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Automation and Labor Demand: The Role of Different Types of Robotic Applications

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Abstract

Recent literature documents significant heterogeneity in the strength of automation and the creation of new tasks across advanced countries. To address the observed cross-country heterogeneity, this paper provides detailed evidence on the role played by the adoption of industrial robots by application. We document that some robots played a more important role in the replacement of workers than others did. After controlling for potential confounding factors such as ICT, manufacturing share, and trade unions, we found significant evidence for a relationship between displacement and industrial robots installed for welding, soldering, and dispensing. The evidence for other industrial robots was mixed. The cross-country heterogeneity in the reinstatement effect remains unexplained and calls for further research.

1. Introduction

There is significant heterogeneity in the adoption of automation technologies and in the creation of new tasks across the European countries identified in the literature. To address this cross-country heterogeneity, this paper provides the first empirical evidence on the role played by different types of industrial robots in the development of labor demand in 10 European countries and the United States. In addition to robot adoption, we control for other confounding factors such as information and communication technology (ICT) adoption, the size of the manufacturing/automotive sector, and the density of trade unions. We find significant evidence for a relationship between displacement and industrial robots installed for welding, soldering, and dispensing. The evidence on the effects of other industrial robots is mixed and mostly insignificant.

The research in this paper is motivated by the fact that although the potential disruptions associated with automation and other new technologies are immense, there is no consensus among economic experts on their employment impacts. The IGM Forum at the University of Chicago's Booth School of Business asked in their panel whether, holding labor market institutions and job training fixed, rising use of robots and artificial intelligence is likely to substantially increase the number of workers in advanced countries who are unemployed for long periods. The results show that 38% of the economists agreed or strongly agreed with this statement, 29%

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were uncertain, 21% disagreed or strongly disagreed, and 2% had no opinion. This uncertainty can also be found in the literature, as estimates of the share of jobs at a high risk from automation differ significantly depending on the approach used (Frey and Osborne, 2017; Arntz et al., 2016; Dengler and Matthes, 2018). To shed some more light on the future of work, an analysis of past trends is necessary. The following two paragraphs illustrate the importance of understanding the development of labor demand in the context of technological change and explain why this paper focuses on European countries.

Data from the International Federation of Robotics (IFR) database show that the total worldwide stock of operational industrial robots increased from roughly 0.5 million in 1993 to almost 2.5 million in 2018 (Litzenberger et al., 2018). Moreover, in subsequent years, growth of the operational stock was expected to slightly accelerate and reach an average of around 16% per year by 2021 . Both robotics development and robot deployment are among the fastest-growing global markets. Between 1995 and 2016, the number of robot-related patent families worldwide almost doubled every five years—while only 35 patent families were filed in 1995, this figure jumped to more than 1,100 in 2016 (Cséfalvay and Gkotsis, 2020).

In 2018, according to IFR and International Labour Organization data, 15 European countries were among the 20 countries with the highest robot density—the stock of industrial robots per 1,000 workers. The remaining countries were South Korea, Singapore, Taiwan, Japan, and the United States. The European countries with the highest robot density were Germany, Slovenia, the Czech Republic, Slovakia, and Italy. Between 1993 and 2018, robot density in EU countries increased from about 0.5 to more than 2.5. In addition to its strong position in robot adoption, Europe concentrates more than half of all patents filed by robot manufacturers. The total number of robotics patents (combining robotics developers, robot manufacturers, and in-house robotics development) in Europe followed a global trend and increased from 444 in 1995 to 1,000 in 2016. However, robotics development in Europe has been concentrated in just a few countries, with almost 60% of the patents filed coming from Germany (Cséfalvay and Gkotsis, 2020).

This paper is divided into four sections. In Section 1, we review the relevant literature. The decomposition of changes in the economy-wide wage bill is described in the second section. This is followed by a description of the estimation strategy and the data used in the empirical analysis, the results of which are presented Section 4. Finally, we summarize the main results and conclude.

2. Literature Review

Using a panel of industries from 17 countries, Graetz and Michaels (2018) showed that between 1993 and 2007, robot densification (positive changes in robot density over time) had no statistically significant effect on total hours worked (overall employment). Carbonero et al. (2020) used a similar industry-country panel setting and found that between 2005 and 2014, robots led to a drop in global employment of 1.3%, with the detrimental effect of robots on employment being concentrated in emerging economies. In contrast, a similar approach used by Klenert et al. (2020) yielded different results. They showed that industrial robots were positively correlated with total employment. Compared to Graetz and Michaels

(2018), these authors used different employment data and examined a longer period of time (1995–2015).

In contrast to this sectoral approach, Gregory et al. (2019) provided the first empirical estimate of the economy-wide effect of routine-replacing technological change (RRTC) on labor demand, assessing that it increased labor demand by up to 11.6 million jobs across Europe between 1999 and 2010, accounting for about half of total employment growth. By performing a decomposition rooted in their theoretical model, they found that sizable substitution effects from RRTC (as workers were replaced by machines in the production of routine tasks) had been more than compensated for by product demand and spillover effects.

A similar idea was behind the approach of Acemoglu and Restrepo (2020). Their model, in which robots and workers compete in the production of different tasks (a task-based model), showed that greater penetration of robots into an economy affected employment and wages in two ways: negatively by directly displacing workers from tasks they were previously performing (a displacement effect) and positively by increasing the demand for labor in other industries and/or tasks (a productivity effect). Their empirical analysis revealed large and robust negative effects from robots on employment and wages across US local labor markets—1 more robot per 1,000 workers reduced the employment-to-population ratio by about 0.2 percentage points and wages by 0.42%. Dauth et al. (2017) and Chiacchio et al. (2018) adopted this local labor market equilibrium approach and used it in the context of the EU labor market. Dauth et al. (2017) focused on Germany and found no evidence for an effect from robots on employment so far. Assessing the impact of robots on employment and wages in six EU countries (Finland, France, Germany, Italy, Spain, and Sweden), Chiacchio et al. (2018) found that 1 additional robot per 1,000 workers reduced the employment rate by 0.16–0.20 percentage points—as in the case of the United States, the displacement effect dominated over the productivity effect. For the impact of industrial robots on wage growth, there have been only mixed results. Conducting an estimation resembling the one by Acemoglu and Restrepo (2020) for Japan, Adachi et al. (2020) showed that an increase of 1 robot unit per 1,000 workers increased employment by 2.2%.

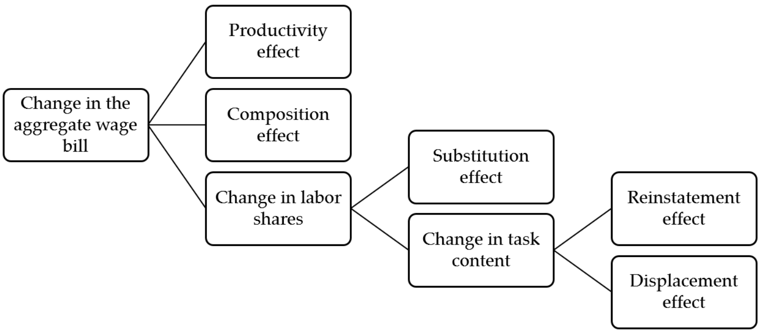
Acemoglu and Restrepo (2019) presented a framework for understanding the effects of automation and other types of technological changes on labor demand and developed a decomposition of observed changes in the total wage bill in the economy. In the framework, the displacement effect of automation is counterbalanced by the reinstatement effect, as technologies create new tasks in which labor has a comparative advantage. Their empirical decomposition showed that the deceleration of US labor demand growth over the past 30 years was a result of a combination of slow productivity growth and adverse shifts in the task contents of production—rapid automation not being counterbalanced by the creation of new tasks. Graetz (2020) used this decomposition method to isolate the component of changes in the labor share due to changes in the task content of production in the following five European countries: France, Germany, Italy, the Netherlands, and the United Kingdom. The paper found that both in the United States and across these five large European economies, the change in task content between 1987 and 2007 was negative, implying that automation outpaced the creation of new tasks over this period. It was shown that the change in task content had a similar magnitude in all of the analyzed countries. Lábaj and Vitáloš (2020) similarly applied the decomposition developed by Acemoglu and Restrepo (2019) to European data. However, these authors worked with a sample of 10 European countries and covered a different period (1997–2016). They showed that, contrary to the US experience, in the EU-10 the displacement effect of automation was completely counterbalanced by technologies that created new tasks in which labor has a comparative advantage. Furthermore, their cross-country comparison revealed substantial variation across countries. The displacement effect was stronger than the reinstatement effect in Austria, the Czech Republic, Germany, the Netherlands, and Sweden. The opposite was true for Finland, France, and the United Kingdom. In Denmark and Italy, the net effect was close to zero. Automation was strongest in Sweden and the Czech Republic, and the creation of new tasks was strongest in the United Kingdom. The paper then addressed this observed heterogeneity and provided empirical evidence for the relationship between the adoption of industrial robots (as a proxy for automation technologies) and the change in the task content of production. The negative association between these factors was driven by the displacement effect—there was a strong association between the displacement effect and the change in robot density. However, cross-country differences in the strength of the reinstatement effect remain unexplained by robot adoption.

In the empirical literature, industrial robots are used as a proxy for automation technologies. These technologies, in contrast to the standard formulation of skill-biased technological progress, are perfect substitutes for labor. This has important implications for labor demand and wages. Automation does not raise the marginal productivity of labor and workers become obsolete. Thus, the implications of automation for income inequality, stagnant wages, and productivity growth have received a lot of attention in the recent theoretical literature. Steigum (2011) was the first to incorporate the use of robots in production into a neoclassical growth model with endogenous savings. Prettner (2019) provided a simpler version of a neoclassical production function based on the Solow growth model (Solow, 1956). Lankisch et al. (2019) extended the model for the skill-specific heterogeneity of workers, which enabled the authors to explain the presence of rising per capita GDP, shrinking wages among low-skilled workers, and rising wage inequality. The primary focus of the recent theoretical and empirical literature has been directed toward a better understanding of the implications of automation in terms of heterogeneity in skills among workers. In several extensions that incorporate automation technologies into a standard theoretical framework, the heterogeneity of industrial robots is modeled implicitly or explicitly. In Steigum (2011), one unit of automation capital was equal to ε units of labor. Similarly, Summers (2013) modeled this explicitly by the parameter λ in relation to automation capital. In this formulation, robots are a perfect substitute for labor but the number of workers that can be replaced by one unit of industrial robots can differ across applications and robot types. In this paper, we elaborate on this heterogeneity across robot applications. We provide the first empirical results on the relationship between the displacement effect and different types of robots. As more and better data on the use of industrial robots are becoming available over time, it will be possible to provide more detailed evidence on their implications for labor demand in the future.

3. Methodology

Following Acemoglu and Restrepo (2019), our aim is to decompose changes in the economy-wide wage bill (which captures the total amount employers pay for labor) into productivity, composition and substitution effects, and changes in the task content of production (Figure 1). This empirical exercise is based on a task-based framework developed to analyse the implications of technology for labor demand and productivity.[1]

Figure 1 Wage Bill Decomposition



Source: Authors' elaboration based on Acemoglu and Restrepo (2019).

Because the economy-wide wage bill is the sum of wage bills across industries, the following applies:

$$\ln(W_t L_t) = \ln\left(Y_t \sum_i \chi_{i,t} s_{i,t}^L\right). \tag{1}$$

Here, $W_t L_t$ is the economy-wide wage bill in year t, Y_t is total value added in year t, $\chi_{i,t}$ is the share of industry i in the total value added in year t, and $s_{i,t}^L$ is the corresponding labor share.

If the base year is indexed with the subscript t_0, the percent change in the wage bill normalized by population (N) between t_0 and t can be expressed as:

$$\begin{aligned} \ln\left(\frac{W_t L_t}{N_t}\right) - \ln\left(\frac{W_{t_0} L_{t_0}}{N_{t_0}}\right) &= \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t_0}}{N_{t_0}}\right)\left[\text{Productivity effect}_{t_0,t}\right] \\ &+ \ln\left(\sum_i x_{i,t} s_{i,t}^L\right) - \ln\left(\sum_i x_{i,t_0} s_{i,t}^L\right)\left[\text{Composition effect}_{t_0,t}\right] \\ &+ \ln\left(\sum_i x_{i,t_0} s_{i,t}^L\right) - \ln\left(\sum_i x_{i,t_0} s_{i,t_0}^L\right)\left[\text{Change in labor shares}_{t_0,t}\right], \end{aligned} \tag{2}$$

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[1] See Acemoglu and Restrepo (2019) for more details.

where the first term on the right-hand side represents changes in the total value added per capita, which directly corresponds to the productivity effect. The productivity effect arises from the fact that automation increases value added, which raises the demand for labor from non-automated tasks. At the same time, it captures the productivity improvements resulting from the fact that new tasks exploit labor's comparative advantage. The productivity effect also captures the positive effect of factor-augmenting technologies. The implications of these technologies are very different from those of automation and new tasks because they do not change the task content of production. With factor-augmenting technological improvements, either labor or capital becomes more productive in all tasks, making the productivity effect proportional to their share in value added.

The second term on the right-hand side captures the impact of shifts in industry shares (changes in $\chi_{i,t}$ over time) on labor demand, holding the labor share within each industry ($s^L_{i,t}$) constant. This corresponds to the composition effect. The composition effect arises from the reallocation of activity across industries with different labor intensities and captures the implications of changes in the share of value added across industries. For example, automation in industry i may reallocate economic activity towards industry j, which contributes positively to aggregate labor demand when industry j has a higher labor share than the contracting industry i and negatively when the opposite holds.

The last term on the right-hand side captures the role of changes in labor shares within industries (changes in $s^L_{i,t}$ over time) on labor demand holding industry shares ($\chi_{i,t}$) constant at their initial value (χ_{i,t_0}). The change in labor shares corresponds to the combined effect of substitution and changes in the task content of production. This is because with competitive factor and product markets, the change in task content and the substitution effect are the only forces affecting the labor share of an industry. For a better understanding of the relationships between these terms, refer to Figure 1, which shows their schematic representation.

The substitution effect captures the substitution between labor- and capital-intensive tasks within an industry in response to a change in task prices, which may be caused, for example, by factor-augmenting technologies making labor or capital more productive at tasks they currently perform. Changes in the task content of production are estimated from residual changes in industry-level labor shares (beyond what can be explained by substitution effects).

Acemoglu and Restrepo (2019) showed that the substitution effect in industry i between t_0 and t can be calculated as:

$$\text{Substitution effect}_{i,t_0,t} = (1-\sigma)\left(1-s^L_{i,t_0}\right)\left(\ln\frac{W_{i,t}}{W_{i,t_0}} - \ln\frac{R_{i,t}}{R_{i,t_0}} - g^A_{i,t_0,t}\right), \tag{3}$$

and the change in task content in industry i between t_0 and t as:

$$\text{Change in task content}_{i,t_0,t} = \ln s^L_{i,t} - \ln s^L_{i,t_0} - \text{Substitution effect}_{i,t_0,t}, \tag{4}$$

where W denotes the price of labor (wages), R denotes the price of capital (rental rates), σ denotes the elasticity of substitution between capital and labor, and g^A stands for the growth rate of factor-augmenting technologies.

For each industry and year, factor prices are calculated as:

$$W_{i,t} = \frac{\text{Labor compensation}_{\text{i,t}}}{\text{Labor services}_{i,t}} \tag{5}$$

$$R_{i,t} = \frac{\text{Capital compensation}_{i,t}}{\text{Capital services}_{i,t}}. \tag{6}$$

In addition to industry-level changes in effective factor prices, the substitution effect also depends on the elasticity of substitution σ. Similarly to Acemoglu and Restrepo (2019), in order to estimate the substitution effect in an industry, the estimate by Oberfield and Raval (2014) of $\sigma = 0.8$ was chosen as the estimate of the elasticity of substitution between capital and labor. To convert observed factor prices into effective ones, it is supposed that A_i^L/A_i^K grows at a common rate equal to average labor productivity—if all technological progress were labor-augmenting, this would be the rate of growth in A_i^L required to match the behavior of labor productivity.

The economy-wide contribution of the substitution effect and the economy-wide change in the task content of production are calculated by aggregating across industry-level contributions of the substitution effect or changes in the task content of production. This can be expressed as:

$$\text{Substitution effect}_{t_0,t} = \sum_{i \in \mathcal{I}} \ell_{i,t_0} \text{Substitution effect}_{i,t_0,t} \tag{7}$$

$$\text{Change in task content}_{t_0,t} = \sum_{i \in \mathcal{I}} \ell_{i,t_0} \text{Change in task contentt}_{i,t_0,t}\,, \tag{8}$$

where ℓ_{i,t_0} is the share of the wage bill generated in industry i in year t_0.

Changes in the task content of production can be further decomposed into displacement and reinstatement effects. To do so, following Acemoglu and Restrepo (2019), it is assumed that over five-year windows, an industry engages in either automation or the creation of new tasks but not in both activities. This assumption implies that:

$$\text{Displacement}_{t-1,t} = \sum_{i \in \mathcal{I}} \ell_{i,t_0} \min\left\{0, \frac{1}{5} \sum_{\tau=t-2}^{t+2} \text{Change in task content}_{i,\tau-1,\tau}\right\} \tag{9}$$

$$\text{Reinstatement}_{t-1,t} = \sum_{i \in \mathcal{I}} \ell_{i,t_0} \max\left\{0, \frac{1}{5} \sum_{\tau=t-2}^{t+2} \text{Change in task content}_{i,\tau-1,\tau}\right\}. \quad (10)$$

Thus, if the average change in the task content of production in industry i over the five-year period (the five-year moving average) is negative, the industry is considered to have experienced a displacement effect. If it is instead positive, a reinstatement effect is assumed to have taken place in the industry. The total contribution of displacement and reinstatement effects can be calculated by cumulating expressions (9) and (10) over time. Displacement effects are caused by automation that replaces labor, while reinstatement effects are driven by the creation of new tasks in which labor has a comparative advantage. Acemoglu and Restrepo (2019) also presented estimates of the displacement and reinstatement effects using yearly changes in the task content of production and found that the implied displacement and reinstatement effects were larger, but the overall patterns were similar.

4. Data

This paper works with industry-level data[2] for 10 European countries (Austria, the Czech Republic, Denmark, Finland, France, Germany, Italy, the Netherlands, Sweden, and the United Kingdom) and the United States for the period 1997–2016. To decompose changes in labor demand into productivity, composition and substitution effects, and changes in the task content of production, the analysis used data from the EU KLEMS and World Bank databases. The EU KLEMS database contains data on labor compensation and services, capital compensation and services, gross value added, and employment and the World Bank database provided population data.

To identify potential drivers of the observed cross-country heterogeneity in the strength of the displacement and reinstatement effects, data on the operational stock of industrial robots with different applications from the IFR database and data on the stock of computing and communications equipment from the EU KLEMS database were used. When working with the IFR database, five broad categories of robot applications can be distinguished: i) handling operations/machine tending, ii) welding and soldering, iii) dispensing, iv) processing, and v) assembling. The IFR defines handling operations/machine tending as “assistant processes for the primary operation (the robot does not process the main operation directly)”. Welding includes arc welding, spot welding, laser welding, ultrasonic welding, gas welding, and plasma welding. Dispensing comprises painting, enamelling, and application of adhesive or sealing or a similar material. Processing covers laser cutting, water jet cutting, and mechanical cutting/grinding/deburring/milling/polishing. Finally, assembling is defined as “enduring positioning of elements”. The EU KLEMS database provides employment data, which in this case were used to calculate robot

[2] The analysis is based on data for 28 industries that are part of a market economy (A, B, C10-C12, C13-C15, C16-C18, C19, C20, C21, C22_C23, C24_C25, C26, C27, C28, C29_C30, C31-C33, D, E, F, G, H, I, J58-J60, J61, J62_J63, K, M_N, R, S).

and ICT densities. In addition to robot and ICT adoption, the role of trade unions was analyzed. In this case, trade union density data from the OECD database were used. However, the OECD database does not contain information on trade union density for 1997, and therefore the average was calculated for 1998–2016.

Table 1 Descriptive Statistics

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Displacement effect	209	-0,705	0,535	-4,108	-0,047
Robot density (all applications)	209	1,405	0,885	0,125	4,338
Handling/tending robot density	199	0,753	0,51	0	2,454
Welding and soldering robot density	198	0,373	0,233	0	1,013
Dispensing robot density	198	0,055	0,043	0	0,186
Processing robot density	199	0,059	0,047	0	0,199
Assembling robot density	194	0,07	0,083	0	0,386
IT density	209	0,936	0,652	0,126	3,576
CT density	209	1,397	1,396	0,095	5,041
Manufacturing share	209	17,414	4,843	9,559	27,643
Trade union density	209	35,668	24,072	8,5	92,6

Source: Authors' elaboration based on data from the EU KLEMS, IFR, OECD, and World Bank databases.

Table 1 contains descriptive statistics of the variables used in the analysis of the impact of different robot types on the displacement effect. It shows that for each disaggregated category of robots, 10 to 15 observations are missing. All but two of these missing observations concern the Czech Republic and the Netherlands. Robot density measures the stock of industrial robots per 1,000 workers. In the case of the aggregated category, it ranged from 0.125 to 4.338. The mean and maximum values for the five broad categories of robot applications show that the use of handling operations/machine tending and welding and soldering robots was several times higher than the values for the other three categories. IT/CT density is the net stock of computing/communications equipment per 1,000 workers (in 2010 prices and millions of national currency). In the case of the Czech Republic, Denmark, Sweden, and the United States, ICT stock data were converted to euros using Eurostat's annual Euro/ECU exchange rates. The manufacturing sector's share was calculated using data on gross value added at current prices from the EU KLEMS database and took values between about 10% and 30% with an average value of 17.414%. Finally, trade union density varied between 8.5% and 92.6%. We included the adoption of ICT, the size of manufacturing sector, and the strength of trade unions in the analysis as they can all play a role in the process of labor replacement (Brambilla and Tortarolo, 2018; Jung et al., 2020; Allen and Funk, 2008; Parolin, 2019).

Our main empirical results are based on a fixed effects estimator of yearly panel data. The most general specification is given by:

$$displacement_{it} = \beta_0 + \beta_1 robots_{it} + X_{it}\gamma + \nu_i + \tau_t + \epsilon_{it}, \tag{11}$$

where $displacement_{it}$ is the size of the displacement effect in country i and period t; $robots_{it}$ is the robot density of a particular robot type; X_{it} are other controls such as IT and CT density, manufacturing share, and trade union density; ν_i is a country-specific time-invariant fixed effect; τ_t is period fixed effect; and ϵ_{it} is an error term. Primary focus is placed on the relationship between the displacement effect and robot density. Other controls are used to mitigate the omitted variable bias for a coefficient for robot density. These controls increase the precision of our estimates for robot density as they explain some part of the overall variability in the displacement effect. Given a potential endogeneity between our controls and the displacement effect, their coefficients must be interpreted with caution. To provide more robust evidence, the end of the paper presents several robusteness checks that were performed. Moreover, in our empirical strategy we assumed that the effects of unobserved factors were captured by the country and time fixed effects. As the estimation period was relatively short, these effects could mitigate estimation bias due to possible endogeneity between variables.

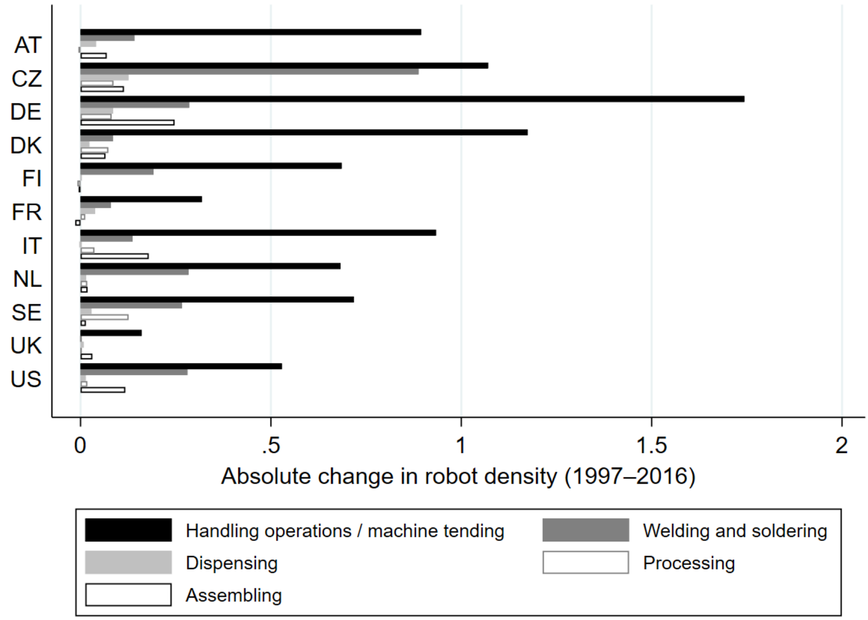
5. Empirical Results

This section first addresses the cross-country heterogeneity in the displacement and reinstatement effects by providing more nuanced evidence regarding its drivers. We document the association between these effects and the adoption of industrial robots by application and other potential drivers such as manufacturing share, ICT, and trade unions. Given the data limitations described in the previous section, cross-section analysis is limited to a sub-sample of European countries and the US economy and does not allow a reasonable regression analysis with multiple controls. For more persuasive evidence, it is important to show that the effects of robot adoption on displacement/reinstatement differ from other potential drivers. Therefore, we carried out regression analysis on yearly panel data that enabled us to analyse these effects while explicitly controlling for the other potential drivers described above. Compared to cross-section analysis, this is not without costs. The literature suggests that these effects should be found in long-run horizons, so cross-section analysis with cumulative changes is a more appropriate option. On the other hand, panel data analysis reveals associations with other confounding factors.

5.1 Cross-Section Analysis

Figure 2 shows that there is considerable heterogeneity in the adoption of robots with different applications across EU-10 countries and the United States. For example, while Germany is the top adopter of industrial robots specialized in handling operations / machine tending and assembling, the Czech Republic is the top adopter of industrial robots specialized in welding and soldering and dispensing. Finally, in the case of adoption of industrial robots specialized in processing, Sweden is the top adopter.

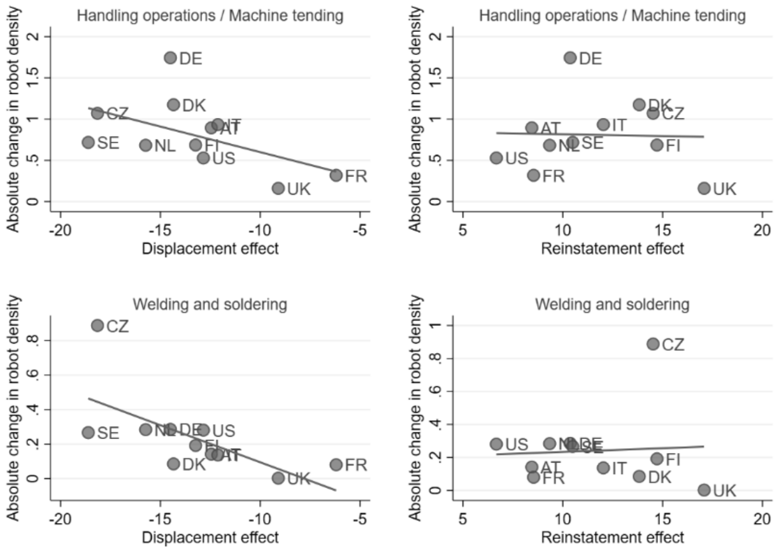
Figure 2 Adoption of Robots with Different Applications



Source: Authors' elaboration based on data from the EU KLEMS and IFR databases.

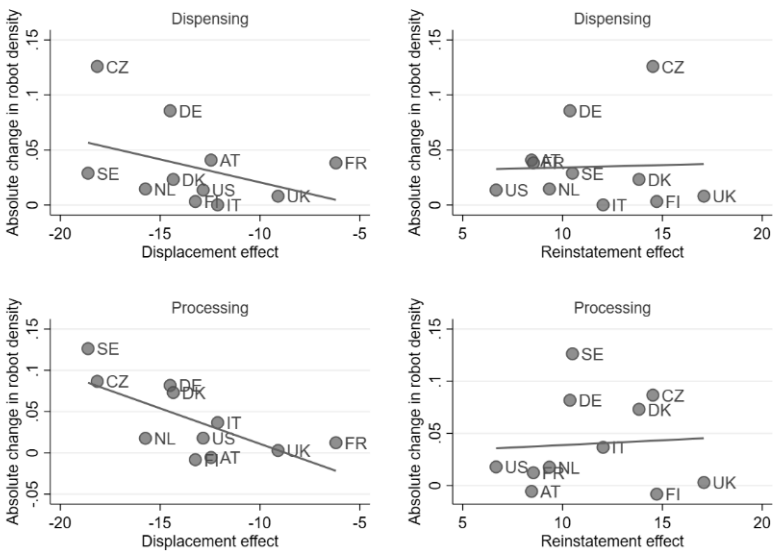
The relationship between the adoption of industrial robots by application and the displacement/reinstatement effects is presented in Figures 3, 4, and 5. The analysis suggests a positive relationship between the adoption of robots and the strength of the displacement effect. This positive relationship was strongest for processing and weakest for assembling, with correlation coefficients of −0.69 and −0.21, respectively. There was no relationship between the adoption of robots and the strength of the reinstatement effect across different applications.

Figure 3 Robot Adoption Versus the Displacement/Reinstatement Effect (Handling Operations / Machine Tending and Welding and Soldering), 1997–2016



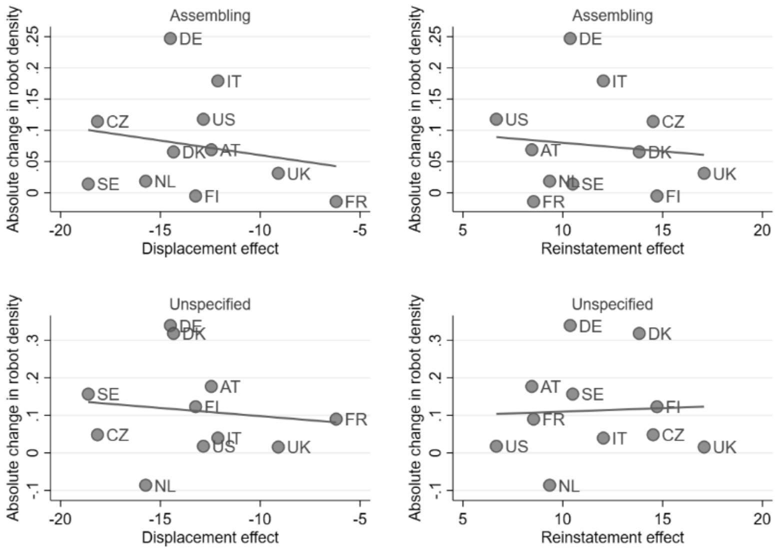
Source: Authors' elaboration based on data from the EU KLEMS, IFR, and World Bank databases.

Figure 4 Robot Adoption Versus the Displacement/Reinstatement Effect (Dispensing and Processing), 1997–2016



Source: Authors' elaboration based on data from the EU KLEMS, IFR, and World Bank databases.

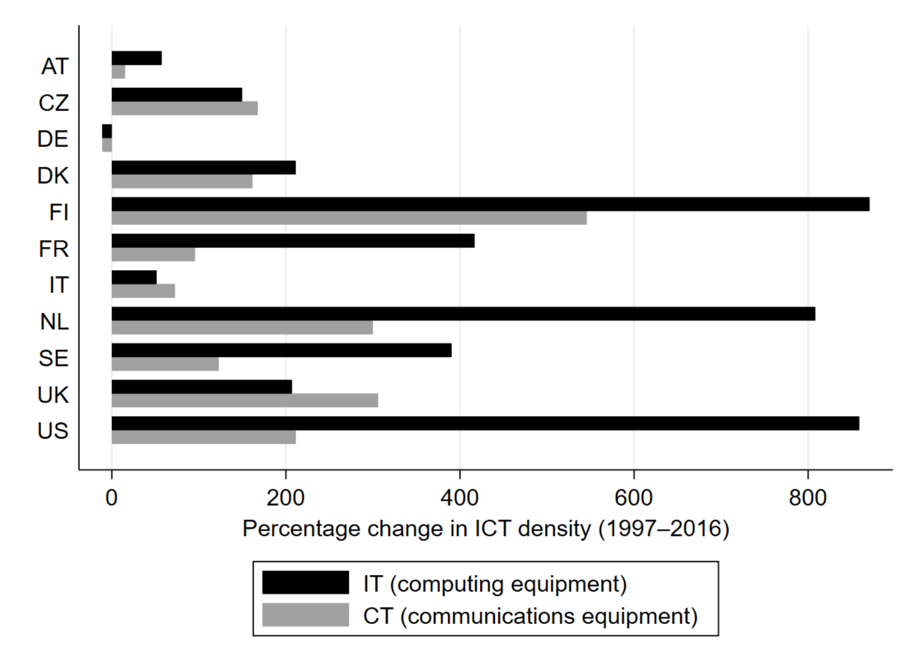
Figure 5 Robot Adoption Versus the Displacement/Reinstatement Effect (Assembling and Unspecified), 1997–2016



Source: Authors' elaboration based on data from the EU KLEMS, IFR, and World Bank databases.

Industrial robots seemed to be a good predictor of the strength of the displacement effect, while their adoption did not correlate with the reinstatement effect. The reinstatement effect is driven by technologies that create new tasks in which labor has a comparative advantage. Unlike in the case of automation technologies, Acemoglu and Restrepo (2019) did not propose or test a proxy variable for technologies that create new tasks in which labor has a comparative advantage. They only tested whether the reinstatement effect was associated with proxies for new tasks. As it is not clear which technologies create new tasks in which labor has a comparative advantage, the adoption of ICT has been chosen as a possible proxy variable for these technologies. Automation technologies, by definition, replace labor, but this is not the case with ICT. Rather, it seems that ICT can both substitute for and complement labor, depending on the type of technology (Jung et al., 2020). Therefore, the relationship between the displacement/reinstatement effect and ICT adoption was analyzed. In the EU KLEMS database, ICT refers to computing and communications equipment.

Figure 6 ICT Adoption in EU-10 Countries and the United States

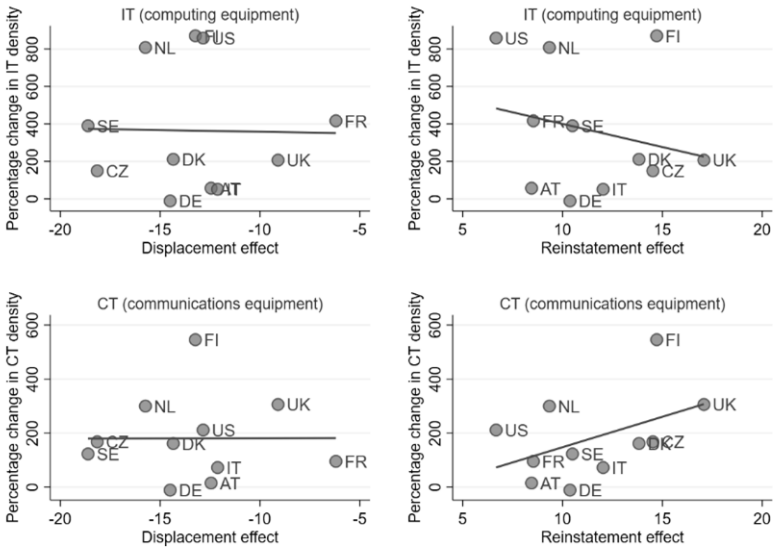


Source: Authors' elaboration based on data from the EU KLEMS database.

As in the case of robot adoption, there was also significant heterogeneity in ICT adoption across the EU-10 countries and the United States (Figure 6). The highest increases in IT density occurred in Finland, the United States, and the Netherlands, and the lowest increases were identified for Germany, Austria, and Italy. Similarly, in the case of CT adoption, Finland, the United Kingdom, and the Netherlands were the top adopters, while Germany, Austria, and Italy were identified as the lowest adopters of these technologies over 1997–2016. Germany is a special case where both IT and CT densities decreased during the analyzed period.

As the left panels of Figure 7 show, there is no link between ICT adoption and the displacement effect. In the case of both IT and CT, the value of the correlation coefficients were close to zero. Turning our attention to the reinstatement effect, the bottom-right panel of Figure 7 suggests a positive relationship between CT adoption and the strength of the reinstatement effect but the regression coefficient in Table 2 is low and insignificant. Our later robustness checks also rejected the seemingly positive effect of CT adoption on reinstatement effects.

Figure 7 ICT Adoption Versus the Displacement/Reinstatement Effect, 1997–2016



Source: Authors' elaboration based on data from the EU KLEMS and World Bank databases.

Table 2 Potential Drivers of Cross-Country Heterogeneity in the Strength of the Displacement and Reinstatement Effects between 1997 and 2016

Potential drivers	*Displacement effect*			*Reinstatement effect*		
	Coef.	*Std. Err.*	R^2	*Coef.*	*Std. Err.*	R^2
Robots (all applications)	-3.396**	(1.283)	0.438	-0.129	(1.531)	0.001
Handling/tending robots	-4.317	(2.379)	0.268	-0.241	(2.487)	0.001
Welding and soldering robots	-10.11**	(3.845)	0.434	0.842	(4.568)	0.004
Dispensing robots	-36.68	(28.73)	0.153	3.037	(27.93)	0.001
Processing robots	-56.13**	(19.36)	0.483	4.838	(24.05)	0.004
Assembling robots	-9.074	(14.39)	0.042	-4.243	(13.08)	0.012
Unspecified robots	-3.377	(9.227)	0.015	1.162	(8.312)	0.002
IT	-0.000206	(0.00358)	0.000	-0.00229	(0.00312)	0.057
CT	7.82e-05	(0.00760)	0.000	0.00939	(0.00604)	0.212
Avg. manufacturing share	-0.447*	(0.215)	0.325	0.133	(0.230)	0.036
Avg. automotive share	-1.114	(0.847)	0.161	-0.105	(0.827)	0.002
Avg. trade union density	-0.0572	(0.0445)	0.155	0.0503	(0.0400)	0.150

Source: Authors' elaboration based on data from the EU KLEMS, IFR, OECD, and World Bank databases.

Notes: The OECD database does not contain information on trade union density for 1997 and therefore the average was calculated for 1998–2016. In the case of robots (industrial robots) and ICT, the explanatory variable is the change in their density between 1997 and 2016. *** p<0.01, ** p<0.05, * p<0.1.

Table 2 provides evidence on the potential drivers of cross-country heterogeneity in the strength of the displacement and reinstatement effects in a cross-section setting that spans the cumulative effects over 1997–2016. It presents the results of a simple regression analysis in which the displacement and reinstatement effects were consecutively regressed on each of the potential drivers. In addition to those drivers analyzed graphically, the last three rows of the table examine the role of three other potential drivers. The reason for including the average shares of the manufacturing and automotive sectors in the analysis is that the manufacturing sector is almost the exclusive user of industrial robots. The intuition behind the inclusion of the strength of trade unions is that different labor market institutions might play an important role in explaining the observed differences. The results of this analysis showed that none of the potential drivers were statistically significantly associated with the reinstatement effect. In the case of the displacement effect, the second column of the table documents that the analyzed relationship was statistically significant only for robots with all applications, robots for welding and soldering, robots for processing, and the size of the manufacturing sector.

These results suggest that different applications of robots may have different effects on workers. Some applications replace workers "more effectively" than others do. To provide more robust evidence, potential confounding factors have to be taken into account. However, it would be inconclusive to conduct a multiple regression analysis on such small sample of countries. While controlling for other potential drivers, the effect of different robot applications on displacement/reinstatement was analyzed in a yearly panel data setting.

5.2 Panel Data Analysis

Table 3 presents the relationship between robot density by application and the displacement effect. In the main specification, we controlled for the effects of IT density, CT density, manufacturing share, and trade union density. Unobserved heterogeneity is captured by country and time fixed effects. Yearly changes in the displacement effect were found to be significantly associated with the density of robots for welding/soldering and robots for dispensing. The evidence provided in this table showed that the effects of welding/soldering and dispensing robots were different from those from other controls. These effects were analysed in a more detail and for various specifications and the results are presented in Tables 4 and 5. The density of other types of robots was not significantly related to changes in displacement.

The results show that the effect of welding/soldering and dispensing robots on displacement was different from the effect of IT and remained statistically significant after controlling for it, while CT density was not significantly related to displacement. These results suggest that the effects of ICT on labor replacement identified in the literature could have been driven primarily by IT technologies. There is weak evidence of a negative effect from trade unions on displacement, which indicates that the link among trade unions, labor costs, and displacement may have played a role. Stronger trade unions have the potential to increase labor costs above competitive levels and indirectly accelerate the motivation to replace workers. In this way, trade union density can be related to the size of the displacement effect and the speed of robot adoption. Controlling for trade unions in the multivariate regression enables us to partial out their effect on displacement. The sign of the coefficient on trade union density was negative, as expected, and statistically significant in the baseline specifications with welding/soldering and processing robots. The share of the manufacturing sector did not play a statistically significant role. This may seem rather surprising (given the evidence in Table 2), but it can be explained by the fact that structural changes require time to reveal their impacts. The variability in manufacturing shares after controlling for country and time fixed effects remained relatively small, as did its potential explanatory power. In this respect, we find the significant effects of welding/soldering and dispensing robots on displacement to be important. They document that welding/soldering and dispensing robots played an important role in replacing labor.

Table 3 Impact of Different Robot Types on the Displacement Effect: Baseline Model

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Robot density: handling/tending	-0.194				
	(0.508)				
Robot density: welding/soldering		-0.793**			
		(0.336)			
Robot density: dispensing			-8.029**		
			(2.970)		
Robot density: processing				0.481	
				(5.440)	
Robot density: assembling					1.339
					(1.204)
IT density	-0.411**	-0.422**	-0.441**	-0.409*	-0.373*
	(0.137)	(0.184)	(0.166)	(0.218)	(0.193)
CT density	0.0791	0.132	0.0128	0.0637	0.0745
	(0.133)	(0.148)	(0.130)	(0.153)	(0.166)
Manufacturing share	0.00263	0.00739	0.0357	0.00684	-0.0386
	(0.0380)	(0.0297)	(0.0286)	(0.0354)	(0.0499)
Trade union density	-0.0230	-0.0241*	-0.0269**	-0.0315	-0.0258
	(0.0166)	(0.0126)	(0.0113)	(0.0264)	(0.0142)
Country fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	199	198	198	199	194
Adjusted R^2	0.453	0.472	0.490	0.498	0.467

Source: Authors' elaboration based on data from the EU KLEMS, IFR, OECD, and World Bank databases.

Notes: Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 Impact of (Welding and Soldering) Robot Adoption on the Displacement Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot density	-0.635	-0.672*	-0.637	-0.667*	-0.688*	-0.719*	-0.785*	-0.793**
	(0.360)	(0.352)	(0.361)	(0.354)	(0.374)	(0.334)	(0.371)	(0.336)
IT density		-0.340		-0.409**				-0.422**
		(0.194)		(0.174)				(0.184)
CT density			-0.0257	0.157				0.132
			(0.150)	(0.167)				(0.148)
Manufacturing share					0.0155		0.0187	0.00739
					(0.0245)		(0.0295)	(0.0297)
Trade union density						-0.0206	-0.0213	-0.0241*
						(0.0150)	(0.0160)	(0.0126)
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	198	198	198	198	198	198	198	198
Adjusted R^2	0.426	0.457	0.423	0.460	0.425	0.436	0.435	0.472

Source: Authors' elaboration based on data from the EU KLEMS, IFR, OECD, and World Bank databases.
Notes: Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5 Impact of (Dispensing) Robot Adoption on the Displacement Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot density	-3.951	-5.803*	-4.923	-5.580*	-6.174**	-4.246*	-6.777**	-8.029**
	(2.221)	(2.705)	(2.756)	(2.901)	(2.562)	(2.251)	(2.599)	(2.970)
IT density		-0.416**		-0.431**				-0.441**
		(0.146)		(0.148)				(0.166)
CT density			-0.136	0.0404				0.0128
			(0.162)	(0.160)				(0.130)
Manufacturing share					0.0442*		0.0497	0.0357
					(0.0220)		(0.0285)	(0.0286)
Trade union density						-0.0192	-0.0213	-0.0269**
						(0.0140)	(0.0151)	(0.0113)
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	198	198	198	198	198	198	198	198
Adjusted R^2	0.426	0.472	0.428	0.469	0.433	0.435	0.444	0.490

Source: Authors' elaboration based on data from the EU KLEMS, IFR, OECD, and World Bank databases.
Notes: Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Tables 4 and 5 present different specifications for welding/soldering and dispensing robots. Unconditional relationships between welding/soldering and dispensing robots and displacement (the first columns in Tables 4 and 5) were significant slightly above a 10% threshold (p-values equal to 0.108 for welding/soldering robot density and 0.106 for dispensing robots). Omitted factors can bias the parameter estimates for robot density as discussed above and in the related literature. Their inclusion can eliminate such bias and increase the precision of estimates. Therefore, we tested the effects of robot density on displacement in several other specifications (columns 2 to 8). For example, to obtain unbiased estimates for the effects of robots on displacement, it is important to control for trade unions because they can be confounded with both displacement and robot adoption. The effect of robots on displacement became stronger and more significant after controlling for trade unions in comparison with univariate regression (columns 6 to 8 in Tables 4 and 5 in comparison with the results in the first column). With the exception of CT density, the other controls operated in the same way. Even though the other controls were not always statistically significant, controlling for them explained some part of the observed displacement heterogeneity that was not captured by country and time fixed effects and mitigated omitted variable bias. Tables 4 and 5 show that our results are not sensitive to various specifications. We provide some other robustness checks in the following section.

5.3 Robustness Checks

First, the relationship between displacement and robot density by application in 3-year panels was analysed. The relatively short period of time under investigation prevented analysis for longer spans such as 5-year panels. Table 6 shows the results. The results were not sensitive to movement from yearly panel data to 3-year panels. There was a significant association between welding/soldering and dispensing robots and the displacement effect, while the relationships between other types of robots and the displacement effect were insignificant. IT density was significantly related to the displacement effect.

Second, the analysis was conducted with cumulative displacement effects as the dependent variable, in contrast to yearly changes in the displacement effects in previous specifications. Table 7 reports the results from regressions with and without a time trend. The outcome from these specifications confirmed the significant effect of welding/soldering and dispensing robots on the displacement effect. The only exception was the effect for dispensing robots in a regression with a time trend, where the coefficient had the expected magnitude and sign but the higher standard error made the coefficient insignificant. The effects of other types of robots were significantly related to the displacement effect in regressions without a time trend (except for processing robots), but their effects were not related to the displacement effect when controlling for time trends. In these models, controlling for time trends was not sufficient to reject the hypothesis of non-stationary residuals by Im–Pesaran–Shin and Fisher-type tests for unbalanced panel data unit-root tests. Therefore, the results based on yearly changes in the displacement effect are preferable.

Finally, to provide more robust evidence of the role played by welding/soldering and dispensing robots in displacement, IT and CT were expressed in the form of their shares in total assets. Tables 8 and 9 report the results from these specifications. The effects of welding/soldering and dispensing robots remained significantly related to the displacement effect, providing further evidence of the robustness of our baseline results.

6. Conclusions

The literature has documented a significant heterogeneity in the change in the task content of production and the strength of automation and the creation of new tasks across European countries and the United States. By creating a displacement effect, automation shifts the task content of production against labor, while the introduction of new tasks in which labor has a comparative advantage increases labor demand via the reinstatement effect. To address the observed cross-country heterogeneity, this paper provided detailed evidence on the role played by the adoption of industrial robots by application type and other potential drivers. This was motivated by the fact that different applications of robots may impact workers differently and by the documented heterogeneity in the adoption of different types of robots across countries. The paper distinguishes five broad categories of robot applications and confirmed significant differences in their impacts on the displacement effect. We documented that some robots played a more important role in the replacement of workers than others did. This was especially true for welding, soldering, and dispensing robots. Moreover, these effects were different from the displacement effects of ICT and other potential drivers. However, it remains a puzzle to explain the cross-country heterogeneity in the reinstatement effect. None of our controls, including robots by application, IT and CT, manufacturing shares, and trade unions, could explain the observed differences. The cross-section relationship between CT and the reinstatement effect did not persist in the robustness checks and seems to be unpersuasive.

We documented that industrial robots played a significant role in the displacement of workers, but these effects differed across the robot types. As is usually the case, the success or failure of policies depends on the details. Therefore, industrial policy that aims to address the impact of automation and industrial robots on labor demand should take this documented heterogeneity into account and adjust its measures accordingly.

APPENDIX

Table 6 Impact of Different Robot Types on the Displacement Effect: 3-Year Panel

	(1)	(2)	(3)	(4)	(5)
Robot density: handling/tending	-1.159				
	(1.402)				
Robot density: welding/soldering		-1.595*			
		(0.873)			
Robot density: dispensing			-19.07**		
			(8.493)		
Robot density: processing				3.439	
				(14.35)	
Robot density: assembling					-0.0845
					(3.300)
IT density	-1.298**	-1.435**	-1.406**	-1.486**	-1.409**
	(0.446)	(0.604)	(0.582)	(0.593)	(0.580)
CT density	0.353	0.673	0.361	0.609	0.609
	(0.484)	(0.511)	(0.448)	(0.503)	(0.489)
Manufacturing share	0.125	0.0909	0.166*	0.0459	0.0582
	(0.0954)	(0.0713)	(0.0814)	(0.0974)	(0.122)
Trade union density	-0.0183	-0.00680	-0.0120	0.00332	-0.00476
	(0.0315)	(0.0315)	(0.0336)	(0.0487)	(0.0296)
Country fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	63	62	62	62	62
Adjusted R^2	0.285	0.284	0.322	0.268	0.264

Source: Authors' elaboration based on data from the EU KLEMS, IFR, OECD, and World Bank databases.
Notes: Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7 Impact of Different Robot Types on the Displacement Effect: Cumulative Effects

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
RD: handling/tending	-7.768***	-1.220								
	(0.671)	(1.194)								
RD: welding/soldering			-8.705**	-3.723***						
			(3.025)	(0.863)						
RD: dispensing					-68.80***	-11.50				
					(20.40)	(11.01)				
RD: processing							-6.418	-1.639		
							(15.29)	(2.395)		
RD: assembling									-22.70**	2.314
									(8.916)	(3.015)
IT density	-0.839	-1.102	-1.668	-1.057	-1.578	-1.188	-1.765	-0.944	-1.970*	-0.719
	(0.666)	(1.352)	(1.863)	(1.470)	(1.470)	(1.314)	(2.086)	(1.449)	(1.035)	(1.334)
CT density	-3.303***	-0.859	-2.285*	-0.874	-3.247***	-0.882	-2.601	-0.894	-2.153*	-0.805
	(0.867)	(1.632)	(1.252)	(1.510)	(0.912)	(1.596)	(1.713)	(1.626)	(1.069)	(1.515)
Manufacturing share	-0.000837	-0.291**	0.108	-0.338**	0.151	-0.308**	0.0822	-0.312**	0.207	-0.336**
	(0.0846)	(0.120)	(0.160)	(0.112)	(0.160)	(0.110)	(0.180)	(0.106)	(0.137)	(0.114)
Trade union density	0.120	-0.0149	0.372*	-0.00269	0.288	-0.00876	0.455**	0.00239	0.373**	0.0149
	(0.0858)	(0.121)	(0.200)	(0.109)	(0.160)	(0.126)	(0.192)	(0.105)	(0.145)	(0.122)
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	199	199	198	198	198	198	199	199	194	194
Adjusted R^2	0.917	0.966	0.773	0.969	0.810	0.966	0.726	0.967	0.830	0.966

Source: Authors' elaboration based on data from the EU KLEMS, IFR, OECD, and World Bank databases.

Notes: RD stands for robot density; robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8 Impact of (Welding and Soldering) Robot Adoption on the Displacement Effect: ICT Shares

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Robot density	-0.635	-0.808**	-0.618	-0.849**	-0.688*	-0.719*	-0.785*	-1.128**
	(0.360)	(0.328)	(0.376)	(0.340)	(0.374)	(0.334)	(0.371)	(0.480)
IT share		0.662		0.916				1.121*
		(0.431)		(0.508)				(0.565)
CT share			-0.438	-0.665**				-0.449
			(0.389)	(0.291)				(0.374)
Manufacturing share					0.0155		0.0187	0.0353
					(0.0245)		(0.0295)	(0.0346)
Trade union density						-0.0206	-0.0213	-0.0243
						(0.0150)	(0.0160)	(0.0160)
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	198	198	198	198	198	198	198	198
Adjusted R^2	0.426	0.442	0.436	0.466	0.425	0.436	0.435	0.479

Source: Authors' elaboration based on data from the EU KLEMS, IFR, OECD, and World Bank databases.

Notes: Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9 Impact of (Dispensing) Robot Adoption on the Displacement Effect: ICT Shares

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Robot density	-3.951	-3.770*	-3.810	-3.480*	-6.174**	-4.246*	-6.777**	-6.717*
	(2.221)	(1.915)	(2.507)	(1.891)	(2.562)	(2.251)	(2.599)	(3.156)
IT share		0.455		0.683				0.830
		(0.443)		(0.511)				(0.516)
CT share			-0.433	-0.608*				-0.343
			(0.389)	(0.331)				(0.437)
Manufacturing share					0.0442*		0.0497	0.0571
					(0.0220)		(0.0285)	(0.0431)
Trade union density						-0.0192	-0.0213	-0.0220
						(0.0140)	(0.0151)	(0.0169)
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	198	198	198	198	198	198	198	198
Adjusted R^2	0.426	0.433	0.436	0.452	0.433	0.435	0.444	0.468

Source: Authors' elaboration based on data from the EU KLEMS, IFR, OECD, and World Bank databases.

Notes: Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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