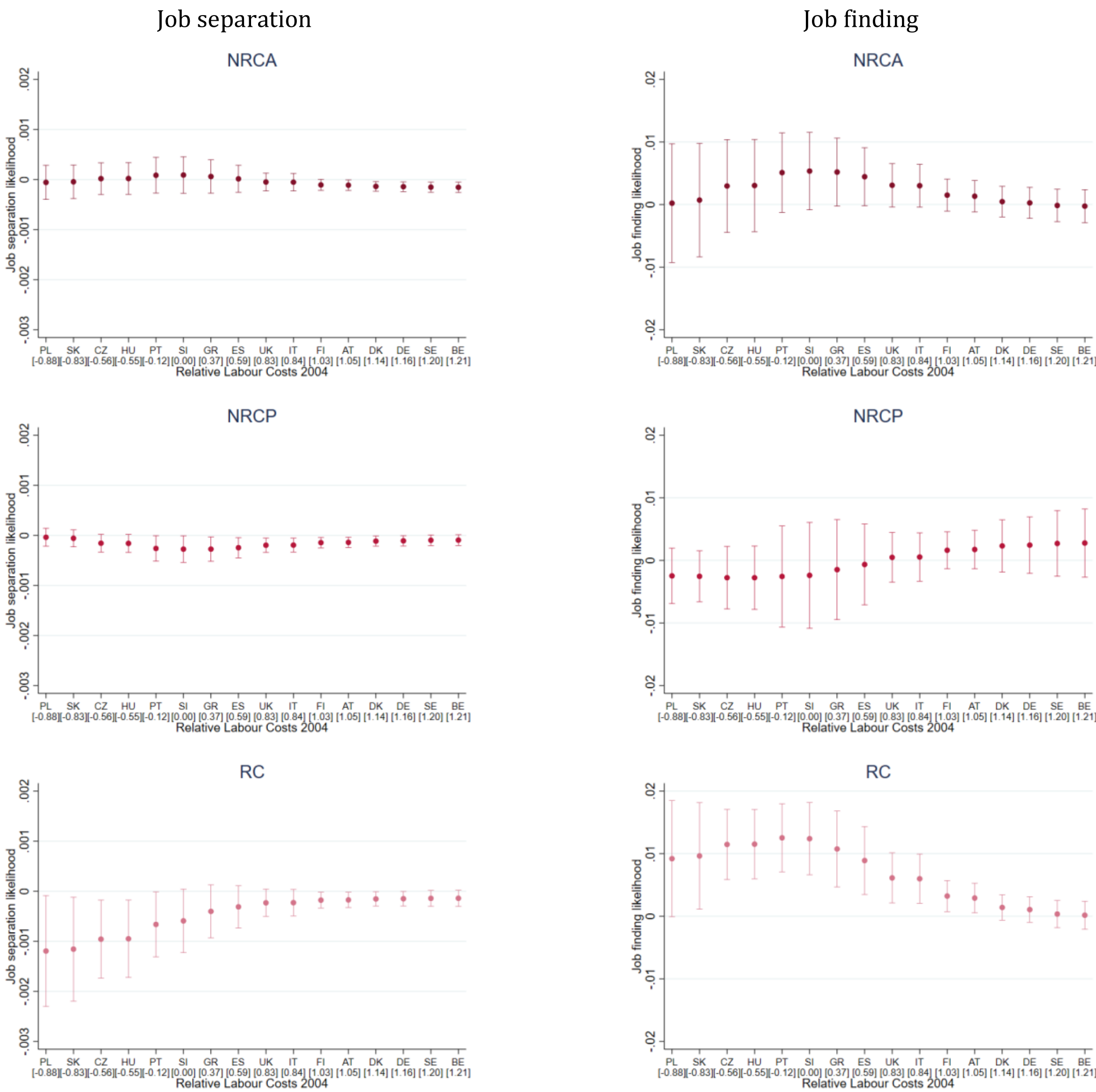
4.2. Heterogeneity according to job tasks and age

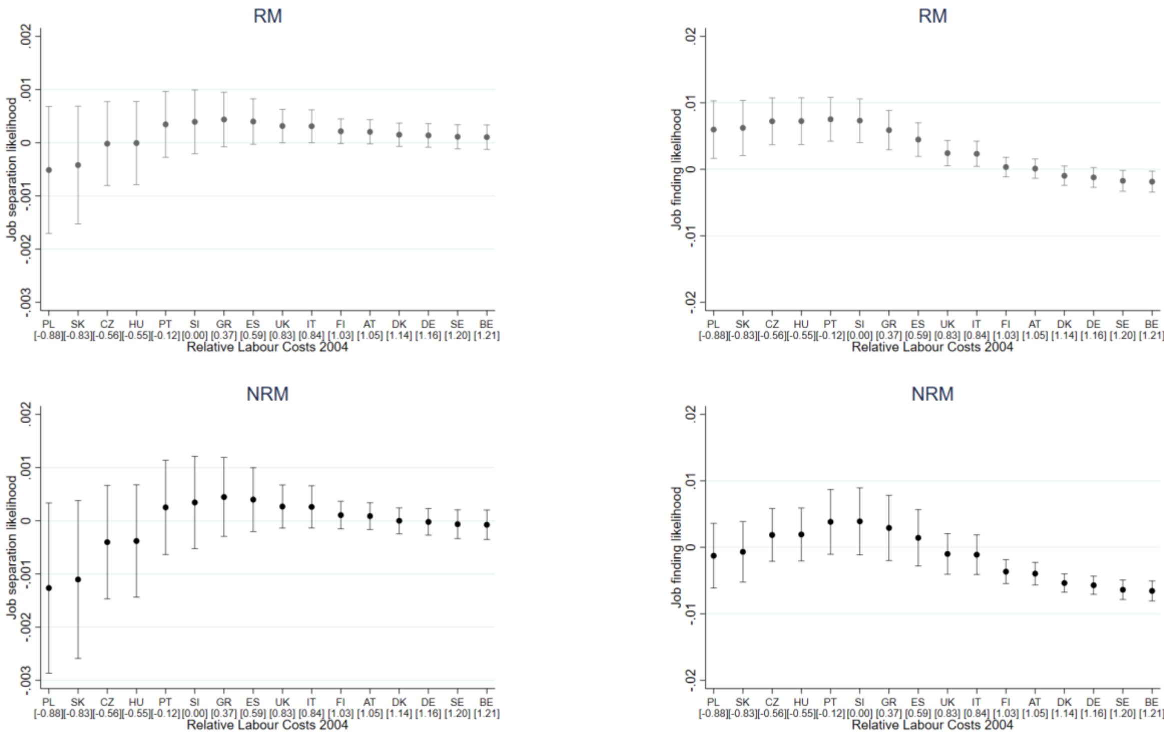
The effects of robot exposure are likely to differ between worker groups for at least three reasons. First, the substitutability of workers by robots depends strongly on the tasks they perform on the job. Second, different groups of workers are likely to differ in their ability to adapt to technological change. Third, job-specific human capital or labour market regulations may lead to differences between workers belonging to different age groups. Therefore, we investigate the effect of robot exposure on labour market transitions for workers performing different job tasks and belonging to different age groups.

In order to examine whether the effects of robot exposure differ by job task, we estimate models (5) separately for subsamples – five occupational groups distinguished according to the dominant job task: routine cognitive (RC), non-routine cognitive analytical (NRCA), non-routine cognitive personal (NRCP), routine manual (RM), and non-routine manual (NRM). The allocation of occupations to task groups is shown in Table A3 in Appendix A. We focus on marginal effects calculated from models with interactions between robot exposure and initial labour costs (level and squared). Coefficients estimated in these models, as well as those without interactions, are presented in Table D3 and D4 in Appendix D.

We find that in countries with low or moderate initial labour costs, the effect of robot exposure on job finding was positive among RM workers (e.g. plant and machine operators, assemblers) and RC workers (e.g. associated professionals, clerks). These effects are quite sizable, at around 0.05 and 0.10, respectively (Figure 7, right panel). Moreover, in countries with low initial labour costs, the effect of robot exposure on the likelihood of job separation among RC workers was negative, but relatively small (-001, Figure 7, left panel). Therefore, our results suggest that higher robot exposure improved job prospects in both types of routine jobs in countries with low initial labour costs, particularly in Central Eastern Europe. While such an effect on routine workers may be surprising, it is worth noting that robot adoption in CEE countries was largely driven by FDI and the integration of plants into global value chains (Cséfalvay 2020). Hence, rising robot exposure was driven by expanding sectors, rather than by introducing new technologies in existing plants, which is a typical pattern in the most advanced economies. This improved the labour market prospects of workers in CEE who were in RM occupations (mainly factory workers), and, in turn, in RC occupations. Indeed, we find that in countries with high initial labour costs, the effect of robot exposure on the likelihood of job flows among both RM and RC workers was insignificant, and the effect on job finding among NRM workers was negative (Figure 7, right panel). Among workers in non-routine cognitive occupations, the effects on both flows were insignificant.

Figure 7. Marginal effects of robot exposure on the likelihood of job separations and findings, by task group



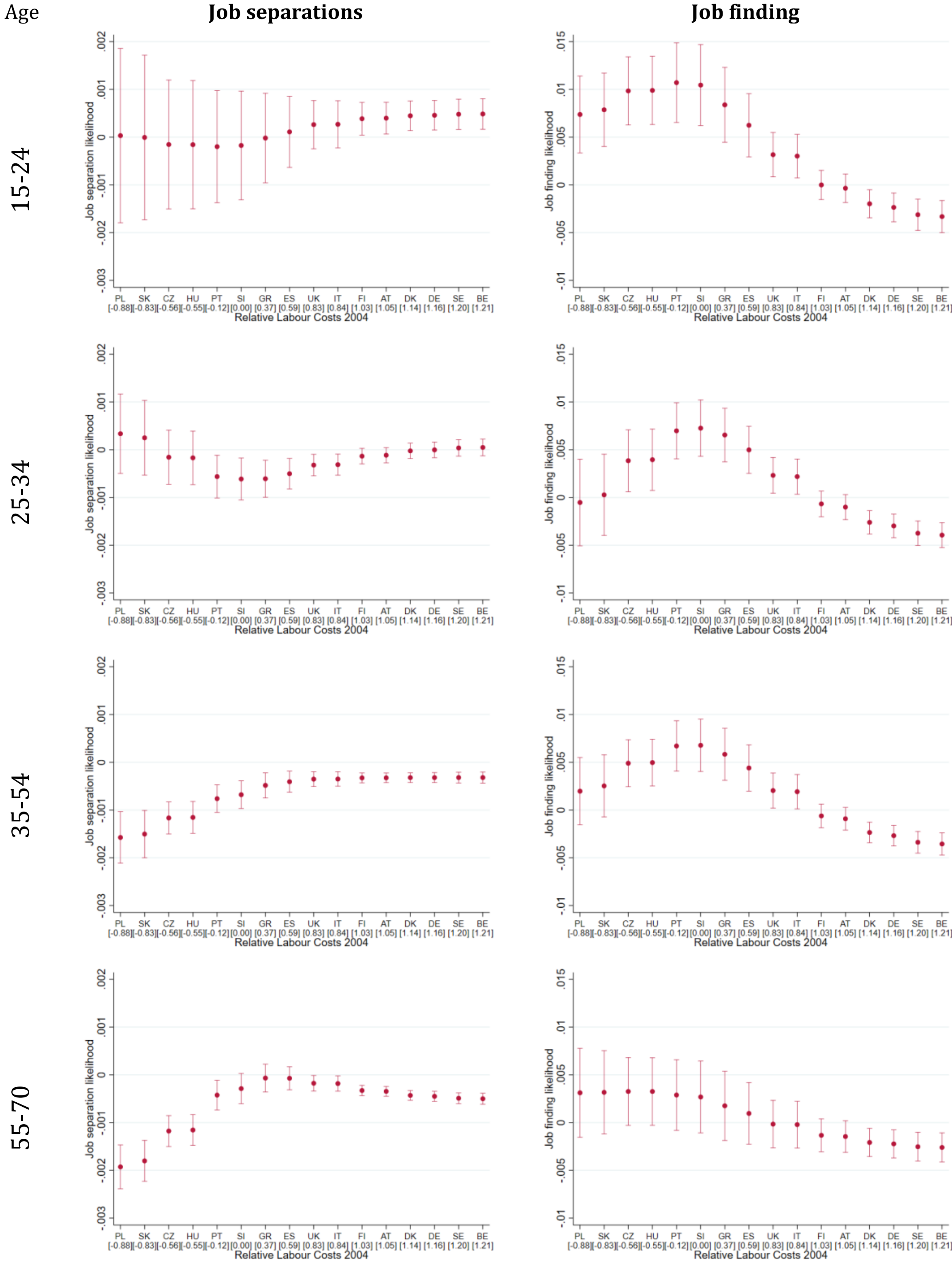


Note: Marginal effects of robot exposure on the likelihood of job separation and on the likelihood of job finding at different development levels measured by labour costs in 2004, for different task groups. The robot exposure is instrumented using robot exposure in the Western European countries in the sample. NRCA - Non-routine cognitive analytical; NRCP - Non-routine cognitive interpersonal; RC - Routine cognitive; RM - Routine manual; NRM - Non-routine manual physical. For regression estimates, see Tables D3-4 in Appendix D. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, UIBE GVC, and O*NET data.

We also investigate the heterogeneity of the effects of robot exposure by worker age. There are two main arguments why the effects of technology adoption can differ for younger and for older workers. First, technological change can reduce returns to old skills related to technology that become obsolete, and increase returns to new skills related to emerging technology (Fillmore and Hall 2021). As older workers are more likely to possess the old skills, and their expected returns from an investment in new skills are lower than those of younger workers, the older workers can be more affected by technological change. Second, older workers are more likely to benefit from insider power, and, as such, may be more protected from changes than younger workers, who are often outsiders or labour market entrants. Indeed, there is evidence that the de-routinisation of work in Europe has affected younger workers to a larger extent (Lewandowski et al. 2020), and that industrial robots in Germany have reduced the labour market prospects of younger workers (Dauth et al. 2021). We find that robot exposure slightly increased the job separation likelihood of young workers (aged 15-24) in countries with initially high labour costs (Figure 8 and Table D5 in Appendix D). However, for prime-aged workers (aged 35-54) and older workers (aged 55-70), we find a negative effect of robot exposure on the job separation likelihood. The effect for the two older age groups was more pronounced in countries with lower initial development levels. We find that the marginal effect of robot exposure on the job finding likelihood was positive for the youngest group (aged 15-24), which included most labour market entrants (Figure 8, right panel, and Table D6 in Appendix D). It was also small and positive for workers aged 25-34 and workers aged 35-54, but only in countries with medium and low initial labour costs. However, it was insignificant for older workers (aged 55 or older). For the countries with the highest labour costs, the effect turned negative for all age groups.

Generally, our results suggest that the dominant channels through which robot exposure affected labour market flows were different among younger and older workers: overall, robot exposure increased job stability (proxied by the job separation likelihood) of older workers, but did not affect their job finding prospects, especially in countries with low initial labour costs. This pattern is consistent with the insider-outsider view on adjustment to technological change. Among younger workers, especially in countries with initially low labour costs, the opposite pattern is observed: i.e., higher robot exposure improved their likelihood of finding a job, but it did not affect the risk of job separation. This pattern is consistent with the skill obsolescence view on adjustment to technological change. However, this finding is in contrast to the finding for Germany that higher robot growth leads to a reallocation of younger workers from the manufacturing to the service sector (Dauth et al. 2021). A reason for the different findings across countries could be that automation in Eastern European countries was driven by new investments and integration in global value chains (Cséfalvay 2020) while in Western Europe robots were deployed in traditional industries.

Figure 8. Marginal effects of robot exposure on the likelihood of job separations and findings, by age group



Note: The figures show the marginal effects of robot exposure on the probability of job separation and job finding at different development levels measured by labour costs in 2004 for different age groups. Countries on the X-axis are displayed in ascending order of labour costs in 2004 (for details, see Table A1). Robot exposure is instrumented using robot exposure in the Western European countries in the sample. For regression estimates, see Tables D5 and D6 in Appendix D. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

4.3. Counterfactual analysis of the effects of robot exposure on past labour market flows in Europe

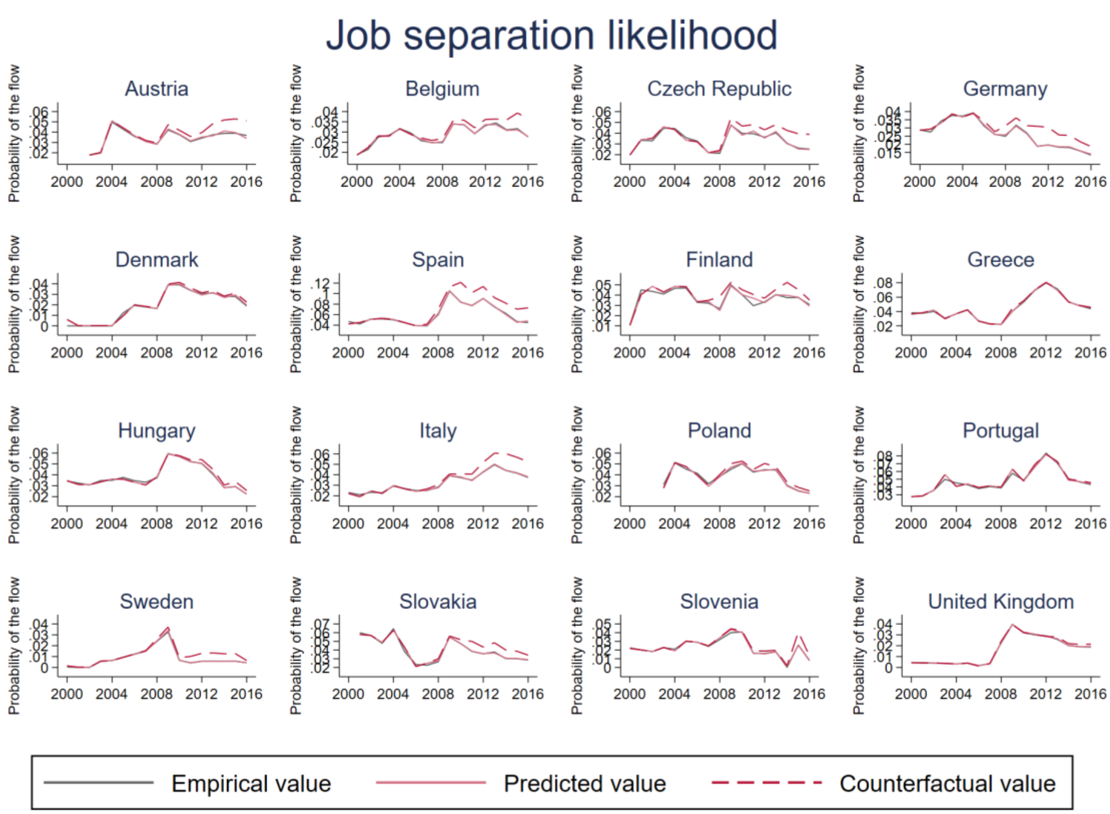
In this subsection, we assess the economic impact of rising robot exposure on labour market flows in European countries. To this end, we use estimated coefficients (equation 5, Tables 1-2) to calculate counterfactual trajectories of labour market flows and resulting employment and unemployment levels, assuming that in each country the robot exposure remained at the level recorded in 2004, and comparing these trajectories with the actual evolution of the relevant labour market variables.

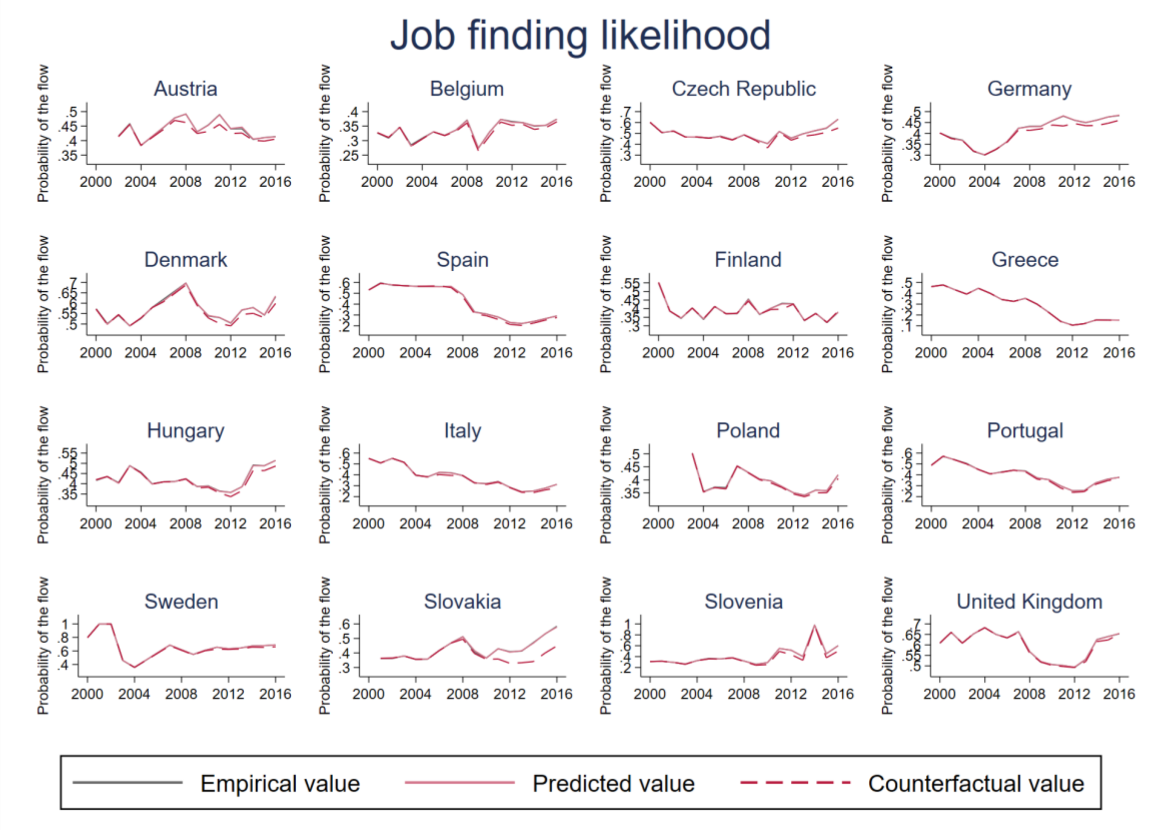
We start by quantifying the effect of robot adoption on the likelihood of particular labour market flows. We find that if robot exposure remained at the level recorded in 2004, the likelihood of job separation would have been higher, while the likelihood of job finding would have been lower than recorded in all countries (Figure 12). The effects on job separations were larger than the effects on job finding. For instance, the job finding likelihood (proxied by the job finding ratio) in Germany in 2017 was 48.2%. According to our estimates, if the robot exposure had remained at the 2004 level, the job finding likelihood would have been 2.2 pp lower, and thus about 5% lower than the likelihood recorded. Likewise, the job separation likelihood (proxied by the job separation rate) in Germany in 2017 was 1.3%. We estimate that if the robot exposure had remained at the 2004 level, the job separation rate would have been 0.5 pp lower, and thus 39% lower than the actual rate. On average, across all countries, the job finding likelihood was 6% higher and the job separation likelihood was 30% lower due to robot adoption in 2017. This means that robot adoption has largely increased the job stability of workers, but it has also improved the job opportunities for the unemployed, albeit only slightly. The effects were most pronounced in the Western European countries with a strong manufacturing base, such as Austria, Belgium, and Germany; as well as in the Central Eastern European countries that experienced strong industrial growth since joining the EU: namely, the Czech Republic, Hungary, and Slovakia. At the other end of the spectrum are the Southern European countries, for which the effects were barely noticeable.

Next, we use the estimated counterfactual labour market flow probabilities to quantify the effect of robot adoption on employment and unemployment levels (see the *Counterfactual analysis methodology* section in Appendix C).

We find that the effects of rising robot exposure on employment were positive; and that the effects of rising robot exposure on unemployment were negative, but moderate in size. In addition, we find that if the level of robot exposure in each country remained at the level recorded in 2004, in most European countries, employment would be lower (and unemployment would be higher) by about 0.5-1% of the working-age population (equivalent to 0.5-1 pp of the employment rate) (Figure 13). These effects were the largest in Slovakia and the Czech Republic (2-2.5% by 2017), and the smallest in Sweden and Denmark (0.4% by 2017). We speculate that the adoption of robots led to an expansion of the firms and sectors adopting automation technologies, which, in turn, translated into higher labour demand, as shown at the firm level for France by Domini et al. (2020) and Acemoglu et al. (2020), or for Spain by Koch et al. (2021).

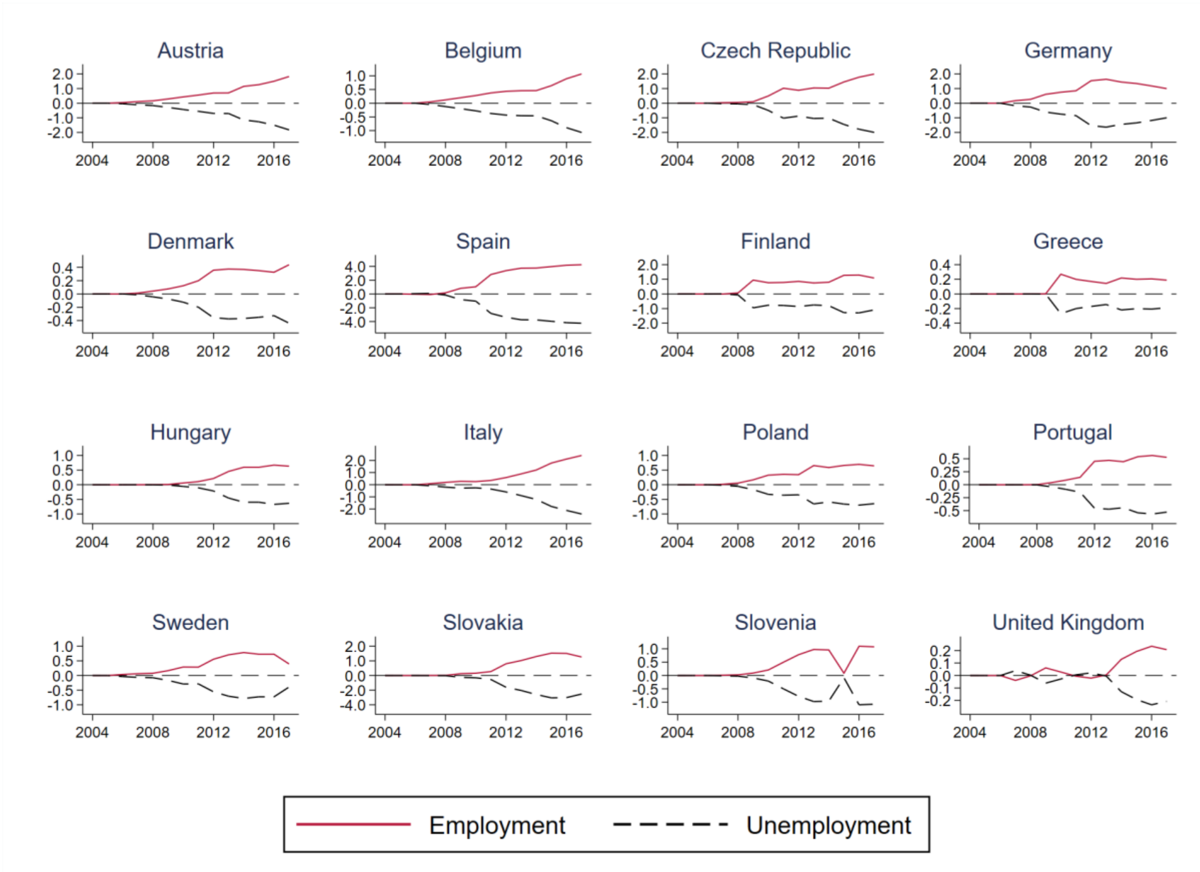
Figure 9. The effect of robot adoption (since 2004) on the likelihood of labour market transition





Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data. Estimations based on model (4) from Tables 1-2.

Figure 10. The estimated effect of robot adoption (since 2004) on employment and unemployment (% of working-age population)



Note: Values on the Y-axis are expressed as shares of the working-age population (aged 15-69), in per cent. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data. Estimations based on estimated equation (4), Tables 1-2.

Finally, we assess the contributions of job separation and job finding channels to the overall effect of rising robot exposure on employment, using a covariance-based decomposition (equations (23)-(26) in Appendix C) originally proposed by Fujita and Ramey (2009).

We find that in 14 out of the 16 countries in our sample, the contribution of jobs separations to changes in employment and unemployment levels attributed to robot exposure was larger than that of job findings, in many cases noticeably (Table 3). This result confirms our assumption that improved job stability is a key mechanism behind the labour market effects of robot adoption in Europe.

The effects of similar exogenous shocks on labour market transitions may differ between countries because of differences in labour market institutions, as shown for EPL by Aghelmaleki et al. (2021). We therefore correlate the contributions of job separations and findings to the changes in employment and unemployment caused by robot exposure with three important labour market institutions: EPL, union coverage, and the unemployment benefit replacement rate. We find relatively strong correlations between the contributions of job separations and findings and labour market institutions (Table 3): the contribution of job separations to employment changes was larger in countries with higher union coverage (correlation 0.31), in countries with lower replacement rates (correlation -0.33), and in countries with lower EPL (correlation -0.33). At the same time, the contribution of job findings to employment changes was larger in countries with lower EPL (correlation 0.31), in countries with lower union coverage (correlation -0.29), and in countries with higher replacement rates (correlation 0.32). The results for unemployment mirror those for employment.

The results on the role of institutions are in line with theoretical expectations. First, stricter EPL tends to raise the costs of firings relative to hirings as a margin of adjustment. Previous empirical evidence also showed that job findings are a more important adjustment margin than job separations in countries with high EPL (Messina and Vallanti 2007). Second, higher union coverage implies more wage rigidity. As firms are less able to adjust wages, they are likely to increase job separations in case of negative exogenous shock. This is also borne out by some empirical evidence that higher wage rigidity leads to more separations (Lechthaler 2013). Thus, we find interesting indications for potential adjustment mechanisms under different institutional regimes. However, we only provide suggestive evidence for the potential role of labour market institutions when analysing the effect of robots on labour market dynamics. Further research along those lines seems warranted.

Table 3. Decomposition of the impact of robots on employment and unemployment (in % of the variance)

	Employment		Unemployment	
Contributions of	**Job separations**	**Job findings**	**Job separations**	**Job findings**
Austria	92.1	6.8	91.2	7.7
Belgium	85.2	13.8	85.7	13.3
Czech Republic	75.8	19.9	73.8	20.7
Germany	82.4	14.6	82.4	14.0
Denmark	57.5	40.5	57.1	40.8
Spain	82.1	15.6	82.1	15.7
Finland	94.0	5.5	93.4	6.1
Greece	90.6	9.3	98.3	1.7
Hungary	56.2	42.3	57.3	40.8
Italy	86.3	11.4	87.4	10.2
Poland	80.2	18.7	77.2	21.4
Portugal	33.7	65.7	34.8	64.6
Sweden	96.2	1.7	94.9	2.6
Slovenia	57.3	38.9	71.5	22.2
Slovakia	42.3	49.4	38.4	52.0
United Kingdom	82.7	16.8	89.0	10.6
Cross-country correlation with labour market institutions				
Replacement rate	-0.33	0.32	-0.34	0.33
EPL	-0.33	0.31	-0.34	0.32
Union coverage	0.31	-0.29	0.35	-0.33

Note: Calculations based on model (4) from Table 1 and Table 2. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, UIBE GVC, OECD, and ICTWSS data.

5. Conclusions

In this paper, we have investigated the effects of robot exposure on worker flows in 16 European countries in the 1998–2018 period. We aimed to answer three research questions. First, what were the effects of rising robot exposure on job separation and job finding rates in Europe, and what role did labour costs play in this context? Second, how did the effects differ between workers performing different tasks and belonging to different age groups? Third, what consequences did the effects of robot exposure on worker flows have for employment and unemployment, and how did these consequences differ by country?

To answer these questions, we estimated worker flow probabilities using individual-level data from the EU-LFS and data from the IFR, which provides yearly information on robot exposure at the industry level. Furthermore, we explicitly included labour costs to quantify their role in the effects of robot exposure on worker flows. To take into account the potential endogeneity of robot adoption, we used a control-function approach in the spirit of Acemoglu and Restrepo (2019) and Dauth et al. (2021).

Our findings can be summarised as follows. First, overall, we found small beneficial effects for worker flows: i.e., robot exposure reduced job separations and increased job findings. More specifically, we detected strong cross-country heterogeneities that depended on labour costs: on the one hand, in countries with low labour costs (mainly CEE countries), higher levels of robot exposure led to lower job separation rates, and thus to higher levels of job stability; whereas in countries with high labour costs, by contrast, robot exposure was associated with lower levels of job stability. On the other hand, in countries with low labour costs, higher levels of robot exposure led to increased job findings; whereas in countries with high labour costs, higher levels of robot exposure led to decreased job findings. These results are in line with the Marshallian laws of labour demand, which states that labour is more likely to be substituted by other factors of production if labour costs are relatively high. An additional explanation for the benign effects of robots in countries with low labour costs could be that in these countries, automation was largely connected to greenfield investment and integration into global value chains (Cséfalvay 2020). This could imply that automation investment was a complement of, rather than a substitute for, labour.

The results of our econometric analysis were robust to the use of different instrumental variables within a control-function approach and to analysing the manufacturing sector only. Excluding industry fixed effects left the results virtually unchanged as well. Furthermore, as we controlled for several variables such as exports and global value chains, our results were unlikely to be driven by factors related to trade and globalisation.

Second, we found important differences between workers performing different job tasks and belonging to different age groups. Perhaps surprisingly, we generally found more beneficial effects for routine workers (both manual and cognitive) than for non-routine workers. This result was more pronounced in countries with low labour costs. We found no effects of robot exposure on labour market flows among workers in non-routine cognitive occupations. Our results are thus somewhat at odds with the notion that routine tasks are always substitutes for robot technology, whereas non-routine tasks are always complements to robot technology. Instead, our results point to the importance of labour costs for the substitutability of workers performing different job tasks by robots: i.e., in countries with low labour costs, workers performing routine tasks seem to be complements of, rather than substitutes for, robots.

We also found strong heterogeneity between age groups. Again, our results showed that even the groups who may be expected to be most at risk from robotisation – i.e., young and old workers – were complements of, rather than substitutes for, robot technology in countries with low labour costs. This showed up as negative effects of robotisation on separations (i.e., greater employment stability) for older workers, and positive effects on hirings for younger workers. An exception to these general results was our observation that job findings were negatively affected by robot exposure for the countries with the highest labour costs.

Third, our counterfactual exercise showed that the effects on worker flows had important implications for employment and unemployment rates. Particularly in countries with low labour costs, increased robot exposure led to increases in employment and decreases in unemployment. Our decomposition showed that these results were mainly driven by reduced separations, rather than increased hirings. We also provide suggestive evidence that the role of separations was more important in countries with low employment protections and low benefit replacement rates, and was less important in countries with high union coverage.

Our results have important policy implications. First, the overall effects of robots appear to be positive. Therefore, this technology should generally be seen as an opportunity for workers, rather than as a threat to them. The key policy challenge is therefore to identify the factors that contribute to this technology being a complement to rather than a substitute for human labour. Our paper is a step in this direction. The next steps include a more explicit analysis of the factors that enable workers to adjust to technological change, especially through the increased use of training. Second, there are large differences between countries, and between worker groups. Therefore, a one-size-fits-all solution for all countries and workers is not the way forward. Third, institutions appeared to matter for our results. Therefore, we see a more explicit analysis of institutions as an important avenue for future research.

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Appendices

Appendix A

Table A1: Relative labour costs (in manufacturing) and GDP in 2004 across countries

	Relative Labour Cost 2004	Relative GDP per capita 2004
Austria	1.05	0.73
Belgium	1.21	0.68
Czech Republic	-0.56	-0.22
Germany	1.16	0.61
Denmark	1.14	1.00
Spain	0.59	0.36
Finland	1.03	0.74
Greece	0.37	0.27
Hungary	-0.55	-0.52
Italy	0.84	0.56
Poland	-0.88	-0.79
Portugal	-0.12	0.03
Sweden	1.20	0.84
Slovenia	0.00	0.00
Slovakia	-0.83	-0.54
United Kingdom	0.83	0.61

Note: The table shows the initial conditions of the countries relative to Slovenia, the richest Central Eastern European country, which we use as a reference. Source: authors' calculations based on the Eurostat data (lc_n04cost and sdg_08_10).

Table A2: Sample descriptives

		EU		UE	
		mean	sd	mean	sd
Women		0.46	(0.5)	0.46	(0.5)
Men		0.54	(0.5)	0.54	(0.5)
Married		0.59	(0.49)	0.43	(0.5)
Age	Age 15-24	0.08	(0.27)	0.15	(0.36)
	Age 25-34	0.26	(0.44)	0.29	(0.45)
	Age 35-54	0.55	(0.5)	0.45	(0.5)
	Age 55-70	0.12	(0.32)	0.12	(0.32)
Education	Low: Lower secondary	0.21	(0.4)	0.35	(0.48)
	Medium: Upper secondary	0.52	(0.5)	0.51	(0.5)
	High: Tertiary education	0.27	(0.45)	0.14	(0.35)
Native Share		0.89	(0.32)	0.86	(0.35)
Industry Groups	Primary sector	0.03	(0.16)	0.04	(0.21)
	Manufacturing	0.22	(0.41)	0.22	(0.41)
	Utilities	0.02	(0.13)	0.01	(0.1)
	Construction	0.07	(0.26)	0.11	(0.31)
	Consumer service activities	0.17	(0.38)	0.23	(0.42)
	Business service activities	0.19	(0.39)	0.17	(0.37)
	Public Services and education	0.31	(0.46)	0.22	(0.42)
Task Groups	Non-Routine Cognitive Analytical	0.16	(0.36)	0.07	(0.25)
	Non-Routine Cognitive Personal	0.2	(0.4)	0.05	(0.22)
	Routine Cognitive	0.22	(0.41)	0.24	(0.43)
	Routine Manual	0.14	(0.34)	0.18	(0.38)
	Non-Routine Manial	0.29	(0.45)	0.47	(0.5)
Labour Costs 2004		0.33	(0.89)	0.3	(0.9)
Robot Exposure		1.82	(5.03)	1.73	(4.88)
Institutions	Employment Protection Legislation (standardised)	-0.01	(1.02)	-0.01	(1.02)
	Replacement Rate (standardised)	-0.02	(1.01)	-0.02	(1.01)
	Union Coverage (standardised)	-0.02	(1.)	-0.02	(1.)
Global value chain participation backward		0.16	(0.09)	0.17	(0.09)
Gross value added		10.5	(1.61)	10.48	(1.61)
Investment to gross value added		0.83	(0.05)	0.83	(0.06)
Gdp growth		101.66	(2.94)	101.68	(2.97)
Export growth		0.38	(1.02)	0.42	(1.07)

Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Table A3: The allocation of occupations to task groups (ISCO-88)

Task group	ISCO-88 code	Occupation
NRCA	11	Legislators and senior officials
	21	Physical, mathematical, and engineering science professionals
	22	Life science professionals
	24	Other professionals
	31	Physical and engineering science associate professionals
NRCP	12	Corporate managers
	13	General managers
	23	Teaching professionals
	32	Life science and health associate professionals
	33	Teaching associate professionals
RC	34	Other associate professionals
	41	Office clerks
	42	Customer services clerks
	52	Models, salespersons, and demonstrators
RM	71	Extraction and building trades workers
	72	Metal, machinery, and related trades workers
	74	Other craft and related trades workers
	81	Stationary-plant and related operators
	82	Machine operators and assemblers
	93	Labourers in mining, construction, manufacturing, and transport
NRM	51	Personal and protective services workers
	61	Market-oriented skilled agricultural and fishery workers
	62	Subsistence agricultural and fishery workers
	71	Extraction and building trades workers
	72	Metal, machinery, and related trades workers
	73	Precision workers in metal and related trades workers
	83	Drivers and mobile-plant operators
	91	Sales and services elementary occupations
	92	Agricultural, fishery, and related labourers

Table A4: The allocation of occupations to task groups (ISCO-08)

Task group	ISCO-08 code	Occupation
NRCA	21	Science and Engineering Professionals
	22	Health Professionals
	24	Business and Administration Professionals
	25	Information and Communications Technology Professionals
	26	Legal, Social, and Cultural Professionals
	31	Science and Engineering Associate Professionals
	35	Information and Communications Technicians
NRCP	11	Chief Executives, Senior Officials, and Legislators
	12	Administrative and Commercial Managers
	13	Production and Specialised Services Managers
	23	Teaching Professionals
	32	Health Associate Professionals
RC	33	Business and Administration Associate Professionals
	34	Legal, Social, Cultural, and Related Associate Professionals
	41	General and Keyboard Clerks
	42	Customer Services Clerks
	43	Numerical and Material Recording Clerks
	44	Other Clerical Support Workers
	52	Sales Workers
RM	72	Metal, Machinery, and Related Trades Workers
	73	Handicraft and Printing Workers
	75	Food Processing, Woodworking, Garment, and Other Craft and Related Trades Workers
	81	Stationary Plant and Machine Operators
	82	Assemblers
	94	Food Preparation Assistants
NRM	51	Personal Services Workers
	53	Personal Care Workers
	54	Protective Services Workers
	61	Market-oriented Skilled Agricultural Workers
	62	Market-oriented Skilled Forestry, Fishery, and Hunting Workers
	63	Subsistence Farmers, Fishers, Hunters, and Gatherers
	71	Building and Related Trades Workers (excluding Electricians)
	74	Electrical and Electronic Trades Workers
	83	Drivers and Mobile Plant Operators
	91	Cleaners and Helpers
	92	Agricultural, Forestry, and Fishery Labourers
	93	Labourers in Mining, Construction, Manufacturing, and Transport
	95	Street and Related Sales and Services Workers
	96	Refuse Workers and Other Elementary Workers

Appendix B

Table B1: The effect of robot exposure on the likelihood of job separation – full specification

	(1) Probit	(2) CF	(3) Probit	(4) CF
Robot Exposure	-0.001	-0.007***	0.002	-0.008***
	[0.001]	[0.001]	[0.002]	[0.002]
Robot Exposure X Labour Costs			0.009***	0.005**
			[0.002]	[0.002]
Robot Exposure X (Labour Costs)^2			-0.011***	-0.001
			[0.003]	[0.003]
Labour Costs	-0.104***	-0.097***	-0.114***	-0.103***
	[0.009]	[0.009]	[0.009]	[0.010]
(Labour Costs)^2	-0.033***	-0.031***	-0.019*	-0.035***
	[0.011]	[0.011]	[0.011]	[0.012]
Age Groups (Base Category: Age 15-24)				
Age 25-34	-0.158***	-0.158***	-0.158***	-0.158***
	[0.006]	[0.006]	[0.006]	[0.006]
Age 35-54	-0.341***	-0.340***	-0.342***	-0.341***
	[0.007]	[0.008]	[0.007]	[0.007]
Age 55-70	-0.343***	-0.342***	-0.343***	-0.342***
	[0.010]	[0.010]	[0.010]	[0.010]
Education Group (Base Category: Low education)				
Medium education	-0.207***	-0.206***	-0.205***	-0.206***
	[0.007]	[0.007]	[0.007]	[0.007]
High education	-0.386***	-0.384***	-0.384***	-0.384***
	[0.013]	[0.013]	[0.013]	[0.013]
Gender (Base category: Female)				
Male	-0.069***	-0.068***	-0.071***	-0.070***
	[0.006]	[0.006]	[0.007]	[0.006]
Native	-0.164***	-0.166***	-0.163***	-0.166***
	[0.011]	[0.011]	[0.011]	[0.011]
Global Value Chain (Backwards)	-0.224***	-0.228***	-0.176**	-0.170**
	[0.070]	[0.074]	[0.072]	[0.071]
Gross value added (Log)	-0.009***	-0.009***	-0.010***	-0.010***
	[0.003]	[0.003]	[0.003]	[0.003]
Investment to Gross value added	-0.167	-0.109	-0.169	-0.132
	[0.105]	[0.106]	[0.105]	[0.105]
GDP Growth	-0.019***	-0.019***	-0.019***	-0.020***
	[0.002]	[0.002]	[0.002]	[0.002]
Bartik instrument	-1.097***	-1.089***	-1.082***	-1.060***
	[0.187]	[0.188]	[0.185]	[0.184]
Export growth	0.020***	0.020***	0.020***	0.020***
	[0.003]	[0.003]	[0.003]	[0.003]
r01_1		0.009***		
		[0.002]		
r02_1				0.022***
				[0.003]
r03_1				0.008**
				[0.003]
r04_1				-0.020***
				[0.004]
Industry Group (Base Category: Agriculture and Mining)				
Manufacturing	-0.105***	-0.081***	-0.108***	-0.093***
	[0.024]	[0.024]	[0.024]	[0.024]
Utilities	-0.303***	-0.285***	-0.307***	-0.293***

	(1) Probit	(2) CF	(3) Probit	(4) CF
	[0.034]	[0.034]	[0.035]	[0.034]
Construction	0.148***	0.165***	0.145***	0.156***
	[0.029]	[0.029]	[0.029]	[0.029]
Consumer Services	-0.047*	-0.058**	-0.044*	-0.054**
	[0.025]	[0.026]	[0.025]	[0.025]
Business Services	-0.173***	-0.188***	-0.171***	-0.182***
	[0.025]	[0.025]	[0.025]	[0.025]
Public Services & Education	-0.317***	-0.329***	-0.314***	-0.322***
	[0.026]	[0.027]	[0.027]	[0.027]
Constant	0.961***	0.929***	0.999***	1.016***
	[0.234]	[0.238]	[0.234]	[0.235]
Year dummies	Yes	Yes	Yes	Yes
Observations	11.8 M	11.8 M	11.8 M	11.8 M

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Year and industry group fixed effects are included. Individual-level controls: age group, education group, gender, and native/non-native. Aggregate-level controls: global value chain participation, gross value added, the ratio of investment added to gross value added, GDP growth, labour demand and growth in exports. For CF, robot exposure is instrumented using robot exposure in the Western countries in the sample. r01_1 are residuals from the first stage regression for the specification without interactions. r02_1, r02_1 and r03_1 are residuals from the first stage regression for robot exposure, interaction of robot exposure with labour costs, and robot exposure with squared labour costs, respectively. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

Table B2: The effect of robot exposure on the likelihood of job finding – full specification

	(1) Probit	(2) CF	(3) Probit	(4) CF
Robot Exposure	-0.001	0.003**	0.013***	0.019***
	(0.001)	(0.002)	(0.002)	(0.003)
Robot Exposure X Labour Costs			-0.006***	-0.002
			(0.002)	(0.003)
Robot Exposure X (Labour Costs)^2			-0.008***	-0.018***
			(0.002)	(0.004)
Labour Costs	0.061***	0.054***	0.063***	0.057***
	(0.019)	(0.019)	(0.020)	(0.020)
(Labour Costs)^2	0.081***	0.078***	0.099***	0.113***
	(0.022)	(0.023)	(0.023)	(0.024)
Age Groups (Base Category: Age 15-24)				
Age 25-34	-0.451***	-0.451***	-0.450***	-0.450***
	(0.009)	(0.009)	(0.009)	(0.009)
Age 35-54	-0.714***	-0.714***	-0.712***	-0.712***
	(0.014)	(0.014)	(0.014)	(0.014)
Age 55-70	-1.120***	-1.120***	-1.118***	-1.117***
	(0.021)	(0.021)	(0.021)	(0.021)
Education Group (Base Category: Low education)				
Medium education	0.168***	0.168***	0.170***	0.171***
	(0.010)	(0.010)	(0.010)	(0.010)
High education	0.363***	0.362***	0.362***	0.363***
	(0.013)	(0.013)	(0.013)	(0.013)
Gender (Base category: Female)				
Male	0.009	0.008	0.012	0.011
	(0.008)	(0.008)	(0.008)	(0.008)
Native	-0.024*	-0.024*	-0.024*	-0.023

	(1) Probit	(2) CF	(3) Probit	(4) CF
	(0.015)	(0.014)	(0.014)	(0.015)
Global Value Chain (Backwards)	0.242***	0.246***	0.146*	0.163**
	(0.077)	(0.078)	(0.075)	(0.074)
Gross value added (Log)	0.034***	0.034***	0.035***	0.035***
	(0.006)	(0.006)	(0.006)	(0.006)
Investment to Gross value added	0.991***	0.938***	0.960***	0.940***
	(0.150)	(0.154)	(0.148)	(0.146)
GDP Growth	0.032***	0.032***	0.033***	0.033***
	(0.004)	(0.004)	(0.004)	(0.004)
Bartik instrument	1.743***	1.731***	1.701***	1.704***
	(0.194)	(0.194)	(0.193)	(0.193)
Export growth	-0.007	-0.007	-0.007	-0.007
	(0.005)	(0.005)	(0.005)	(0.005)
r01_1		-0.008***		
		(0.002)		
r02_1				-0.014***
				(0.004)
r03_1				-0.013***
				(0.005)
r04_1				0.025***
				(0.006)
Industry Group (Base Category: Agriculture and Mining)				
Manufacturing	0.147***	0.127***	0.146***	0.144***
	(0.019)	(0.021)	(0.019)	(0.019)
Utilities	0.333***	0.323***	0.333***	0.331***
	(0.034)	(0.035)	(0.034)	(0.033)
Construction	0.125***	0.106***	0.122***	0.118***
	(0.025)	(0.026)	(0.025)	(0.024)
Consumer Services	0.191***	0.199***	0.190***	0.194***
	(0.019)	(0.019)	(0.019)	(0.019)
Business Services	0.332***	0.343***	0.331***	0.335***
	(0.019)	(0.019)	(0.019)	(0.019)
Public Services & Education	0.432***	0.440***	0.429***	0.432***
	(0.022)	(0.022)	(0.022)	(0.022)
Constant	-4.396***	-4.368***	-4.485***	-4.469***
	(0.419)	(0.419)	(0.416)	(0.412)
Year dummies	Yes	Yes	Yes	Yes
Observations	1.3 M	1.3 M	1.3 M	1.3 M

Note: See notes to Table B1. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

Table B3: The effect of robot exposure on the likelihood of job separation, First Stage regressions

Independent variable:	(1) 1st First Stage Robot Exposure	(2) 2nd First Stage Robot Exposure X Labour Costs	(3) 3rd First Stage Robot Exposure X (Labour Costs)²
Instrument	0.720***	0.022*	-0.022*
	(0.024)	(0.012)	(0.011)
Instrument X Labour Costs	0.488***	0.861***	0.424***
	(0.019)	(0.022)	(0.012)
Robot Exposure X (Labour Costs)²	0.245***	0.487***	1.142***
	(0.030)	(0.022)	(0.030)
Labour Costs	0.084*	-0.327***	0.118***
	(0.049)	(0.047)	(0.036)
(Labour Costs)²	0.163**	0.232***	-0.157***
	(0.063)	(0.044)	(0.060)
Constant	3.428**	-4.193***	-0.168
	(1.474)	(1.492)	(1.489)
Observations	11.8 M	11.8 M	11.8 M
Kleibergen-Paap F statistic	17,067,368		

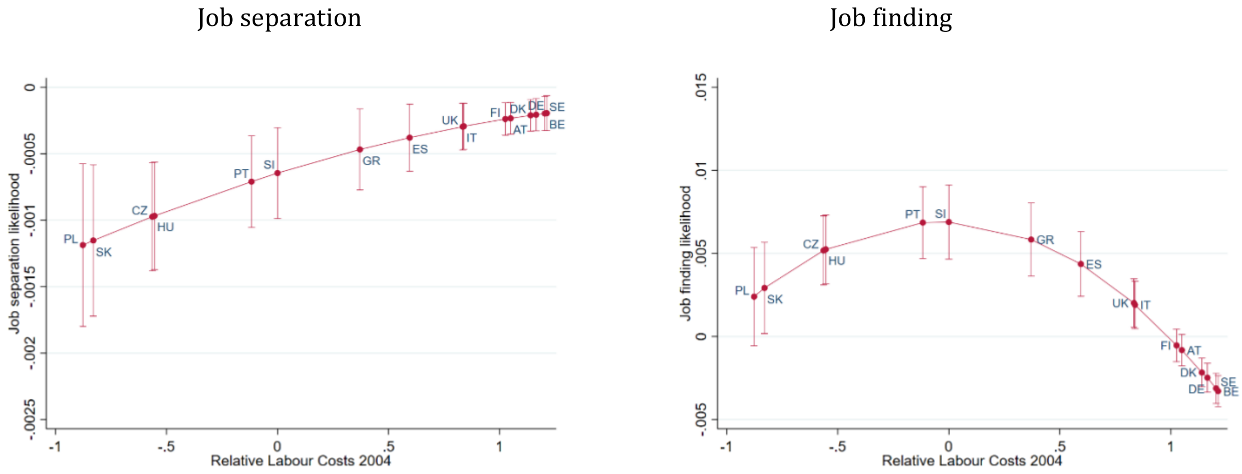
Note: See notes to Table B1. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, and IFR data.

Table B4: The effect of robot exposure on the likelihood of job finding, First Stage regressions.

Independent variable:	(1) 1st First Stage Robot Exposure	(2) 2nd First Stage Robot Exposure X Labour Costs	(3) 3rd First Stage Robot Exposure X (Labour Costs)²
Instrument	0.710***	0.026**	-0.020*
	(0.022)	(0.012)	(0.012)
Instrument X Labour Costs	0.456***	0.886***	0.415***
	(0.022)	(0.029)	(0.014)
Robot Exposure X (Labour Costs)²	0.316***	0.490***	1.189***
	(0.034)	(0.031)	(0.041)
Labour Costs	0.110**	-0.360***	0.121***
	(0.050)	(0.059)	(0.041)
(Labour Costs)²	0.167**	0.300***	-0.155*
	(0.069)	(0.060)	(0.083)
Constant	2.766	-4.668**	1.145
	(1.758)	(1.826)	(1.823)
Observations	1.3 M	1.3 M	1.3 M
Kleibergen-Paap F statistic		18,259,748	

Note: See notes to Table B1. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

Figure B1: Marginal effects of robot exposure on the likelihood of job separation / finding – across initial labour cost distribution.



Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

Table B5: List of sectors covered with industrial robot data provided by International Federation of Robotics

IFR class	Categories, divisions and classes of economic activities, ISIC, rev.4	Definitions
A-B	Agriculture, hunting and forestry; fishing	Crop and animal production, hunting and related service activities, forestry and logging, fishing and aquaculture
C	Mining and quarrying	Mining of coal and lignite, extraction of crude petroleum and natural gas, mining of metal ores, mining support service
D	Manufacturing	
10-12	Food products and beverages; Tobacco products	
13-15	Textiles, leather, wearing apparel	Textiles; wearing apparel; dressing & dyeing of fur; luggage, handbags, saddlery, harnesses, and footwear
16	Wood and wood products (incl.) furniture	Manufacture of wood, products of wood (incl. wood furniture) and products of cork
17-18	Paper and paper products, publishing & printing	Manufacture of pulp, paper, and converted paper production; printing of products, such as newspapers, books, periodicals, business forms, greeting cards, and other materials; and associated support activities, such as bookbinding, plate-making services, and data imaging; reproduction of recorded media, such as compact discs, video recordings, software on discs or tapes, records, etc.
19	Chemical products, pharmaceuticals, cosmetics	Manufacture of basic pharmaceutical products and pharmaceutical preparations. This also includes the manufacture of medicinal chemical and botanical products.
20-21	Unspecified chemical, petroleum products	Transformation of crude petroleum and coal into usable products, transformation of organic and inorganic raw materials by a chemical process and the formation of products
22	Rubber and plastic products without automotive parts*	e.g., rubber tires, plastic plates, foils, pipes, bags, boxes, doors, etc.; rubber and plastic parts for motor vehicles should be reported in 29.3
23	Glass, ceramics, stone, mineral products n.e.c. (without automotive parts*)	Manufacture of intermediate and final products from mined or quarried non-metallic minerals, such as sand, gravel, stone or clay; manufacture of glass, flat glass ceramic and glass products, clinkers, plasters, etc.
24	Basic metals (iron, steel, aluminum, copper, chrome)	e.g., iron, steel, aluminum, copper, chrome, etc.

25	Metal products (without automotive parts*), except machinery and equipment	e.g., metal furniture, tanks, metal doors, forging, pressing, stamping and roll forming of metal, nails, pins, hand tools, etc.
28	Industrial machinery	e.g., machinery for food processing and packaging, machine tools, industrial equipment, rubber and plastic machinery, industrial cleaning machines, agricultural and forestry machinery, construction machinery, etc.
26-27	Electrical/electronics	
29	Automotive	
30	Other transport equipment	
E	Electricity and water supply	e.g., ships, locomotives, airplanes, spacecraft vehicles
F	Construction	General construction and specialised construction activities for buildings and civil engineering works. This includes new work, repairs, additions and alterations, the erection of prefabricated buildings or structures on the site, and construction of a temporary nature.
P	Education, research and development	

Source: IFR (2017).

Table B6: Construction of task contents measures based on O*NET data

Task content measure (*T*)	**Task items (*J*)**
Non-routine cognitive analytical	Analysing data/information Thinking creatively Interpreting information for others
Non-routine cognitive interpersonal	Establishing and maintaining personal relationships Guiding, directing, and motivating subordinates Coaching/developing others
Routine cognitive	The importance of repeating the same tasks The importance of being exact or accurate Structured vs. unstructured work
Routine manual	Pace determined by the speed of equipment Controlling machines and processes Spending time making repetitive motions
Non-routine manual physical	Operating vehicles, mechanised devices, or equipment Spending time using hands to handle, control, or feel objects, tools, or controls Manual dexterity

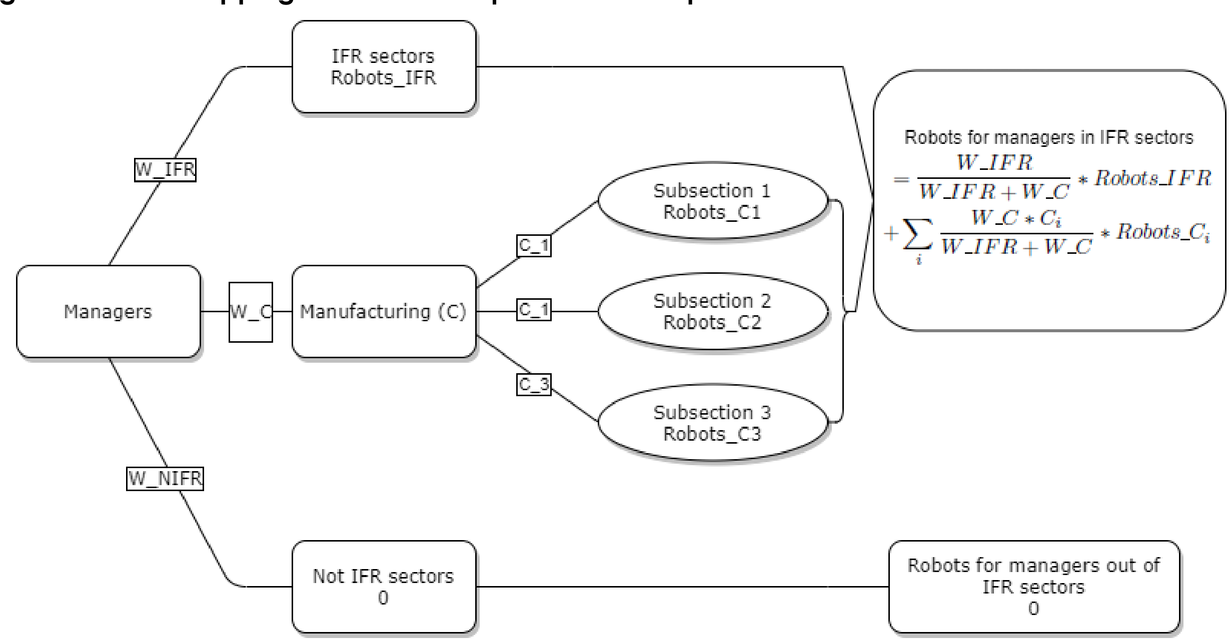
Source: Own elaboration based on Acemoglu and Autor (2011).

Appendix C - Technical details

In order to map the IFR data on robots to individual workers, we use the information on economic sectors and occupations available in the EU-LFS. Sectors are coded at the one-digit level of NACE rev. 1 between 1998-2007, and of NACE rev. 2 between 2008-2017. Occupations are coded at the two-digit level of ISCO-88 between 1998-2010, and of ISCO-08 between 2011-2017.

The industries reported by the IFR are in accordance with the International Standard Industrial Classification of All Economic Activities (ISIC) revision 4 (see Table 1A, Appendix A). The IFR data distinguish between six main industries: (A-B) Agriculture, Hunting and Forestry; Fishing; (C) Mining and Quarrying; (D) Manufacturing; (E) Electricity, Gas, and Water Supply; (F) Construction; and (P) Education, Research and Development. We will call these industries the "IFR industries". The manufacturing industry, which is the industry with the highest robot stock, is divided further into 13 sub-industries. In each occupation, we classify workers into two subgroups depending on their sector of employment: those in the IFR sectors and those in the non-IFR (NIFR) sectors. We then use the sector-occupation mapping as in equation (1) to map robot exposure to workers in the IFR sectors. Workers in the NIFR sectors receive a zero weight as there are no robots in these sectors, and IFR sectors are reweighted such that weights sum up to one (see Figure 1).

Diagram C1. The mapping of the robot exposure to occupations across sectors with and without robots.



Note: We classify each occupation into two groups depending on the sector of employment: IFR sector and not IFR sector. We use the structure of occupations across sectors provided by Eurostat as occupation weights to extrapolate exposure to robots (if managers account for 20% of all workers employed in construction, their weight equals 0.2, etc.). The not IFR sectors automatically receive zero weight, as there are no robots (e.g. *Real estate activities*; W_NIFR in the figure); the IFR sectors (*agriculture, mining and quarrying, water supply, construction, education*) receive one level of weight (if 10% of all managers work in agriculture, they receive 0.1 weight*; W_IFR in the figure*); and *manufacturing,* thanks to its more accurate data on robots, receives two levels of weights (if 10% of all managers work in manufacturing and 5% of them are employed in the automotive industry, they have 0.005 weight; W_C * C_1, etc. in the figure). Weights for the IFR sectors are reweighted to sum up to one. Finally, we end up with two types of managers: managers in the not IFR sectors with null exposure to robots and managers in the IFR industries with exposure to robots, given by the formula presented in the above figure.

Counterfactual analysis methodology

In order to assess the economic significance of the estimated effects, we perform a counterfactual analysis to quantify the effect of robot adoption on labour market flows. In the counterfactual scenario, in each country we keep the level of robot exposure between 2004-2017 at the 2004 level. This assumption means that new robot installations would have only compensated for the depreciation of robot stock and for the aggregate changes in labour force.

In the first step, we use the coefficients estimated with equation (3) to calculate the predicted likelihood of job separation (EU) and job finding (EU) of individual i in country c and time $t \geq 2004$. In the second step, we use the estimated coefficients (the control function approach, with labour costs as a control for the initial conditions in a country) and substitute the actual level of robot exposure with its counterfactual value. Formally:

$$Pr(flow = 1|X)_{i,o,c,r,t} = \alpha * R_{i,c,t} + \beta * X_{i,c,t} + \epsilon_{i,c,t} \quad (1)$$

$$PR\widehat{(flow)}_{i,c,t} = \widehat{\alpha} * R_{i,c,t} + \widehat{\beta} * \mathrm{X}_{i,c,t} \quad (2)$$

$$\Pr\ (\widehat{flow\_counter})_{\iota,c,t} = \widehat{\alpha} * R_{i,c,2004} + \widehat{\beta} * \mathrm{X}_{i,c,t} \quad (3)$$

where $PR\widehat{(Flow)}_{i,c,t}$ is the likelihood of a given flow predicted with the model, $PR(\widehat{Flow\_counter})$ is a counterfactual likelihood of the same flow, and $flow = \{eu, ue\}$. Then, for each country and year, we compute the share of individuals for whom the expected value of the flow is equal to one in a given simulation, namely:

$$\widehat{flow}_{c,t} = \frac{\sum_i^{I_{c,t}} 1\{flow=1\}}{I_{c,t}}, \quad (4)$$

where $I_{c,t}$ is the mass of individuals i observed for particular flow in country c and time t.

In the third step, we use estimated probabilities of labour market flows to recursively calculate the levels of employment and unemployment flows and stocks, according to the formulas:

$$\widehat{EU}_{c,t} = EMP_{c,t} * \widehat{eu}_{c,t} \quad (5)$$

$$\widehat{UE}_{c,t} = UNEMP_{c,t} * \widehat{ue}_{c,t} \quad (6)$$

$$\widehat{EMP}_{c,t+1} = \begin{cases} \widehat{EMP}_{c,t} - \widehat{EU}_{c,t} + \widehat{UE}_{c,t} \ if \ t \geq 2004 \\ EMP_{c,t+1} \ if \ t < 2004 \end{cases} \tag{7}$$

$$U\widehat{NEMP}_{c,t+1} = \begin{cases} U\widehat{NEMP}_{c,t} + \widehat{EU}_{c,t} - \widehat{UE}_{c,t} \ if \ t \geq 2004 \\ UNEMP_{c,t+1} \ if \ t < 2004 \end{cases} \tag{8}$$

where $\widehat{EU}_{c,t}$ is an estimated flow from employment to unemployment (job separations), $\widehat{UE}_{c,t}$ is an estimated flow from unemployment to employment (job findings), $\widehat{EMP}_{c,t}$ and $U\widehat{NEMP}_{c,t}$ are estimated levels of employment and unemployment in country c and time t, respectively. The initial values of $\widehat{EMP}_{c,t}$ ($U\widehat{NEMP}_{c,t}$) are equal to actual employment (unemployment) levels in a particular country in 2004. We repeat all computations for predicted and counterfactual (marked with cf superscript) scenarios.

In the fourth step, we calculate the effect of the robot adoption on the labour market as a relative difference between the counterfactual and predicted scenarios for each year t, namely:

$$\Delta EMP_{c,t} = \frac{\widehat{EMP}_{c,t} - EMP^{cf}_{c,t}}{\widehat{EMP}_{c,t}} * 100 \tag{9}$$

$$\Delta UNEMP_{c,t} = \frac{U\widehat{NEMP}_{c,t} - UNEMP^{cf}_{c,t}}{UNEMP_{c,t}} * 100 \tag{10}$$

where $\Delta EMP_{c,t}$ and $\Delta UNEMP_{c,t}$ stand for the relative impact of robot adoption on employment and unemployment in country c and time $t \geq 2004$, respectively.

We apply this decomposition method to the model estimated on a pooled sample, as well as to models estimated on subsamples that included workers in occupations that belong to particular task groups. This allows us to assess what the contributions of particular task groups are to the overall effect.

Finally, we analyse to what extent the overall effects of robot adoption on employment and unemployment are driven by the impacts on job separations (EU) versus on job findings (UE). To this end, we perform a semi-counterfactual analysis. To quantify the importance of the job separation channel (JS superscript), we multiply the predicted employment stock ($\widehat{EMP}^{s,JS}_{c,t}$) (unemployment stock ($U\widehat{NEMP}^{s,JS}_{c,t}$)) with the counterfactual likelihood of job separations ($\widehat{eu}^{cf}_{c,t}$) (likelihood of job finding ($\widehat{ue}_{c,t}$)), and calculate flows and levels recursively, using the formulas:

$$\widehat{EU}^{s,JS}_{c,t} = \widehat{EMP}^{s,JS}_{c,t} * \ \widehat{eu}^{cf}_{c,t} \tag{11}$$

$$\widehat{UE}^{s,JS}_{c,t} = U\widehat{NEMP}^{s,JS}_{c,t} * \ \widehat{ue}_{c,t} \tag{12}$$

$$\widehat{EMP}_{c,t+1}^{s,JS} = \begin{cases} \widehat{EMP}_{c,t}^{s,JS} - \widehat{EU}_{c,t}^{s,JS} + \widehat{UE}_{c,t}^{s,JS} \text{ } if \text{ } t \geq 2004 \\ EMP_{c,t+1} \text{ } if \text{ } t < 2004 \end{cases} \quad (13)$$

$$U\widehat{NEMP}_{c,t+1}^{s,JS} = \begin{cases} U\widehat{NEMP}_{c,t}^{s,JS} + \widehat{EU}_{c,t}^{s,JS} - \widehat{UE}_{c,t}^{JS} \text{ } if \text{ } t \geq 2004 \\ UNEMP_{c,t+1} \text{ } if \text{ } t < 2004 \end{cases} \quad (14)$$

where the initial values of $\widehat{EMP}_{c,t}^{s,JS}$ and $U\widehat{NEMP}_{c,t}^{s,JS}$ are the actual employment and unemployment levels, respectively, in a particular country in 2004.

To quantify the job finding channel (JF superscript), we use the counterfactual likelihood of job finding and the predicted likelihood of job separation, using the formulas:

$$\widehat{EU}_{c,t}^{s,JF} = \widehat{EMP}_{c,t}^{s,JF} * \widehat{eu}_{c,t} \quad (15)$$

$$\widehat{UE}_{c,t}^{s,JF} = U\widehat{NEMP}_{c,t}^{s,JF} * \widehat{ue}_{c,t}^{cf} \quad (16)$$

$$\widehat{EMP}_{c,t+1}^{s,JF} = \begin{cases} \widehat{EMP}_{c,t}^{c,t} - \widehat{EU}_{c,t}^{s,JF} + \widehat{UE}_{c,t}^{s,JF} \text{ } if \text{ } t \geq 2004 \\ EMP_{c,t+1} \text{ } if \text{ } t < 2004 \end{cases} \quad (17)$$

$$U\widehat{NEMP}_{c,t+1}^{s,JF} = \begin{cases} U\widehat{NEMP}_{c,t}^{s,JF} + \widehat{EU}_{c,t}^{s,JF} - \widehat{UE}_{c,t}^{s,JF} \text{ } if \text{ } t \geq 2004 \\ UNEMP_{c,t+1} \text{ } if \text{ } t < 2004 \end{cases} \quad (1$$

where the initial values of $\widehat{EMP}_{c,t}^{s,JF}$ and $U\widehat{NEMP}_{c,t}^{s,JF}$ are the actual employment and unemployment levels, respectively, in particular country in 2004.

For each of semi-counterfactual simulations, we calculate its effect as a relative difference between the counterfactual and predicted scenarios, given by:

Job Separation (JS) Channel:

$$\Delta\widehat{EMP}_{c,t}^{s,JS} = \frac{\widehat{EMP}_{c,t} - \widehat{EMP}_{c,t}^{s,JS}}{EMP_{c,t}} * 100 \quad (18)$$

$$\Delta U\widehat{NEMP}_{c,t}^{s,JS} = \frac{U\widehat{NEMP}_{c,t} - U\widehat{NEMP}_{c,t}^{s,JS}}{UNEMP_{c,t}} * 100 \quad (19)$$

Job Finding (JF) Channel:

$$\Delta\widehat{EMP}_{c,t}^{s,JF} = \frac{\widehat{EMP}_{c,t} - \widehat{EMP}_{c,t}^{s,JF}}{EMP_{c,t}} * 100 \quad (20)$$

$$\Delta \widehat{UNEMP}_{c,t}^{s,JF} = \frac{\widehat{UNEMP}_{c,t} - \widehat{UNEMP}_{c,t}^{s,JF}}{\widehat{UNEMP}_{c,t}} * 100 \tag{21}$$

Finally, we use these values to assess the contributions of the separation and of the finding channels to the estimated effect of robot adoption on employment and unemployment, respectively. We use a covariance-based decomposition, originally proposed by Fujita and Ramey (2009), to quantify the contributions of job separation and job finding rates to unemployment fluctuations, in line with the following equations:

$$\sigma_{\Delta \widehat{EMP}_{c,t}^{s,JS}, \Delta EMP_{c,t}} = \frac{cov(\Delta \widehat{EMP}_{c,t}^{s,JS}, \Delta EMP_{c,t})}{var(\Delta EMP_{c,t})} \tag{22}$$

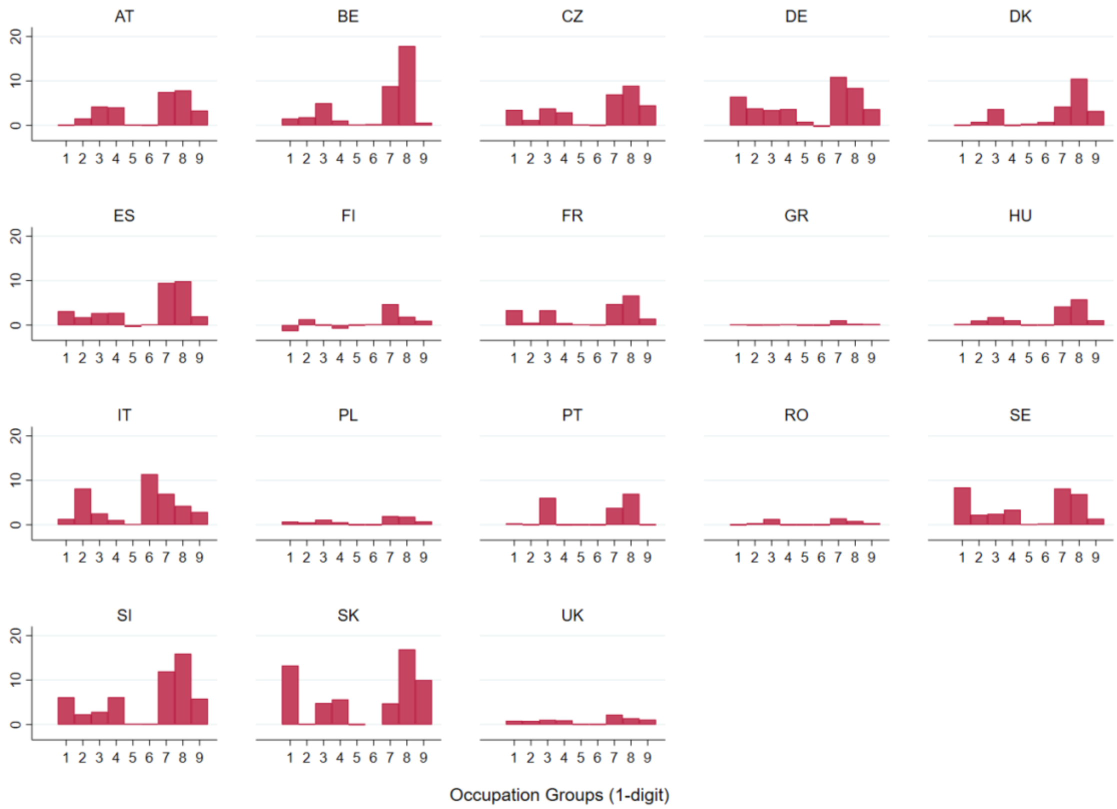
$$\sigma_{\Delta \widehat{EMP}_{c,t}^{s,JF}, \Delta EMP_{c,t}} = \frac{cov(\Delta \widehat{EMP}_{c,t}^{s,JF}, \Delta EMP_{c,t})}{var(\Delta EMP_{c,t})} \tag{23}$$

$$\sigma_{\Delta \widehat{UNEMP}_{c,t}^{s,JS}, \Delta UNEMP_{c,t}} = \frac{cov(\Delta \widehat{UNEMP}_{c,t}^{s,JS}, \Delta UNEMP_{c,t})}{var(\Delta UNEMP_{c,t})} \tag{24}$$

$$\sigma_{\Delta \widehat{UNEMP}_{c,t}^{s,JF}, \Delta UNEMP_{c,t}} = \frac{cov(\Delta \widehat{UNEMP}_{c,t}^{s,JF}, \Delta UNEMP_{c,t})}{var(\Delta UNEMP_{c,t})} \tag{25}$$

Appendix D – Additional descriptive evidence

Figure D1: Change in robot exposure at one-digit occupation-level between 1998/2004-2016.



Note: The figure displays the changes in robot exposure between 1998/2004 and 2016 in occupation groups across all sectors by country. Robot exposure is measured as the number of robots per 1,000 workers. Occupations are classified according to the ISCO Standard: 1 Managers; 2 Professionals; 3 Technicians and Associates; 4 Clerks; 5 Services and Sales; 6 Agriculture, Fishery, Forestry; 7 Craft and Trade; 8 Machine Operators; 9 Elementary Occupations). – Source: authors' calculations based on the EU-LFS and IFR.

Figure D2: Transition rates between employment and unemployment by country, 1998-2018.

Note: The figure displays the average transition rates (a) from employment to unemployment and (b) from unemployment to employment by country. – Source: authors' calculations based on the EU-LFS.

Additional results: alternative interaction - initial GDP level

Table D1: The effect of the robot exposure on the transition probability from employment to unemployment (job separation) flows controlling for initial development level (GDP)

	(1) Probit	(2) CF	(3) Probit	(5) CF
A: All Sectors				
Robot Density	-0.002*	-0.008***	-0.001	-0.009***
	[0.001]	[0.001]	[0.002]	[0.002]
Robot Density X GDP per capita			0.011***	0.008**
			[0.003]	[0.003]
Robot Density X (GDP per capita)^2			-0.017***	-0.003
			[0.005]	[0.005]
GDP per capita	-0.161***	-0.147***	-0.168***	-0.157***
	[0.010]	[0.010]	[0.010]	[0.010]
(GDP per capita)^2	-0.114***	-0.123***	-0.097***	-0.126***
	[0.016]	[0.016]	[0.017]	[0.018]
No. of observations	11.8 M	11.8 M	11.8 M	11.8 M
Kleibergen-Paap		1,104,227.8		5,582,877.4
B: Manufacturing				
Robot Density	-0.001	-0.009***	-0.003*	-0.009***
	[0.001]	[0.002]	[0.001]	[0.002]
Robot Density X GDP per capita			0.009***	0.013***
			[0.003]	[0.003]
Robot Density X (GDP per capita)^2			-0.008*	-0.007
			[0.004]	[0.006]
GDP per capita	-0.187***	-0.121***	-0.210***	-0.188***
	[0.016]	[0.020]	[0.016]	[0.018]
(GDP per capita)^2	-0.014	-0.030	-0.004	-0.028
	[0.026]	[0.026]	[0.031]	[0.041]
No. of Observations	2.6 M	2.6 M	2.6 M	2.6 M
Kleibergen-Paap		401,967.32		2,371,970.3

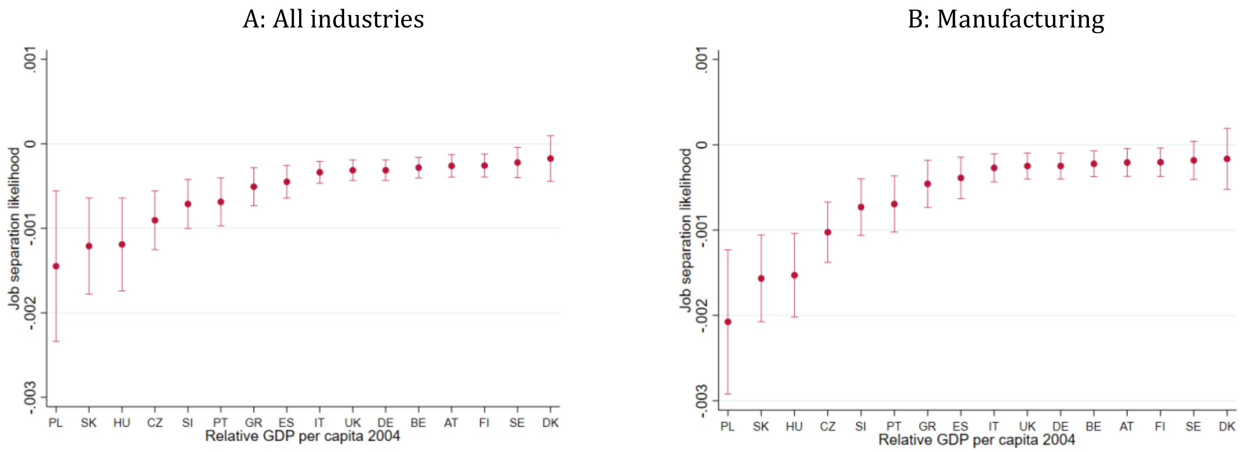
Note: See notes to Table B1. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

Table D2: The effect of the robot exposure on the transition probability of unemployment to employment (job finding) flows controlling for initial development level (GDP)

	(1) Probit	(2) CF	(3) Probit	(5) CF
A: All Sectors				
Robot Density	-0.001	0.005**	0.002	0.015***
	[0.001]	[0.002]	[0.002]	[0.002]
Robot Density X GDP per capita			-0.018***	-0.005
			[0.003]	[0.004]
Robot Density X (GDP per capita)^2			0.015**	-0.033***
			[0.005]	[0.007]
GDP per capita	0.166***	0.149***	0.179***	0.166***
	[0.019]	[0.019]	[0.020]	[0.020]
(GDP per capita)^2	0.183***	0.191***	0.175***	0.237***
	[0.026]	[0.026]	[0.027]	[0.029]
No. of Observations	1.3 M	1.3 M	1.3 M	1.3 M
Kleibergen-Paap		111,206.3		7,724,757.2
B: Manufacturing				
Robot Density	-0.000	0.010***	0.002	0.024***
	[0.001]	[0.002]	[0.002]	[0.004]
Robot Density X GDP per capita			-0.019***	-0.009**
			[0.004]	[0.004]
Robot Density X (GDP per capita)^2			0.017***	-0.052***
			[0.006]	[0.011]
GDP per capita	0.204***	0.128***	0.255***	0.257***
	[0.026]	[0.031]	[0.027]	[0.028]
(GDP per capita)^2	0.022	0.026	-0.005	0.289***
	[0.042]	[0.041]	[0.051]	[0.063]
No. of Observations	260,180	260,180	260,180	260,180
Kleibergen-Paap		38,592.302		3,581,667.9

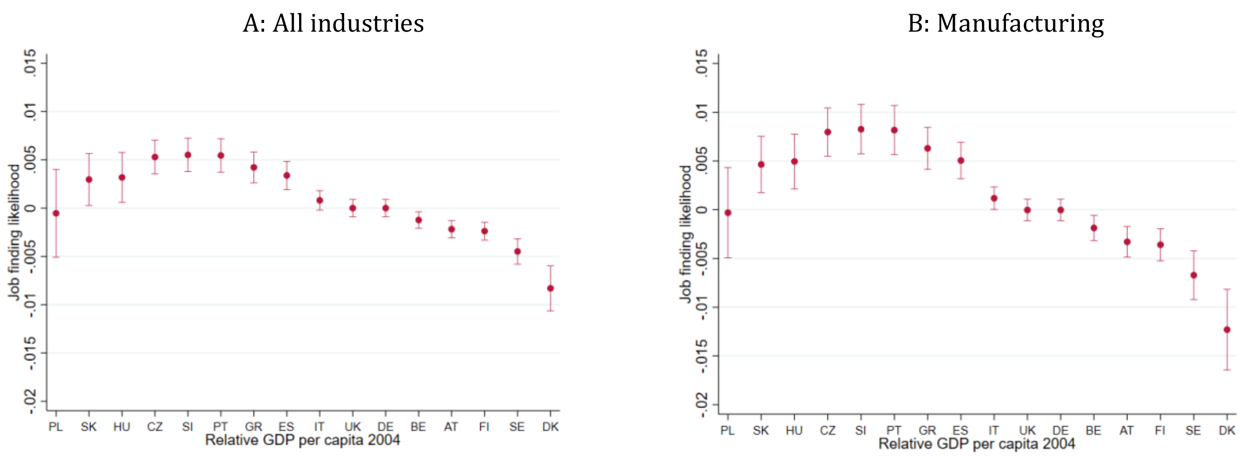
Note: See notes to Table B1. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

Figure D3: Marginal Effects of Robot Exposure for the Employment to Unemployment Flows



Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment. Robot exposure is interacted with GDP per capita in 2004. The results are obtained by instrumenting robot exposure with robot exposure in the Western European countries in the sample. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

Figure D4: Marginal Effects of Robot Exposure for the Unemployment to Employment Flows



Note: The figures show the marginal effects of robot exposure on the probability of transitioning from unemployment to employment. Robot exposure is interacted with GDP per capita in 2004. The results are obtained by instrumenting robot exposure with robot exposure in the Western European countries in the sample. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

Heterogeneity by task groups

Table D3: Effect of robot exposure on the likelihood of job separation, by task group

	(1) NRCA	(2) NRCP	(3) RC	(4) RM	(5) NRM
I: All Sectors					
A: Probit Estimation					
Robot Density	0.004	-0.000	-0.001	0.005**	0.014***
	[0.003]	[0.003]	[0.003]	[0.002]	[0.004]
Robot Density X Labour Costs	0.012***	-0.000	0.004	0.004	0.009**
	[0.003]	[0.002]	[0.004]	[0.002]	[0.003]
Robot Density X (Labour Costs)^2	-0.015***	-0.001	-0.006	-0.007*	-0.019***
	[0.003]	[0.004]	[0.004]	[0.003]	[0.004]
Labour Costs	0.018	-0.035*	-0.120***	-0.182***	-0.169***
	[0.017]	[0.017]	[0.016]	[0.021]	[0.016]
(Labour Costs)^2	-0.121***	-0.076**	-0.049**	0.057*	0.050**
	[0.019]	[0.025]	[0.017]	[0.023]	[0.018]
B: Control Function Approach:					
Robot Density	0.002	-0.009*	-0.008	0.004	0.004
	[0.004]	[0.004]	[0.004]	[0.003]	[0.005]
Robot Density X Labour Costs	0.000	-0.003	0.006	0.005	0.008
	[0.003]	[0.002]	[0.004]	[0.003]	[0.004]
Robot Density X (Labour Costs)^2	-0.005	0.006	-0.002	-0.006	-0.010
	[0.004]	[0.005]	[0.005]	[0.004]	[0.005]
Labour Costs	0.041*	-0.031	-0.120***	-0.184***	-0.164***
	[0.018]	[0.017]	[0.016]	[0.024]	[0.016]
(Labour Costs)^2	-0.137***	-0.080**	-0.053**	0.050*	0.037
	[0.020]	[0.025]	[0.017]	[0.024]	[0.019]
Observations	69,534	60,800	306,704	220,948	663,105
II: Manufacturing					
A: Probit Estimation					
Robot Density	0.000	0.011	-0.011**	0.003	0.004
	[0.004]	[0.006]	[0.003]	[0.002]	[0.003]
Robot Density X Labour Costs	0.019***	0.002	-0.004	0.005*	0.001
	[0.004]	[0.003]	[0.005]	[0.002]	[0.003]
Robot Density X (Labour Costs)^2	-0.018***	-0.010	0.003	-0.006*	-0.007*
	[0.005]	[0.007]	[0.005]	[0.003]	[0.003]
Labour Costs	-0.076**	-0.081	-0.105***	-0.177***	-0.168***
	[0.028]	[0.050]	[0.027]	[0.024]	[0.025]
(Labour Costs)^2	0.002	0.050	-0.004	0.074**	0.060*
	[0.044]	[0.082]	[0.033]	[0.026]	[0.025]
B: Control Function Approach:					
Robot Density	-0.001	-0.008	-0.034***	0.000	-0.012**
	[0.006]	[0.006]	[0.006]	[0.003]	[0.004]
Robot Density X Labour Costs	0.012	-0.008	-0.009	0.006*	-0.003
	[0.007]	[0.005]	[0.006]	[0.003]	[0.004]
Robot Density X (Labour Costs)^2	-0.015	0.002	0.024***	-0.005	0.010*
	[0.009]	[0.007]	[0.007]	[0.003]	[0.005]
Labour Costs	-0.033	-0.033	-0.069	-0.177***	-0.142***
	[0.038]	[0.055]	[0.035]	[0.028]	[0.030]
(Labour Costs)^2	0.002	0.043	-0.087*	0.067*	-0.004
	[0.053]	[0.091]	[0.036]	[0.028]	[0.026]
Observations	421,280	269,173	364,965	1597423	618,084

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Year and industry group fixed effects are included. Individual-level controls: age group, education group, gender, and native/non-native. Aggregate-level controls: global value chain participation, gross value added, the ratio of investment added to gross value added, GDP growth, labour demand, and growth in exports. Robot exposure is instrumented using robot exposure in the Western European countries in the sample. NRCA – Non-routine cognitive analytical; NRCP – Non-routine cognitive interpersonal; RC – Routine cognitive; RM – Routine manual; NRM – Non-routine manual physical. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Table D4: Effect of robot exposure on the likelihood of job finding, by task group

	(1) NRCA	(2) NRCP	(3) RC	(4) RM	(5) NRM
			I: All Sectors		
A: Probit Estimation					
Robot Density	0.010	-0.005	0.030***	0.016***	0.000
	[0.006]	[0.006]	[0.006]	[0.003]	[0.004]
Robot Density X	-0.010*	0.002	-0.012	-0.002	-0.010***
Labour Costs	[0.004]	[0.003]	[0.007]	[0.002]	[0.003]
Robot Density X	0.002	-0.002	-0.011	-0.011***	0.001
(Labour Costs)²	[0.006]	[0.008]	[0.008]	[0.003]	[0.005]
Labour Costs	0.136***	0.178***	0.173***	0.076*	0.041
	[0.032]	[0.038]	[0.015]	[0.034]	[0.031]
(Labour Costs)²	-0.036	0.097*	0.033	0.045	0.103**
	[0.037]	[0.041]	[0.027]	[0.044]	[0.038]
B: Control Function Approach:					
Robot Density	0.013	-0.006	0.032***	0.019***	0.010
	[0.008]	[0.011]	[0.007]	[0.004]	[0.007]
Robot Density X	0.004	0.005	-0.006	-0.006	-0.000
Labour Costs	[0.007]	[0.005]	[0.008]	[0.003]	[0.004]
Robot Density X	-0.013	0.005	-0.016	-0.011**	-0.018*
(Labour Costs)²	[0.007]	[0.014]	[0.011]	[0.004]	[0.007]
Labour Costs	0.114***	0.175***	0.171***	0.082*	0.029
	[0.032]	[0.037]	[0.016]	[0.034]	[0.032]
(Labour Costs)²	-0.013	0.094*	0.034	0.051	0.126**
	[0.039]	[0.041]	[0.027]	[0.046]	[0.039]
Observations	89,121	76,066	357,004	249,705	761,421
			II: Manufacturing		
A: Probit Estimation					
Robot Density	0.001	-0.007	0.033***	0.016***	0.020***
	[0.007]	[0.017]	[0.007]	[0.004]	[0.006]
Robot Density X	-0.017**	-0.009	0.002	-0.001	-0.012***
Labour Costs	[0.006]	[0.012]	[0.007]	[0.002]	[0.003]
Robot Density X	0.009	0.003	-0.033**	-0.012***	-0.009
(Labour Costs)²	[0.008]	[0.019]	[0.010]	[0.003]	[0.007]
Labour Costs	0.148*	0.238	0.146**	0.067	0.132***
	[0.073]	[0.172]	[0.048]	[0.039]	[0.037]
(Labour Costs)²	-0.140	0.028	0.149*	0.083	-0.039
	[0.094]	[0.241]	[0.072]	[0.049]	[0.061]
B: Control Function Approach:					
Robot Density	0.001	0.004	0.042***	0.020***	0.050***
	[0.008]	[0.038]	[0.011]	[0.005]	[0.011]
Robot Density X	-0.002	-0.007	0.022*	-0.004	-0.003
Labour Costs	[0.013]	[0.019]	[0.011]	[0.003]	[0.005]
Robot Density X	-0.004	0.005	-0.066***	-0.014**	-0.042***
(Labour Costs)²	[0.015]	[0.038]	[0.015]	[0.004]	[0.011]
Labour Costs	0.101	0.236	0.122*	0.080*	0.093**
	[0.067]	[0.164]	[0.055]	[0.040]	[0.036]
(Labour Costs)²	-0.081	-0.043	0.267***	0.098	0.081
	[0.121]	[0.249]	[0.078]	[0.051]	[0.061]
Observations	17,234	4,003	29,147	171,488	70,853

Note: See notes to Table B5. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Heterogeneity by age

Table D5: The effect of robot exposure on the likelihood of job separation – by age group

	(1) Probit	(2) CF	(3) Probit	(4) CF
A: Age 15-24				
Robot Exposure	0.004***	0.003	0.011***	-0.001
	(0.001)	(0.002)	(0.003)	(0.004)
Robot Exposure X Labour Costs	.	.	0.010***	0.002
			(0.003)	(0.003)
Robot Exposure X (Labour Costs)^2			-0.015***	0.004
			(0.004)	(0.004)
Labour Costs	-0.195***	-0.194***	-0.205***	-0.195***
	(0.014)	(0.014)	(0.015)	(0.015)
(Labour Costs)^2	-0.078***	-0.077***	-0.061***	-0.087***
	(0.019)	(0.019)	(0.020)	(0.020)
B: Age 25-34				
Robot Exposure	0.000	-0.001	0.004**	-0.007***
	(0.001)	(0.002)	(0.002)	(0.002)
Robot Exposure X Labour Costs			0.004	-0.004
			(0.002)	(0.003)
Robot Exposure X (Labour Costs)^2			-0.008***	0.009***
			(0.003)	(0.003)
Labour Costs	-0.073***	-0.072***	-0.078***	-0.065***
	(0.011)	(0.011)	(0.011)	(0.012)
(Labour Costs)^2	-0.077***	-0.077***	-0.066***	-0.090***
	(0.016)	(0.016)	(0.016)	(0.017)
C: Age 35-54				
Robot Exposure	-0.004***	-0.011***	-0.001	-0.012***
	(0.001)	(0.002)	(0.002)	(0.003)
Robot Exposure X Labour Costs			0.011***	0.009***
			(0.003)	(0.003)
Robot Exposure X (Labour Costs)^2			-0.013***	-0.004
			(0.003)	(0.003)
Labour Costs	-0.111***	-0.102***	-0.123***	-0.113***
	(0.010)	(0.010)	(0.010)	(0.011)
(Labour Costs)^2	0.017	0.021*	0.033***	0.019
	(0.012)	(0.012)	(0.011)	(0.012)
D: Age 55-70				
Robot Exposure	-0.004***	-0.013***	-0.001	-0.005*
	(0.001)	(0.002)	(0.002)	(0.003)
Robot Exposure X Labour Costs			0.014***	0.018***
			(0.003)	(0.003)
Robot Exposure X (Labour Costs)^2			-0.015***	-0.019***
			(0.003)	(0.004)
Labour Costs	-0.054***	-0.045***	-0.077***	-0.078***
	(0.012)	(0.012)	(0.012)	(0.013)
(Labour Costs)^2	-0.056***	-0.053***	-0.030*	-0.014
	(0.017)	(0.017)	(0.016)	(0.017)

Note: *** p<0.01, ** p<0.05, * p<0.1. Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.

Table D6: The effect of robot exposure on the likelihood of job finding - by age group

	(1) Probit	(2) CF	(3) Probit	(4) CF
A: Age 15-24				
Robot Exposure	-0.001	0.010***	0.009**	0.028***
	(0.002)	(0.003)	(0.004)	(0.006)
Robot Exposure X Labour Costs			-0.015***	-0.007**
			(0.003)	(0.003)
Robot Exposure X (Labour Costs)^2			0.001	-0.020***
			(0.004)	(0.006)
Labour Costs	0.102***	0.089***	0.111***	0.097***
	(0.018)	(0.018)	(0.018)	(0.018)
(Labour Costs)^2	-0.024	-0.029	-0.012	0.014
	(0.028)	(0.028)	(0.029)	(0.031)
B: Age 25-34				
Robot Exposure	-0.001	0.001	0.010***	0.018***
	(0.001)	(0.002)	(0.003)	(0.004)
Robot Exposure X Labour Costs			-0.005*	0.003
			(0.003)	(0.004)
Robot Exposure X (Labour Costs)^2			-0.008**	-0.022***
			(0.003)	(0.004)
Labour Costs	0.076***	0.071***	0.078***	0.068***
	(0.018)	(0.018)	(0.018)	(0.019)
(Labour Costs)^2	0.071***	0.070***	0.088***	0.105***
	(0.023)	(0.023)	(0.023)	(0.024)
C: Age 35-54				
Robot Exposure	-0.001	0.003	0.014***	0.018***
	(0.001)	(0.002)	(0.002)	(0.004)
Robot Exposure X Labour Costs			-0.004*	-0.001
			(0.002)	(0.003)
Robot Exposure X (Labour Costs)^2			-0.011***	-0.018***
			(0.003)	(0.004)
Labour Costs	0.059**	0.053**	0.058**	0.054**
	(0.023)	(0.023)	(0.024)	(0.025)
(Labour Costs)^2	0.130***	0.127***	0.153***	0.163***
	(0.028)	(0.028)	(0.029)	(0.030)
D: Age 55-70				
Robot Exposure	-0.002	-0.000	0.012***	0.009
	(0.002)	(0.003)	(0.004)	(0.007)
Robot Exposure X Labour Costs			-0.013***	-0.006
			(0.003)	(0.005)
Robot Exposure X (Labour Costs)^2			-0.001	-0.007
			(0.004)	(0.007)
Labour Costs	-0.010	-0.014	0.001	-0.003
	(0.035)	(0.034)	(0.037)	(0.038)
(Labour Costs)^2	0.126***	0.124***	0.137***	0.144***
	(0.042)	(0.043)	(0.045)	(0.047)

Note: *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, UN Comtrade, and UIBE GVC data.