The Impact of Robots on Labour Market Transitions in Europe

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Abstract

We study the effects of robot exposure on worker flows in 16 European countries between 2000-2017. Overall, we find small negative effects on job separations and no effects on job findings. We detect significant cross-country differences and find that labour costs are a major driver: the effects of robot exposure are generally larger in absolute terms in countries with relatively low or average levels of labour costs than in countries with high levels of labour costs. These effects are particularly pronounced for workers in occupations intensive in routine manual or routine cognitive tasks but are insignificant in occupations intensive in non-routine cognitive tasks. A counterfactual analysis suggests that robot adoption increased employment and reduced unemployment, especially in European countries with relatively low or average levels of labour costs, and that these effects were driven mainly by lower job separations.

JEL codes: J23, J24, O33

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, and it has doubled in Germany, a European leader in robot adoption. 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. Robot adoption has reduced total employment in the US (Acemoglu and Restrepo, 2020) but not in other highly industrialised countries such as Germany or Japan (Adachi et al., 2022; Dauth et al., 2021). It also appears that the employment effects of robots may depend on the development level. Robot adoption was associated with a decline in employment shares of jobs intensive in routine manual tasks in high-income countries but not in emerging or transition economies (de Vries et al., 2020). The reasons for such cross-country differences and the labour market mechanisms behind the aggregate employment effects of automation remain largely unexplored.

This paper fills this gap by investigating the impact of industrial robots on worker flows in Europe, paying particular attention to the role of labour costs for cross-country differences. We focus on worker flows as they constitute a key mechanism behind changes in employment and unemployment levels and are essential for worker welfare. For example, an adjustment to robots through changes in the job separation probability affects workers' welfare very differently than an adjustment through changes in the job finding rate: while job separations, in particular firings, often lead to immediate and potentially long-lasting earnings losses, the job finding rate is an important determinant of unemployment duration, which in turn implies a gradual loss of human capital and deteriorating labour-market prospects. Therefore, optimal policy responses differ strongly between these two cases. Worker flows are also a common short term labour market indicator that reacts almost immediately to shocks (Bachmann and Felder, 2020; Elsby et al., 2012), in contrast to long-term employment changes which have been the focus of most previous literature on automation (Acemoglu and Restrepo, 2020; Dauth et al., 2021).

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, how did automation-driven job findings and job separations contribute to changes in employment rates?

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 annual data on robot exposure by country and sector from the International Federation of Robotics (IFR). 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 potential confounders, such as general investment, participation in global value chains and trade, and labour demand shocks. As our analysis takes place at the industry-occupation level, we capture direct effects at firms adopting robots and indirect effects through spillovers which could occur, for instance, through the reallocation of output and workers to firms adopting robots (Acemoglu et al., 2020).

Conceptually, technological innovations can trigger a range of mechanisms beyond direct substitution of labour. They include reductions in prices and wages, new investments, introduction of new products and market expansion, increases in incomes and sectoral reallocations which jointly have an a priori ambiguous impact on the labour market (Calvino and Virgillito, 2018; Pianta, 2006; Vivarelli, 2014). While industrial robots seem to be a technology particularly conducive to labour substitution, their effects on employment and labour-market transitions are not clear-cut either. On the one hand, they can directly reduce employment as machines replace humans in performing specific tasks (the labour-saving effect). On the other hand, the product demand effect – i.e., an increase in activity through 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 (Gregory et al., 2022). Empirically, the positive impact of robots on productivity has been found in cross-country, sector-level studies (Graetz and Michaels, 2018) and firm-level studies (Acemoglu et al., 2020; Duan et al., 2023; Koch et al., 2021). Moreover, the product demand effect and the demand spillover effect tend to dominate over the labour-saving effect for routine-replacing technologies in Europe, increasing employment (Gregory et al., 2022).

Labour costs can play a vital role in shaping the labour market effects of labour-saving technologies, particularly industrial robots. As the price of robots is roughly uniform worldwide (Graetz and Michaels, 2018), 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 weaker impact on job separation rates and job finding rates in countries with lower levels of labour costs than in countries with higher labour costs. Indeed, 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 labour costs at the beginning of the observation period. These initial labour costs are plausibly exogenous to the robot adoption during the observation period and are not affected by feedback effects from robot adoption to labour costs.

We find that, on average, robot exposure has a small and significant negative impact on the likelihood of job separations, but has no effect on the likelihood of job finding. In addition, lower initial labour costs were generally associated with a more beneficial impact of robot adoption on labour market flows. In particular, in countries with initially low or average levels of labour costs, robot exposure reduced job separations more strongly.[1] Moreover, the effect of robot exposure on job findings was positive and significant in countries with low or average initial labour costs, but insignificant in countries with very low and very high initial labour costs. As explained in detail later, these small effects in countries with the lowest initial labour costs (such as Poland and Slovakia) likely reflect skilled workforce shortages that limited the scope of employment expansion driven by robot adoption associated with the rising role of these countries in European value chains (Altzinger and Landesmann, 2008).

To evaluate the heterogeneity in the effects of robot exposure on labour market flows, we focus on occupational tasks performed by workers, which are a crucial determinant of robots' substitutability of human labour. We apply widely-used categories of routine and non-routine cognitive, and routine and non-routine manual job tasks proposed by Acemoglu and Autor (2011) and distinguish occupational groups accordingly. We find more beneficial effects for workers in routine occupations than for workers in non-routine occupations. These are particularly pronounced for job separations where robots reduced separations amongst workers in routine manual and routine cognitive occupations. The increase of job findings in countries with medium labour costs occurred mainly

[1] 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.

among routine occupations. However, we also find a small positive effect in non-routine analytical and non-routine manual occupations. As we discuss in more detail in the conclusions, these results provide evidence to what extent job tasks matter for the substitutability of workers with robots, and the potentially important role of scale effects in shaping the labour market effects of automation in Europe.

We also find important differences between workers belonging to different age groups. In most countries, young and prime-aged workers benefitted from robots, while the results for older workers are mixed. Robot exposure reduced job separations and increased job findings among young and prime-aged workers, except for countries with the highest levels of initial labour costs. For older workers, robots increased job separations and decreased job findings across all industries, but decreased job separations and had no impact on job findings in manufacturing.

Finally, using a counterfactual analysis, we assess the contributions of robot-driven job separations and hirings to changes in aggregate employment levels. We find that rising robot exposure increased aggregate employment levels in European countries by about 1-2% of the working-age population between 2004 and 2017. Our reduced-form estimation results reflect the sum of the abovementioned effects of robots: the labour-saving effect, the product-demand effect, and the demand-spillover effect. We show that lower job separations were the key driving factor behind the positive, aggregate employment effects of robot adoption in Europe.

Our paper makes the following contributions to the literature. First, we provide the first evidence on the flow mechanisms behind the aggregate employment effects of automation in a European cross-country setting. Up to now, the literature has mainly focused on employment stocks or structures, focusing either on regional (Acemoglu and Restrepo, 2020; Dauth et al., 2021) or worker-level (Bessen et al., 2023; Domini et al., 2021; Koch et al., 2021; Dauth et al., 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 et al., 2021; de Vries et al., 2020; Klenert et al., 2022). 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 lower separation rates.

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 et al., 2022) did not shed much light on the factors that may explain international differences. They used broad country categorisations and did not quantify the role of differences in countries' labour costs (or other factors), as we do here. At the same time, lower labour costs have been a key trigger of industrial development in peripheral countries (both in Europe and globally) and their integration in global value chains (Bellak et al., 2008; Milberg and Winkler, 2013), especially in highly-automated sectors such as the automotive industry (Grodzicki and Skrzypek, 2020). Our findings that the labour market impacts of industrial robots were more benign in European countries with lower labour costs align with arguments that robot investments in those countries were driven by modernisation and attempts to expand product lines rather than a need to reduce labour inputs (Cséfalvay, 2020; Jürgens and Krzywdzinski, 2009), suggesting dominant scale effects.

Third, we indicate age-related differences in the labour market impacts of robots. Our findings are consistent with arguments that young workers more familiar with emerging technologies benefit more from the adoption of new technologies (Cavounidis and Lang, 2020; Fillmore and Hall, 2021), which empirically were also highlighted by Albinowski and Lewandowski (2024).

Fourth, using our causal estimates of the impact of robots on labour market flows to indirectly calculate robots' contributions to changes in employment levels, we contribute to the literature focused on employment impacts of automation. We find a positive effect of robots on employment in several European countries, in line with the findings of Koch et al. (2021) for Spain, Dauth et al. (2021) for Germany, and Adachi et al. (2022) for Japan, and results of Gregory et al. (2021) for routine-replacing technologies more broadly. Our findings also complement Klenert et al. (2022) who found a positive aggregate employment effect of robots at the industry level in Europe and align with Fernández-Macías et al. (2021) suggestion that robots intensify the long-term trend of industrial automation rather than introduce a ground-breaking change in the scope of automation. They contrast, however, with results for the US that robots reduced employment and widened wage inequality (Acemoglu and Restrepo, 2022, 2020).

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 measurements and our econometric methodology. 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 2000–2017 (Eurostat, 2019), a period of rapid robotisation in many industrialised countries. The EU-LFS includes information on all European Union member states. However, due to missings in key variables in EU-LFS and the lack of availability of other data discussed below for specific 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 aged 15 years or older who live in private households. The EU-LFS data are available as repeated cross-sections. The respondents reported their labour market status during the month of the survey and 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 the person 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 employed (unemployed) counterparts 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[2] 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 high reliability. For the Western European countries, we use the data on robots from 2000 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 International Organization for Standardization (ISO 8373:201), an

[2] For a detailed description of the sectors covered, see Table B5 in Appendix B.

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).

Apart from industry-level data on robots (IFR 2017), we use data on GDP per capita, gross fixed capital formations in sectors, and gross value added from the EU KLEMS Growth and Productivity Accounts database. We construct yearly GDP per capita growth rates and merge them with a lag at the country level. We map data on investment (gross fixed capital formation) and gross value added to occupations and merge them with the EU-LFS data on the occupational level. We also control for participation in global value chains using data from the Research Institute on Global Value Chains (RIGVC UIBE, 2016). In addition, we account for trade flows by using total export data 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 (WITS, 2021), and are aggregated and merged with the EU-LFS data at the one-digit sector level.

To quantify workers' exposure 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 performed before becoming jobless.

Merging the worker-level data from the EU-LFS with the industry-level data requires additional calculations to ensure the required granularity. The EU-LFS provides information on the economic sector at the one-digit NACE level. Such sectoral disaggregation is too broad for the precise measurement of robot adoption, as there are substantial differences in robot use between two-digit sectors within a given one-digit sector, particularly in manufacturing (IFR 2017). We, therefore, use the data on two-digit occupations contained in the EU-LFS together with external information on the distribution of occupations across sectors to assign robot adoption at the two-digit occupational level.

To obtain this 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. We use data provided by Eurostat for the period 2000-2017 via the tailor-made extraction procedure.[3] 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:

$$Y_{o,s,c,t} = \begin{cases} \sum_{s=1}^{S} \frac{L_{o,s,c,t}}{L_{o,c,t}} Y_{s,c,t} \; if \; s \; \in S^{E} \\ 0 \; otherwise \end{cases} \tag{1}$$

where L_{osct} denotes the level of employment in occupation o, sector s, country c, and year t. We also use the broad industry classification in the EU-LFS dataset and define S^E as a set of sectors which are adopting robots according to IFR data. Thus, we differentiate between sectors adopting and not adopting robots. Using this approach, we can assign industry-specific information to each worker based on a two-digit level occupation and broad industry classification. In particular, it allows us to measure the exposure of a specific occupation (at the two-digit level) to robots. Importantly, we allow

[3] 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. (2022).

occupational exposure to robots to differ between sectors that adopt robots and those that do not. Thus, robot exposure of managers employed in manufacturing differs from exposure of managers employed in services.

To account for cross-country differences in the effects of robots, we focus on differences in initial labour costs in manufacturing (Eurostat, 2020). We transform labour costs (and GDP in a robustness check) into relative values by taking logs and deducting Slovenia's value, which is close to the average labour costs 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 initial conditions capture differences in the first year for which all key data are available. We use GDP per capita as a robustness check, also using the Eurostat data. Table A1 in Appendix A provides an overview of the relative labour costs and GDP per capita in 2004 across countries.

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 (details in Table B6 in Appendix B). In doing so, we 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 present methodological details.[4] 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 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 about two robots per 1,000 workers in Western European countries such as Belgium, Italy, and, in particular, Germany.

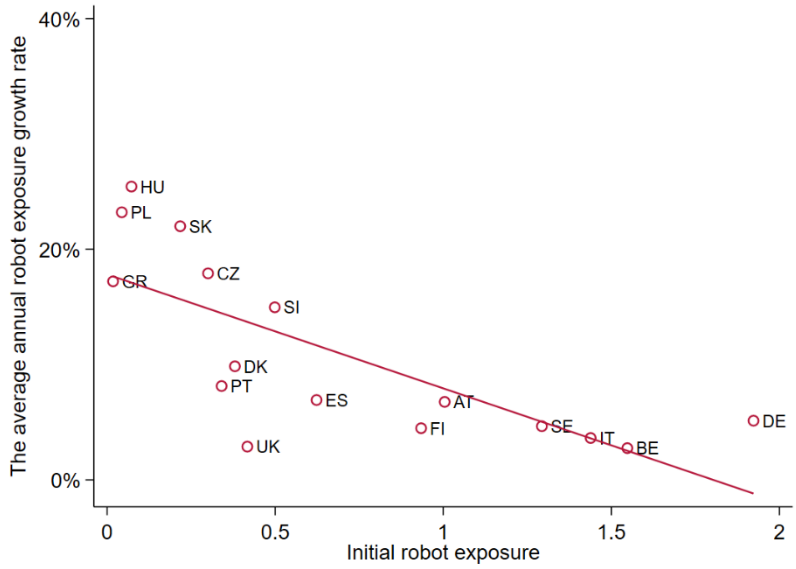
Between 2000 and 2017, robot exposure converged across European countries. The countries with the lowest initial level of robot exposure, such as Poland, Hungary, and Slovakia, experienced the highest average growth rate (about 25% per year); while the countries with initially high levels of robot exposure experienced lower growth rates. Overall, the correlation between initial robot exposure and its average growth rate over the observation period was strong and negative (-0.75), indicating considerable convergence in robot exposure across European countries. However, we observe differences in robot applications across countries. In countries with low initial labour costs, robots tend to be used for welding and soldering, while in countries with relatively high initial labour costs to handle operations and tend machines (see Figure D1). Nonetheless, there is no a priori evidence

[4] O*NET is a US dataset of occupational descriptors that has been commonly applied to European data (Fonseca et al., 2018; Goos et al., 2014; Hardy et al., 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).

suggesting that some robot applications are affecting labour markets differently than other robot applications.

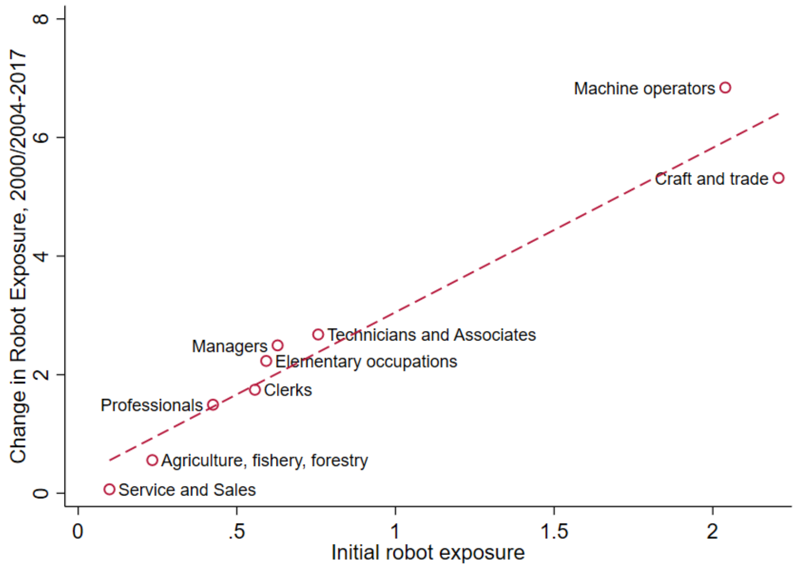
Robot exposure also differed strongly between occupation groups (Figure 2). Initial robot exposure was by far the highest for machine operators (2.04) and craft and trade workers (2.21). While technicians and associates had a medium initial level of robot exposure (0.76), the level was lowest for service and sales (0.10) and agriculture, fishery, and forestry workers (0.23). In contrast to robot exposure across countries, which converged over time, the exposure across occupations diverged: 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 (0.96). The two occupational groups that initially faced the highest exposure levels also had the highest growth rates of exposure (e.g. machine operators: 6.84; craft and trade workers: 5.32). In the remaining occupations, the growth rate was much lower (e.g., 2.68 for technicians and associates and 0.07 for service and sales workers).

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



Note: Robot exposure – the number of robots per 1,000 workers. The detailed data on industrial robots start in 2000 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.

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



Note: Robot exposure – the number of robots per 1,000 workers. The detailed data on industrial robots start in 2000 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. The figures displayed refer to averages by occupation groups across all countries. For the change in robot exposure by occupation group and country, see Figure D2 in Appendix D. – Source: authors' calculations based on the EU-LFS and IFR data.

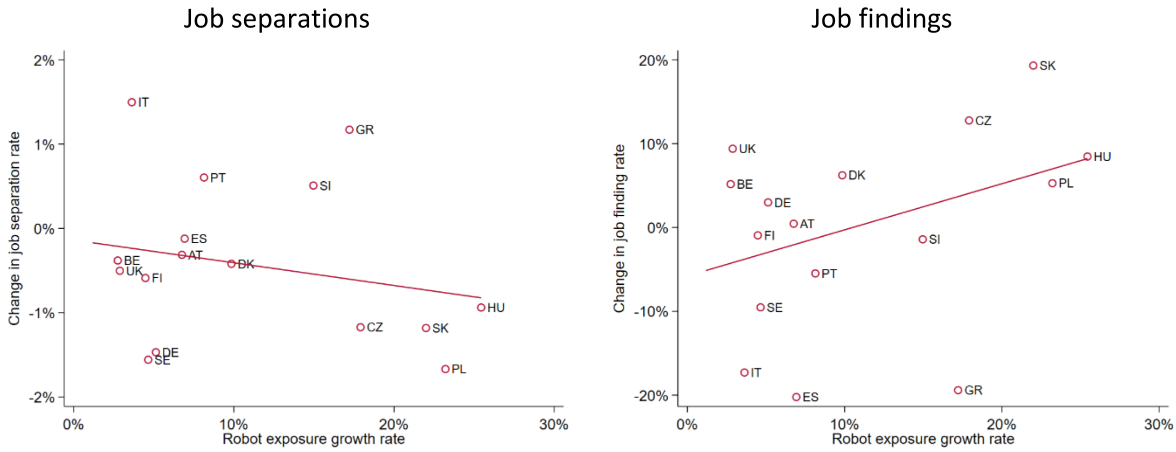
Turning to the labour market variables, at the country level, there was a moderately negative correlation between the changes in the job separation rate and the robot exposure growth rate -0.24, see Figure 3).[5] Thus, in countries with a stronger increase in robot exposure, job stability has remained constant or even improved. 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. Different country clusters partly drive these patterns. First, a group of CEE countries recorded high robot exposure growth rates and a relatively strong reduction in job separation rates and 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. However, these descriptive results may reflect reverse causality or common trends, especially because robot adoption may be highest in the sectors with the highest productivity and the best labour-market prospects. This would lead to a spurious correlation between robot adoption and beneficial labour-market developments. In the following, we investigate the causal effects of robots

[5] 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. Job separation and finding rates display strong variation between countries over time, with cyclical fluctuations playing an important role (see also Bachmann and Felder, 2020). 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 (see Figure D3 in the appendix).

on labour market transitions using within-country, between-sector differences in robot exposure, as well as instrumental variables.

Figure 3: Changes in job flow rates and average robot exposure growth rates



Note: The changes in the job flow 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 EU-LFS data are available. The first three years are 2000-2002 for Denmark, Finland, 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. For the average job flow rates by country, see Figure D3 in Appendix D. – Source: authors' calculations based on the EU-LFS and IFR data.

3 Methodology

3.1 Estimation framework and instruments

We focus on two key labour market 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).[6] 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 ($R_{s,c,t}$):

$$R_{s,c,t} = \frac{ROB_{s,c,t}}{EMP_{s,c,1995}} \qquad (2)$$

Where $ROB_{c,s,t}$ is the total stock of industrial robots, and $EMP_{c,s,1995}$ is employment (in thousands of workers) in sector s, country c, and year t. We use employment levels from 1995 – i.e., before our study period – as denominators. This ensures that changes 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).

[6] 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.

To estimate the causal effects of robot adoption, we need to account for the potential endogeneity of robot exposure to labour market outcomes. This could, for instance, be the case if worker shortages lead to an increase in the relative price of labour relative to capital, and firms react by investing in industrial robots. We, therefore, use an instrumental variables strategy, generalising the "technology frontier" instrument previously applied by Acemoglu and Restrepo (2019) and Dauth et al. (2021).[7] We instrument the robot exposure in country c, sector s, and year t with the average robot exposure in most advanced European economies ($I_{c,s,t}$). 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 for which the instrument is computed.[8] 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 robot data are available. Instrumented robot exposure is thus given by the formula:

$$I_{s,c,t} = \frac{\sum_{c \neq k}^{C,k \in C} \sum_{s}^{S} \frac{ROB_{s,k,t}}{EMP_{s,k}^{1995}}}{C}, where\ C = \begin{cases} 11\ if\ c\ \in E \\ 10\ if\ c\ \in W \end{cases} \tag{3}$$

where $ROB_{k,s,t}$ stands for the total stock of industrial robots in country k ($country\ k \neq country\ c$), sector s and year t $and\ EMP_{k,s}^{1995}$ for the employment level in thousand workers in country k and sector s in 1995. C is the number of countries in a particular group. We use the definition of the robot stock and of the instrument defined by equations (2) and (3) and use the sector-occupation mapping (see equation (1)) to map robot exposure at the sectoral level to individual workers (for details, see *Technical details* in Appendix C).

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

$$\begin{aligned} Pr(flow = 1|X)_{i,o,s,c,r,t} \\ = F(R_{o,s,c,t-1}, X_{it},\ M_{o,c,t-1}, T_{s,c,t-1}, C_{c,t-1}, B_{r,t-1}, \rho_s, \delta_t, \mu_c, \mu_c \times \tau) \end{aligned} \tag{4}$$

where Pr $(flow)_{i,o,s,c,r,t}$ is the likelihood of a given worker flow (*eu* or ue). Flow $eu(ue)$ indicates that a person i, in occupation o, sector s, country c, region r made a transition from employment (unemployment) in year t-1 to unemployment (employment) in year t.

Our main variable of interest is $R_{o,s,c,t-1}$ – robot exposure in occupation o, in sector s, country c in the previous year.[9] In all regressions, we account for individual characteristics (X_{it}) such as gender,

[7] Examples of studies instrumenting robot adoption in European economies with adoption in peer economies include Anelli et al. (2021), Damiani et al. (2023), Doorley et al. (2023), and Nikolova et al. (2024).

[8] 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 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.

[9] 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

age, education, and native or migrant worker status. We also add industry group (ρ_s) and year (δ_t) fixed effects to control for potential changes across years and industries that are common to all countries. 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, public services and education. We also add country fixed effects (μ_c) and country-specific linear trends ($\mu_c \times \tau$) to account for country-specific differences and trends over time. Robot exposure data are merged with the EU-LFS data at the country-occupation-industry level (sectors with and without industrial robots, according to IFR, 2017). Hence, the variance used for identification is the difference in robot exposure between occupations within a country and industry group.[10]

To control for macroeconomic conditions, we include a vector of several macro indicators ($M_{o,c,t-1}$): sectoral gross value added, the ratio of investments to the gross capital formation (see Stehrer et al., 2019), and we account for the effects of globalisation using sector-specific measures of participation in global value chains proposed by Wang et al. (2017). We transform two-digit industry indicators into two-digit occupation-specific variables according to equation (1). We also control for lagged GDP growth at the country level ($C_{c,t-1}$), for country-specific trade flows at the sector level ($T_{s,c,t-1}$), especially growth in exports, and labour demand shocks at the regional level (NUTS2) ($B_{r,t-1}$) calculated with the Bartik (1991) method.

As we are particularly interested in reasons for cross-country differences, 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; and GDP per capita in 2004 as a robustness check.[11] We interact these measures with robot exposure. Therefore, the main specification of our model is an augmented version of equation (4):

$$Pr(flow = 1|X)_{i,o,s,c,r,t} = F(R_{o,s,c,t-1}, R_{o,s,c,t-1} \times L_c, R_{o,s,c,t-1} \times (L_c)^2, \\ X_{i,t},\ M_{o,c,t-1}, T_{s,c,t-1}, C_{c,t-1}, B_{r,t-1}, \rho_s, \delta_t, \mu_c, \mu_c \times \tau) \tag{5}$$

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 ($R_{o,c,t-1}$). We implement the IV specification with a control function approach (Aghelmaleki et al., 2022) with instrumental variables described in the previous subsection. This approach allows for the estimation of marginal effects when using interaction terms.[12]

based on the last occupation performed before becoming 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 $t-1$.

[10] We 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.

[11] We use 2004 labour costs as this is the first year for which labour costs are available. Moreover, five out of the six Central and Eastern Europe in our sample joined the EU in 2004. The labour costs are a proxy for the relative price of robots and labour. Still, they are not a proxy for the share of potentially automatable jobs: the cross-country correlation between the level of initial labour costs and the employment share of routine occupations is only 0.15. At the same time, the cross-country differences in average labour costs in Europe are quite persistent, the correlation between their 2004 and 2016 values is 0.97. Hence, the 2004 labour costs are a solid proxy for relative prices of robots and labour over the period studied.

[12] 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.

To implement our instrumental variable approach, we use the control function method which is a limited information maximum likelihood approach and follows a two-step procedure. In the first step, we regress all exogenous variables – including the instruments – on the endogenous variable. In the case of N endogenous variables, we estimate N first-stage regressions. In the second step, we include residuals obtained from the first stage 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 (4) and (5). This approach allows us to isolate the changes in exposure driven by technological progress and simultaneously remove occupation-specific shocks that affect robot adoption and the probability of transitioning out of or into a particular occupation. Our results can be interpreted as the average causal effect of robot exposure on the job separation likelihood for those employed and on the job finding likelihood for those unemployed during the study period.[13]

3.2 Counterfactual analysis

To assess the economic significance of estimated effects, we perform a counterfactual historical analysis. We calculate counterfactual scenarios of labour market flows and the employment levels that these flows imply. In the counterfactual scenario, we keep robot exposure constant in each country and sector 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.

The counterfactual analysis proceeds in four steps (see Section C2 in Annex C for the detailed methodology used to calculate the counterfactual). First, we use the estimated coefficients from equation 4 and actual values of all variables to predict job separation (EU) and job finding (UE) likelihoods. Second, we use the same coefficients and the counterfactual values of robot exposure to calculate the counterfactual flow likelihoods. Third, we use the predicted and the counterfactual flow likelihoods from the first two steps to recursively calculate each country's predicted and counterfactual employment levels until 2017. To do so, we use the actual employment levels in 2004 as the starting point. Fourth, we calculate the effect of robot exposure on employment as the relative difference between the counterfactual and the predicted scenarios for each country and year.

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. Next, we present the counterfactual analysis to asses the economic significance of the impact of robot exposure on worker flows and their contributions to the resulting changes in employment rates. Finally, we show robustness checks.

[13] While the short-term effects of robots may be affected by potential selection effects (workers may avoid entering occupations heavily exposed to robots), they are unlikely to affect our findings. First, firm-level evidence from European countries shows that robot-adopting firms tend to grow faster and pay better than similar firms not adopting robots (Bessen et al., 2023; Koch et al., 2021). Second, investments in automation tend to be bulky and sporadic (Domini et al., 2021), so it is difficult for workers to anticipate their future exposure to robots. Third, our results show that job findings, which would be the driver of selection effects, are much less affected by robots than job separations. Finally, our analysis of cumulative impacts combines the results for job separations and job findings and therefore considers potential selection effects.

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 a significant negative effect of robot exposure on the likelihood of job separation (Table 1, column 1).[14] The IV results using the control function approach double the size of this effect (column 2 of Table 1): i.e., robot exposure reduces the job separation rate, which implies an increase in job stability.[15] Accounting for interactions between robot exposure and countries' initial labour costs (equation 5), we find a noticeable heterogeneity in this size depending on labour costs (columns 3 and 4 of Table 1). 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).

The importance of initial labour costs is visible in the marginal effects of robot exposure on job separations by country.[16] We do so for our preferred specification, including the interaction of robots with labour costs, and display the results in Figure 5, with countries ordered according to their initial labour costs. The negative effect of robot exposure on job separations was much more pronounced for countries with average levels of labour costs (Figure 5). In particular, in the country with an average level of initial labour costs – Slovenia – the marginal effect of robot exposure amounted to a reduction in the likelihood of job separation of -0.07 pp (the average job separation rate in our sample was 4 pp). In countries with 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 half the size (-0.04 pp).

Figure 5 also reveals a U-shape relationship between the effects of robot exposure and labour costs. In the countries with the lowest initial labour costs, namely Central Eastern European countries, the effects were also half the size (about -0.04 pp in Hungary and the Czech Republic) or even weaker (Poland and Slovakia) than in countries with medium labour costs. We attribute these weak effects in countries with the lowest labour costs to country-specific factors that counterbalanced the positive employment impact of low labour costs. First, the adoption of automation technologies tends to increase skill requirements (Chun, 2003; Goldin and Katz, 2010), but CEE countries specialised (both across and within sectors and occupations) in routine-intensive jobs (Hardy et al., 2018; Lewandowski et al., 2022) with lower skill requirements than in Western European countries, especially in manufacturing (Krzywdzinski, 2017). In CEE countries, skill shortages and mismatches were identified as crucial constraints on firm growth despite low labour costs (Sondergaard et al., 2012).[17]

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

[15] The results of the first stage of the estimation are presented 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.

[16] 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.

[17] Sectoral studies of the highly automated automotive industry show that firms in CEE countries were less likely to move to more advanced tasks than similar firms in Germany, and therefore displayed a lower demand for skills in the aftermath of automation (Krzywdzinski, 2017). Cross-country evidence confirms the relative

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	-0.003**	-0.005***	-0.011***	-0.012***
	(0.001)	(0.001)	(0.002)	(0.003)
Robot Exposure X Labour Costs			-0.006***	-0.005***
			(0.001)	(0.001)
Robot Exposure X $(\text{Labour Costs})^2$			0.011***	0.008***
			(0.002)	(0.002)
Country FE	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of Observations	11.8 M	11.8 M	11.8 M	11.8 M
Kleibergen-Paap F-statistic for weak identification		408 872.3		18 537.4
B: Manufacturing				
Robot Exposure	-0.001	-0.006***	-0.013***	-0.014***
	(0.001)	(0.002)	(0.003)	(0.004)
Robot Exposure X Labour Costs			-0.005***	-0.003*
			(0.001)	(0.002)
Robot Exposure X $(\text{Labour Costs})^2$			0.014***	0.011***
			(0.003)	(0.004)
Country FE	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of Observations	2.6 M	2.6 M	2.6 M	2.6 M
Kleibergen-Paap F-statistic for weak identification		197 835.2		10 947.6

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. [18] *** p<0.01, ** p<0.05, * p<0.1. Individual-level controls: age group, education group, gender, and native/non-native status. Aggregate-level controls: global value chain participation, gross value-added, the ratio of investment added to gross value-added, GDP growth, regional 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. For the first stage regressions of model (4), see Table B3 in Appendix B.– Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

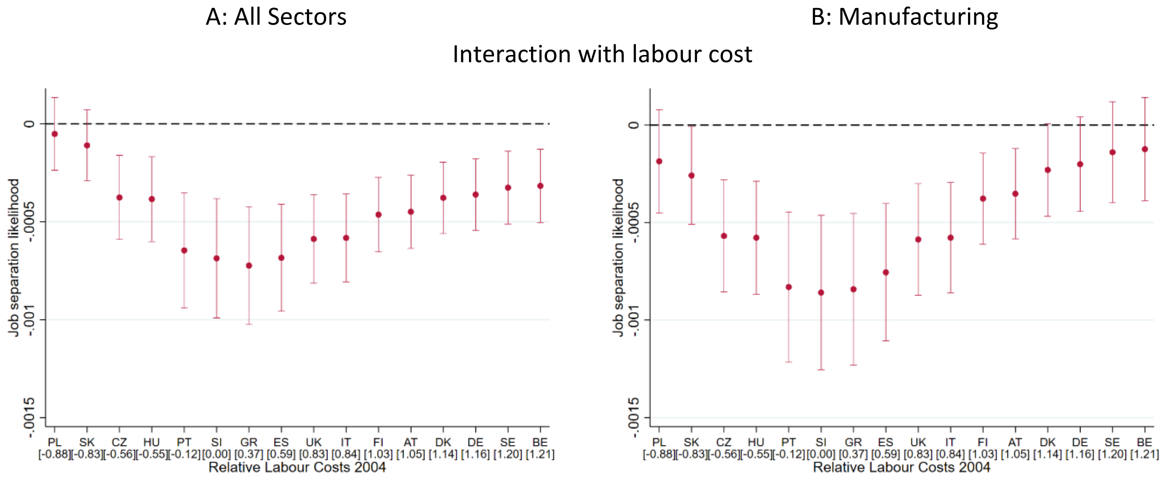
Consequently, firms in CEE countries might have struggled to benefit fully from these investments, especially in terms of hiring, despite low labour costs. Second, in CEE countries, robot adoption primarily followed greenfield investment and integration into global value chains (Caséfalvay 2020). The

upgrading of occupational structures of supplier countries, such as CEE countries, in highly automated sectors over time (Fana and Villani, 2022).

[18] Clustering standard errors at the sector-year or occupation-country-year level does not affect the interpretation of our result- see Figures D10 and D11 in the appendix.

introduction of robots and other modern technologies was largely driven by modernisation and expansion of product ranges in CEE plants rather than the need to reduce labour intensity and labour costs (Jürgens and Krzywdzinski, 2009). It led to considerable growth in robot exposure but was driven by sectors that grew almost from scratch. As the robot exposure shock was thus substantial but concerned a relatively small segment of the economy, the overall effect on job separations was low in CEE countries.[19]

Figure 4: Marginal effects of robot exposure on the likelihood of job separation.



Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment for all sectors (A) and for manufacturing (B) based on regressions presented in Table 1, columns (2) and (4). The vertical lines represent the 95% confidence intervals. 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) (for details, see Table A1). 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, Eurostat, 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. On average, robot exposure in our sample increased by 1.44 units (between 2004 and 2017) decreasing the job separation likelihood by 0.06 pp. In the meantime, the average job separation rate declined by 0.15 pp. Hence, the change in the likelihood associated with robot exposure totalled 43%. However, country-specific results are more nuanced. For instance, in Germany, growth in robot exposure by 2.8 units (between 2004 and 2017) reduced the likelihood by 0.1 pp, while the probability of job separation decreased by 1.4 pp over the same period. Thus, the change associated with the increase in robot exposure amounted to 7% 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 10.50 units in manufacturing and by 2.6 units in total economy), the effects attributed to this factor were even more pronounced, as they amounted to 14% to the recorded change in job

[19] Slovakia recorded the largest robot exposure growth, driven by the automotive sector. In 1995 (we use 1995 employment levels to normalise robot exposure), the automotive industry had accounted for only 0.8% of employment in Slovakia. By 2017, its employment share increased four-fold, but was still below 3.5%.

separations. We perform a systematic assessment of the contributions of robot exposure to employment in all countries in our sample in subsection 4.3.

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

	(1)	**(2)**	**(3)**	**(4)**
	Probit	**CF**	**Probit**	**CF**
A: All Sectors				
Robot Exposure	-0.002	0.002	0.018***	0.011***
	(0.001)	(0.001)	(0.003)	(0.004)
Robot Exposure X Labour Costs			0.008***	0.003
			(0.002)	(0.002)
Robot Exposure X (Labour Costs)^2			-0.022***	-0.012***
			(0.003)	(0.004)
Country FE	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of Observations	1.3 M	1.3 M	1.3 M	1.3 M
Kleibergen-Paap F-statistic for weak identification		27 783.8		3 714.4
B: Manufacturing				
Robot Exposure	0.000	0.002	0.005	0.003
	(0.001)	(0.002)	(0.003)	(0.004)
Robot Exposure X Labour Costs			0.001	-0.004*
			(0.002)	(0.002)
Robot Exposure X (Labour Costs)^2			-0.006	-0.001
			(0.003)	(0.004)
Country FE	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of Observations	0.26 M	0.26 M	0.26 M	0.26 M
Kleibergen-Paap F-statistic for weak identification		14 791.2		2 457.2

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. *** p<0.01, ** p<0.05, * p<0.1. Individual-level controls: age group, education group, gender, and native/non-native status. Aggregate-level controls: global value chain participation, gross value-added, the ratio of investment added to gross 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. For the first stage regressions of model (4), see Table B4 in Appendix B.– Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

We re-estimate our models on the subsample of workers in manufacturing, i.e., the sector with the highest robot usage. While this yields very similar results to those for the total economy (Table 1, Panel B; Figure 4, Panel B), the effects for manufacturing are slightly stronger in most countries. This aligns with intuition, as robot exposure is the largest in manufacturing. Therefore, the direct impacts of robot exposure are more substantial in manufacturing than in the entire economy, leading to higher marginal effects when analysing manufacturing only.

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, robot exposure did not affect job findings (Table 2, column 2).[20] However, as for job separations, we find important heterogeneity between more and less-developed countries concerning job findings. 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 the interactions between robot exposure and initial labour costs (level and squared) suggest a non-linear relationship.

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 5): the positive impact was the largest in the countries with a medium level of labour costs, such as Slovenia (about 0.42 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. The results for the countries with the lowest labour costs likely result from the same factors discussed for job separations, i.e. skill shortages. 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 negative (about 0.1 pp).

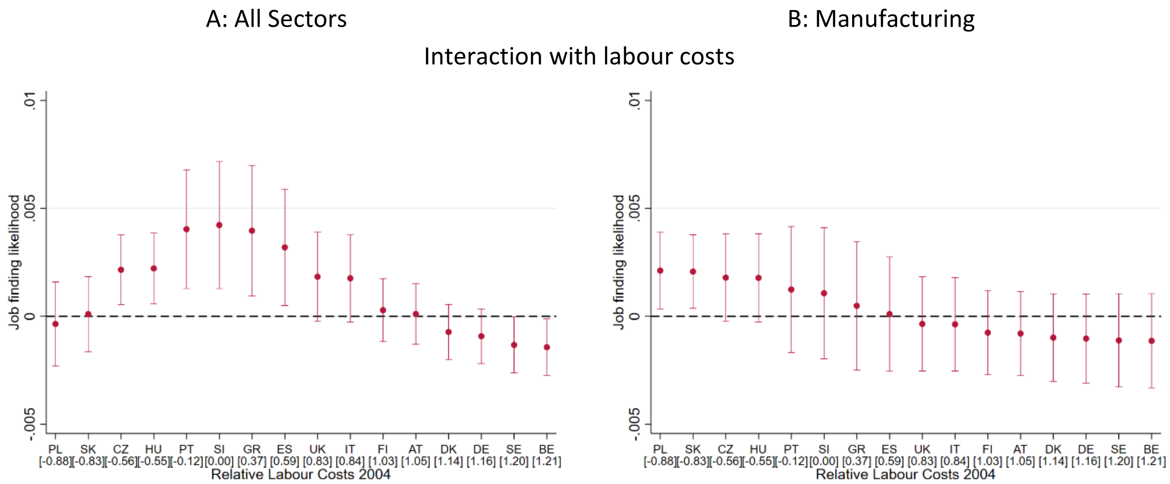
We use the estimated effects to quantify the economic effects of increasing robot exposure. The average increase in robot exposure by 1.44 units corresponds to an increase in the job finding likelihood by 0.17 pp, despite the overall decrease in this likelihood by 2.54 pp. However, the effect differs across countries. The Czech Republic is an example of a CEE country that had low levels of labour costs in 2004 and recorded substantial increases in robot exposure between 2000 and 2017 (by 8.7 units in manufacturing and 2.4 units in total economy). This translates into an almost 0.5 pp increase in the likelihood of finding a job, equivalent to 30% of the increase recorded over this period. While, according to our estimates, in some most developed countries, the growth of robot exposure reduced the likelihood of finding a job, the effect is minor. For instance, an increase in robot exposure by 1.7 units in Sweden reduced this likelihood by 0.2 pp, equivalent to 4% 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 most developed countries, the net effect was ambiguous because of the reduced likelihood of job separation and finding, negatively affecting labour market dynamics and turnover. We later formalise the analysis of robot exposure's aggregate consequences via labour market flows.

As a robustness check, we again re-estimate our model for a subsample of manufacturing workers. The results are noisy – they are slightly positive in countries with the lowest level of labour costs (Poland and Slovakia) and insignificant in other countries (Table 2, Panel B, and Figure 5, Panel B). However, later we will show that the job separation channel of the effects of robots is quantitatively more relevant than the job-finding channel. The comparison of the results for job findings for all sectors and manufacturing also indicates that the effects are less pronounced in the manufacturing sector. This is likely to be caused by a demand spillover effect, i.e. higher labour demand in the service sector, e.g. for the maintenance of robots, which has also been stressed by (Dauth et al., 2021).

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

Figure 5: 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 for all sectors (A) and for manufacturing (B) based on the regressions presented in Table 2, columns (2) and (4). The vertical lines represent the 95% confidence intervals. 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, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

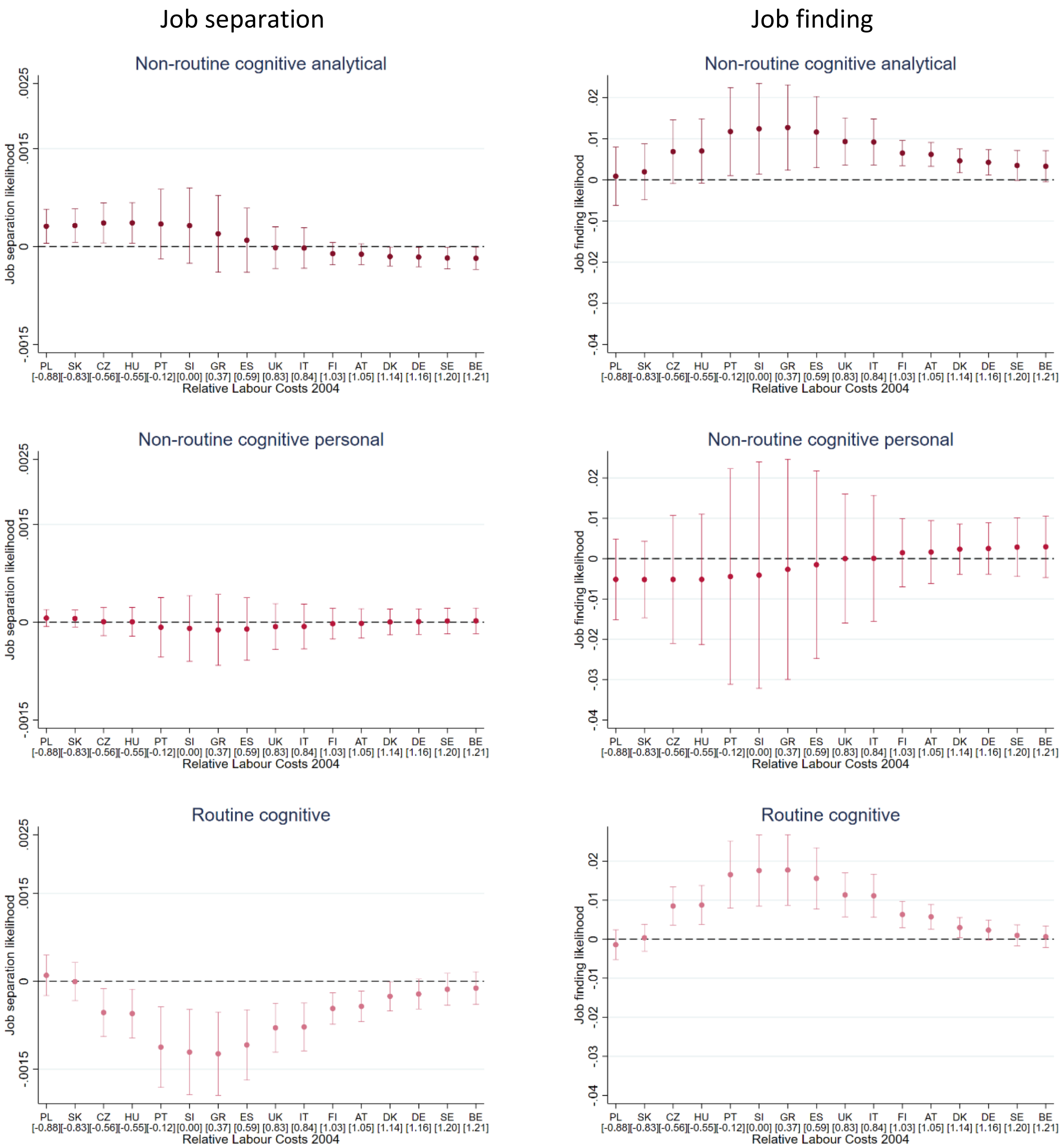
4.2 Heterogeneity according to job tasks and age

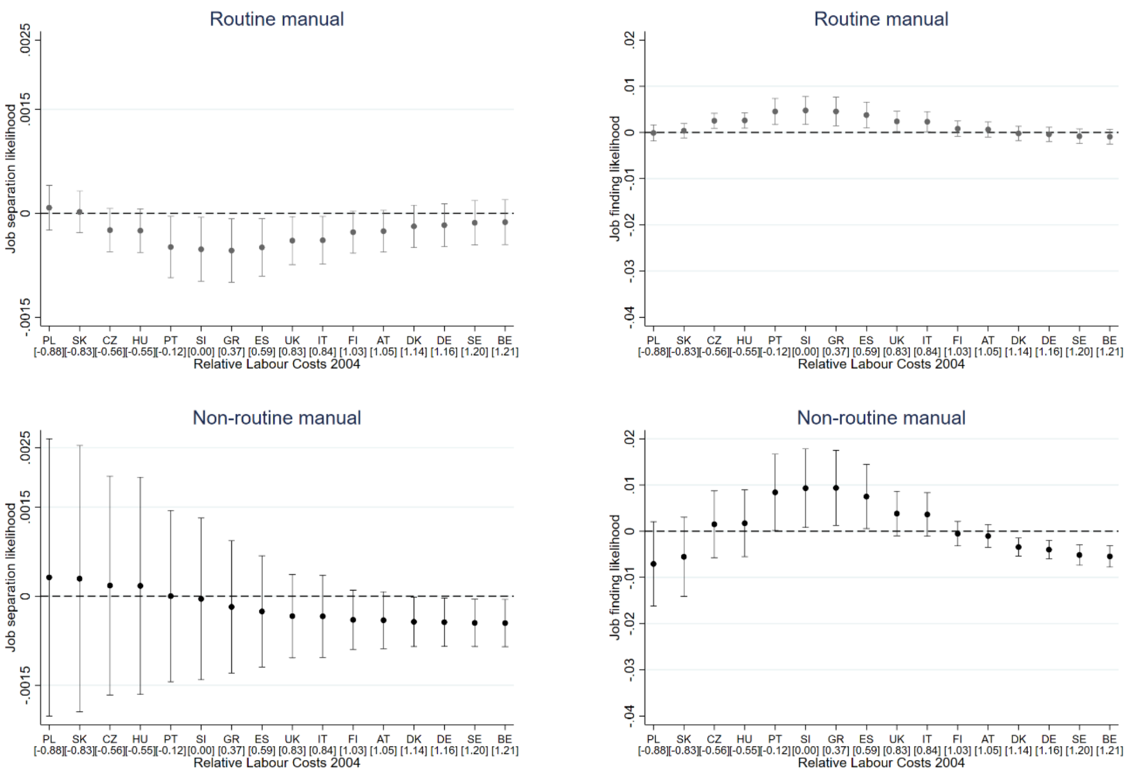
The effects of robot exposure are likely to differ between worker groups for at least three reasons. First, the substitutability of workers by robots depends strongly on the tasks they perform. Second, workers are likely to differ in their ability to adapt to technological change. Third, job-specific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

In order to examine whether the effects of robot exposure differ by job task, we estimate model (5), including an indicator variable (and interactions) for 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 follows Lewandowski et al. (2020) (see data section and Tables A3-A4 in Appendix A for details). We focus on marginal effects from the model with interactions between robot exposure, initial labour costs (level and squared) and task dummy. We present the estimated coefficients and those from a model without interactions in Tables D1-D2 in Appendix D.

In countries with average levels of initial labour costs, the effect of robot exposure on job finding was slightly positive among RM workers (e.g. plant and machine operators, assemblers) and NRCA workers and positive among RC workers (e.g. associated professionals, clerks). These effects are sizable, at around 0.005, 0.012 and 0.018, respectively (Figure 6, right panel). The effect on job findings among NRM workers was positive in countries with average initial labour costs (0.009) and negative in countries with high initial labour costs (-0.005). For job separations, the effect of robot exposure was negative among RC and RM workers in countries with average and low levels of labour costs and among NRM workers in countries with high levels of labour costs (Figure 6, left panel). Therefore, our results suggest that higher robot exposure improved job prospects in routine jobs in countries with average initial labour costs, particularly in Central and Eastern Europe, but also in some Southern European countries. While such an effect on routine workers may be surprising, it is worth noting that robot adoption in CEE countries primarily resulted from FDI and the integration of plants into global value chains (Cséfalvay, 2020). Hence, rising robot exposure was driven by expanding sectors rather than introducing new technologies in existing plants, a typical pattern in the most advanced economies. This improved the labour market prospects of CEE workers in RC and NRM occupations. Indeed, in countries with high initial labour costs, the effect of robot exposure on the likelihood of job flows among RM and RC workers was mainly insignificant.

Figure 6: Marginal effects of robot exposure on the likelihood of job separations and finding, by task groups





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 vertical lines represent the 95% confidence intervals. 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 costs (in parentheses). 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 D1-2 in Appendix D. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, 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 for why the impact of technology can differ between younger and 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). Older workers are more likely to possess outdated skills, and their expected returns from investing in new skills are lower than younger workers. Accordingly, 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).

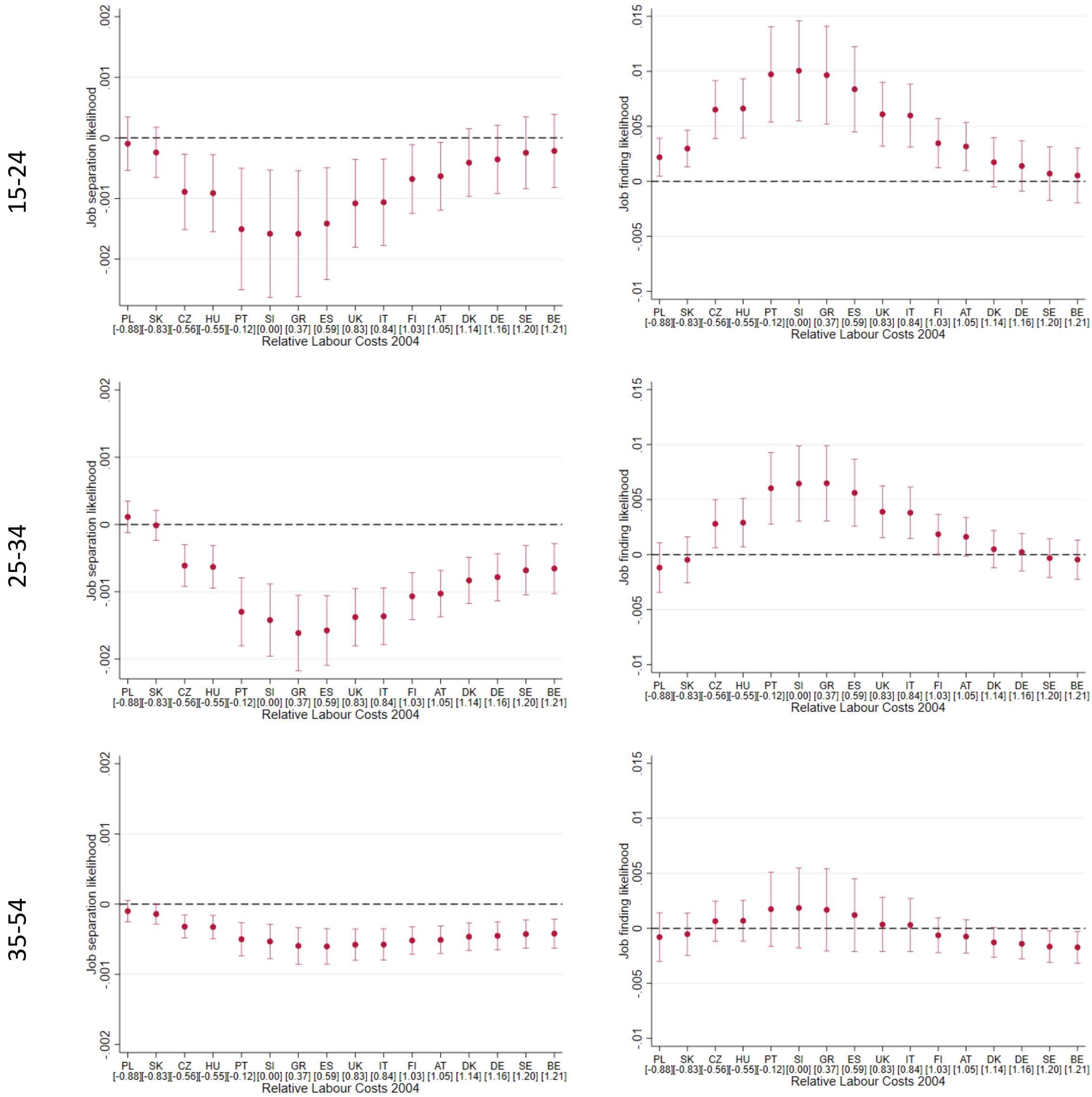
We find that robot exposure significantly reduced the likelihood of job separation for young workers (aged 25-34), prime-age workers (aged 35-54) and the youngest workers (aged 15-24) in most countries in our sample (Figure 7, left panel and Table D3 in Appendix D).[21] However, exposure to robots increased the probability of job separation for older workers (aged 55-70) in countries with an

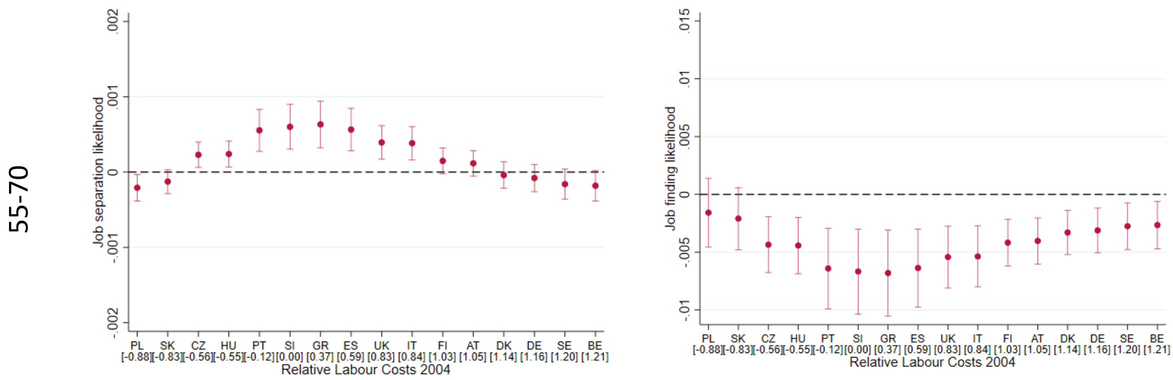
[21] For marginal effects of robot exposure on the likelihood of job separation and job finding by age group in manufacturing, see Figure D9 in the appendix.

average level of labour costs. For manufacturing (Figure D9 in Appendix D), robot exposure significantly reduced job separations for all age groups, also for older workers, in countries with average labour costs, and to a lesser extent in countries with low labour costs. However, we find insignificant effects for workers in high labour cost countries and for young workers. The marginal effect of robot exposure on the job finding likelihood was positive for young and prime-age workers in countries with an average level of labour costs (Figure 7, right panel, and Table D4 in Appendix D). We find adverse effects on the job finding likelihood for older workers in most countries. Within manufacturing, the positive effects on job finding are even more pronounced for young (aged 25-34) and prime-age workers (aged 35-54) for countries with average labour costs, but coefficients for the youngest and oldest workers are insignificant.

Figure 7: Marginal effects of robot exposure on the likelihood of job separations and finding, by age group

Age **Job separations** **Job finding**





Note: Marginal effects of robot exposure on the probability of job separation and job finding at different development levels measured by labour costs in 2004. The vertical lines represent the 95% confidence intervals. 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).). Robot exposure is instrumented using robot exposure in the Western European countries in the sample. For regression estimates, see Tables D3 and D4 in Appendix D. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Overall, robot exposure was beneficial for young workers as it reduced job separations and increasing job findings especially in countries with average labour costs. Prime-age workers also benefited from exposure to robots, especially in manufacturing. In contrast, the effects for older workers are mixed. While older workers in countries with average labour costs faced higher job separations and lower job findings, they experienced increased job stability in manufacturing. This indicates that older workers can benefit from the productivity-enhancing effects of robots by staying in manufacturing, but that they are less able to benefit from demand-spillover effects outside of manufacturing than younger workers. This may be related to the differences in skill sets: new technologies tend to reduce returns to skills that older workers have (Fillmore and Hall, 2021). Moreover, a shorter time to benefit from investment in new skills discourages older workers from learning these new skills (Cavounidis and Lang, 2020).

4.3 Implications for employment and mechanisms

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

This analysis suggests that the rising robot exposure increased employment levels in most European countries. If the level of robot exposure had remained at the level recorded in 2004, in all CEE countries except for Poland, employment in 2017 would have been lower (and unemployment would have been higher) by about 1.0-2.5% of the working-age population (equivalent to 1.0-2.5 pp of the employment rate, Table 3). These effects were the largest in Slovakia (2.5% by 2017) and the smallest in Slovenia and Hungary (0.5-0.7% by 2017). In southern European countries, but Greece, the contribution of robots is smaller, but noticeable (0.3-1.0% of the working-age population). Overall, our counterfactual simulations show that an increase in robot adoption led to a rise in total employment by about 800 thousand additional jobs across all countries in our sample, which amounts to 0.47% of total employment. This suggests 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. Similar findings at the firm level were presented for France by Domini et al. (2021) and Acemoglu et al. (2020), and for Spain by Koch et al. (2021).

Finally, we decompose the overall contribution of rising robot exposure to employment into the sub-contributions of job separations and job findings. In all 16 countries studied, the contribution of job separations was larger than that of job findings, in many cases noticeably so (the contribution of job findings is negative in some countries, Table 3). Hence, improved job stability appears to be a key mechanism behind the labour market effects of robot adoption in Europe.

Table 3: The estimated cumulative contribution of robots to employment between 2004 and 2017, with sub-contributions of job separations and job findings (in % of working-age population)

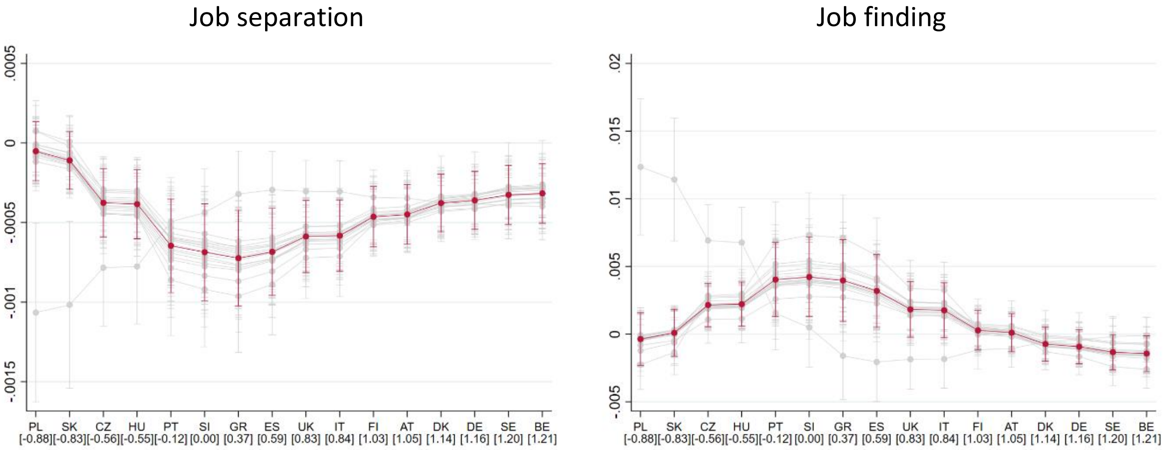
	The cumulative effect on employment (% of working-age population)	Of which:		
		Job separation	Job finding	Residual
Poland	-0.01	0.00	0.00	0.00
Sweden	0.02	0.02	0.00	0.00
United Kingdom	0.06	0.06	0.01	0.00
Belgium	0.08	0.09	-0.01	0.00
Denmark	0.09	0.10	-0.01	0.00
Greece	0.12	0.11	0.00	0.00
Germany	0.14	0.17	-0.02	0.00
Italy	0.25	0.21	0.03	0.00
Finland	0.28	0.23	0.05	0.00
Spain	0.45	0.36	0.08	0.00
Slovenia	0.47	0.38	0.08	0.01
Austria	0.66	0.63	0.03	0.00
Hungary	0.72	0.57	0.15	0.01
Portugal	1.03	0.93	0.10	0.00
Czech Republic	1.74	1.51	0.19	0.05
Slovakia	2.54	2.50	0.03	0.00

Note: Calculations based on model (4) from Table 1 and Table 2. To asses the contributions of particular channels to the overall effect we utilize the decomposition method proposed by Fujita and Ramey (2009) (see Section C2 in Appendix C for technical details.) The residual indicates the difference between the counterfactual scenario (total effect) and the sum of semi-counterfactual scenarios (contributions of particular flows) which arises because the simulations are calculated recursively. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and OECD data.

4.4 Robustness checks

We conduct several robustness checks to test the validity of our regression results. First, to check whether any specific countries do not drive our results, we run 16 additional regressions, excluding one country at a time (Figure 8). Point estimates from all these regressions are within confidence intervals from our baseline specifications, apart from the regressions estimated on a subsample without Slovakia. Excluding Slovakia makes the results stronger for Central and Eastern European countries with the lowest initial level of labour costs, but it does not affect the results for other countries, including the most robot-exposed economies, such as Germany and Belgium. Slovakia recorded particularly large increases in robot exposure, but starting from very low levels and mostly due to the automotive sector.[22] Thus, the associated changes in overall labour market outcomes in Slovakia were moderate. As a result, the exclusion of Slovakia strengthens the estimated effects of automation, especially for job separations, in similar countries with low initial labour costs.

Figure 8: The effects of robot exposure on the likelihood of the flows for reduced sample regressions



Note: Red lines represent the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (left panel) and unemployment to employment (right panel) for the baseline regressions using the full country sample (Figures 4-5). Each grey line represents the results obtained from separate regressions, omitting one country at a time from the sample. If a particular country is excluded from the sample, we calculate the marginal effect for this country based on its labour cost value. For example, even if Germany is omitted from the regression, we calculate the marginal effect for Germany using its labour cost value (1.16) and present it in Figure 8. Countries on the x-axis are displayed in ascending order of initial labour cost (in parentheses). The vertical lines represent the 95% confidence intervals. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, Eurostat, UN Comtrade, and UIBE GVC data.

Second, we only include country fixed effects instead of country fixed effects and country-specific time trends. For job separations, only including country fixed effects does not affect our results. The coefficients of interest in the preferred specification increase slightly in absolute terms and remain sizeable and significant (Table 5, columns 1 and 3, and Figure D4 in Appendix D). For job findings, the coefficients of interest remain similar in size in the specification with labour costs interaction and become significant and positive in the specification without interaction. However, as shown in the previous section, the overall impact of robots on employment is mostly through the job separation channel. Hence, the minor change in the job-finding likelihood leaves our overall results intact.

Third, we exclude variables from our baseline regressions that may be influenced by robot exposure and may be bad controls, particularly value-added and gross fixed capital formation. This does not affect our results (Table 5, columns 2 and 4, and Figure D5 in Appendix D).

[22] In Slovakia, the robot exposure in the automotive industry was close to zero in 2004, but soared to over 280 robots per 1000 workers in 2016. No other country witnessed such a massive growth in robot exposure in any sector (the automotive industry in the Czech Republic recorded the second largest increase, by 95 robots per 1000 workers). At the same time, the automotive industry in Slovakia accounted for only 1.8% of total employment in 2004 and 3.2% of total employment in 2016.

Table 5: The effects of robot exposure on the likelihood of job separation and job finding- robustness checks

Job separation

	(1)	(2)	(3)	(4)
	CF	CF	CF	CF
Robot Exposure	-0.008***	-0.008***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Robot Exposure X Labour Costs			-0.003***	-0.002
			(0.001)	(0.001)
Robot Exposure X (Labour Costs)^2			0.007***	0.007***
			(0.002)	(0.002)
Country FE	Yes	No	Yes	No
VA and GFCF	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Job finding

	(1)	(2)	(3)	(4)
	CF	CF	CF	CF
Robot Exposure	0.005***	0.006***	0.016***	0.018***
	(0.001)	(0.001)	(0.004)	(0.004)
Robot Exposure X Labour Costs			0.003	0.002
			(0.002)	(0.002)
Robot Exposure X (Labour Costs)^2			-0.015***	-0.016***
			(0.004)	(0.004)
Country FE	Yes	No	Yes	No
VA and GFCF	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Note: The table presents the estimated coefficients of the control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Individual-level controls: age group, education group, gender, and native/non-native status. Aggregate-level controls: global value chain participation, GDP growth, labour demand shocks, and growth in exports. VA and GFCF stand for value added and gross fixed capital formations. Robot exposure is instrumented using robot exposure in Western European countries. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Fourth, 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. The results confirm the findings from our baseline specification for both job separations and job findings (Table D5 and D6, and Figure D6 and D7 in Appendix D). Fifth, we use the percentiles of robot exposure instead of actual values of robot exposure as our variable of interest, in line with the literature (e.g. Graetz and Michaels 2018).[23] The estimated marginal effects are qualitatively similar (Table D7 and D8, and Figure D8 in Appendix D). Sixth, we test whether the results are robust to the use of alternative clustering specifications. Our results do not change when we apply alternative clustering by occupation, year and country (Figure D10) and by sector and year (Figure D11).

[23] The percentiles are defined based on sectors with non-zero values of robots.

Fifth, we estimate linear probability models instead of probit models to facilitate a comparison between models and other studies in the literature. This does not change our results. The marginal effects of both models are almost the same as in the case of the probit estimation (Figures D12 and D13).

5 Conclusions

In this paper, we have investigated the effects of robot exposure on worker flows in 16 European countries between 2000–2017. 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 differing in age? Third, what consequences did the effects of robot exposure on worker flows have for employment?

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. We explicitly included labour costs to analyse their role in the effects of robot exposure on worker flows. To account for the potential endogeneity of robot adoption, we used a control-function approach with instruments in the spirit of Acemoglu and Restrepo (2019) and Dauth et al. (2021).

Our findings can be summarised as follows. First, overall, we found minor beneficial effects of robot exposure on job separations and no effect on job findings. We detected significant cross-country heterogeneities that depend on initial labour costs. On the one hand, in countries with relatively low or average levels of labour costs, higher robot exposure led to lower job separation rates, and, thus, improved job stability, to a much larger extent than in countries with high levels of labour costs. On the other hand, in countries with relatively low or average levels of labour costs, higher levels of robot exposure led to increased job findings.

Overall, our results support a negative link between labour costs and the employment effects of robots – the lower the labour costs, the more positive the employment outcomes. However, the relatively weak effects in countries with the lowest initial levels of labour costs (Central Eastern European countries such as Slovakia and Poland) induce a U-shaped relationship between labour costs and the effects of robot exposure on the transition probabilities. We think they result from another force, namely skill shortages in CEE countries (Krzywdzinski, 2017; Sondergaard et al., 2012), which constrained employment responses to robot adoption, i.e. productivity-improving investments that also raised skill requirements. Our results are, therefore, generally in line with the Marshallian laws of labour demand, which state that labour is more likely to be substituted by other factors of production if labour costs are relatively high.

Second, we found important differences between workers performing different job tasks. Perhaps surprisingly, we generally found more beneficial effects for routine workers than for non-routine workers. This result was most pronounced in countries with average initial labour costs. We found minor effects of robot exposure on labour market flows among workers in non-routine cognitive occupations. Our results contradict the notion that routine tasks are always strongly substituted by robots. 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 average levels of labour costs, workers performing routine tasks seem to be complements of, rather than substitutes for, robots. This result is weaker in CEE countries, which can be explained by two factors. First, robot investment in these countries was mainly driven by FDI and greenfield investments, modernisations, and attempts to expand product ranges, especially in the automotive sector, which can explain the beneficial impacts on labour market flows that we have found. At the same time, these robot-adopting sectors were initially quite small, implying a modest impact on job separations. Second, the shortages of skilled workers and specialization of CEE countries mentioned above, particularly in less skill-demanding task, could have limited the response of hiring in the aftermath of robot adoption that probably required different skills than older technologies.

We also found heterogeneity across age groups. Except for countries higher labour costs, robots improved labour market prospects of young and prime-age workers in particular: they reduced job separation rates and increased job finding among these age groups. However, workers aged 55 years or older face challenges in certain environments. In particular, we detect some positive effects for older workers within manufacturing, which are likely due to the productivity-enhancing effects of robots. However, outside of manufacturing, the effects on older workers are less benign, indicating that they benefit less from demand-spillover effects than younger workers. Intergenerational differences in skills required to work with new technologies, e.g. working in service-sector firms which perform robot maintenance, are a probable mechanism behind this difference. Surveys of adult skills show that older workers have lower levels of skills needed in a technology-rich environment (OECD, 2013). The shorter period of time to benefit from investment in new skills also incentivises older workers to remain in sectors and occupations in which they have specific knowledge, even if technological progress reduces returns to their skills (Cavounidis and Lang, 2020).

Third, our counterfactual exercise showed that the effects of robots on worker flows had important implications for employment rates. Rising robot exposure increased employment, particularly in countries with low or average labour costs. These aggregate results were mainly due to reduced separations rather than increased hirings.

Our results have important policy implications. First, the overall effects of robots are positive in several countries. In Europe, this technology generally acted as an opportunity for workers rather than a threat. The key policy challenge is to identify the factors contributing 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 may include a more explicit analysis of the factors that enable workers to adjust to technological change, especially through the increased use of training. Second, our finding that the relative importance of hirings and separations as adjustment mechanisms to robot adoption differs strongly between countries implies that policy measures to support worker adjustment to technology have to take into account these country-specificities. Third, it is important to improve our understanding of how labour market institutions mediate the impacts of robots (and other novel automation technologies) in various countries. As institutions generally differ between countries rather than within them, our framework and sample size do not allow identification of the role of institutional factors. However, Leibrecht et al. (2023) provided descriptive evidence that robots are positively correlated with unemployment in countries where collective bargaining is weak, while Kostøl and Svarstad (2023) showed that unions improve relative wages of routine workers, who are more substitutable with automation, thus potentially strengthening its substitution effects. Future research that provides causal findings on how collective bargaining and other institutions shape the labour market impacts of automation would have high scientific and policy relevance.

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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 Manual	0.29	(0.45)	0.47	(0.5)
Labour Costs 2004		0.33	(0.89)	0.3	(0.9)
Robot Exposure		1.38	(4.72)	1.29	(4.79)
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, Eurostat, 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

Note: The allocation is based on Hardy et al. (2018), see data section for details.

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
	14	Hospitality, Retail and Other Service 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

Note: The allocation is based on Hardy et al. (2018), see data section for details.

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	-0.003**	-0.005***	-0.011***	-0.012***
	(0.001)	(0.001)	(0.002)	(0.003)
Robot Exposure X Labour Costs			-0.006***	-0.005***
			(0.001)	(0.001)
Robot Exposure X (Labour Costs)^2			0.011***	0.008***
			(0.002)	(0.002)
Age Groups (Base Category: Age 15-24)				
Age 25-34	-0.170***	-0.170***	-0.170***	-0.170***
	(0.006)	(0.006)	(0.006)	(0.006)
Age 35-54	-0.354***	-0.354***	-0.353***	-0.354***
	(0.007)	(0.007)	(0.007)	(0.007)
Age 55-70	-0.340***	-0.340***	-0.340***	-0.340***
	(0.011)	(0.011)	(0.011)	(0.011)
Education Group (Base Category: Low education)				
Medium education	-0.189***	-0.188***	-0.189***	-0.189***
	(0.007)	(0.007)	(0.007)	(0.007)
High education	-0.388***	-0.386***	-0.388***	-0.387***
	(0.014)	(0.014)	(0.014)	(0.014)
Gender (Base category: Female)				
Male	-0.081***	-0.082***	-0.080***	-0.081***
	(0.007)	(0.007)	(0.007)	(0.007)
Native	-0.175***	-0.175***	-0.175***	-0.175***
	(0.009)	(0.009)	(0.009)	(0.009)
Global Value Chain (Backwards)	0.004	0.068	-0.018	0.034
	(0.090)	(0.091)	(0.096)	(0.095)
Gross value added (Log)	-0.026**	-0.027***	-0.030***	-0.028***
	(0.010)	(0.010)	(0.011)	(0.011)
Investment to Gross value added	-0.102	-0.079	-0.095	-0.078
	(0.097)	(0.095)	(0.096)	(0.095)
GDP Growth	-0.018***	-0.018***	-0.017***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)
Bartik instrument	-0.868***	-0.864***	-0.885***	-0.879***
	(0.137)	(0.137)	(0.138)	(0.137)
Export growth	0.017***	0.016***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
Residual 1		0.006***		
		(0.002)		
Residual 2				-0.002
				(0.004)
Residual 3				-0.002
				(0.002)
Residual 4				0.007**
				(0.004)

	(1)	(2)	(3)	(4)
	Probit	**CF**	**Probit**	**CF**
Industry Group (Base Category: Agriculture and Mining)				
Manufacturing	-0.071***	-0.062***	-0.056**	-0.053**
	(0.023)	(0.023)	(0.022)	(0.022)
Utilities	-0.276***	-0.271***	-0.265***	-0.264***
	(0.034)	(0.033)	(0.033)	(0.033)
Construction	0.172***	0.173***	0.178***	0.178***
	(0.027)	(0.027)	(0.026)	(0.026)
Consumer Services	-0.004	-0.005	-0.006	-0.006
	(0.023)	(0.024)	(0.023)	(0.023)
Business Services	-0.125***	-0.127***	-0.128***	-0.129***
	(0.022)	(0.022)	(0.022)	(0.022)
Public Services & Education	-0.259***	-0.259***	-0.261***	-0.260***
	(0.024)	(0.024)	(0.024)	(0.024)
Constant	0.807***	0.813***	0.791***	0.786***
	(0.222)	(0.222)	(0.221)	(0.221)
Year dummies	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Country linear trends	Yes	Yes	Yes	Yes
Industry Group FE	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, r03_1 and r04_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, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

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

	(1)	(2)	(3)	(4)
	Probit	CF	Probit	CF
Robot Exposure	-0.002	0.002	0.018***	0.011***
	(0.001)	(0.001)	(0.003)	(0.004)
Robot Exposure X Labour Costs			0.008***	0.003
			(0.002)	(0.002)
Robot Exposure X (Labour Costs)^2			-0.022***	-0.012***
			(0.003)	(0.004)
Age Groups (Base Category: Age 15-24)				
Age 25-34	-0.411***	-0.411***	-0.411***	-0.411***
	(0.009)	(0.009)	(0.009)	(0.009)
Age 35-54	-0.675***	-0.674***	-0.674***	-0.674***
	(0.014)	(0.014)	(0.014)	(0.014)
Age 55-70	-1.116***	-1.115***	-1.115***	-1.115***
	(0.021)	(0.021)	(0.021)	(0.021)
Education Group (Base Category: Low education)				
Medium education	0.190***	0.189***	0.191***	0.190***
	(0.009)	(0.009)	(0.009)	(0.009)
High education	0.363***	0.361***	0.364***	0.363***
	(0.012)	(0.012)	(0.012)	(0.012)
Gender (Base category: Female)				
Male	0.011	0.012	0.011	0.012
	(0.008)	(0.008)	(0.008)	(0.008)
Native	-0.082***	-0.082***	-0.081***	-0.082***
	(0.011)	(0.011)	(0.011)	(0.011)
Global Value Chain (Backwards)	-0.024	-0.097	-0.070	-0.121
	(0.077)	(0.078)	(0.082)	(0.080)
Gross value added (Log)	0.004	0.003	0.000	-0.001
	(0.012)	(0.012)	(0.012)	(0.012)
Investment to Gross value added	0.479***	0.459***	0.456***	0.460***
	(0.114)	(0.113)	(0.111)	(0.110)
GDP Growth	0.022***	0.022***	0.022***	0.022***
	(0.003)	(0.003)	(0.003)	(0.003)
Bartik instrument	1.010***	1.003***	1.015***	1.005***
	(0.145)	(0.145)	(0.146)	(0.145)
Export growth	-0.010**	-0.010**	-0.010**	-0.010**
	(0.005)	(0.005)	(0.005)	(0.005)
Residual 1		-0.006***		
		(0.002)		
Residual 2				0.019***
				(0.005)
Residual 3				0.013***
				(0.003)
Residual 4				-0.026***
				(0.006)
Industry Group (Base Category: Agriculture and Mining)				
Manufacturing	0.132***	0.123***	0.116***	0.124***
	(0.023)	(0.023)	(0.023)	(0.023)
Utilities	0.327***	0.323***	0.318***	0.324***

	(1) Probit	(2) CF	(3) Probit	(4) CF
	(0.033)	(0.034)	(0.033)	(0.033)
Construction	0.110***	0.108***	0.104***	0.110***
	(0.027)	(0.027)	(0.027)	(0.027)
Consumer Services	0.152***	0.152***	0.152***	0.152***
	(0.023)	(0.023)	(0.023)	(0.023)
Business Services	0.295***	0.297***	0.295***	0.296***
	(0.022)	(0.023)	(0.022)	(0.022)
Public Services & Education	0.378***	0.377***	0.376***	0.376***
	(0.024)	(0.025)	(0.024)	(0.024)
Constant	-2.413***	-2.400***	-2.322***	-2.347***
	(0.352)	(0.351)	(0.351)	(0.348)
Year dummies	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Country linear trends	Yes	Yes	Yes	Yes
Industry Group FE	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, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

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

	(1)	(2)	(3)
	1st First Stage	2nd First Stage	3rd First Stage
Independent variable:	Robot Exposure	Robot Exposure X Labour Costs	Robot Exposure X (Labour Costs)^2
Instrument	0.760***	0.016	-0.008
	(0.027)	(0.020)	(0.013)
Instrument X Labour Costs	-0.153	1.329***	-0.002
	(0.151)	(0.123)	(0.105)
Robot Exposure X (Labour Costs)^2	0.740***	-0.103	1.410***
	(0.150)	(0.142)	(0.116)
Constant	6.856**	-10.927***	4.832**
	(3.136)	(2.797)	(2.205)
Observations	11.8 M	11.8 M	11.8 M
Kleibergen-Paap F-statistic for weak identification	18 537.4		

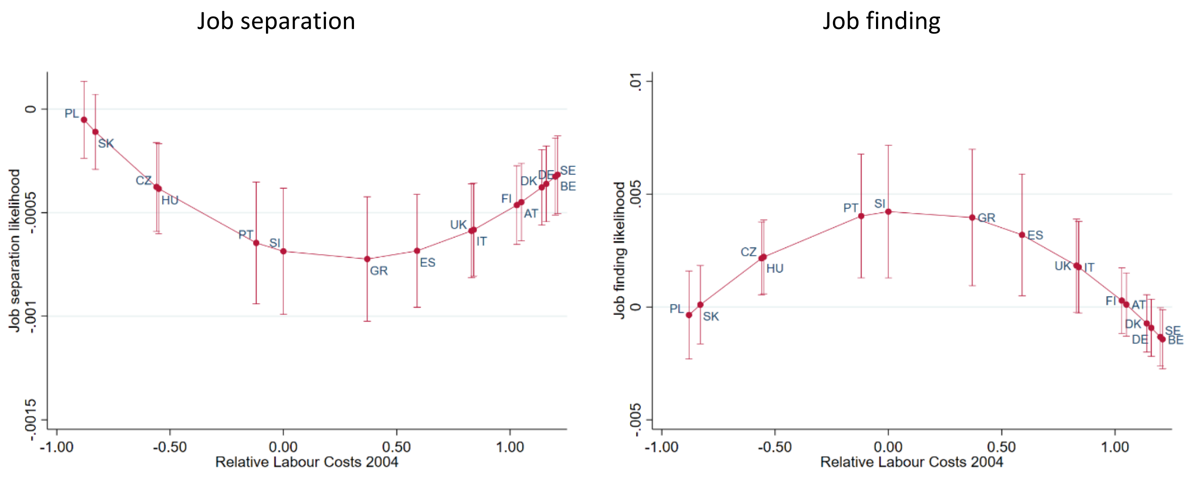
Note: See notes to Table B1. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, and IFR, UN Comtrade, and UIBE GVC data.

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

	(1)	(2)	(3)
	1st First Stage	2nd First Stage	3rd First Stage
Independent variable:	Robot Exposure	Robot Exposure X Labour Costs	Robot Exposure X (Labour Costs)^2
Instrument	0.700***	0.030	-0.016
	(0.031)	(0.027)	(0.019)
Instrument X Labour Costs	-0.254*	1.352***	-0.058
	(0.146)	(0.122)	(0.102)
Robot Exposure X (Labour Costs)^2	0.843***	-0.171	1.427***
	(0.140)	(0.143)	(0.119)
Constant	7.863**	-12.027***	5.759**
	(3.556)	(3.364)	(2.494)
Observations	1.3 M	1.3 M	1.3 M
Kleibergen-Paap F-statistic for weak identification	3 714.4		

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, Eurostat, 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: See notes to

Figure 4. Authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, 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

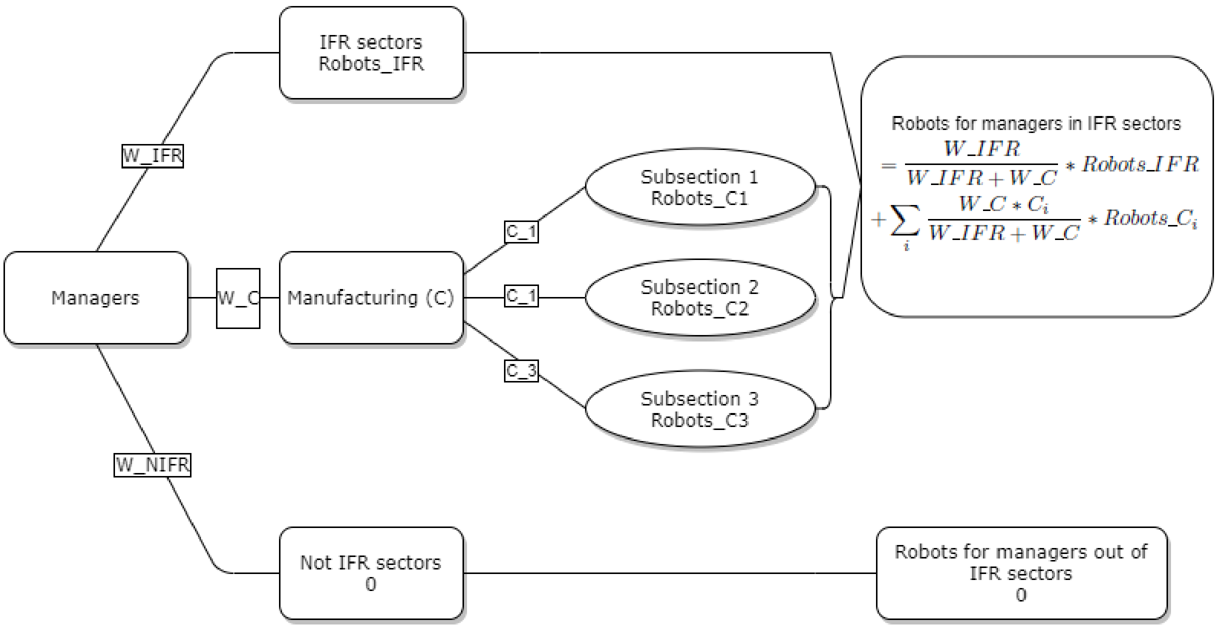
Source: Own elaboration based on Acemoglu and Autor (2011).

Appendix C – Technical details

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 2000-2007, and of NACE rev. 2 between 2008-2017. Occupations are coded at the two-digit level of ISCO-88 between 2000-2010, 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; € Mining and Quarrying; (D) Manufacturing; € 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 Diagram 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.

C2. Counterfactual analysis methodology

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:

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

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

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

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:

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

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:

$$\widehat{EU}_{c,t} = EMP_{c,t} * \widehat{eu}_{c,t} \tag{5}$$

$$\widehat{UE}_{c,t} = UNEMP_{c,t} * \widehat{ue}_{c,t} \tag{6}$$

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

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

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 $UN\widehat{EMP}_{c,t}$ 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 difference between the counterfactual and predicted scenarios for each year t, normalised with working-age population $POP_{c,t}$, namely:

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

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

Finally, we analyse to what extent the overall effects of robot adoption on employment 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 ($\widehat{EMP}_{c,t}^{s,JS}$) with the counterfactual likelihood of job separations ($\widehat{eu}_{c,t}^{cf}$) (likelihood of job finding ($\widehat{ue}_{c,t}$)), and calculate flows and levels recursively, using the formulas:

$$\widehat{EU}_{c,t}^{s,JS} = \widehat{EMP}_{c,t}^{s,JS} * \widehat{eu}_{c,t}^{cf} \tag{10}$$

$$\widehat{UE}_{c,t}^{s,JS} = U\widehat{NEMP}_{c,t}^{s,JS} * \widehat{ue}_{c,t} \tag{11}$$

$$\widehat{EMP}_{c,t+1}^{s,JS} = \begin{cases} \widehat{EMP}_{c,t}^{s,JS} - \widehat{EU}_{c,t}^{s,JS} + \widehat{UE}_{c,t}^{s,JS} \; if \; t \geq 2004 \\ EMP_{c,t+1} \; if \; t < 2004 \end{cases} \tag{12}$$

$$U\widehat{NEMP}_{c,t+1}^{s,JS} = \begin{cases} U\widehat{NEMP}_{c,t}^{s,JS} + \widehat{EU}_{c,t}^{s,JS} - \widehat{UE}_{c,t}^{JS} \; if \; t \geq 2004 \\ UNEMP_{c,t+1} \; if \; t < 2004 \end{cases} \tag{13}$$

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:

$$\widehat{EU}_{c,t}^{s,JF} = \widehat{EMP}_{c,t}^{s,JF} * \widehat{eu}_{c,t} \tag{14}$$

$$\widehat{UE}_{c,t}^{s,JF} = U\widehat{NEMP}_{c,t}^{s,JF} * \widehat{ue}_{c,t}^{cf} \tag{15}$$

$$\widehat{EMP}_{c,t+1}^{s,JF} = \begin{cases} \widehat{EMP}_{c,t}^{c,t} - \widehat{EU}_{c,t}^{s,JF} + \widehat{UE}_{c,t}^{s,JF} \; if \; t \geq 2004 \\ EMP_{c,t+1} \; if \; t < 2004 \end{cases} \tag{16}$$

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

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:

$$\Delta\widehat{EMP}_{c,t}^{s,JS} = \frac{\widehat{EMP}_{c,t} - \widehat{EMP}_{c,t}^{s,JS}}{EMP_{c,t}} * 100 \tag{17}$$

Job Finding (JF) Channel:

$$\Delta\widehat{EMP}_{c,t}^{s,JF} = \frac{\widehat{EMP}_{c,t} - \widehat{EMP}_{c,t}^{s,JF}}{EMP_{c,t}} * 100 \tag{19}$$

Note that because the simulations are calculated recursively, the difference between the counterfactual and the sum of semi-counterfactuals may differ from zero, we show this difference as a residual.

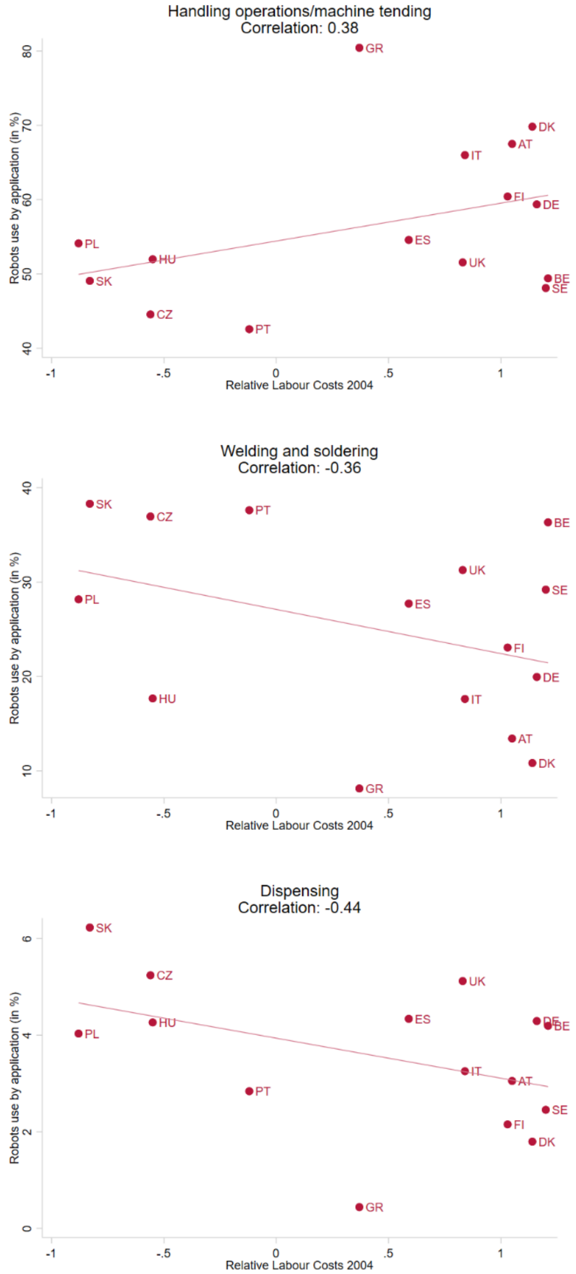
Finally, we use these values to assess the contributions of the separation and of the finding channels to the estimated effect of robot adoption on employment. We use a covariance-based decomposition, originally proposed by Fujita and Ramey (2009), to quantify the contributions of job separation and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

$$\sigma_{\Delta\widehat{EMP}_{c,t}^{s,JS}, \Delta EMP_{c,t}} = \frac{cov(\Delta\widehat{EMP}_{c,t}^{s,JS}, \Delta EMP_{c,t})}{var(\Delta EMP_{c,t})} \tag{20}$$

$$\sigma_{\Delta\widehat{EMP}_{c,t}^{s,JF}, \Delta EMP_{c,t}} = \frac{cov(\Delta\widehat{EMP}_{c,t}^{s,JF}, \Delta EMP_{c,t})}{var(\Delta EMP_{c,t})} \tag{18}$$

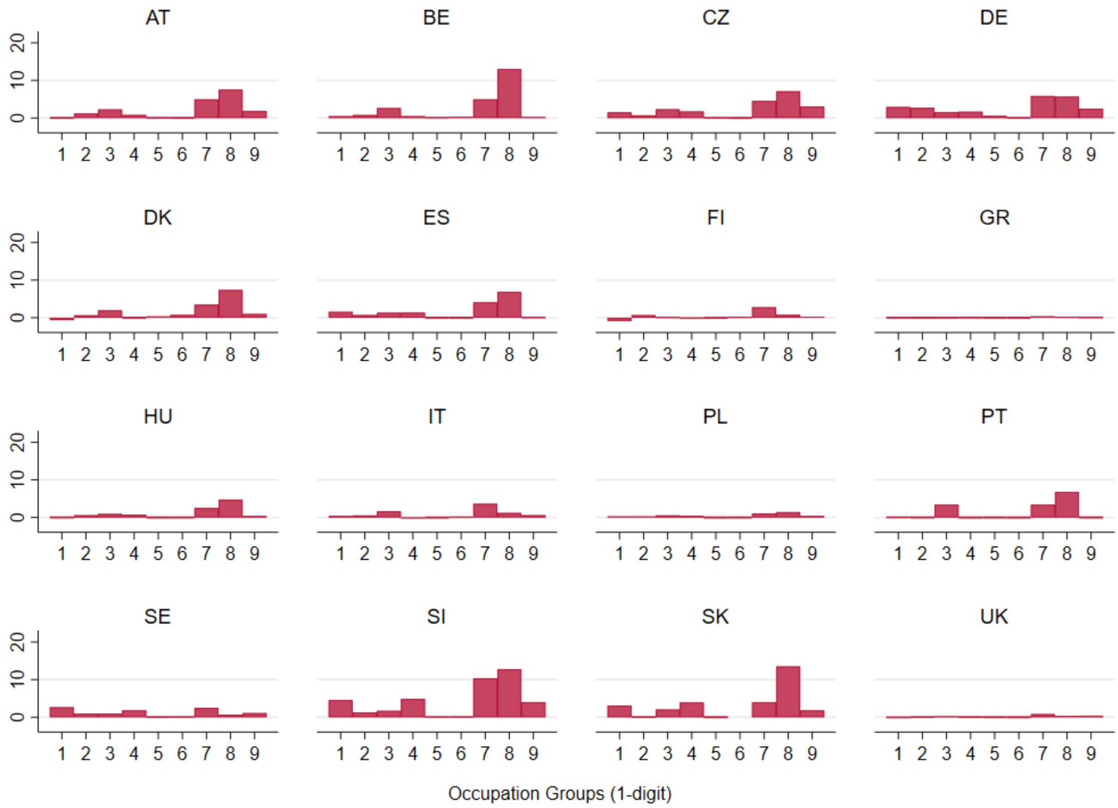
Appendix D – Additional descriptive evidence and results

Figure D1. Correlation between initial labour costs and robot application within countries



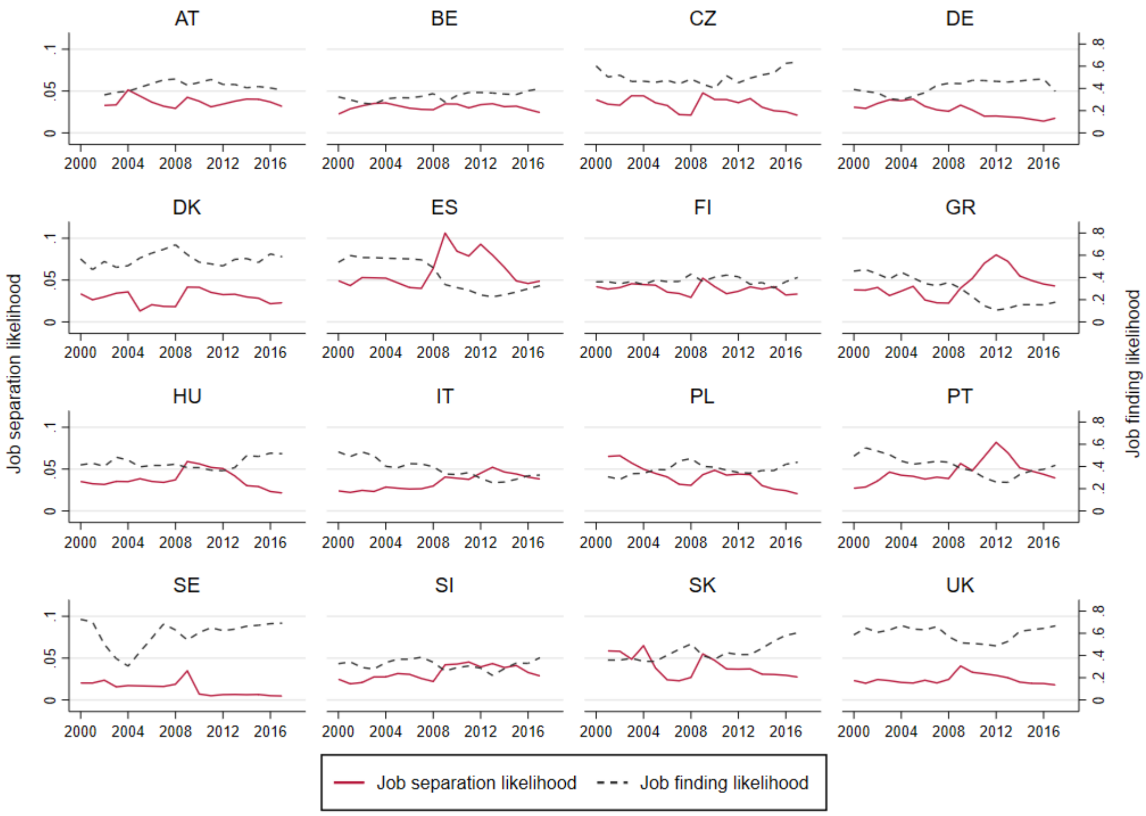
Note: Scales on Y-axis differ. Robot application shares are calculated in 2016. – Source: authors' calculations based on IFR data.

Figure D2: Change in robot exposure at one-digit occupation-level between 2000/2004-2016



Note: The figure displays the changes in robot exposure between 2000/2004 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 D3: Transition rates between employment and unemployment by country, 2000-2018



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.

Heterogeneity by task groups

Table D1: The effect of robot exposure on the likelihood of job separation – by task group group

	(1)	(2)	(3)	(4)
	Probit	**CF**	**Probit**	**CF**
Robot Exposure	-0.000	-0.002	0.002	0.001
	(0.002)	(0.005)	(0.005)	(0.008)
Robot Exposure X Labour Costs			-0.009***	-0.005
			(0.003)	(0.007)
Robot Exposure X (Labour Costs)^2			0.003	-0.000
			(0.005)	(0.006)
NRCA X Robot Exposure	-0.000	0.000	-0.006	0.008
	(0.003)	(0.005)	(0.007)	(0.010)
NRCP X Robot Exposure	0.004	0.000	-0.005	-0.003
	(0.003)	(0.006)	(0.008)	(0.011)
RC X Robot Exposure	-0.003	-0.003	-0.021***	-0.019**
	(0.003)	(0.005)	(0.006)	(0.008)
RM X Robot Exposure	-0.001	-0.000	-0.012**	-0.007
	(0.003)	(0.005)	(0.005)	(0.008)
NRCA X Robot Exposure x Labour Cost			-0.001	-0.005
			(0.004)	(0.008)
NRCP X Robot Exposure x Labour Cost			0.004	0.001
			(0.005)	(0.008)
RC X Robot Exposure x Labour Cost			-0.003	-0.003
			(0.004)	(0.008)
RM X Robot Exposure x Labour Cost			0.003	0.001
			(0.004)	(0.007)
NRCA X Robot Exposure x (Labour Costs)^2			0.006	-0.001
			(0.006)	(0.010)
NRCP X Robot Exposure x (Labour Costs)^2			0.005	0.006
			(0.008)	(0.010)
RC X Robot Exposure x (Labour Costs)^2			0.017***	0.018**
			(0.006)	(0.008)
RM X Robot Exposure x (Labour Costs)^2			0.008	0.007
			(0.005)	(0.006)
NRCA	-0.285***	-0.285***	-0.220***	-0.234***
	(0.016)	(0.017)	(0.024)	(0.024)
NRCP	-0.386***	-0.382***	-0.333***	-0.333***
	(0.020)	(0.020)	(0.027)	(0.028)
RC	-0.171***	-0.169***	-0.124***	-0.124***
	(0.012)	(0.012)	(0.017)	(0.018)
RM	0.078***	0.077***	0.104***	0.093***
	(0.021)	(0.021)	(0.024)	(0.026)
NRCA x Labour Cost			0.155***	0.163***
			(0.016)	(0.016)
NRCP x Labour Cost			0.151***	0.152***
			(0.018)	(0.018)
RC x Labour Cost			0.031*	0.031*
			(0.016)	(0.016)

RM x Labour Cost			-0.014	-0.022
			(0.017)	(0.016)
NRCA x (Labour Costs)^2			-0.173***	-0.168***
			(0.023)	(0.023)
NRCP x (Labour Costs)^2			-0.160***	-0.160***
			(0.030)	(0.031)
RC x (Labour Costs)^2			-0.077***	-0.078***
			(0.023)	(0.023)
RM x (Labour Costs)^2			-0.020	-0.007
			(0.028)	(0.029)
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. Country, year, industry group fixed effects, and country linear trends 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. NRM is a reference group.*** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Table D2: The effect of robot exposure on the likelihood of job finding – by task group

	(1)	(2)	(3)	(4)
	Probit	**CF**	**Probit**	**CF**
Robot Exposure	-0.007***	-0.004	0.020**	0.022**
	(0.003)	(0.004)	(0.008)	(0.011)
Robot Exposure X Labour Costs			0.015**	0.014*
			(0.007)	(0.008)
Robot Exposure X (Labour Costs)^2			-0.034***	-0.036***
			(0.010)	(0.012)
NRCA X Robot Exposure	0.012***	0.018***	0.015	0.008
	(0.003)	(0.005)	(0.013)	(0.017)
NRCP X Robot Exposure	-0.006	0.001	-0.034	-0.034
	(0.005)	(0.010)	(0.023)	(0.036)
RC X Robot Exposure	0.011***	0.013***	0.031***	0.021
	(0.003)	(0.005)	(0.010)	(0.015)
RM X Robot Exposure	0.006**	0.007	0.000	-0.008
	(0.003)	(0.004)	(0.009)	(0.011)
NRCA X Robot Exposure x Labour Cost			0.007	-0.003
			(0.007)	(0.009)
NRCP X Robot Exposure x Labour Cost			-0.008	-0.007
			(0.010)	(0.015)
RC X Robot Exposure x Labour Cost			0.009	0.002
			(0.007)	(0.009)
RM X Robot Exposure x Labour Cost			-0.006	-0.011
			(0.007)	(0.008)
NRCA X Robot Exposure x (Labour Costs)^2			-0.007	0.012
			(0.014)	(0.017)
NRCP X Robot Exposure x (Labour Costs)^2			0.031	0.044
			(0.024)	(0.037)
RC X Robot Exposure x (Labour Costs)^2			-0.022*	-0.005
			(0.011)	(0.016)
RM X Robot Exposure x (Labour Costs)^2			0.010	0.022*
			(0.010)	(0.012)
NRCA	-0.060***	-0.070***	-0.001	0.004
	(0.017)	(0.018)	(0.028)	(0.029)
NRCP	-0.154***	-0.162***	-0.216***	-0.218***
	(0.033)	(0.034)	(0.051)	(0.051)
RC	-0.031***	-0.035***	-0.042**	-0.039*
	(0.011)	(0.012)	(0.021)	(0.022)
RM	-0.084***	-0.083***	-0.135***	-0.111***
	(0.015)	(0.016)	(0.025)	(0.026)
NRCA x Labour Cost			-0.037	-0.018
			(0.023)	(0.026)
NRCP x Labour Cost			0.048*	0.049*
			(0.026)	(0.027)
RC x Labour Cost			0.044**	0.049**
			(0.019)	(0.020)
RM x Labour Cost			-0.030	-0.009

			(0.028)	(0.026)
NRCA x (Labour Costs)^2			-0.044	-0.071*
			(0.037)	(0.040)
NRCP x (Labour Costs)^2			0.044	0.035
			(0.046)	(0.048)
RC x (Labour Costs)^2			-0.018	-0.028
			(0.032)	(0.033)
RM x (Labour Costs)^2			0.083**	0.047
			(0.037)	(0.037)
Observations	1.3 M	1.3 M	1.3 M	1.3 M

Note: See notes to Table D1. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Heterogeneity by age

Table D3: The effect of robot exposure on the likelihood of job separation – by age group

	(1) Probit	(2) CF	(3) Probit	(4) CF
Robot Exposure	-0.003**	-0.007**	-0.004*	-0.015***
	(0.002)	(0.003)	(0.002)	(0.005)
Robot Exposure X Labour Costs		-0.004***		-0.005**
		(0.001)		(0.002)
Robot Exposure X (Labour Costs)^2		0.005		0.013**
		(0.003)		(0.005)
Age 25-34 X Robot Exposure	-0.000	-0.006*	-0.005***	-0.006
	(0.001)	(0.003)	(0.001)	(0.004)
Age 35-54 X Robot Exposure	0.000	-0.006**	-0.002*	0.002
	(0.001)	(0.003)	(0.001)	(0.004)
Age 55-70 X Robot Exposure	0.006***	0.007*	0.007***	0.030***
	(0.002)	(0.004)	(0.002)	(0.006)
Age 25-34 X Robot Exposure x Labour Cost		-0.005***		-0.006***
		(0.001)		(0.002)
Age 35-54 X Robot Exposure x Labour Cost		-0.002*		-0.000
		(0.001)		(0.002)
Age 55-70 X Robot Exposure x Labour Cost		0.004**		0.011***
		(0.002)		(0.003)
Age 25-34 X Robot Exposure x (Labour Costs)^2		0.006*		0.005
		(0.004)		(0.005)
Age 35-54 X Robot Exposure x (Labour Costs)^2		0.007**		-0.005
		(0.003)		(0.005)
Age 55-70 X Robot Exposure x (Labour Costs)^2		-0.003		-0.031***
		(0.004)		(0.007)
Age 25-34	-0.170***	-0.200***	-0.163***	-0.201***
	(0.006)	(0.011)	(0.006)	(0.012)
Age 35-54	-0.354***	-0.420***	-0.349***	-0.430***
	(0.007)	(0.013)	(0.008)	(0.014)
Age 55-70	-0.350***	-0.414***	-0.355***	-0.446***
	(0.011)	(0.020)	(0.011)	(0.019)
Age 25-34 x Labour Cost		0.093***		0.094***
		(0.009)		(0.009)
Age 35-54 x Labour Cost		0.045***		0.043***
		(0.009)		(0.009)
Age 55-70 x Labour Cost		0.028**		0.023*
		(0.012)		(0.013)
Age 25-34 x (Labour Costs)^2		0.001		0.005
		(0.016)		(0.016)
Age 35-54 x (Labour Costs)^2		0.079***		0.095***
		(0.016)		(0.017)

Age 55-70 x (Labour Costs)^2		0.076***		0.116***
		(0.023)		(0.022)
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. Country, year, industry group fixed effects, and country linear trends 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. Aged 15-24 are a reference group.*** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Table D4: The effect of robot exposure on the likelihood of job finding – by age group

	(1)	(2)	(3)	(4)
	Probit	**CF**	**Probit**	**CF**
Robot Exposure	0.004***	0.022***	0.013***	0.027***
	(0.001)	(0.005)	(0.002)	(0.006)
Robot Exposure X Labour Costs		0.006***		0.005**
		(0.002)		(0.002)
Robot Exposure X (Labour Costs)^2		-0.022***		-0.022***
		(0.005)		(0.007)
Age 25-34 X Robot Exposure	-0.005***	-0.004	-0.011***	-0.011**
	(0.001)	(0.004)	(0.002)	(0.006)
Age 35-54 X Robot Exposure	-0.006***	-0.004	-0.014***	-0.022***
	(0.001)	(0.004)	(0.002)	(0.007)
Age 55-70 X Robot Exposure	-0.011***	-0.020***	-0.023***	-0.051***
	(0.002)	(0.006)	(0.004)	(0.008)
Age 25-34 X Robot Exposure x Labour Cost		0.002		0.002
		(0.002)		(0.002)
Age 35-54 X Robot Exposure x Labour Cost		0.003*		-0.004
		(0.002)		(0.002)
Age 55-70 X Robot Exposure x Labour Cost		-0.003		-0.012***
		(0.003)		(0.004)
Age 25-34 X Robot Exposure x (Labour Costs)^2		-0.000		0.005
		(0.005)		(0.006)
Age 35-54 X Robot Exposure x (Labour Costs)^2		-0.003		0.014**
		(0.005)		(0.007)
Age 55-70 X Robot Exposure x (Labour Costs)^2		0.011*		0.038***
		(0.006)		(0.008)
Age 25-34	-0.404***	-0.428***	-0.396***	-0.423***
	(0.010)	(0.018)	(0.010)	(0.018)
Age 35-54	-0.666***	-0.728***	-0.654***	-0.715***
	(0.015)	(0.025)	(0.015)	(0.025)
Age 55-70	-1.098***	-1.161***	-1.081***	-1.139***
	(0.022)	(0.031)	(0.022)	(0.031)
Age 25-34 x Labour Cost		0.098***		0.095***
		(0.013)		(0.013)
Age 35-54 x Labour Cost		0.084***		0.087***
		(0.015)		(0.015)
Age 55-70 x Labour Cost		-0.020		-0.022
		(0.023)		(0.024)
Age 25-34 x (Labour Costs)^2		-0.019		-0.018
		(0.024)		(0.024)
Age 35-54 x (Labour Costs)^2		0.043		0.037
		(0.028)		(0.028)
Age 55-70 x (Labour Costs)^2		0.110***		0.103***

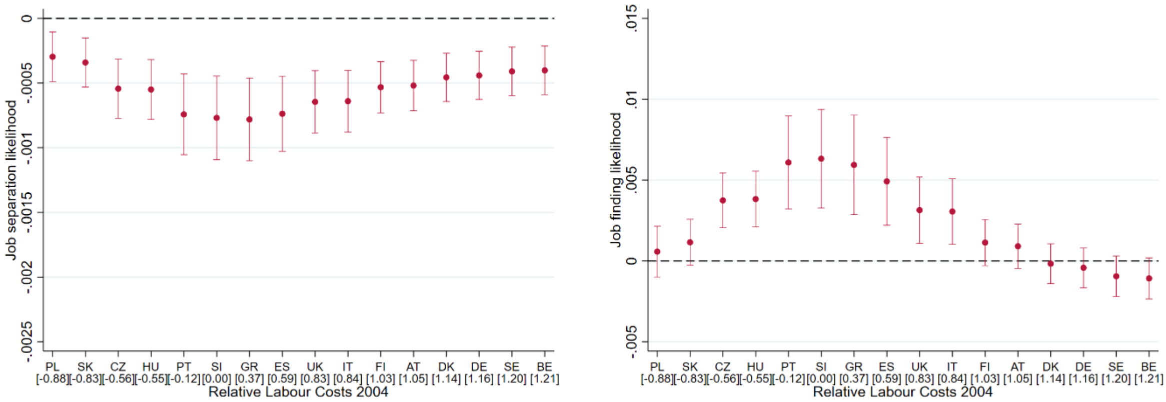
		(0.034)		(0.035)
Observations	1.3 M	1.3 M	1.3 M	1.3 M

Note: See notes to Table D3. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors’ calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Robustness

Figure D4: Effects of robot exposure on likelihood of the flows, regressions with country FE

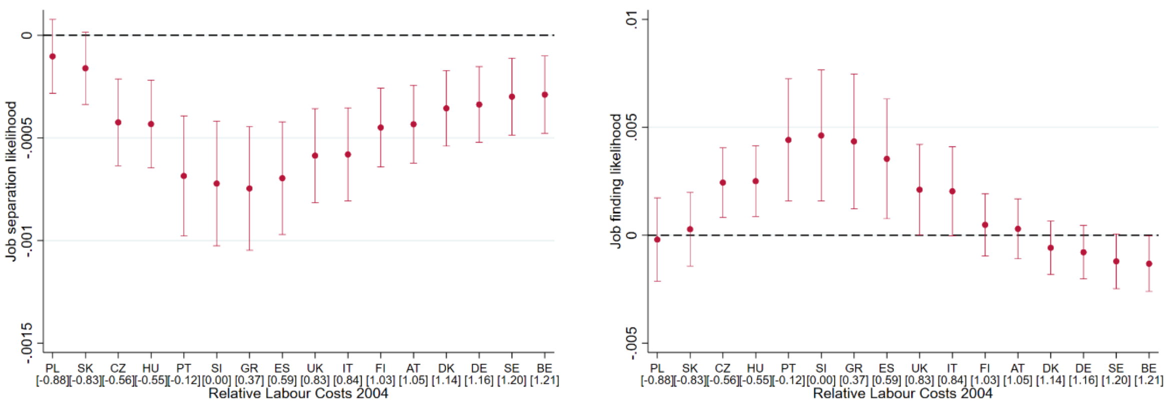
Job separation | Job finding



Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (left panel) and unemployment to employment (right panel), based on regressions presented in Table 4 column (3) . 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). – Source: authors’ calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure D5: Effects of robot exposure on likelihood of the flows, regressions without controls for value added and gross fixed capital formations

Job separation | Job finding



Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (left panel) and unemployment to employment (right panel), based on regressions presented in Table 4 column (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). – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Table D5: The effect of robot exposure on the likelihood of job separation, initial development proxied with GDP

	(1) Probit	(2) CF	(3) Probit	(5) CF
A: All Sectors				
Robot Exposure	-0.003**	-0.005***	-0.010***	-0.009***
	(0.001)	(0.001)	(0.002)	(0.002)
Robot Exposure X GDP per capita			-0.008***	-0.005***
			(0.001)	(0.002)
Robot Exposure X (GDP per capita)^2			0.021***	0.012**
			(0.004)	(0.005)
No. of observations	11.8 M	11.8 M	11.8 M	11.8 M
Kleibergen-Paap F-statistic for weak identification		372 874.1		22 886.2
B: Manufacturing				
Robot Exposure	-0.001	-0.006***	-0.008***	-0.008***
	(0.001)	(0.002)	(0.002)	(0.003)
Robot Exposure X GDP per capita			-0.006***	-0.000
			(0.002)	(0.002)
Robot Exposure X (GDP per capita)^2			0.019***	0.006
			(0.007)	(0.008)
No. of Observations	2.6 M	2.6 M	2.6 M	2.6 M
Kleibergen-Paap F-statistic for weak identification		197 835.2		13 977.7

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, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Table D6: The effect of robot exposure on the likelihood of job finding, initial development proxied with GDP

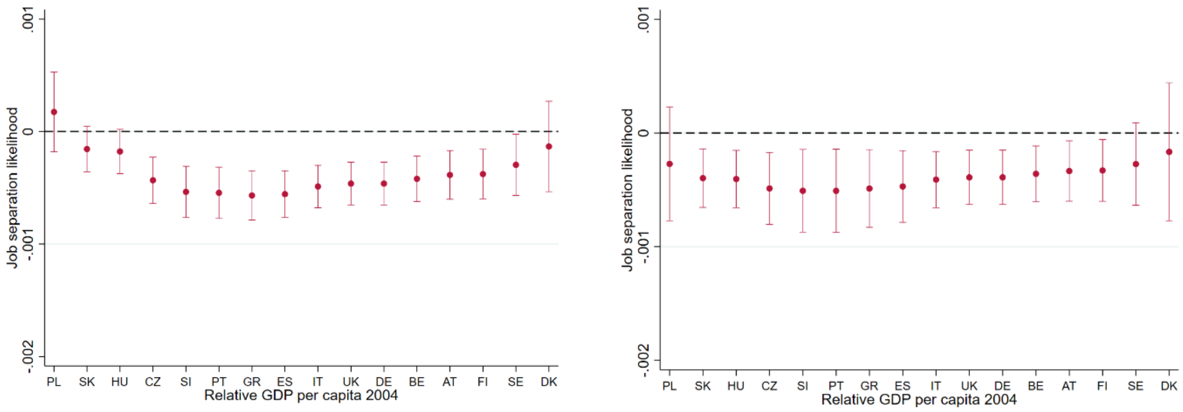
	(1) **Probit**	**(2)** **CF**	**(3)** **Probit**	**(5)** **CF**
A: All Sectors				
Robot Exposure	-0.002	0.002	0.007***	0.003
	(0.001)	(0.001)	(0.002)	(0.002)
Robot Exposure X GDP per capita			0.007***	-0.001
			(0.002)	(0.003)
Robot Exposure X (GDP per capita)^2			-0.024***	-0.005
			(0.005)	(0.006)
No. of Observations	1.3 M	1.3 M	1.3 M	1.3 M
Kleibergen-Paap F-statistic for weak identification		25 778.1		3 187.2
B: Manufacturing				
Robot Exposure	0.000	0.002	0.003	0.002
	(0.001)	(0.002)	(0.003)	(0.003)

Robot Exposure X GDP per capita			0.001	-0.006**
			(0.002)	(0.003)
Robot Exposure X (GDP per capita)^2			-0.007	0.002
			(0.007)	(0.009)
No. of Observations	260 180	260 180	260 180	260 180
Kleibergen-Paap F-statistic for weak identification		14 791.2		2 236.7

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, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure D6: Marginal effects of robot exposure on the likelihood of job separation, initial development proxied with GDP

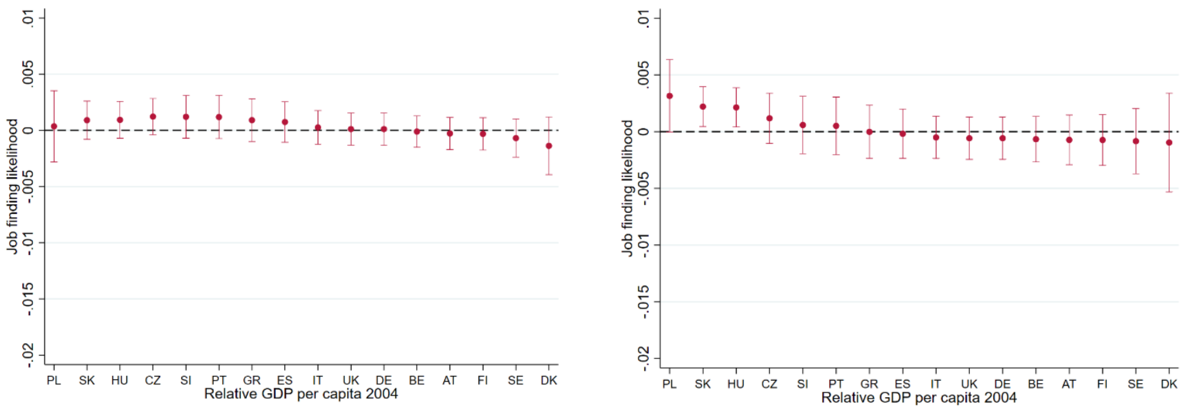
A: All industries B: Manufacturing



Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment. The vertical lines represent the 95% confidence intervals. 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, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure D7: Marginal effects of robot exposure on the likelihood of job finding, initial development proxied with GDP

A: All industries B: Manufacturing



Note: The figures show the marginal effects of robot exposure on the probability of transitioning from unemployment to employment. The vertical lines represent the 95% confidence intervals. 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, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Table D7: The effect of percentiles of robot exposure on the job separation likelihood

	(1) Probit	(2) CF	(3) Probit	(4) CF
Percentile Robot Exposure	-0.095***	-0.247***	-0.110***	-0.292***
	[0.022]	[0.032]	[0.026]	[0.042]
Percentile Robot Exposure X Labour Costs 2004			-0.025	0.025
			[0.019]	[0.024]
Percentile Robot Exposore X Squared Labour Costs 2004			0.037	0.040
			[0.027]	[0.034]
No. of Observations	11.8 M	11.8 M	11,8 M	11.8 M
Kleibergen-Paap F-statistic for weak identification		8.5 M		2.2 M

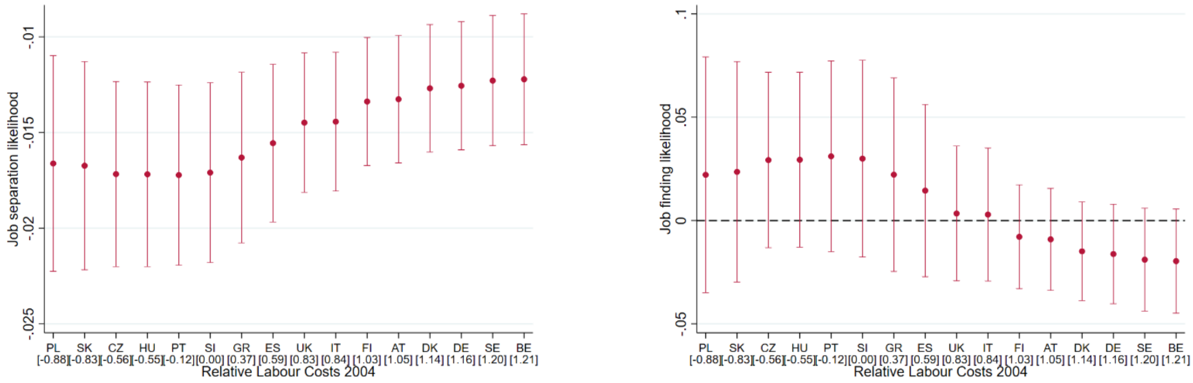
Note: See notes to Table B1. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Table D8: The effect of percentiles of robot exposure on the job finding likelihood

	(1) Probit	(2) CF	(3) Probit	(4) CF
Percentile Robot Exposure	-0.022	0.015	0.133***	0.076
	[0.023]	[0.038]	[0.038]	[0.062]
Percentile Robot Exposure X Labour Costs 2004			0.150***	-0.031
			[0.043]	[0.044]
Percentile Robot Exposore X Squared Labour Costs 2004			-0.281***	-0.061
			[0.055]	[0.067]
No. of Observations	1.3 M	1.3 M	1.3 M	1.3 M
Kleibergen-Paap F-statistic for weak identification		771 655.9		187 741.6

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, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure D8: Marginal Effects of Percentiles of Robot Exposure for job separation/job finding likelihood



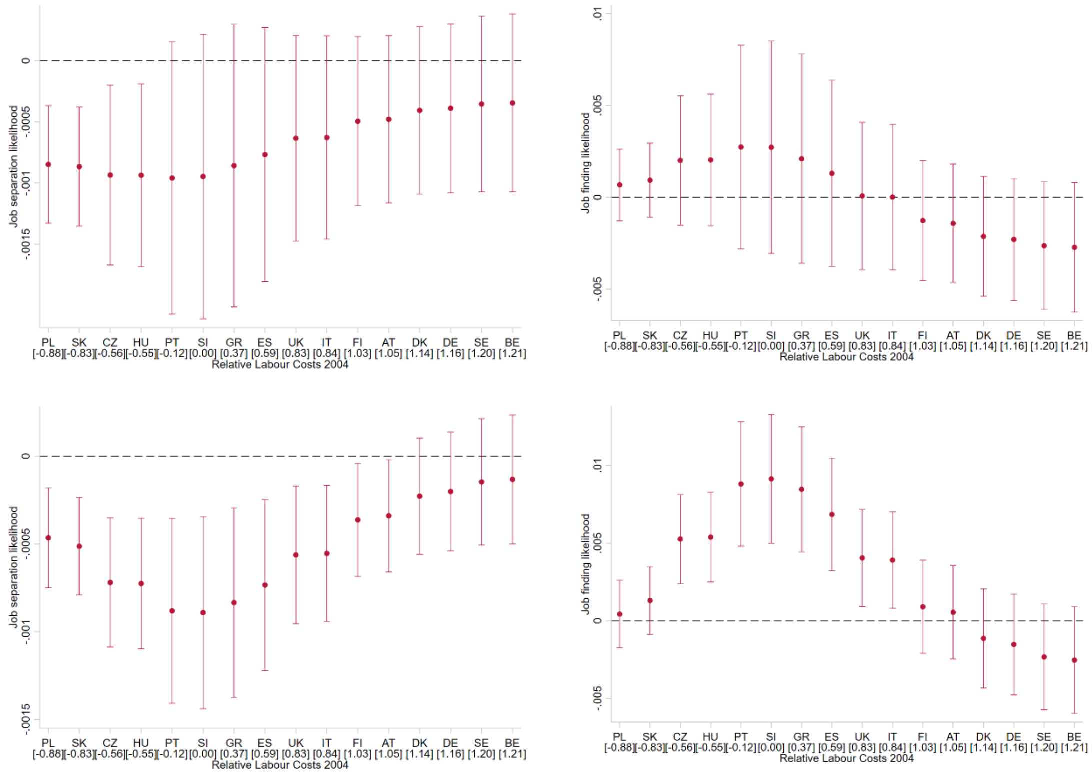
Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (left panel) and unemployment to employment (right panel), based on regressions presented in Table D7 and D8 column (4). The vertical lines represent the 95% confidence intervals. Robot exposure is instrumented using the percentiles of 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).-Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

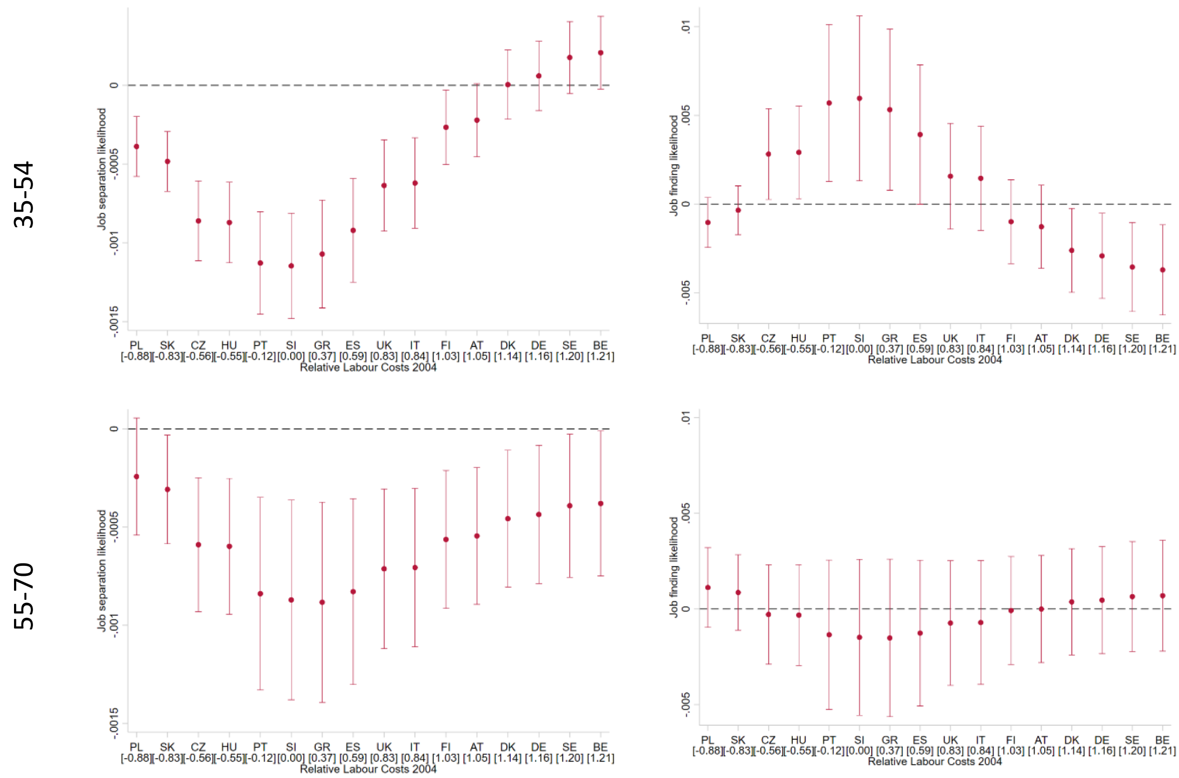
Figure D9: Marginal effects of robot exposure on the likelihood of job separations and finding, by age group in manufacturing

Age **Job separations** **Job finding**

15-24

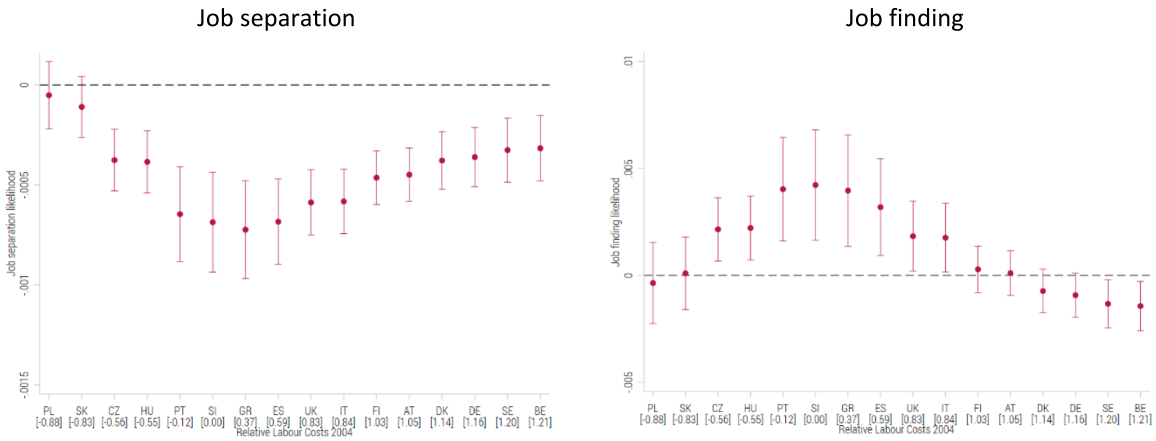
25-34





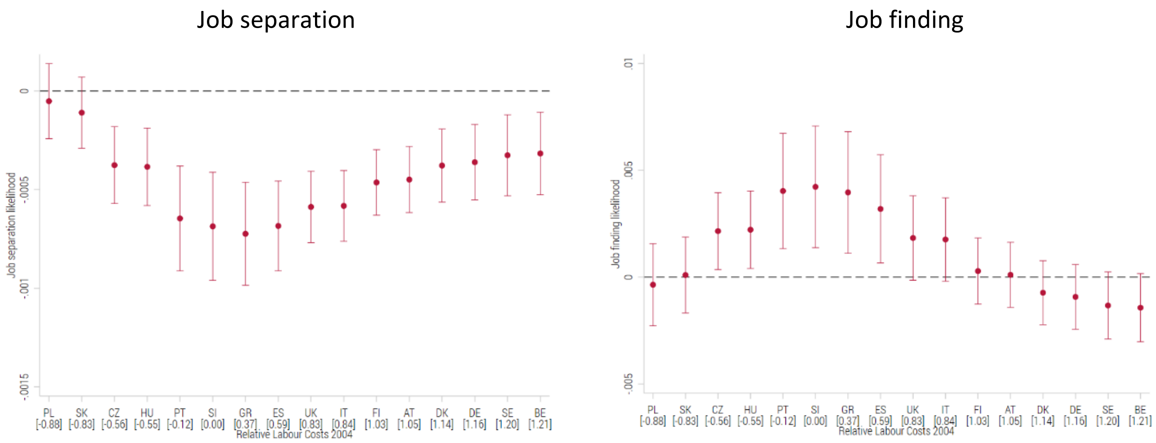
Note: Marginal effects of robot exposure on the probability of job separation and job finding at different development levels measured by labour costs in 2004. The vertical lines represent the 95% confidence intervals. Countries on the x-axis are displayed in ascending order of labour costs in 2004 (for details, see Table A1). Robot exposure is instrumented using robot exposure in the Western European countries in the sample. For regression estimates, see Tables D3 and D4 in Appendix D. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure D10: Effects of robot exposure on likelihood of the flows, clusters by country, occupation, and year



Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (see also Figure 5) and probability of transitioning from unemployment to employment (see also Figure 6) with standard errors clustered at country-occupation-year level. The vertical lines represent the 95% confidence intervals. 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 linear labour costs scale on the x-axis. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure D11: Effects of robot exposure on likelihood of the flows, clusters by sector and year

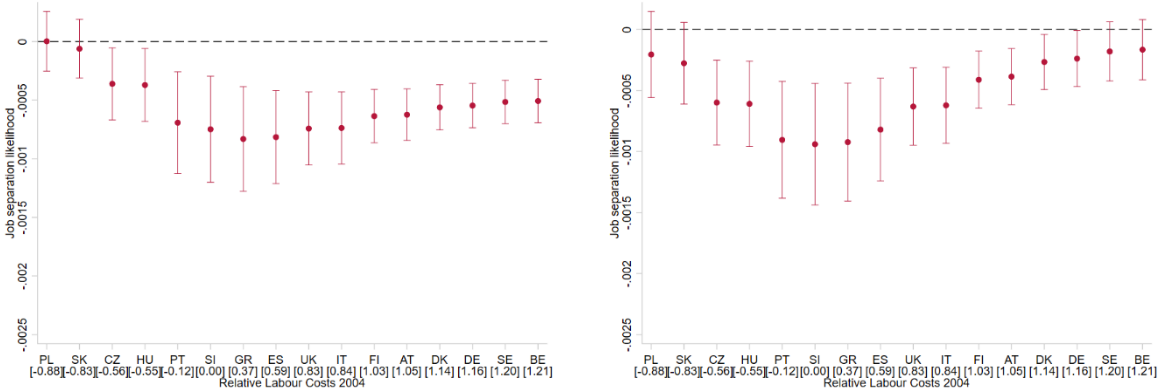


Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (see also Figure 5) and probability of transitioning from unemployment to employment (see also Figure 6) with standard errors clustered at sector-year level. The vertical lines represent the 95% confidence intervals. 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 linear labour costs scale on the x-axis. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure D12: Marginal effects of robot exposure on the likelihood of job separation, estimated with linear probability model

A: All Sectors B: Manufacturing

Interaction with labour cost

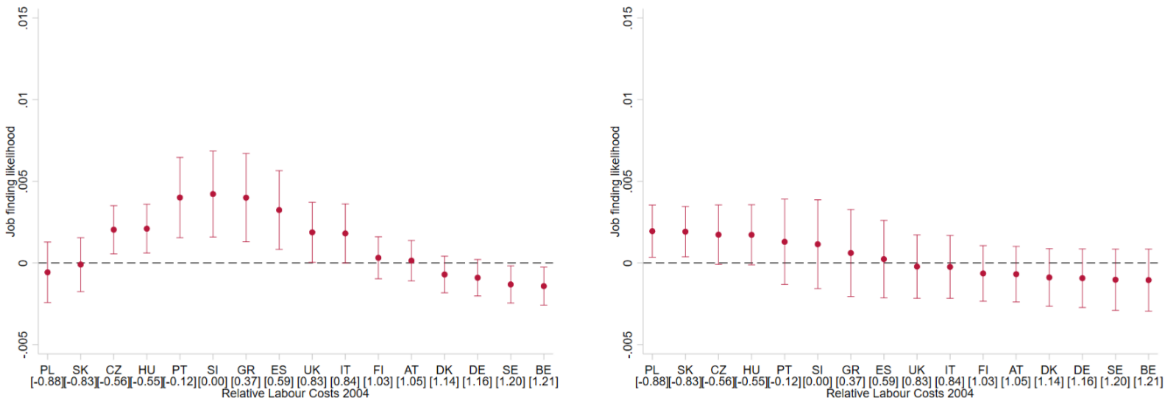


Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment based on regressions presented in Table 1, columns (2) and (4). The vertical lines represent the 95% confidence intervals. Robot exposure is instrumented using the average 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 linear labour costs scale on the x-axis. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure D13: Marginal effects of robot exposure on the likelihood of job finding, estimated with linear probability model

A: All Sectors B: Manufacturing

Interaction with labour costs



Note: The figures show the marginal effects of robot exposure on the probability of transitioning from unemployment to employment based on the regressions presented in Table 2. The vertical lines represent the 95% confidence intervals. 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, Eurostat, IFR, UN Comtrade, and UIBE GVC data.