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THE EFFECTS OF AUTOMATION ON WORKERS' WAGES

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Abstract

This study examines the impact of automation on workers' wages across 20 European countries between 2010–2018. Overall, it identifies a net positive effect of robot adoption on average wages at the sectoral level, especially pronounced among routine manual and nonroutine manual occupations. Importantly, these effects differ between countries- workers in Eastern European countries benefit twice as much from automation as their Western European counterparts. In Western European countries, higher average wages are associated with a decreasing share of routine workers. Results are robust to the exclusion of different capital measures, a battery of fixed effects, a change of instrument and an alternative measure of wages.

Keywords: automation, job tasks, wages, technological change, Europe

JEL: E24, J30, O33

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♦ Institute for Structural Research (IBS), SGH Warsaw School of Economics, Warsaw, Poland, email: karol.madon@ibs.org.pl, https://orcid.org/0000-0002-8321-069X

1. Introduction

Over recent decades, rapid technological advancements have reshaped labour markets. Technologies such as robots, artificial intelligence (AI), and sophisticated software primarily influence routine-intensive jobs, making them susceptible to replacement. Such dynamics create winners and losers in the technological transformation, with workers in routine professions often finding themselves disadvantaged (Johnson and Acemoglu, 2023). Routine-biased technological change (RBTC) has contributed to wage polarisation in numerous countries, leading to discussions on automation's implications for wage structures and inequality (Autor et al. 2006; Goos et al. 2014; Lankisch et al. 2019; Acemoglu and Loebbing 2022; Adachi 2023).

In theory, the effect of robot adoption on wages is not clear. On the one hand, robots and other labour-saving technologies should decrease the real wages of workers with a comparative advantage in performing displaced tasks (Acemoglu and Restrepo 2018; Acemoglu and Loebbing 2022). This argument is closely related to labour market polarisation literature, which points to the losers and winners of technology adoption and general technological change. Typically, low- and mid-skilled workers in routine-intensive jobs experience a wage decline as the demand for unskilled labour diminishes (Autor et al. 2006; DeCanio 2016; Acemoglu and Restrepo 2019, 2022; Acemoglu et al. 2023). In contrast, the changing nature of work amplifies the demand for high-skilled labour, benefiting their wages through an increase in skill premia (Spitz-Oener 2006; D. Autor, Goldin, and Katz 2020; Barth et al. 2020; Goldin and Katz 2010). This dynamic has intensified labour market polarisation concerning employment and wages (Autor et al. 2008; Goos et al. 2014; Cortes 2016; Lábaj and Vitáloš 2024).

On the other hand, robot adoption induces positive productivity shock and ripple effects. Automation elevates total factor productivity (TFP), real value-added, and aggregate demand (Autor and Salomons 2018; Graetz and Michaels 2018; Alguacil et al. 2022), subsequently leading to wage growth (Acemoglu and Restrepo 2018). Moreover, the evolving nature of professions mandates skill enhancement (Chun 2003; Goldin and Katz 2010), stimulating wage growth due to an upskilled workforce. Current evidence involving the general equilibrium approach indicates that automation positively affects employment (Autor and Salomons 2018; Gregory et al. 2022; Mann and Püttmann 2023). However, its impacts are heterogeneously distributed across sectors. Mann and Püttmann (2023) find that automation measured with patents, and therefore accounting not only for robots, increased total employment in the US. The rise was driven by an increase in labour force participation rather than a decrease in unemployment. Employment in manufacturing decreased but was more than compensated by increased employment in services. However, in commuting zones, which are more abundant in routine jobs, automation has a less positive effect on employment. Similarly, Gregory et al. (2022) found that the labour-augmenting effects of routine-replacing technological change (RRTC) were about 2.5 times stronger than labour-displacing effects in Europe – the product demand effect and product demand spillovers offset the substantial displacement of routine labour. The first effect is due to lower capital prices and higher productivity, which enhanced economic activity, and the second is due to spillovers to the non-tradable sectors (primarily services).

Substantial relocation of labour from manufacturing to services may induce negative repercussions for worker wages, first due to the necessity of reskilling and second due to increased labour supply. The evidence for the US indicates the negative impacts of robots on wages (Borjas and Freeman 2019; Acemoglu and Restrepo 2020). In contrast, Dauth et al. (2021) found hardly any effect on average wages in Germany. However, workers who retained jobs in their original plants benefited from automation, while the wages of workers forced to change employment substantially decreased. Finally, Graetz and Michaels (2018) found a positive impact of robots on average wages across European countries.

However, studies concerning the impact of automation on workers' wages covering many European countries are scarce. Existing literature focuses mainly on selected countries and refers primarily to high-income Western states. For instance, Acemoglu et al. (2023) show that blue-collar workers performing routine tasks directly affected by automation face lower earnings and employment rates in the Netherlands. Humlum (2023) finds that robot adoption led to production workers' real wages decrease in Denmark, and Koch et al. (2021) claim that robot adoption decreased labour share in Spanish firms. At the same time, Eastern European countries remain largely unexplored in terms of research on automation and wages.

This paper aims to fill this gap by studying the effects of automation on workers' wages across 20 European countries, including Central and Eastern Europe. [1] In this study, I address three main research questions: What is the impact of robot adoption on workers' wages at the sectoral level? How does it differ between high-income Western and Eastern European countries? What are the potential drivers of these differences?

To answer these questions, I estimate the effect of robot adoption on workers' relative wages. I focus on the job tasks performed by workers, which are a crucial determinant of robots' substitutability for human labour. I apply widely used categories of nonroutine cognitive, routine cognitive, routine manual and nonroutine manual job tasks proposed by Acemoglu and Autor (2011). Relative wages are defined as a ratio of the median wage of workers in different task groups compared to the country's median wage. I use individual-level data from the European Structure of Earnings Survey (EU-SES) to calculate the relative wages of workers in different sectors, countries and task groups. I combine the relative wages with data on robot adoption from the International Federation of Robotics (IFR) and estimate panel regressions at the sector-level data. To address potential endogeneity in robot adoption, I employ an instrumental variable approach. As the instrument, I use the average robot adoption in similar countries. It is generalisation of "technology frontier" instrument previously applied by Acemoglu and Restrepo (2020) Dauth et al. (2021), and similar to the instrument used by Bachmann et al. (2024). The instrument is meant to isolate the variation coming from global technological advancements. I control for potential confounders, such as development level, globalisation, trade and demographic characteristics.

This paper contributes to the literature as follows. First, I find a positive effect of robot adoption on relative wages in European countries. These results are consistent with existing literature, e.g. increased robot adoption positively impacted wages in Germany (Graetz and Michaels 2018) and Japan (Adachi et al. 2022). Importantly, these effects differ across worker groups. I find positive effects on the relative wages of routine and nonroutine manual workers but not among nonroutine cognitive workers, whose wages are unaffected. Positive effects on wages of workers who are not directly exposed to automation- routine cognitive and nonroutine manual workers- can be explained by the emergence of positive spillover effects of robot adoption on other sectors and workers (Gregory et al. 2022). Positive effects among workers directly exposed to automation can be explained by upskilling, shifting towards more demanding tasks, and productivity gains (Dauth et al. 2021). Further, firm-level evidence suggests that automating firms are larger, more productive and tend to pay better than their non-adopting competitors (Acemoglu

[1] In this paper, I divide countries into two groups: Western and Eastern European countries. The group of Western European countries consists of Belgium, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Spain, and Sweden. The Eastern European countries are Bulgaria, Croatia, Czech Republic, Estonia, Latvia, Lithuania, Poland, Romania, and Slovakia (Table A1 in Appendix A).

et al. 2020; Koch et al. 2021; Bessen et al. 2023). In Spain, automation led to dropping off less productive firms (Koch et al. 2021). Such mechanism, may lead to higher wages at the sectoral level.

Second, the effects significantly differ between Western and Eastern European countries. The positive effect of robot adoption on the relative wages of nonroutine manual workers is more than two times stronger in Eastern than in Western European countries. I also find some positive effects on wages among routine cognitive workers in Eastern European countries. It may be related to the improvement within values chains subsequent to expansion of robot intensive sectors, like automotive sector. Kordalska and Olczyk (2021) show that Baltic and CEE countries managed to establish high value-added supporting activities in manufacturing, finance and transportation. The effect on wages of routine manual workers is similar in both country groups.

Third, the surge in automation aligns with a decline in the share of routine manual workers, but only in Western European countries. The difference likely originates in the distinct nature of investments in automation technology in both country groups. In Central and Eastern European (CEE) countries, growth in robot adoption relates to significant investments of international firms, inclusion in global value chains and expansion of whole sectors, mainly the automotive industry (Pavlínek 2018; Cséfalvay 2020; Cséfalvay and Gkotsis 2022). In Western European countries, robot adoption is more diversified between manufacturing sectors and is coupled with high labour costs (Cséfalvay 2020). Decline in the share of routine workers goes in line with task displacement literature (Goos et al. 2014; Autor and Salomons 2018; Gregory et al. 2022) and literature showing the decreasing share of low-skilled workers (Graetz and Michaels 2018; Dahlin 2019; Acemoglu et al. 2020).

The remainder of this paper is organised as follows. In section 2, I present the data sources, econometric strategy, and descriptive statistics. In section 3, I discuss the research findings and the mechanisms behind them. In section 4, I conclude the study with an overview of the insights.

2. Data and Methods

In this section, I describe data sources, measurement methods and econometric strategy. Then, I present descriptive statistics.

Data and Definitions

The main data source are Scientific Use Files (SUF) of the European Structure of Earnings Survey (EU-SES), which is the most reliable source of cross-country data on wages in the EU. This large employer-employee-matched survey data provide harmonised information on earnings across European countries. It includes information on worker earnings, individual-, job-, and firm characteristics. The data cover enterprises employing more than ten employees, but it does not limit my analysis, as small firms are unlikely to install industrial robots at a large scale. I aggregate the data into 16 sectors, such that they are similar across countries. For details, see Table A2 in Appendix A. Importantly, the data allows for variation within manufacturing, which accommodates nearly all installed industrial robots and, therefore, is crucial when analysing the impact of robot adoption on labour market outcomes. Due to data availability reasons, I use three issues of the EU-SES: 2010, 2014 and 2018. The earlier releases of the EU-SES use previous sectoral classification (NACE rev 1), which allows mapping of robot adoption only on a broad sectoral level (so there is no variation within the manufacturing sector).

The data on robots come from the International Federation of Robotics (IFR), which delivers annual information covering the current stock and the installations of new robots across countries by sector and applications (e.g. bending, laser cutting, assembling), and accounting for depreciation. The data are based on consolidated information collected by nearly all industrial robot suppliers worldwide. The IFR ensures the comparability of the data across countries and its high reliability. According to the definition by the International Organization for Standardization (ISO 8373:201), an industrial robot is an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications". Moreover, an industrial robot usually operates in a series of movements in several directions to grasp or move something. I merge information on robot exposure to the sectors mentioned in the former paragraph – 8 out of 16 sectors install industrial robots (5 of them are within "manufacturing" according to 1-digit NACE rev. 2 classification).

The IFR data have some shortcomings. Due to lack of disaggregated data and compliance rules (Jurkat et al. 2022) some robots are not assigned to any sector. The share of unclassified robots in the sample of countries used in this study varies between 9-13% depending on the year. Following Acemoglu and Restrepo (2020), I classify these unclassified robots to sectors in the same proportions as classified data.

To control for macroeconomic conditions and effects of globalisation I use several sector level measures from the EORA database (Lenzen et al. 2012, 2013). In particular, I use log exports, sectoral output and backward and forward GVCs participation. The measure for other forms of capital come from EU KLEMS (gross fixed capital formation). The data on employment comes from Eurostat.

I classify workers into four groups, depending on the dominant task of their occupations: nonroutine cognitive, routine cognitive, routine manual and nonroutine manual. To do so, I follow Lewandowski et al. (2020) who adapted

Acemoglu and Autor's (2011) methodology to European classification.[2] Then, I assign occupations to groups according to the task with the highest value. Table A3 in Appendix A presents the allocation of occupations to the task groups.

This study covers 20 European countries (see Table A1 in Appendix A). The baseline specification observation unit is a country-sector-task group cell. The final sample consists of 3 726 cells. I have dropped groups with less than 15 observations, and the average number of observations in the group is 7 460. The number of worker-level observations in the final data set used to calculate sectoral averages is about 28 million.

Measurement and Econometric Strategy

Following Graetz and Michaels (2018) and Acemoglu and Restrepo (2020), I calculate robot adoption as the ratio of the number of industrial robots to every one thousand workers at a 2-digit sector level ($\mathrm{R}_{\mathrm{c,s,t}}$). The formula is as follows:

$$R_{c,s,t} = \frac{ROB_{c,s,t}}{EMP_{c,s,2010}} \tag{1}$$

Here $ROB_{c,s,t}$ represents the entire stock of industrial robots, whereas $EMP_{c,s,2010}$ denotes the employment (expressed in thousands) within sector s, country c, and year t. I use 2010 employment as a numerator to ensure that time variation in the explanatory variable comes from changes in robot adoption and is independent of changes in employment.

For the dependent variable, I use relative wages $Y_{c,s,t}$ expressed as the ratio of the median wage of task group j , in sector s, country c, and year t, to the median wage at the country level. Formally:

$$Y_{c,s,j,t} = \frac{w_{c,s,j,t}}{w_{c,t}} \tag{2}$$

As a baseline model, I estimate the first differenced panel regressions. Since I use three releases of EU-SES (2010, 2014, 2018), effectively, these are two-period panel regressions ($t = 2$). First-difference transformation eliminates individual effects (e.g. country, sector fixed effects) as they are time-invariant and cancel out. Formally:

$$\Delta Y_{c,s,j,t} = \Delta ROB_{c,s,t} + \Delta X_{c,s,j,t} + \Delta M_{c,s,t} + \epsilon_{c,s,j,t} \tag{3}$$

Here, $\Delta Y_{c,s,t}$ symbolises the relative wage change, $\Delta ROB_{c,s,t}$ depicts the change in robot adoption, $\Delta X_{c,s,t}$ illustrates a change in workers' characteristics (share of women, share of workers with high education, the share of part-time workers). Lastly, $\Delta M_{c,s,t}$ embodies a change in macro controls (log of gross exports and output, change in global value chains participation) in country c, sector s and year t.

However, robot adoption might be endogenous to economic conditions in a sector or country, and the effects of robot adoption could not be identified properly. For example, robot adoption could be endogenous to labour market shortages, and reverse causality may be an issue. Therefore, I use the instrumental variable approach. As the

[2] O*NET database used for tasks calculation has been commonly applied to European data (Goos et al. 2014; Fernández-Macías and Hurley 2017; Koch et al. 2021; Bachmann et al. 2024), as the differences between the demand for occupations between the US and Europe are small (Handel 2012; Lewandowski et al. 2022).

instrument, I use the average robot adoption in other countries in my sample (leave-one-out instrument). The instrument is standardised with the employment level from 2010 to account for potential employment level changes endogenous to robot adoption. The instrument ($R^{\mathrm{IV}}_{c,s,t}$) is calculated according to the following formula:

$$R^{\mathrm{IV}}_{c,s,t} = \frac{\sum_{c\neq k,k}^{C} ROB_{k,s,t}}{\sum_{c\neq k,k}^{C} EMP_{k,s,2010}} \tag{4}$$

Here $ROB_{k,s,t}$ is the total stock of industrial robots, and $EMP_{k,s,2010}$ is employment level in thousands in country k, sector s and year t. This type of instrument has been previously employed in studies by Acemoglu and Restrepo (2019), Bachmann et al. (2022) and Dauth et al. (2021).[3] I re-estimate equation (3) following a two-stage least-squared procedure (2SLS), with the instrument's validity verified by the Stock and Yogo (2005) weak instrument test.

Descriptive Statistics

The total number of industrial robots has increased immensely since the early 2000s in the countries covered in this study. From 2010 to 2018, the period this study covers, the number of industrial robots increased by about 50% and exceeded 450 thousand (see Figure 1).

The average robot adoption in the pooled sample amounts to 2.18 robots per 1000 workers (see Table 1), but it varies significantly across countries and sectors (std. deviation is 5.27). Robot adoption is much higher in Western European countries (3.42) than in Eastern European countries (0.69). Also, the change in average robot adoption between 2010 and 2018 is higher among Western European countries (0.76 versus 0.48 robots per 1000 workers in Eastern European countries).

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

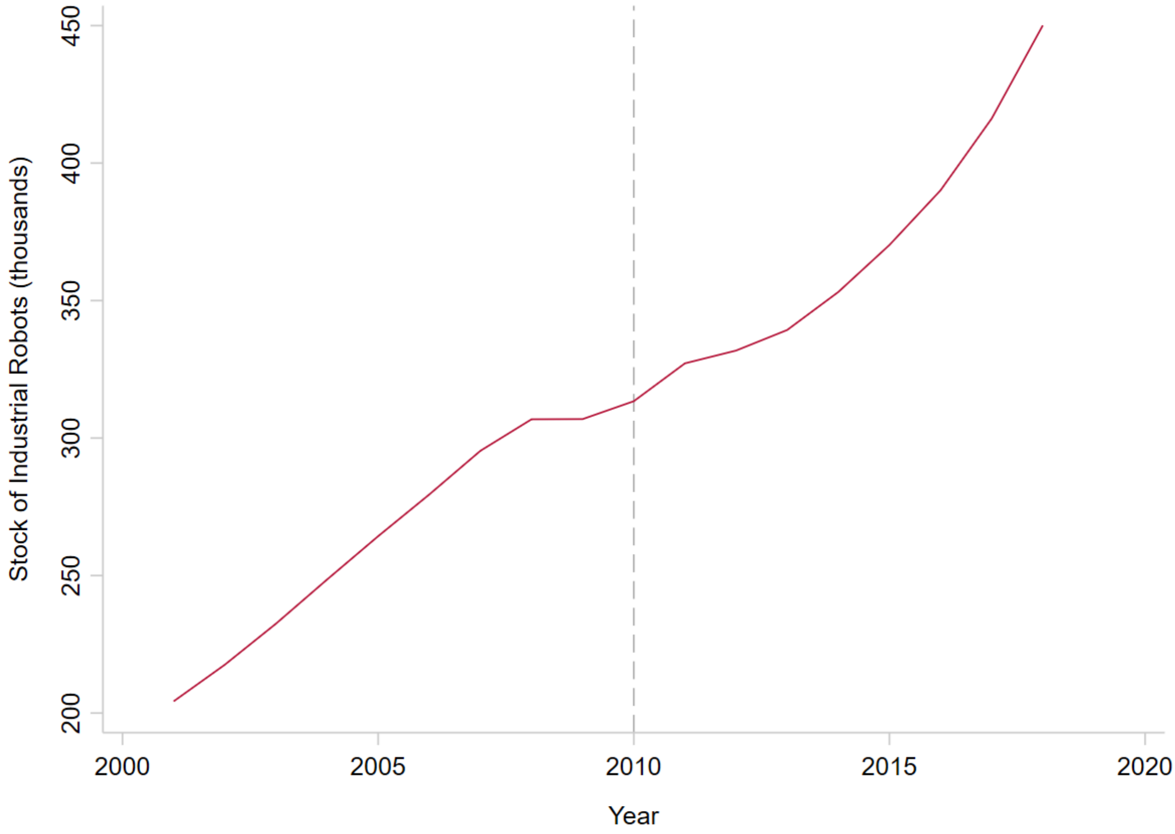

Figure 1. The Cumulative Stock of Industrial Robots Across Studied European Countries

Source: own elaboration based on IFR data.

Table 1. Average Robot Adoption and its Variation from 2010 to 2018, by Country Groupings

	Pooled Sample	Western Europe	Eastern Europe
Robot Adoption	2.18	3.42	0.69
Sd	(5.27)	(6.50)	(2.53)
Δ Robot Adoption	0.63	0.76	0.48
Sd	(1.75)	(1.90)	(1.53)

Source: own elaboration based on the EU SES and IFR data

The relative wages differ mainly between task groups. Workers performing nonroutine cognitive occupations earn, on average, 150% of the median wage in the country; routine cognitive occupations pay about the median wage, followed by routine manual just below the median wage. Workers of nonroutine manual jobs get about 86% of the median wage (see Panel A of Table 2). The differences in relative wages between Western European countries and Eastern European countries concentrate among nonroutine cognitive and nonroutine manual workers- the relative wages in Western European countries among these groups are about 6-7 p.p. higher.

The average changes in relative wages across task groups and country groups are negligible, but the standard deviations are high. It suggests that changes concentrate in particular sectors (see Panel A of Table 2).

Most workers perform nonroutine cognitive and nonroutine manual occupations (about 30% each), followed by routine cognitive and routine manual occupations (about 20% each). The employment structure is not changing significantly over time (see Panel B of Table 2).

Table 2. Descriptive Statistics

	Pooled Sample	NRC	RC	RM	NRM
Panel A:					
Pooled Sample:					
Relative wage	1.08	1.50	1.02	0.95	0.86
	(0.34)	(0.34)	(0.19)	(0.23)	(0.17)
Western Europe					
Relative wage	1.08	1.47	1.02	0.95	0.89
	(0.31)	(0.30)	(0.17)	(0.18)	(0.14)
Eastern Europe					
Relative wage	1.08	1.54	1.02	0.95	0.83
	(0.38)	(0.37)	(0.20)	(0.27)	(0.19)
Pooled Sample:					
Δ Relative wage	-0.01	-0.02	-0.01	0.00	-0.01
	(0.13)	(0.16)	(0.11)	(0.14)	(0.10)
Western Europe					
Δ Relative wage	0.00	0.00	0.00	-0.01	-0.01
	(0.11)	(0.14)	(0.08)	(0.12)	(0.10)
Eastern Europe					
Δ Relative wage	-0.02	-0.04	-0.02	0.00	0.00
	(0.15)	(0.18)	(0.13)	(0.17)	(0.11)
Panel B:					
Pooled Sample					
Employment share		0.30	0.22	0.20	0.29
		(0.20)	(0.15)	(0.20)	(0.20)
Western Europe					
Employment share		0.30	0.25	0.19	0.27
		(0.20)	(0.15)	(0.19)	(0.20)
Eastern Europe					
Employment share		0.31	0.19	0.21	0.30
		(0.19)	(0.14)	(0.21)	(0.19)
Pooled Sample:					
Δ Employment share		0.01	0.00	-0.01	0.00
		(0.04)	(0.03)	(0.04)	(0.04)
Western Europe					
Δ Employment share		0.02	0.00	-0.01	0.00
		(0.05)	(0.04)	(0.05)	(0.04)
Eastern Europe					
Δ Employment share		0.01	0.00	0.00	0.00
		(0.04)	(0.03)	(0.03)	(0.04)

Note: NRC – nonroutine cognitive, RC – routine cognitive, RM – routine manual, NRM – nonroutine manual. Standard errors in parentheses.
Source: own elaboration on the EU SES and IFR data.

3. Econometric Results

In this section, I analyse the impact of robot adoption on the relative wages of workers performing occupations from different task groups. Likely, wages of workers performing occupations most exposed to automation technologies (e.g. routine manual occupations) are differently affected than those not exposed (e.g. nonroutine cognitive occupations). As highlighted in the previous section, wage discrepancies between task groups are significant. To understand the impact of robot adoption on wages, I conducted two distinct regression analyses: one for the pooled sample and another segmented by task groups.

Main Findings

Overall, I find a positive association between the change in robot adoption and relative wages in the baseline specification (Panel A of Table 3, column 1). Positive OLS coefficients indicate that an increase in robot adoption correlates positively with the relative wage (relative to the country's median). This effect is driven by workers performing manual occupations (routine and nonroutine; see Panel A of Table 3, columns 4 and 5). No association exists between the change in robot adoption and relative wages across workers performing cognitive occupations (Panel A of Table 3, columns 2 and 3). The above results suggest that workers in manual occupations also benefit from increased productivity and resultant ripple effects due to robot adoption. Since wages of manual workers tend to be below countries' median, robot adoption can contribute to lower within-country wage inequality.

However, due to the potential endogeneity between robot adoption and workers' wages, I estimate the model using an instrumental variable approach. The IV estimates confirm the findings concerning manual workers, but the magnitude of the effects is even stronger (Panel B of Table 3, columns 4 and 5). The IV estimation also reveals the positive impact of the change in robot adoption on the relative wages among routine cognitive workers (Panel B of Table 3, column 3), which supports the existence of "rippling effects". The size of Kleibergen-Paap statistics confirms the instrument's validity (Table 3).

Table 3. Impact of Robot Adoption on Relative Wages, by Task Group

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.004***	0.002	0.001	0.006***	0.005***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.012***	0.007	0.010**	0.014***	0.015***
	(0.002)	(0.005)	(0.004)	(0.004)	(0.003)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	279.4	68.1	70.2	68.8	67.9

Note: The regressions account for various controls, such as sectoral output, exports, participation in global value chains, and shifts in the shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category). Pooled regression includes task groups' fixed effects. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 16.4. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

The interpretation of the coefficient is that the change in robot adoption by 1 robot per 1000 workers increases the relative wages by about 1.2-1.5 percents of the country median (Panel B of Table 3, columns 3-5). The average change in robot adoption in manufacturing in my sample equals 1.95 robots per thousand workers. Therefore, according to the above estimates, the change in robot adoption increased relative wages by 1.95-2.93 percent of the country median, especially among routine workers.

I find no effect among workers performing nonroutine cognitive occupations.

Heterogeneity of Effects

The results presented in the previous subsection might not be homogenous between country groups. Therefore, I divide the sample into Western and Eastern European countries (see Table A1 in Appendix A). There are two reasons behind such a division. First, some Eastern European countries, especially in Central and Eastern Europe, like the Czech Republic and Slovakia, experienced substantial growth in robot adoption in recent years, while Western countries already had accumulated higher number of robots. Therefore, the automation shock in Eastern Europe states should be much more intense due to a relatively higher increase in robot adoption. Moreover, the distribution of robot adoption differs between country groups- robots in Eastern European countries are mostly concentrated in the automotive sector, while in Western European countries, they are more spread out within the whole manufacturing sector (Cséfalvay 2020). Second, most of the Eastern European countries are still converging with the Western economies in many economic outcomes, including wages (Stanisic 2013; Bakker and Krogulski 2016; Monfort et al. 2018; Dorn and Zweimüller 2021; Glawe and Wagner 2021). There are reasons to expect different outcomes for both groups of countries.

I find a positive impact of the change in robot adoption on relative wages in the pooled sample (Panel A of Table 4, column 1). The estimate of robot adoption for Western European countries (reference group) is similar in size to the baseline specification. However, the positive impact of robot adoption on relative wages in Eastern European countries is about two times stronger (see interaction term in Panel A of Table 4, column 1). It suggests that workers in Eastern European countries could have benefited more from robot adoption during the investigated period. Likely, it is related to relatively lower robot adoption in these countries (see Descriptive results subsection for the details). According to the law of diminishing returns, the marginal gain of installing robots should be higher in countries with lower capital stock, ceteris paribus. Therefore, higher increase in labour productivity, can translate to stronger effect on wages. Zhao et al. (2024) find that installing robots yields higher labour productivity gains in sectors with lower robot density. In addition, they find some support for diminishing marginal effect of industrial robots in promoting labour productivity.

Similarly to the baseline regressions, the positive impact on relative wages is driven by workers of manual occupations (Panel A of Table 4, columns 4 and 5). In Eastern European countries, the positive effect on relative wages of nonroutine manual workers is more than double those in Western European countries in the case of OLS estimation (Panel A of Table 4, column 5).

Turning to IV estimation for pooled sample regressions corroborates a significant positive impact of the robot adoption in both country groups (Panel B of Table 4, column 1). Again, this positive effect is much stronger in Eastern European countries than in Western European countries.

Estimating the model by task groups reveals that Eastern European countries drive a positive effect on wages among routine cognitive workers in baseline specification (Panel B of Table 4, column 3). The increase in robot adoption, especially in Eastern European countries, is linked to large greenfield investments (Cséfalvay 2020), which also required setting up whole back-end support for the industry (e.g. accountants). Therefore, a positive effect on the wages of workers who are not directly exposed to automation may occur.

Similarly to the baseline specification, I find a significant positive effect of robot adoption on the relative wages among routine manual workers in Western countries and nonroutine manual workers in Western countries and Eastern European countries (Panel B of Table 4, columns 4 and 5). The magnitude of this effect in Western countries is similar to the baseline specification and about twice as large in the case of Eastern European countries. Overall, the above estimates will translate to an increase of relative wages by about 1 percentage point among manual workers in Western countries and by 2.5 percentage points among nonroutine manual workers in Eastern European countries for each additional robot per 1000 workers. The values of Kleibergen-Paap's statistics confirm the instrument's validity.

Table 4. Impact of Robot Adoption on Relative Wages, by Task Group and Country Heterogeneity

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.003***	0.000	0.001	0.005***	0.003**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Δ Robot adoption * Eastern Europe dummy	0.003*	0.004	-0.000	0.004	0.005*
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.007***	0.002	0.004	0.011**	0.009**
	(0.002)	(0.005)	(0.003)	(0.005)	(0.003)
Δ Robot adoption * Eastern Europe dummy	0.013***	0.013	0.017*	0.008	0.016**
	(0.005)	(0.011)	(0.010)	(0.008)	(0.008)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	148.6	35.5	36.9	36.2	35.9

Note: The regressions account for various controls, such as sectoral output, exports, participation in global value chains, and shifts in the shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category), as well as an Eastern Europe dummy. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. Eastern European countries: BG, CZ, EE, HR, LT, LV, PL, RO, SK. Western European countries: BE, DE, ES, FI, FR, GR, IT, NL, NO, PT, SE. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Robustness Checks

I conduct several robustness checks to test the validity of my regression results. First, I use average robot adoption in the United States as an instrumental variable instead of a "leave-one-out" instrument.[4] Overall, the obtained results are very similar to the baseline specification and confirm the robustness of the baseline results (Table B3 in the Appendix B). Similarly, results for Western and Eastern European countries align with baseline specification (Table B4 in the Appendix B). However, according to Kleibergen-Paap statistics, the performance of US robots as an instrument is worse than that of a "leave-one-out" instrument, though still enough to confirm its validity. Moreover, I use the "replaceability" instrument proposed by Graetz and Michaels (2018). The results are very similar to the ones obtained with "leave-one-out" instrument (Table B5 in the Appendix B). However, the stronger effect of robot adoption on nonroutine manual workers' wages in Eastern European countries disappears (Table B6 in the Appendix B).

Second, I extend the model with a set of country and year fixed effects. Including fixed effects, I can account for unobserved differences which can occur between countries and years. However, including country-year fixed effects implies the assumption that year dummies are the same across European countries, and this may not be the case. There might be unobservable differences across countries that may vary over time. E.g. robot adoption can be correlated with country-level, unobserved, time-varying factors. To address these concerns, I additionally extend the model with country-specific time trends.

Table 5 presents the results of the model extended with country-year FE and country-specific time trends (see Table B7 in Appendix B for estimates for country heterogeneity). Notably, the estimates of robot adoption are very robust to the inclusion of additional controls, mirroring the results of the baseline specification in Table 3. Therefore, the interpretation of the results does not change: robot adoption positively impacts workers' wages, with this effect primarily seen in manual occupations. Moreover, the Kleibergen-Paap statistics suggest that the instrument's performance has improved. Further regression outcomes, which integrate country-year fixed effects without the country-specific time trend, also align with these findings (Tables B8 and B9 in Appendix B).

Table 5. Impact of Robot Adoption on Relative Wages, by Task Groups, With Country-Specific Time Trends

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.003***	0.002	0.001	0.004***	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.011***	0.006	0.010**	0.011**	0.014***
	(0.002)	(0.005)	(0.004)	(0.004)	(0.003)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	339.0	79.1	79.5	78.2	79.8

Note: The regressions account for various controls, such as sectoral output, exports, participation in global value chains, and shifts in the shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category), country-year FE, and country-specific time trends. Pooled regression includes task groups' fixed effects. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test

[4] Similar instrument was used by Albinowski and Lewandowski (2024) in European context.

for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 16.4. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Third, I exclude from the model macroeconomic controls as they can be influenced by robot adoption. Especially, sectoral output and exports may be considered as "bad controls", because they can clearly depend on automation. However, the results obtained from the reduced model are almost the same as the baseline specification and do not change the interpretation of my results (Tables B10 and B11 in Appendix B).

Fourth, I include controls for gross fixed capital formations to control for other capital forms that can affect workers' wages. Despite this inclusion, the results were consistent with the baseline specification, reiterating the positive influence of robot adoption on workers' wages (Table B12 and B13 in Appendix B).

Fifth, I use an alternative measure for workers' wages. Instead of relying on the median wage in the country-sector-task group cell relative to the country median, I employed the average country-sector-task group cell wage in relation to the country's average wage. The outcomes of this approach, both for the pooled sample and task groups, aligned with prior results (Table B14 in the Appendix). Furthermore, the estimation of the model for heterogeneity between Western and Eastern European countries upheld the robustness of previous findings (Table B15 in Appendix B).

Potential Mechanisms

The positive impact of robot adoption on wages, especially among routine workers, may be counterintuitive as robots are considered as displacing technology. Especially studies concerning the US tend to find negative effects of robot adoption on workers' wages at the sectoral level (Acemoglu and Restrepo 2020, 2022), followed by some European studies based on firm-level data (Humlum 2023). In contrast, some other studies find overall positive effects on wages (Graetz and Michaels 2018). Several potential explanations underpin these positive outcomes.

First, even workers within the same task group may differ concerning their skills and experience. One possibility is that robots primarily replace those at the wage lower tail of wage distribution, pushing the group's relative wage higher. In this scenario, the share of workers should decrease, and their wages should increase. Hence, the increase of the relative wages is conditional on the remaining in employment. If this were the case, this displacement effect could be especially pronounced in Western European countries, where labour costs are relatively high, and displacement effects could be expected.

Second, robot adoption may boost the productivity of entire sectors. Introducing labour-complementary technology may require labour force upskilling, enhancing quality and overall wages. In Eastern European countries this effects may be strengthened. Here, the average robot adoption remains low, and the surge in robot investments often coincides with sectoral growth and job creation.

To test the first and second hypotheses, I estimate the regressions where the dependent variable is the share of employment of the following task groups in different sectors, and the explanatory variable is the change in robot adoption. The negative impact of the change in robot adoption on the share of routine manual workers, especially in Western European countries, would support the worker displacement hypothesis.

Table 6. Impact of Robot Adoption on Employment Shares

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0	0.002	0.001	-0.005***	0.002**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Δ Robot adoption * Eastern Europe dummy	-0.000	-0.002	-0.000	0.004**	-0.002*
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	-0.000	0.003	0.002	-0.009**	0.003*
	(0.001)	(0.003)	(0.002)	(0.004)	(0.002)
Δ Robot adoption * Eastern Europe dummy	-0.000	-0.006*	-0.000	0.008*	-0.002
	(0.002)	(0.004)	(0.002)	(0.005)	(0.003)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	147.4	35.5	36.2	35.6	35.9

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and shifts in the shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category), and an Eastern Europe dummy. Eastern European countries: BG, CZ, EE, HR, LT, LV, PL, RO, SK. Western European countries: BE, DE, ES, FI, FR, GR, IT, NL, NO, PT, SE. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 16.4. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Indeed, I find a negative impact of the change in robot adoption on the share of routine manual workers in Western countries but not in Eastern European countries (Panel A of Table 6, column 3). There is some positive effect on the increase of the share of nonroutine manual workers in Western countries (Panel A of Table 6, column 4). This finding supports the hypothesis of relocating routine manual workers to nonroutine jobs, e.g. in the services. It is in line with Autor and Salomons (2018) and Graetz and Michaels (2018), who found that robot adoption decreased the share of workers in low-skilled occupations (which overlap with RM occupations), and with Dauth et al. (2021), who found that loss of jobs in manufacturing were offset by new jobs in services in Germany. Lábaj and Vitáloš (2020) provide similar evidence, showing that displacement effect of automation was completely counterbalanced by job creation of new technologies across 10 European countries under study.

The firm-level evidence from Spain shows that low-skilled and manufacturing workers face increased risks of dismissal in adopting firms, since they perform less complex tasks which are ones being automated (Koch et al. 2021). Moreover, they find substantial negative effect on non-adopting firms employment. They show, that ex ante better performing firms tend to be the ones adopting robots.[5] They are better in the beginning and further reduce marginal costs due to automation. Consequently, it raises the cut-off productivity at which firms are able to survive on the market. Therefore, from sectoral perspective, robot adoption prompts least productive firms to exit the

[5] Acemoglu et al. (2020) find similar findings in France, where the large companies are automating, which led to increase in employment and wages in adopting firm, and decline in employment in non-adopting competitors.

market. Finally, firm-level evidence from European countries shows that robot-adopting firms tend to grow faster and pay better than similar firms not adopting robots (Acemoglu et al. 2020; Koch et al. 2021; Bessen et al. 2023). These results support the first hypothesis stated in the previous section.

No effect on the share of manual workers in the Eastern European countries could be explained by the nature of robot investments in both country groups. Robot adoption in Eastern European countries is mostly concentrated in the automotive industry and heavily dependent on the decisions of global firms (Céfalvay 2020). These were often greenfield investments that expanded sectors and created new workplaces rather than displaced workers. In particular, CEE countries benefited from nearshoring and extending global value chains of the automotive industry (Pavlínek 2018). Further, CEE countries not only attracted low-value added manufacturing but also managed to move up in the integration ladder and now concentrate on higher value-added suppliers and supportive activities (Pavlínek and Ženka 2011). For example – Baltic countries and the Czech Republic built strong relationships between the financial sector and manufacturing, while Poland, Hungary, and Slovakia do so by providing competitive transport services to manufacturing (Kordalska & Olczyk, 2021). Therefore, wages of workers performing these additional activities, for example, drivers in transport services (non-routine manual workers) and accountants (routine cognitive workers), could have benefited from automation. On the contrary, robot adoption in Western European countries is more diversified among sectors and driven by falling robot costs that could substitute for expensive labour (Céfalvay 2020). Therefore, the lack of displacement effects in Eastern European countries supports the second hypothesis stated in the previous section (investment in robots goes in pair with industry expansion rather than job displacement).

The IV estimates confirm that change in robot adoption decreases the share of routine manual workers in Western countries and addresses endogeneity concerns. Kleibergen-Paap statistics confirm the validity of the instrument.

4. Conclusions

This paper investigates the relationship between the change in robot adoption and the relative wages of workers performing different tasks in Western and Eastern European countries between 2010 and 2018. I aimed to answer the following questions. First, what is the impact of robot adoption on workers' wages at the sectoral level? Second, does this effect differ between European countries? Third, what are the potential drivers of these differences?

To answer these questions, I estimate panel regressions on sector-level wages, drawing on EU SES data. To address the potential endogeneity of robot adoption, I use an instrumental variable approach in the spirit of Acemoglu and Restrepo (2019) and Bachmann et al. (2022). The outcomes of this research are robust to several robustness tests. The results can be summarised as follows.

First, I find a positive impact of robot adoption on relative wages. The effect is heterogeneous between workers performing different tasks- while the average wages of nonroutine cognitive workers remain unchanged, the average wages of workers performing routine and nonroutine manual occupations benefit from robot adoption. However, the wage increase goes in pair with the decrease in the share of routine manual workers, but only in Western European countries. This suggests possible displacement effects, even in the face of rising average wages.

Second, the magnitude of these effects differs between countries- the overall positive impact of robot adoption on wages in Eastern European countries is more than double that in Western European countries. It is driven mainly by the wages of workers performing routine cognitive and nonroutine manual. The difference between country groups originates from the distinct nature of automation investments. In Western European countries, increasing robot adoption is linked to general investments that mitigate high labour costs and improve productivity. However, as studies involving general equilibrium analysis indicate, workers displaced by automation find employment in other sectors, often in services. While employment effects of automation typically counterbalance labour displacement, the substantial increase in labour supply may impose negative pressure on wages in those sectors. This is likely why I find no effects on wages or routine cognitive and nonroutine manual workers in Western European countries.

In contrast, in Eastern European countries, attracted significant foreign direct investment (FDI) from Western European firms looking to outsource production to lower-cost regions (Pavlínek 2018; Cséfalvay 2020). These foreign firms often paid higher wages than local companies, pushing overall wage levels upward. Moreover, expanding sectors boosted productivity and enabled development oof a range of manufacturing supporting activities, like finance and transportation.

Third, I test a few potential mechanisms behind the positive effects of robot adoption on workers' wages. I find some support for the job displacement hypothesis in Western European countries due to the decreasing employment share of routine manual jobs. Potentially, workers from the lower tail of wage distribution are displaced in the first place, which positively affects workers' wages on average. This finding is supported by firm-level evidence, that indicates that robot investments prompts less productive firms to exit markets (Koch et al. 2021). Also, Majzlíková and Vitáloš (2022) find that workers with lower incomes in Slovakia face greater risk of losing job due to automation. In contrast, workers who keep their jobs may improve their skills and take over new tasks, as shown by Dauth et al. (2021), which may positively affect aggregate wages.

This study delivers credible and robust results but has also its limitations. The data used in this study are a repeated cross-section and do not allow for following individuals when changing jobs. Therefore, the positive results on the relative wages are conditional on remaining employed and do not account for the decreased income of displaced workers. While this is a limitation, it still delivers an important insight- workers performing manual jobs who managed to remain employed are better off due to the increase in automation in the employment sector.

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Appendix A – Technical Details

Table A1. List of Countries in the Sample, by Country Groups

Western Countries	Eastern Countries
Belgium	Bulgaria
Germany	Czech Republic
Greece	Estonia
Finland	Lithuania
France	Latvia
Italy	Poland
Netherlands	Romania
Norway	Slovakia
Portugal	Croatia
Spain	
Sweden	

Source: own elaboration.

Table A2. Aggregation of Sectors, NACE rev. 2/ ISIC rev. 4

Aggregated Sector	Sectors
B	Mining and quarrying
C10-C15	Manufacture of food, beverage, and tobacco products; Manufacture of textiles, wearing apparel and leather products
C19-C23	Manufacture of coke and refined petroleum products, chemicals and chemical products; Manufacture of basic pharmaceutical products and preparations; Manufacture of rubber, plastic and other non-metallic mineral products
C24-C25	Manufacture of basic metals, and fabricated metal products, except machinery and equipment
C28	Manufacture of machinery and equipment
Other manufacturing (C16-C18, C26-C27, C29-C33, J58-J60)	Manufacture of wood and products of wood and cork, paper and paper products, printing and reproduction of recorded media; Manufacture of computer, electronic, optical and electrical products; Manufacture of motor vehicles, trailers and semi-trailers; Manufacture of other transport equipment; Manufacture of furniture and other manufacturing; Publishing activities (motion pictures, video, programming and broadcasting activities)
D-E	Electricity, gas and water supply
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J61-J63	Information and communication
K-M	Financial and insurance activities; Real estate activities; Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P-S	Education; Human health and social work activities; Arts, entertainment and recreation; Other service activities

Source: own elaboration.

Table A3. Task Group Allocation, by Occupation (ISCO08 2-digit)

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

Source: own elaboration based on Acemoglu and Autor (2011)

Note: NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

5. Appendix B – Additional Results

Table B1. Impact of Robot Adoption on Relative Wages, by Task Group – Full Specification

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.003***	0.002	0.001	0.004***	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
RC dummy	0.004				
	(0.007)				
RM dummy	0.013*				
	(0.007)				
NRM dummy	0.010				
	(0.007)				
Δ Backward GVC participation	-0.032	1.749**	-0.483	-0.203	-1.086***
	(0.309)	(0.780)	(0.464)	(0.723)	(0.389)
Δ Forward GVC participation	-0.773	0.320	-0.305	-1.460	-1.871*
	(0.635)	(1.314)	(0.937)	(1.653)	(0.963)
Δ log Sector Export	-0.037	-0.080	0.050	-0.163*	-0.005
	(0.049)	(0.136)	(0.067)	(0.092)	(0.074)
Δ log Sector Output	0.109*	0.009	-0.081	0.416***	0.139
	(0.063)	(0.155)	(0.091)	(0.125)	(0.104)
Δ Female workers share	-0.183***	-0.280***	-0.101	-0.221***	-0.117
	(0.048)	(0.107)	(0.104)	(0.081)	(0.089)
Δ Part-time workers share	-0.294***	-0.360*	-0.152	-0.268**	-0.358***
	(0.060)	(0.214)	(0.128)	(0.115)	(0.085)
Δ Secondary educated share	0.131**	1.155***	-0.070	0.046	0.226*
	(0.064)	(0.323)	(0.090)	(0.070)	(0.121)
Δ Tertiary educated share	0.203***	1.177***	0.117	0.050	0.150
	(0.066)	(0.294)	(0.098)	(0.094)	(0.140)
Constant	-0.029***	-0.011	-0.019**	-0.029**	-0.034***
	(0.008)	(0.012)	(0.009)	(0.015)	(0.009)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.012***	0.007	0.010**	0.014***	0.015***
	(0.002)	(0.005)	(0.004)	(0.004)	(0.003)
RC dummy	0.004				
	(0.007)				
RM dummy	0.012*				
	(0.007)				
NRM dummy	0.010				
	(0.007)				
Δ Backward GVC participation	0.015	1.776**	-0.429	-0.158	-1.037***
	(0.310)	(0.776)	(0.463)	(0.727)	(0.390)
Δ Forward GVC participation	-1.098*	0.129	-0.670	-1.788	-2.266**
	(0.663)	(1.334)	(0.978)	(1.729)	(1.011)
Δ log Sector Export	-0.025	-0.072	0.061	-0.152*	0.012
	(0.049)	(0.135)	(0.067)	(0.092)	(0.073)
Δ log Sector Output	0.111*	0.010	-0.074	0.420***	0.138

	(0.063)	(0.153)	(0.091)	(0.124)	(0.104)
Δ Female workers share	-0.181***	-0.285***	-0.081	-0.221***	-0.119
	(0.048)	(0.107)	(0.103)	(0.081)	(0.088)
Δ Part-time workers share	-0.300***	-0.364*	-0.162	-0.267**	-0.373***
	(0.060)	(0.213)	(0.127)	(0.114)	(0.086)
Δ Secondary educated share	0.129**	1.137***	-0.055	0.045	0.219*
	(0.064)	(0.325)	(0.092)	(0.070)	(0.121)
Δ Tertiary educated share	0.203***	1.161***	0.133	0.049	0.159
	(0.066)	(0.295)	(0.100)	(0.092)	(0.140)
Constant	-0.037***	-0.016	-0.027***	-0.037**	-0.043***
	(0.008)	(0.014)	(0.010)	(0.016)	(0.010)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	279.4	68.1	70.2	68.8	67.9

Note: The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 16.4. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B2. Impact of Robot Adoption on Relative Wages, by Task Group and Country Heterogeneity – Full Specification

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.003***	0.000	0.001	0.005***	0.003**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Eastern Europe dummy	-0.022***	-0.037***	-0.037***	-0.014	0.003
	(0.005)	(0.013)	(0.009)	(0.010)	(0.009)
Δ Robot adoption * Eastern Europe dummy	0.003*	0.004	-0.000	0.004	0.005*
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
RC dummy	0.004				
	(0.007)				
RM dummy	0.013*				
	(0.007)				
NRM dummy	0.010				
	(0.007)				
Δ Backward GVC participation	0.096	1.949**	-0.308	-0.124	-1.112***
	(0.316)	(0.797)	(0.468)	(0.739)	(0.396)
Δ Forward GVC participation	-0.876	0.154	-0.481	-1.503	-1.847*
	(0.641)	(1.341)	(0.917)	(1.673)	(0.951)
Δ log Sector Export	-0.054	-0.114	0.022	-0.173*	-0.002
	(0.050)	(0.139)	(0.067)	(0.091)	(0.072)
Δ log Sector Output	0.144**	0.077	-0.024	0.436***	0.134
	(0.063)	(0.160)	(0.091)	(0.124)	(0.101)
Δ Female workers share	-0.185***	-0.305***	-0.091	-0.219***	-0.111
	(0.048)	(0.107)	(0.104)	(0.081)	(0.090)
Δ Part-time workers share	-0.314***	-0.425**	-0.184	-0.275**	-0.351***
	(0.060)	(0.212)	(0.128)	(0.114)	(0.088)
Δ Secondary educated share	0.101	1.012***	-0.190**	0.032	0.232*
	(0.068)	(0.335)	(0.094)	(0.074)	(0.126)
Δ Tertiary educated share	0.176**	1.047***	0.027	0.036	0.154
	(0.068)	(0.305)	(0.100)	(0.096)	(0.141)
Constant	-0.020**	0.005	-0.003	-0.022	-0.036***
	(0.008)	(0.013)	(0.009)	(0.015)	(0.011)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.007***	0.002	0.004	0.011**	0.009**
	(0.002)	(0.005)	(0.003)	(0.005)	(0.003)
Eastern Europe dummy	-0.027***	-0.042***	-0.046***	-0.015	-0.003
	(0.006)	(0.015)	(0.010)	(0.011)	(0.010)
Δ Robot adoption * Eastern Europe dummy	0.013***	0.013	0.017*	0.008	0.016**
	(0.005)	(0.011)	(0.010)	(0.008)	(0.008)
RC dummy	0.004				
	(0.007)				
RM dummy	0.013*				
	(0.007)				
NRM dummy	0.010				
	(0.007)				

Δ Backward GVC participation	0.152	1.991**	-0.238	-0.082	-1.056***
	(0.319)	(0.796)	(0.469)	(0.743)	(0.397)
Δ Forward GVC participation	-1.199*	-0.052	-0.840	-1.823	-2.214**
	(0.670)	(1.367)	(0.961)	(1.745)	(0.999)
Δ log Sector Export	-0.045	-0.109	0.028	-0.162*	0.010
	(0.050)	(0.139)	(0.066)	(0.091)	(0.072)
Δ log Sector Output	0.153**	0.085	-0.006	0.440***	0.141
	(0.063)	(0.160)	(0.090)	(0.122)	(0.099)
Δ Female workers share	-0.181***	-0.307***	-0.080	-0.218***	-0.104
	(0.048)	(0.107)	(0.103)	(0.081)	(0.091)
Δ Part-time workers share	-0.320***	-0.430**	-0.187	-0.274**	-0.368***
	(0.060)	(0.211)	(0.127)	(0.113)	(0.088)
Δ Secondary educated share	0.101	1.005***	-0.183*	0.034	0.226*
	(0.068)	(0.336)	(0.096)	(0.073)	(0.126)
Δ Tertiary educated share	0.179***	1.041***	0.042	0.037	0.161
	(0.068)	(0.305)	(0.101)	(0.094)	(0.141)
Constant	-0.025***	0.002	-0.008	-0.030*	-0.042***
	(0.008)	(0.014)	(0.010)	(0.017)	(0.012)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	148.6	35.5	36.9	36.2	35.9

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category), an interaction term between robot adoption, and an Eastern Europe dummy. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. Eastern European countries: BG, CZ, EE, HR, LT, LV, PL, RO, SK. Western European countries: BE, DE, ES, FI, FR, GR, IT, NL, NO, PT, SE. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B3. Impact of Robot Adoption on Relative Wages, by Task Group, Instrumented with US Robots

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.004***	0.002	0.001	0.006***	0.005***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
N	2,473	624	623	603	623
Panel C: IV Estimation					
Δ Robot adoption	0.010***	0.009	0.012*	0.012***	0.010***
	(0.002)	(0.006)	(0.006)	(0.003)	(0.003)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	67.8	17.0	16.7	16.4	16.9

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category). Pooled regression includes task groups' fixed effects. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 16.4. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual. *** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B4. Impact of Robot Adoption on Relative Wages, by Task Group, Country Heterogeneity – Instrumented with US Robots

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.003***	0.000	0.001	0.005***	0.003**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Δ Robot adoption * Eastern Europe dummy	0.003*	0.004	-0.000	0.004	0.005*
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.005**	0.001	0.004	0.009***	0.005
	(0.002)	(0.005)	(0.004)	(0.003)	(0.003)
Δ Robot adoption * Eastern Europe dummy	0.011**	0.015	0.016	0.007	0.009
	(0.005)	(0.011)	(0.011)	(0.007)	(0.007)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	28.3	7.0	6.9	6.8	7.1

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, those with secondary and tertiary education (using primary-educated workers as the reference category), an interaction term between robot adoption, and an Eastern Europe dummy. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. Eastern European countries: BG, CZ, EE, HR, LT, LV, PL, RO, SK. Western European countries: BE, DE, ES, FI, FR, GR, IT, NL, NO, PT, SE. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B5. Impact of Robot Adoption on Relative Wages, by Task Group, Instrumented with Replaceability (Graetz and Michaels, 2018)

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.004***	0.002	0.001	0.006***	0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
N	2,473	624	623	603	623
Panel C: IV Estimation					
Δ Robot adoption	0.007***	-0.003	0.009*	0.009*	0.013***
	(0.003)	(0.006)	(0.005)	(0.005)	(0.005)
N	2,467	622	621	603	621
Kleibergen-Paap F-stat.	180.1	43.7	45.4	43.7	42.8

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category). Pooled regression includes task groups' fixed effects. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 16.4. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual. *** p<0.01, ** p<0.05, * p<0.1.
Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B6. Impact of Robot Adoption on Relative Wages, by Task Group, Country Heterogeneity – Instrumented with Replaceability (Graetz and Michaels, 2018)

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.003***	0.000	0.001	0.005***	0.003**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Δ Robot adoption * Eastern Europe dummy	0.003*	0.004	-0.000	0.004	0.005*
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.010***	0.004	0.008*	0.013**	0.011*
	(0.003)	(0.007)	(0.004)	(0.006)	(0.005)
Δ Robot adoption * Eastern Europe dummy	-0.004	-0.014	0.003	-0.009	0.005
	(0.005)	(0.014)	(0.010)	(0.009)	(0.009)
N	2,467	622	621	603	621
Kleibergen-Paap F-stat.	69.6	17.0	18.1	16.6	16.7

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, those with secondary and tertiary education (using primary-educated workers as the reference category), an interaction term between robot adoption, and an Eastern Europe dummy. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. Eastern European countries: BG, CZ, EE, HR, LT, LV, PL, RO, SK. Western European countries: BE, DE, ES, FI, FR, GR, IT, NL, NO, PT, SE. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B7. Impact of Robot Adoption on Relative Wages, by Task Groups, Country Heterogeneity, With Country-Specific Time Trends

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.002**	-0.001	0.001	0.002	0.004*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Δ Robot adoption * Eastern Europe dummy	0.002	0.006*	-0.001	0.003	0.003
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.004*	-0.002	0.002	0.005	0.009**
	(0.003)	(0.006)	(0.004)	(0.005)	(0.004)
Δ Robot adoption * Eastern Europe dummy	0.012***	0.015	0.015*	0.010	0.014*
	(0.005)	(0.010)	(0.009)	(0.008)	(0.008)
N	2,467	622	621	603	621
Kleibergen-Paap F-stat.	139.3	31.2	34.0	32.0	33.3

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, those with secondary and tertiary education (using primary-educated workers as the reference category), an interaction term between robot adoption, and an Eastern Europe dummy. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. Eastern European countries: BG, CZ, EE, HR, LT, LV, PL, RO, SK. Western European countries: BE, DE, ES, FI, FR, GR, IT, NL, NO, PT, SE. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B8. Impact of Robot Adoption on Relative Wages, by Task Group, With Country-Year Fixed Effects

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.003***	0.002	0.001	0.004***	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.011***	0.006	0.010**	0.011**	0.014***
	(0.002)	(0.005)	(0.004)	(0.004)	(0.003)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	339.0	79.1	79.5	78.2	79.8

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category), and country-year FE, and country-specific time trends. Pooled regression includes task groups' fixed effects. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 16.4. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B9. Impact of Robot Adoption on Relative Wages, by Task Group, Country Heterogeneity, With Country-Year Fixed Effects

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.002***	-0.000	0.001	0.003**	0.003*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Δ Robot adoption * Eastern Europe dummy	0.003*	0.006	0.001	0.004	0.004
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.005**	-0.001	0.003	0.008*	0.008**
	(0.002)	(0.005)	(0.003)	(0.004)	(0.004)
Δ Robot adoption * Eastern Europe dummy	0.014***	0.016	0.018**	0.009	0.017**
	(0.005)	(0.010)	(0.009)	(0.008)	(0.008)
N	2,467	622	621	603	621
Kleibergen-Paap F-stat.	171.0	42.0	42.0	42.0	41.0

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, those with secondary and tertiary education (using primary-educated workers as the reference category), an interaction term between robot adoption, and an Eastern Europe dummy. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. Eastern European countries: BG, CZ, EE, HR, LT, LV, PL, RO, SK. Western European countries: BE, DE, ES, FI, FR, GR, IT, NL, NO, PT, SE. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B10. Impact of Robot Adoption on Relative Wages, by Task Group, Without Macroeconomic Controls

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.003***	0.001	0.002	0.005***	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.010***	0.006	0.010***	0.011***	0.013***
	(0.002)	(0.005)	(0.004)	(0.004)	(0.003)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	285.7	70.1	72.1	70.7	69.6

Note: The regressions account for various controls, such as changes in shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category). Pooled regression includes task groups' fixed effects. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 16.4. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B11. Impact of Robot Adoption on Relative Wages, by Task Group, Country Heterogeneity, Without Macroeconomic Controls

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.003***	0.001	0.001	0.004**	0.003*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Δ Robot adoption * Eastern Europe dummy	0.002	0.003	0.001	0.001	0.004
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.006***	0.001	0.003	0.009**	0.007**
	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
Δ Robot adoption * Eastern Europe dummy	0.013***	0.014	0.018*	0.007	0.016**
	(0.004)	(0.010)	(0.009)	(0.008)	(0.007)
N	2,467	622	621	603	621
Kleibergen-Paap F-stat.	118.4	34.1	41.0	36.4	29.2

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, those with secondary and tertiary education (using primary-educated workers as the reference category), an interaction term between robot adoption, and an Eastern Europe dummy. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. Eastern European countries: BG, CZ, EE, HR, LT, LV, PL, RO, SK. Western European countries: BE, DE, ES, FI, FR, GR, IT, NL, NO, PT, SE. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B12. Impact of Robot Adoption on Relative Wages, by Task Group, With Gross Fixed Capital Formations

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.003***	-0.000	0.000	0.005***	0.005***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
N	2,227	562	561	543	561
Panel B: IV Estimation					
Δ Robot adoption	0.009***	0.003	0.007*	0.011**	0.015***
	(0.002)	(0.005)	(0.004)	(0.004)	(0.003)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	279.5	68.0	69.4	68.6	68.1

Note: The regressions account for various controls, such as changes in shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category). Pooled regression includes task groups' fixed effects. The top 1% of earners have been omitted from the data. According to data availability HR and NO are dropped from the sample. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 16.4. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B13. Impact of Robot Adoption on Relative Wages, by Task Group, Country Heterogeneity, With Gross Fixed Capital Formations

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.002**	-0.001	0.000	0.004**	0.004**
	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)
Δ Robot adoption * Eastern Europe dummy	0.002	0.002	-0.002	0.003	0.005*
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.005**	-0.001	0.001	0.009*	0.008**
	(0.002)	(0.005)	(0.003)	(0.005)	(0.003)
Δ Robot adoption * Eastern Europe dummy	0.011**	0.011	0.016*	0.006	0.016**
	(0.004)	(0.010)	(0.009)	(0.008)	(0.007)
N	2,467	622	621	603	621
Kleibergen-Paap F-stat.	133.0	32.4	33.3	31.9	32.1

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, those with secondary and tertiary education (using primary-educated workers as the reference category), an interaction term between robot adoption, and an Eastern Europe dummy. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. Eastern European countries: BG, CZ, EE, HR, LT, LV, PL, RO, SK. Western European countries: BE, DE, ES, FI, FR, GR, IT, NL, NO, PT, SE. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B14. Impact of Robot Adoption on Relative Wages, by Task Group, Alternative Wage Measure

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.004***	0.003	0.002	0.006***	0.003***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.013***	0.013*	0.014**	0.012***	0.011***
	(0.003)	(0.007)	(0.006)	(0.003)	(0.003)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	278.6	68.1	68.8	68.3	67.8

Note: The regressions account for various controls, such as sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category). Pooled regression includes task groups' fixed effects. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 16.4. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

Table B15. Impact of Robot Adoption on Relative Wages, by Task Group, Country Heterogeneity, Alternative Wage Measure

	(1) Pooled	(2) NRC	(3) RC	(4) RM	(5) NRM
Panel A: OLS Estimation					
Δ Robot adoption	0.002***	-0.000	0.000	0.005***	0.002*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Δ Robot adoption * Eastern Europe dummy	0.004**	0.007	0.003	0.003	0.003
	(0.002)	(0.005)	(0.003)	(0.002)	(0.002)
N	2,473	624	623	603	623
Panel B: IV Estimation					
Δ Robot adoption	0.008***	0.005	0.007*	0.010***	0.007**
	(0.002)	(0.006)	(0.004)	(0.003)	(0.003)
Δ Robot adoption * Eastern Europe dummy	0.013***	0.022	0.018	0.005	0.011*
	(0.005)	(0.014)	(0.011)	(0.006)	(0.006)
N	2,473	624	623	603	623
Kleibergen-Paap F-stat.	147.4	35.5	36.2	35.6	35.9

Note: Regressions include controls for sectoral output, exports, global value chain participation, and changes in shares of female workers, part-time workers, and those with secondary and tertiary education (using primary-educated workers as the reference category), as well as an interaction term between robot adoption and an Eastern Europe dummy. The top 1% of earners have been omitted from the data. According to the Stock-Yogo (2005) test for weak instruments, maximal size distortions of a Wald statistic are below 10% when the Kleibergen-Paap rk Wald F statistic is above 7. Eastern European countries: BG, CZ, EE, HR, LT, LV, PL, RO, SK. Western European countries: BE, DE, ES, FI, FR, GR, IT, NL, NO, PT, SE. NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Own calculations based on EU SES, IFR, EORA and Eurostat data.

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