Robot, Trade and Employment: unravelling the relationship

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Abstract

Our paper deals with the impact of robot adoption diffusing through global value chain (GVC) relationships on the employment dynamics within the European context. We empirically contributes to the literature investigating the broader effects of robot adoption, departing from previous bilateral case studies and providing insights into employment dynamics in a trade-integrated European context. We concentrate on the top five European economies as robot adopters over the period from 1995 to 2018 and develop a composite indicator that captures both the penetration of industrial robots within these economies and the export reliance of other European nations on them. Our findings show a positive association between top five robot adoption and employment outcomes, suggesting the prevalence of a productivity effect within the highly integrated European market, pulled by lower income countries.

Keywords: robot; trade; employment; GVCs
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1 Introduction

The issue dealing with the role of new technologies in generating impact on the labour market has always been a focal point in economic and public discussions. The concept of "technological unemployment" often takes centre stage when we experience significant technological advancements (Keynes, 1930). The resurgence of this debate is evident due to recent progress in artificial intelligence, robotics, and related innovations.

In this paper, we focus our attention on the role of industrial robots, a crucial technological transformation that has characterized the latest wave of industrial revolution. One of the key and most investigated area of research is the one about the influence of robot adoption on employment dynamics of adopting countries. From a theoretical point of view, as discussed by Aghion et al. (2022), the adoption of robots can lead to two opposing effects. On one side, productivity could rise, resulting in increased labour demand and higher wages. Conversely, we could observe displacement effects due to the substitution of labour with machines: this effect could partially be more relevant for low-skilled labour. The empirical analyses on this topic reveal quite a high heterogeneity in results, which is also due to the different levels of analysis. Nevertheless, a still not wide literature has started to investigate whether the robot adoption can have effects also on countries that are connected through trade or Global Value Chain (GVC) relationships. It supports the idea that effects of robot adoption may not be confined to the country itself but rather can expand abroad through following the lines of trade relationships. The channels that are at work to produce the finale effect are always two: firstly, robot adoption can enhance the competitiveness of adopters, mainly in the form of lower costs, resulting in the domestic sourcing of certain products that were previously imported from less developed countries. It means that production (or part of production) abroad may be substituted with production at home Rodrik (2018), possibly generating a decrease in demand of low skilled labor that were previously the bulk of demand in developing countries. Secondly, robotization may also expand production scale, leading to greater demand for input sources, especially intermediates, from abroad (Baur et al., 2022). Conversely, this should act as a boost to local employment dynamics. Moreover, less developed or emerging countries have also begun introducing industrial robots into their economies in recent years, further complicating the overall picture Díaz Pavez and Martínez-Zarzoso (2023).
Recently, just one attempt to put together the two perspectives have been carried out with respect to Germany by Graf and Mohamed (2024), finding a positive relationship between robot adoption in Germany and employment content of its imports. Still, a comprehensive analysis on the overall European context is missing.

In this paper, our first contribution is to develop an innovative measure of robots diffusion trough GVC relationships. Specifically, we investigate the influence of robot adoption on various employment components by weighting automation adoption through a measure of trade relationship. We develop a comprehensive indicator that can concurrently assess the level of industrial robot penetration in the five major European economies (France, Germany, Italy, Spain and the UK) and the extent to which other European nations export to these five top countries. Using this novel indicator, we investigate the indirect impact of robot adoption, estimating the effects of robot investments in the top 5 European economies on the employment of other European countries and quantifying the domestic employment exposure to foreign robot investments. Secondly, our research approach differs from previous studies that primarily focused on specific bilateral cases (see, for example, Faber 2020), but rather, while prior authors often emphasized the analysis of the effects occurring between developed and developing countries, our research provides new insights into the European context, an economically integrated system involving only developed nations. As a third contribution, we also provide evidence of a direct channel through which domestic robot investments impact on employment dynamics by analyzing the effects of variation in the number of robot operational stocks, weighted by the number of employees, within each specific country-sector. This approach allows us to investigate how introducing robots in smaller countries influences their employment.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on the impact of robotization on employment within and outside the adopting country. Section 3 describes the data we use in our empirical analysis and the construction of our novel indicator. Section 4 and 5 provides our main econometric elaborations and further analyses. Finally, in section 6, we discuss our findings and we offer some conclusive remarks.

2 Literature

2.1 Robot and Employment

The role industrial robots may play in affecting employment has been empirically analyzed at different levels, by making use of data on countries, sectors and firms. The heterogeneity of the results is displayed in two recent literature reviews (refer to Filippi et al. 2023 and Reljic et al. 2023), in which it is explained how the specific circumstances, research methods, and the types of industries and regions studied can greatly affect the findings in these investigations. These divergent outcomes highlight the complexity of the relationship between industrial robot adoption and employment dynamics. As Fernandez-Macias et al. (2021) explain in their descriptive work, the potential to be a disruptive technology seems not so relevant in Europe, except in a few sectors, but still this impact needs to be carefully evaluated.

Indeed, most of the research conducted at the country-sectoral or regional level in various countries has generated mixed results regarding the overall impact on aggregate employment. In their seminal work on the European labour markets, utilizing a sectoral approach, Graetz and Michaels (2018) observe no notable connections between the adoption of industrial robots and overall employment levels even though observing a decline in the share of low-skilled labour. Klenert et al. (2023) reveals distinct findings for Europe as their work does not yield significant evidence concerning the reduced share of low-skilled workers and evidencing a positive association between total employment and robot adoption[1]. In contrast, Acemoglu and Restrepo's 2020 study on the United States adopts a different approach, concentrating on the local labor market as the unit of analysis. Their results indicate that an additional robot per thousand workers corresponds to a decline of 0.39 percentage points in the local employment-to-population ratio.

Some works, instead, adopts a country perspective also giving more emphasis on the impact on workers: Dauth et al. (2021) using administrative data set show that in Germany, exposure to robots results in displacement effects within the manufacturing sector. However, these job losses are completely compensated for by the creation of new jobs in the service industry. Furthermore, the study indicates that robotization leads to the emergence of new roles and responsibilities for workers within their original manufacturing plants. Dottori (2021) explore the case of Italy finding that does not have a negative impact on overall employment. Nevertheless, it is worth noting that the spreading of industrial robots in Italy has reduced the likelihood of new workers entering the manufacturing sector.

At the firm level, several studies indicate a positive association between robot adoption and both productivity and employment levels. Koch et al. (2021), using a panel data set of Spanish manufacturing firms, show that an increase in the output is accompanied by a net increase in job creation at a rate of 10%. They also underline substantial job losses among companies that choose not to adopt robots, leading to a productive redistribution of labour from non-adopting firms to adopting ones. Focusing on French manufacturing firms, Domini et al. (2021) find similar evidence on employment dynamics that can be attributed to both an increased rate of hiring and a decreased rate of

[1] Anton et al. (2022) focus on Europe as well, but adopting a regional perspective highlighting two different patterns: during the initial analysis period from 1995 to 2005, they observed a negative association between robotization and European employment levels but this relationship evolved into a positive association in the following period from 2005 to 2015.

employee separations. In the UK a similar results as in Germany is detected by Kariel (2021) who evidence that jobs lost in manufacturing are recovered in services. However, not all firm level studies are unanimous in finding positive results: for example, analyzing the French case again, Acemoglu et al. (2020) illustrate that firms adopting robots experience a decrease in their labour share by 4 to 6.3 percentage points. Furthermore, the aggregate picture shows that the decline in labour share prevails over the job creation effects resulting from increased productivity. China is a specific case analyzed because of its massive and still increasing rate of adoption: Zhang et al. (2023) show a large positive effect on overall employment.

What all these papers have in common is that the impact of robots is examined considering that the process of adoption mainly generates impact within the country. Instead, in our interconnected world, to comprehend the intricacies of the relationship between robots and employment, it is fundamental to consider also whether the impact of robots can go beyond borders as a consequence of the fragmented production.

2.2 Robot and Employment: a relationship complicated by Trade

While the widespread adoption of industrial robots has primarily been observed in high-income countries, the effects of robotization extend far beyond national borders: the increasing fragmentation of production deploying through global value chains also cause robots to impact foreign countries. From a theoretical point of view, we can discern two primary channels through which robotization can impact employment dynamics through trade across different countries. The first pathway regards the transformation of relative production costs: automation adoption could reduce production costs for high-income nations, eroding the labour cost advantage traditionally held by less developed countries in the production of labour-intensive goods. Consequently, a phenomenon often referred to as "re-shoring" may emerge, involving the relocation of production units from developing countries to high-income nations. Naturally, this dynamic could reduce imports and negatively affect employment in less developed countries (Rodrik, 2018). On the other side, a contrasting trend may emerge as well: as robot adoption frequently leads to increased productivity, adopting firms often requires more intermediate inputs that can be sourced from third countries. A greater demand of intermediate inputs can generate a corresponding increase in imports from less developed countries, drawing great benefits also in terms of employment (Artuc et al., 2023).
This theoretical ambiguity reflects heterogeneity in the empirical results.

Adopting a macroeconomic approach to explore the presence of a reshoring effect Krenz et al. (2021) and Krenz and Strulik (2021) both find positive results in developed and emerging countries, but without estimating whether reshoring can cause a loss in employment from sourcing countries[2]. A step toward the understanding of the impact on employment dynamics is offered by Carbonero et al. (2020) who show that robot diffusion has caused a general reduction in global employment, especially concentrated in emerging economies. Specifically, focusing on cross-country effects, robot adoptions in high-income countries negatively affect developing countries' labour markets, suggesting

[2] Similarly, the paper by De Backer and DeStefano (2021) reveals that investments in robots reduce the need for offshoring from developed countries but without finding an emerging pattern of reshoring. The impact on employment dynamics is not examined as well.

a possible pattern of re-shoring. Nevertheless their approach is not built on a GVC measure of exposure to foreign robots but just as a trade-weighted average of robots from developed countries. Reinforcing the evidence on the reshoring channel is the paper by Gravina and Pappalardo (2022) who employ an approach similar to ours: they build an index accounting for the spreading of robots through GVC at the country-sector level, they points out that robotization in Europe negatively impacts emerging countries' employment share, especially for Asian economies. However, the index they use to capture robot exposure through GVC does not imply accounting for the demand in term of workers. Moreover they limit the analysis to a developed-developing countries framework, while we believe that examining the impact within Europe can possibly lead to different results due to the high interconnection of the European common market. In addition, a recent paper by Fontagné et al. (2023) further explores the relationship between technology adoption, GVC and labor. Their main finding reveal that, while robot adoption do not have a direct impact on labour share, they have, instead, an indirect effect altering the GVC position by increasing the degree of upstreamness of production tasks. This works puts into evidence that automation adoption and international production dynamics are strictly interrelated to explain employment dynamics.

Studies accounting for the case of emerging countries are developing as well: Díaz Pavez and Martínez-Zarzoso (2023) find that it is foreign exposure to robots that have negative impacts on employment and labour share rather than the amount of robots adopted locally. However, the foreign exposure measure does not use a GVC approach like ours. Different and contradicting results comes from studies at the firm level: for example, Stapleton and Webb (2020) investigate the consequences of automation in Spain on imports and multinational operations, including nations with lower income levels. Their findings reveal that companies adopting robots in Spain tend to increase both the value of imports from lower-income countries and the establishment of new affiliates in those regions. This result proves that the second channel identified can be at work as the integration of robotic technology positively influences the extensive margin of trade and multinational projects[3].

Further evidence, but rather confirming the first channel of the likely reshoring effect, comes from Faber (2020) who examines the impact of robot adoption in the US on employment dynamics in Mexico. The study confirms that an increasing rate of robot adoption in the United States leads to decreased employment opportunities in Mexico while simultaneously increasing the number of employees in the US. Stemmler (2019) for Brazil and Kugler et al. (2020) for Colombia find comparing results.

In conclusion, different studies report different part of the story about the linkage between the adoption of robots in a country (or groups of countries) and their impact on trade-connected countries. As the need to account for the high fragmentation of production that GVC have brought, giving a more precise measure of the likely effect of spreading of technology through trade linkage can become relevant for the final effect to occur. Still, due to the opposing theoretical effects implied in this relationship, the final outcome is an empirical matter.

[3]Still connected with the trade topic but conducting an analysis on the direct impact on export is the work by Alguacil et al. (2022) who demonstrated that in Spain, firms using robots experience a substantial increase in their probability of exporting, export sales and the proportion of exports in their overall output.

3 Data

This section provides a comprehensive overview of the data sources employed in this study and the original database we built based on them. Subsequently, we present a new indicator designed to simultaneously measure the level of industrial robot penetration in the five major European economies (France, Germany, Italy, Spain and the UK) and assess the extent to which other European nations rely on these top five economies for their exports.

3.1 Data Sources

In this work, we integrate various sources of data at the country-sectoral level.
One of our primary sources is the Trade in Employment (TiM) database provided by the OECD[4]. This database provides a collection of labour market indicators designed to clarify the complexities of global production networks and supply chains. Indeed, looking at the estimation of workers embodied in foreign final demand, we can estimate the extent to which a specific country-sector workforce depends on and integrates with foreign economies. All the indicators are developed starting from the 2021 OECD's Inter-Country Input-Output (ICIO) Tables[5]. In addition, recent estimates of employment and employees' compensation by industrial activity, taken from official sources, are integrated into the computation. The TiM database provides indicators for 45 individual industries, categorized according to the ISIC Rev.4 classification, across approximately 50 countries. The period spans from 1995 to 2018.

The second source, from which we extrapolate data on industrial robots, is the International Federation of Robotics (IFR) database. This dataset contains comprehensive information on industrial robot stocks at the country-sector level. The robots catalogued in this dataset fall within the definition established by the International Standards Organisation. According to this definition, a robot is characterized as "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment" (ISO, 2012)[6]. IFR offers annual statistics on the operational stock of industrial robots by country and industry, starting from 1993.

Lastly, to incorporate control variables into our econometric estimations, we extract indicators such as GDP, labour costs, fixed capital, hours worked and imports from China from the Database for Structural Analysis (STAN) developed by the OECD. These indicators are specific to the country-sector combinations under investigation, and economic sectors are classified based on the ISIC Rev.4 classification, like in the TiM database.

We need to properly merge the three datasets described above to conduct our analysis. Specifically, we focus on 23 European countries (in our work, Europe is defined by its geographical dimension rather than economic union) and 20 economic sectors. In

[4]The last version of the database is available at the following link: `https://stats.oecd.org/Index.aspx?DataSetCode=TIM_2021`

[5]see http://oe.cd/icio

[6]These machines are primarily tailored for functions such as material handling, machine tending, welding, soldering, assembly, and disassembly. The industries are classified following the International Standard Industrial Classification for all economic activities, reaching a three-digit level for manufacturing industries.

Table 1, we report a comprehensive list of the countries utilized in our analysis, while in Table A1 there are the selected IFR sectoral code and the corresponding ISIC code. To transition from the IFR sectoral code to the ISIC classification, we employ the conversion table outlined in Jurkat et al. (2022). By merging the three data sources, we obtain a unique panel database containing 11,040 observations covering a time-period from 1995 to 2018.

Table 1: List of European Countries included in our analysis

Selected Countries	Austria; Belgium; Bulgaria; Croatia; Czech Republic; Denmark; Estonia; Finland; Greece; Hungary; Ireland; Latvia; Lithuania; Netherlands; Norway; Poland; Romania; Slovakia; Slovenia; Sweden; Switzerland; Turkey
Top 5 Economies	France; Germany; Italy; Spain; United Kingdom

3.2 Top5 Robot Adoption and Export Dependence Index

One of the major innovations in this study is the introduction of the Top5 Robot Adoption and Export Dependence (TRAED) Index. As discussed extensively in the literature review, understanding the intricate interplay between robots, employment, and trade is a difficult task. While analyzing the separate relationships between robots and employment and robots and trade could simplify the analysis, it may also result in a fragmented perspective. Therefore, we have developed a novel indicator that serves a dual purpose: it quantifies the level of industrial robot penetration in the top five European economies while also evaluating the extent to which other European nations rely on these dominant economies for their export activities. Specifically, the latter dimension is assumed by looking at the share of domestic employment embodied in the foreign final demand of European Top 5 economies. For each economic sector i, country c and time t, the TRAED indicator is defined as follows:

$$\text{TRAED}_{c,i,t} = \log[(\frac{\text{FFD\_DEM\_Top5}_{c,i,1995}}{\sum_p \text{FFD\_DEM}_{c,i,p,1995}} \times \text{RD\_Top5}_{i,t}) + 1] \tag{1}$$

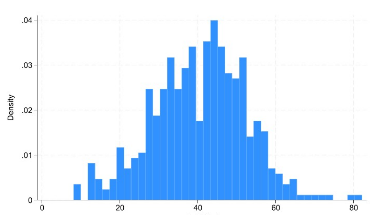
where:

- $\mathbf{FFD\_DEM\_Top5_{c,i,1995}}$: The Domestic Employment Embodied in Foreign Demand of Top 5 countries represents the number of persons (in thousands) in country c and industry i employed to meet the foreign final demand in the top five European economies in 1995. To build this measure, we have taken the sum of the workers of country c embodied in the foreign demand of Germany, France, Italy, Spain, and the UK ;
- $\mathbf{FFD\_DEM_{c,i,p,1995}}$: the Domestic Employment Embodied in Foreign Demand is the number of persons (in thousands) engaged in industry i in country c to fulfil final demand for goods and services in country p (set of all the countries commercially related to country c). It refers to 1995;

- **RD_Top5**: the robot density in the top five European economies is calculated as the number of robots per 1,000 workers.

The fraction $\frac{\text{FFD\_DEM\_Top5}_{c,i,1995}}{\sum_p \text{FFD\_DEM}_{c,i,p,1995}}$, within our equation, represents the weight assigned to each country; henceforth, we will refer to it as "Top 5 dependence". This variable quantifies the proportion of workers engaged in the production of final products for the top 5 European economies relative to the total workforce involved in export activities during the initial period. We keep the 1995 shares to avoid endogenous and serially correlated changes in the exposure variables. In line with Artuc et al. (2023), we add 1 within the logarithmic function to prevent issues with zero values. Panel A of Figure 1 displays the distribution of the Top5 dependence within our equation, illustrating the weights of all country-sector combinations. The mean value is 40.46, with a standard deviation of 12.09. Therefore, we have reason to believe that in such integrated labour markets, the adoption of robots by major economies may provoke significant effects on other European nations. In Panel B, we present the distribution of our TRAED index by country. The multiple plots reveal a remarkable degree of similarity in its distribution across European countries. Only a closer examination of the data reveals that Portugal's economic sectors exhibit the highest TRAED values, while Baltic and Scandinavian countries appear to have the lowest exposure.

Figure 1: Distribution of the Top5 dependence and the TRAED Index by country



(a) Panel A

(b) Panel B

However, the picture changes significantly when we shift our focus to the heterogeneity of distribution among economic sectors. As shown in Table A2 in the appendix, the TRAED index values display considerable variation among different economic sectors. For instance, sectors such as Motor vehicles, Rubber and plastics products, and products of wood and cork consistently exhibit the highest levels of the TRAED indicator on average. In contrast, sectors like Construction, Electricity services, coke manufacturing and refined petroleum products consistently have the lowest average values. This divergence primarily stems from differing levels of robot adoption across sectors. However, the wide range of values within each sector underscores the effectiveness of our indicator in quantifying economic dependence on France, Germany, Italy, Spain, and the UK by including a share of domestic employment embodied in exports.

3.3 Descriptive Analysis

This section presents some initial descriptive findings as a prelude to our econometric analysis. We begin by showing the mean and standard deviations of the key variables employed in our study, as depicted in Table 2. These statistics are provided for the whole sample, the initial year of observation and the last available period, allowing us to discern time patterns in the data. Remarkably, each variable exhibits a distinct trajectory over time. On the one hand, the TRAED index, the value-added deflator, the export workers' share, labour cost, and robot density all reveal upward trends. The substantial percentage increase in the TRAED index is particularly noteworthy, surpassing 70% during this period, keeping the Top 5 dependence variable constant. In parallel, we see a significant boost in the 23 Robot Density across the countries of our sample.
On the other hand, we observe a decrease in variables such as employment, and employment share. The reduction in total employment and employment share aligns with expectations, given our primary focus on the manufacturing sectors.

We then explore potential patterns associated with the development status to establish a connection between our paper and the existing literature. In Panel A of Figure 2, we present data on the GDP per capita of the 23 countries included in our analysis. While making a clear distinction between developed and developing countries in the European context is challenging, we can discern the presence of at least two major groups, which we will henceforth refer to as "high-income" and "low-income" countries.
Notably, when we examine the correlation between our TRAED index and changes in employment since 1995, we observe a contrasting relationship for these two groups (as shown in Figure 2, Panel B). Our initial findings suggest that adopting robots in the top 5 European Union countries positively impacts employment dynamics in less prosperous nations. In contrast, the effect on richest countries appears negligible or negative.
This preliminary result, which we further investigate in the econometric section, hints at the existence of a pattern linked to a country's income status. Importantly, it implies a direction contrary to what the majority of previous empirical literature has found. This divergence in dynamics is also apparent when we consider the correlation between the TRAED index and changes in the number of workers involved in exports (as shown in Figure A1).

Table 2: Descriptive Statistics

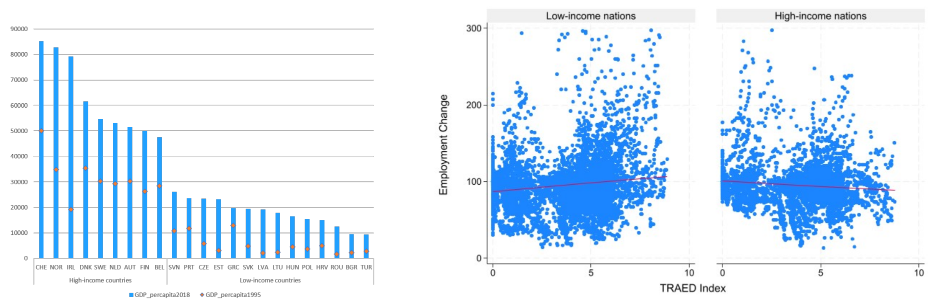
Variable	**Mean (Standard Deviations)**		
	Whole Sample	1995	2018
TRAED Index	3.893	2.819	4.813
	(2.205)	(2.214)	(1.921)
Robot Density	1.922	0.244	5.553
	(6.328)	(1.458)	(12.370)
Robot Installation	11.130	0.783	29.515
	(54.975)	(6.294)	(95.938)
Robot Stock	72.839	8.907	243.378
	(296.755)	(66.000)	(687.630)
Empl. Embodied in Foreign Demand	30.266	28.105	36.351
	(60.441)	(56.486)	(74.959)
Share of Export Workers	0.507	0.444	0.576
	(0.227)	(0.220)	(0.222)
Labour Cost	25.339	15.318	35.808
	(23.987)	(14.171)	(24.133)
Employment	97.974	108.672	94.478
	(344.787)	(420.217)	(310.299)
Value Added Deflator	93.857	88.705	106.237
	(52.478)	(137.872)	(27.433)
Share of Employment	1.817	2.104	1.564
	(3.025)	(3.626)	(2.323)
Observations[7]	11.040	240	240

As the final aspect of our descriptive analysis, we analyze the connection between our robot-related metrics and the variables of interest at the sectoral level throughout the analyzed period. Initially, we aggregate our data at the sectoral level, incorporating all 23 European countries in our study into a single comprehensive geographical unit. To achieve this, we take sum of the various robot-related metrics, the employment variable, and the number of workers involved in exports. Subsequently, we reconstruct our TRAED index by computing a weighted average of the Top 5 dependence, factoring in the workforce composition of each sector.
In Figure 3, we illustrate the correlation between the TRAED Index and changes in employment compared to 1995. Although we encounter some divergent results, such as in the Electrical Equipment sector, there is a clear overall positive association between the robotization of the top 5 countries and the employment trends in the other European nations. The same positive relationship is also observable in the context of the correlation between the TRAED Index and changes in Export Workers (as depicted in Figure A2). In the appendix, we also present scatter plots illustrating the association between the domestic robot density of the 23 countries and changes in employment and export workers. This analysis displays a positive relationship, suggesting a more pro-

[7]The total observations for Value Added Deflator and Labour Cost are 7.999

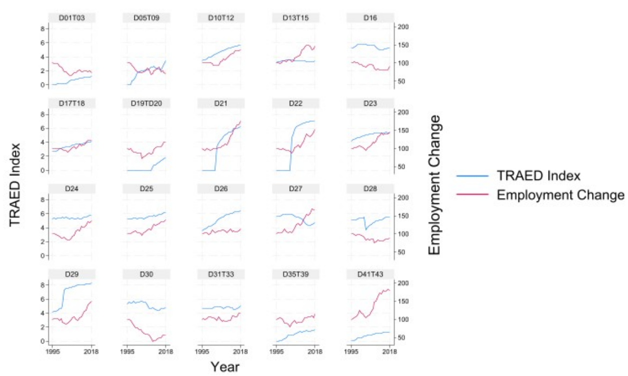
nounced productivity-enhancing effect than a displacement effects at the European level (see Figure A3).

Figure 2: Division by GDP per capita and correlation between the TRAED Index and Employment change by macro-groups



(a) Panel A **(b)** Panel B

Figure 3: Correlation between the TRAED Index and the Employment Change by sector



4 Econometric analysis

In this chapter, we report the main regression analysis to study the relationships between top 5 European countries robot adoption and change in employment outcomes.

Our baseline model for estimating the impact of the Top 5 robot adoptions on the labour outcomes in other European countries is as follows:

$$Y_{ict} = \alpha + \beta TI_{ict} + \gamma X_{ict} + \lambda_c + \delta_i + \eta_t + \epsilon_{ict}$$

where Y is the dependent variable (employment change and export workers change). In our baseline model, we normalize the initial year's dependent variable to a scale of 100, after which we calculate the annual changes for each subsequent year. TI is our TRAED index, as specified in the previous section. Then, X is a vector of covariates (value added, cost of labour), while λ_c, δ_i and η_t denote, respectively, country, sector and year fixed effects[8].

When examining the relationship between the TRAED index and the change in total employment relative to 1995, we observe positive associations using both the OLS and the FE estimators (col 1-4). This results stands for the fact that, as found in previous literature, the robot adoption in the Top 5 generates an increase in the employment of countries that are in trade relationship with them. It means that the employment content is affected by the augmented Top 5 productivity. However, due to the strong integration among European nations, these benchmark results may be affect by endogeneity as the decision to adopt industrial robots in the top 5 countries could be significantly influenced by the labour market conditions in the other 23 nations resulting in the TRAED index to be endogenous. Therefore, following the approach of Acemoglu and Restrepo (2020), we employ an Instrument Variable (IV) approach, using the robot density in Japan as an instrument for the TRAED index. The rationale behind this instrument is to identify a country ahead of the top 5 European nations in robot adoption, thus isolating the source of variation resulting from global technological advances[9]. Furthermore, despite their close technological ties, the commercial relationships between Japan and Europe are relatively minimal. Consequently, we can reasonably assume that this instrument is not correlated with unobserved European labour market conditions that could influence our dependent variables.

In all the specifications, we observe a positive and statistically significant correlation between the TRAED index and the change in total employment relative to 1995. Referring to Table 3, the magnitudes are reasonably consistent across all the specifications, and the instrumental approach appears to validate the robustness of our findings[10]. In columns (4) and (6), we can interpret these results as indicating that a one percent increase in our TRAED index, on average, leads to a 0.04 percentage point increase in employment compared to the year 1995. Regarding the control variables, the VA deflator is positively associated with the change in employment, although the effect is minimal in magnitude.

[8] In a robustness check, we have also included a control variable for imports from China within the Top5 sectors and a variable capturing the inward multinational activity as the change in the number of enterprises under foreign control. The results remain consistent with those of our baseline model.

[9] In Figure A4, we present the time trend of the operational robot stock for Japan and the top 5 European countries.

[10] In Table A3, we report the first stage IV regressions

Table 3: Dependent var: Change in Total Employment

	OLS		FE		IV	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TRAED Index	2.466**	4.565***	4.024***	4.033***	3.318***	4.193**
	(0.991)	(1.249)	(1.114)	(1.321)	(0.946)	(1.905)
Value Added Deflator		0.0753*		0.0855*		0.0752*
		(0.0410)		(0.0490)		(0.0414)
Labour Cost		0.315		0.944**		0.315
		(0.254)		(0.455)		(0.245)
Constant	96.09***	64.67***	93.62***	81.84***	94.74***	64.62***
	(1.426)	(9.936)	(3.511)	(7.226)	(1.536)	(11.45)
Observations	11,040	7,999	11,040	7,999	11,040	7,999
R-squared	0.060	0.412	0.097	0.130	0.056	0.412
Sector/Country FE		YES	YES	YES		YES
Kleibergen-Paap F-statistics					122.283	95.379

Notes: Standard errors in parentheses are clustered at the country-industry level. Year dummies included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

We then proceed to assess the influence of the TRAED index on various indicators of changes in workers embodied in exports. As shown in Table 4, all our model specifications reveal a positive and statistically significant relationship. Our IV specification consistently reinforces these findings, displaying results close to the fixed effects (FE) specification. When focusing on the overall change in workers embodied in exports, we observe that, on average, a one percent increase in the TRAED index results in approximately a 0.12 percentage point increase in workers embodied in exports relative to the first observed year. Comparing employment embodied in exports of final and intermediate products, we identify positive and significant relationships with the TRAED Index in both cases. However, the notable increase in employment is exceptionally high in the case of employment embodied in exports of intermediate products, suggesting a rise in demand for this specific product category.

Table 4: Dependent var: Change in Exports Workers

	Work. embodied in Exp.			*Work. embodied in Interm. Input*			*Work. embodied in Final Input*		
Variables	(OLS)	(FE)	(IV)	(OLS)	(FE)	(IV)	(OLS)	(FE)	(IV)
TRAED Index	11.92***	11.94***	12.34***	17.70***	19.10***	21.27***	12.95***	13.48***	11.52***
	(2.81)	(2.99)	(4.07)	(3.97)	(4.89)	(5.05)	(3.11)	(3.39)	(4.46)
Constant	74.65***	71.79***	55.15***	3.23	52.75*	13.32	47.09	84.60***	43.50
	(11.81)	(11.66)	(16.73)	(67.90)	(30.72)	(56.12)	(39.91)	(16.38)	(37.80)
Observations	7,999	7,999	7,999	7,975	7,975	7,975	7,975	7,975	7,975
R-squared	0.267	0.141	0.275	0.283	0.082	0.283	0.287	0.091	0.287
Kleibergen-Paap F-stat.			95.324			95.317			95.317

Notes: Standard errors in parentheses are clustered at the country-industry level. Year, sector and country fixed effects included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

In conclusion, when considering the indirect effects of robots at the European level, we observe a positive impact on several employment outcomes. This positive association suggests that the productivity-enhancing effect tends to outweigh the reshoring effect within such an integrated economic market. In addition, highly robotized sectors may be less vulnerable to competition from developing countries outside Europe, primarily due to the absence of competitive advantage in labour costs[11]. This phenomenon could stimulate a dynamic connected to increased intra-European trade.

Subsequently, we aim to discern distinct patterns associated with the development status of the countries under examination. Typically, the prevailing approach in the literature is to investigate the influence of robotization in highly developed countries on less developed commercial partners. In our study, we classify the 23 European countries in our sample into two groups based on their GDP per capita levels, as previously shown in Figure 2 (panel A).

Our baseline model yields contrasting results for these two groups. As evident in Table 5, the positive impact of the Top 5 robotization disappears in the case of high-income countries, where the instrumental variable (IV) regression fails to reveal any significant effects. Conversely, when focusing on low-income European countries, the impact is of greater magnitude than the entire sample, indicating that this category of countries drives the previous findings. For this specific group of nations, the coefficients consistently exhibit statistical significance.

[11] In our analysis, we find that the country-sector units with the highest level of robotization tend to have the lowest wage-capital ratio.

Table 5: Dependent var: Change in total Employment

	High-Income Countries			*Low-Income Countries*		
Variables	(OLS)	(FE)	(IV)	(OLS)	(FE)	(IV)
TRAED Index	1.678*	1.655*	1.067	5.372***	5.499***	6.128**
	(0.965)	(0.945)	(1.607)	(1.767)	(1.813)	(2.496)
Value Added Deflator	0.214***	0.273***	0.212***	0.0291	0.0360	0.0271
	(0.0688)	(0.0768)	(0.0693)	(0.0384)	(0.0417)	(0.0376)
Labour Cost	0.410*	0.349	0.413**	1.347**	2.053**	1.343**
	(0.214)	(0.268)	(0.211)	(0.605)	(0.856)	(0.598)
Constant	60.34***	63.83***	71.30***	73.73***	87.95***	74.17***
	(10.52)	(12.04)	(10.23)	(9.359)	(6.047)	(9.837)
Observations	3,428	3,428	3,428	4,571	4,571	4,571
R-squared	0.529	0.262	0.529	0.440	0.176	0.440
Kleibergen-Paap F-stat.			95.649			47.689

Notes: Standard errors in parentheses are clustered at the country-industry level. Year, sector and country fixed effects included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

In the appendix (refer to Table A4), we present the effects of the TRAED index on changes in workers embodied in exports for the two groups. Once again, we observe a consistent pattern. Significant effects are exclusively noticeable in the context of low-income countries, whereas the impact on high-income nations is essentially negligible.

5 Further Analysis

In this chapter, we present several supplementary analyses. We aim to assess the robustness of the primary estimates and provide additional perspectives on the impact of robotization on the European labour market.

5.1 Domestic impact of robotization

In this section, as a way to make a comparison with a more standard empirical exercise, we introduce a slight modification to our previous equation. This exercise highlights two points of interest. On one hand, it represents one of the first empirical investigations considering robot impact on such a large number of European countries. On the other hand, it also takes into account low-income European nations that began their adoption of robotics just after 2005. This inclusion underscores the broader impact and relevance of our study in understanding the dynamics of technological adoption across different economic contexts. Here, we aim to assess the impact of increasing robot density within a specific country-sector combination on the same unit of analysis, therefore the regression equation is as follows:

$$Y_{sct} = \alpha + \beta RDom_{ict} + \gamma X_{ict} + \lambda_c + \delta_i + \eta_t + \epsilon_{ict}$$

The only change we make is substituting the TRAED Index with a widely-used Robot Density ($RDom$) measure of domestic investments, representing the number of robots per 1000 workers. The remainder of the equation remains consistent with our previous specification. In this scenario, we prefer to avoid adopting the IV strategy due to the substantial diversity in robot adoption across the 23 countries. Consequently, it was impossible to find a suitable instrument that fits this variation across all our units of analysis.

In the first specification, when we utilize the entire dataset, we do not observe any statistically significant coefficients (see Table A5). This outcome aligns with expectations, as both the existing literature and our previous findings concur on the importance of distinguishing the impact of robots based on the development status of each country. Consequently, we have chosen to replicate the analysis by stratifying our sample according to GDP per capita levels (see Table 6). Interestingly, even when examining the direct impact of industrial robot adoption, the outcomes vary significantly between these groups. The impact is small and negative for high-income countries, yet consistently statistically significant. We observe that a one-unit increase in the RD variable leads to a 0.294 reduction in employment. Similar results are observed for the employment component associated with exports. Conversely, in the case of low-income economies, the effect is positive and statistically significant. Here, a one-unit increase in Robot Density results in a 2.6% rise in employment.

Table 6: Domestic impact of robotization

	High-Income				Low-Income			
	Empl. Change		*Work. embodied in Exp.*		*Empl. Change*		*Work. embodied in Exp.*	
Variables	(OLS)	(FE)	(OLS)	(FE)	(OLS)	(FE)	(OLS)	(FE)
Robot Density	-0.320***	-0.294***	-0.533***	-0.459***	3.755***	2.613***	6.023***	3.634***
	(0.101)	(0.0976)	(0.163)	(0.151)	(0.910)	(0.707)	(1.374)	(1.186)
Value Added Deflator	0.202***	0.260***	0.243***	0.315***	0.0503	0.0579	-0.00544	-0.0137
	(0.0670)	(0.0741)	(0.0692)	(0.0808)	(0.0412)	(0.0424)	(0.0530)	(0.0578)
Labour Cost	0.450**	0.415	-0.132	-0.408	1.183*	1.894**	1.661**	1.698
	(0.221)	(0.286)	(0.198)	(0.258)	(0.652)	(0.907)	(0.790)	(1.121)
Constant	60.78***	67.13***	73.66***	81.90***	71.21***	94.46***	60.98***	99.49***
	(10.39)	(11.70)	(11.14)	(8.893)	(9.246)	(5.387)	(18.25)	(8.213)
Observations	3,428	3,428	3,428	3,428	4,571	4,571	4,571	4,571
R-squared	0.534	0.270	0.496	0.135	0.462	0.193	0.281	0.149

Notes: Standard errors in parentheses are clustered at the country-industry level. Year, sector and country fixed effects included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

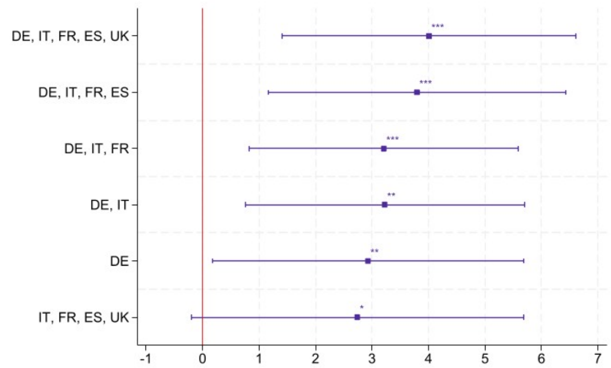
Interestingly, in our sample both theoretical mechanisms described in the literature appear simultaneously in play. In high-income countries, we observe a displacement effect, where the increase in productivity may not fully compensate for the substitution of workers caused by robot installation. Conversely, in low-income countries, adopting this technology substantially boosts productivity, leading to favourable employment effects.

5.2 Decomposing the TRAED Index

Here, our objective is to decompose the TRAED index to discern which among the top 5 economies influences more substantially the labor markets of other European nations. In Figure 4, we present the coefficients of modified versions of the TRAED index, considering different subgroups of countries[12]. As expected, Germany turns out to be the primary contributor, since it simultaneously exhibits higher values in terms of workers from other nations embodied in exports and robot density. With the exception of France, it appears that Italy, Spain, and the UK also make positive contributions, although less pronounced than Germany, to the changes in employment among the 23 European nations. Notably, even though the results are significant only at the 10% level, when Germany is excluded from the TRAED index, a positive association with employment change remains evident.

[12]In the figure, we report the coefficients related to the FE specifications with controls.

Figure 4: Decomposed contribution to the TRAED index



Notes: ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

5.3 Hours Worked

In this section, as an additional robustness check, we use the change in hours worked compared to the first observed year as the dependent variable. The results for the indirect analysis are presented in Table 7. Although this additional analysis is feasible only for a smaller sample, the findings reported in Table 3 are corroborated. The TRAED index maintains its positive and significant impact on the dependent variable, suggesting a prevalence of the productivity effect at the European level.

In Table A7, we replicate the same analysis for the direct impact of robotization by categorizing countries based on their GDP levels. Similar to the previous section, the substitution effect appears to outweigh the productivity effect for high-income countries. Conversely, in the case of low-income countries, we observe the opposite dynamics.

Table 7: Dependent var: Change in Hours Worked

	OLS		**FE**		**IV**	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TRAED Index	1.900	5.742**	4.476*	4.640*	3.263*	3.679*
	(1.601)	(1.426)	(1.325)	(1.383)	(1.413)	(2.210)
Value Added Deflator		0.0528**		0.0290		0.0526**
		(0.0267)		(0.0325)		(0.0266)
Labour Cost		-0.541*		0.396		-0.554*
		(0.276)		(0.255)		(0.287)
Constant	96.62**	92.04*	92.04*	84.76*	94.19*	93.45**
	(2.554)	(11.42)	(4.752)	(7.078)	(2.279)	(13.53)
Observations	6,394	6,175	6,394	6,175	6,394	6,175
R-squared	0.040	0.362	0.099	0.110	0.031	0.361
Sector/Country FE		YES	YES	YES		YES
Kleibergen-Paap F-statistics					87.727	70.341

Notes: Standard errors in parentheses are clustered at the country-industry level. Year dummies included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

6 Conclusions

Despite the level of empirical analysis, when considering the robot-employment relationship scholars are primarily interested in the impact generated within the country of adoption (Acemoglu and Restrepo, 2020; Koch et al., 2021). Still, a small part of this literature is also concerned in addressing the impact on other trade-related countries: it means that adoption of robots can generate an impact on countries that are connected with the adopting country through trade relationships. These papers are mainly devoted to understand what happens to employment dynamics in developing countries (Faber, 2020). However, the empirical evidence remains marked by significant contradictions, mainly due to the difficulties in understanding which kind of channel is going to work to generate the final impact. Both displacement and productivity effects can be at work, thus affecting employment negatively and positively respectively. Moreover, the diversity in empirical approaches and levels of analysis introduces additional complexity to the relationship.

Thus, the main aim of our paper is that of providing an alternative perspective on the intricate relationship between robot adoption and changes in employment outcomes in a highly trade-integrated market focusing on the European experience. In particular, we focused on the indirect impact of Top 5 European countries robot adoption on employment and export-related workers. This is particularly relevant because the question of whether robot adoption generates employment in other European trade-related countries has not been explored previously, except for a study specifically focused just on Germany Díaz Pavez and Martínez-Zarzoso (2023). Instead, within an integrated market such as the European one, we provided a new perspective by furnishing new empirical evidence on the impacts of robot adoption: delving into the nuances of the European context, we find that cross-border effect may still be at work even within a quite homogeneous economic area. Nevertheless, the most important contribution is the use of a novel index (TRAED index) to assess how robotization in the top five economies influences employment outcomes in the rest of Europe: to the best of our knowledge, our indicator is the first attempt to integrate trade and employment components by incorporating the proportion of workers engaged in exports. This approach allows us to incorporate a weighting factor encompassing both employment and trade aspects.

Our main results indicate a positive association between this index and the various employment measures. This suggests that, within the strongly integrated European market, the productivity effect deriving from robot adoption outweighs any potential reshoring effect. Furthermore, the instrumental variable strategy confirms the robustness of our findings, highlighting a positive and significant causal relationship of the TRAED index on employment outcomes.

It seems quite relevant also that when extending the analysis, positive results are more significant in countries with lower GDP levels. This may stand for the fact that intermediate input needs in high-income countries are satisfied mainly by workers in low-income countries, thus positively influencing their employment dynamics. This finding appears to be unique to the European case, as contrasting results are evident in other economic contexts (see, for example, Díaz Pavez and Martínez-Zarzoso 2023). The diversity in results may be attributed to the high level of economic integration achieved at the European level and the specificity of this economic system. As clearly described in a recent paper by Bontadini et al. (2024), European countries exhibit a structure characterized by headquarters and factory economies, where central economies can purchase intermediate products at lower prices from Eastern European countries. This evidence aligns well with our results, suggesting that an increase in productivity in top economies, driven by robot adoption, leads to a subsequent increase in employment in low-income countries. According to our estimations, the latter result seems to be pulled by workers embodied in the exports of intermediate inputs.

Also in the analysis of the domestic impact of robotization, we confirm that high-income countries tend to experience a small, negative effect on employment, while low-income countries benefit from a positive impact on employment, likely driven by increased productivity. We thus confirm that two opposite effects could be at play based on the degree of development of a country.

These results, that are corroborated by several robustness checks, show that different kind of employment effects can be at work even when considering a group of homogeneous countries, indicating that within Europe each countries has its own peculiarity both in technological and employment dynamics. Among the policy implications that can be drawn from these results two mainly stand out: the first is that it is not enough to care about the effects of automation investments within the same country of adoption as the consideration of international linkages of the country may generate effects that can be relevant as well. The second, which is connected to the first, refers to the idea that the technological policy of a country needs to be intertwined with the consideration of the employment dynamics of countries that are productively connected. As a final remark and as a way to open further lines of research, we evidence that our framework and new empirical approach can be extended also to consider trade linkages outside Europe, to understand whether the negative effect of employment usually found for the bilateral cases can still hold considering other country-sector contexts.

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Appendix

Table A1: Matching between IFR and TiM sectoral classifications

Industry IFR	Industry TiM
All Industries	D01: TOTAL
Agriculture, forestry, fishing	D01T03: Agriculture, hunting, forestry and fishing
Mining and quarrying	D05T09: Mining and quarrying
Food and beverages	D10T12: Food products, beverages and tobacco
Textiles	D13T15: Textiles, textile products, leather and footwear
Wood and furniture	D16: Wood and products of wood and cork
Paper	D17T18: Paper products and printing
Other chemical products n.e.c.	D19TD20: Manufacture of coke and refined petroleum prod.
Pharmaceuticals, cosmetics	D21: Pharmaceutic, medicinal chemical and botanical prod.
Rubber and plastic products (non-automotive)	D22: Rubber and plastics products
Glass, ceramics, stone, mineral products (non-auto	D23: Other non-metallic mineral products
Basic metals	D24: Basic metals
Metal products (non-automotive)	D25: Fabricated metal products
Household/domestic appliances	D26: Computer electronic and optical equipment
Computers and peripheral equipment	D26: Computer electronic and optical equipment
Info communication equipment, domestic and prof.	D26: Computer electronic and optical equipment
Electronic components/devices	D26: Computer electronic and optical equipment
Semiconductors, LCD, LED	D26: Computer electronic and optical equipment
Medical, precision, optical instruments	D26: Computer electronic and optical equipment
Electrical machinery n.e.c. (non-automotive)	D27: Electrical equipment
Electrical/electronics unspecified	D27: Electrical equipment
Industrial machinery	D28: Machinery and equipment, nec
Motor vehicles, engines and bodies	D29: Motor vehicles, trailers and semi-trailers
Metal (AutoParts)	D29: Motor vehicles, trailers and semi-trailers
Other vehicles	D30: Other transport equipment
All other manufacturing branches	D31T33: Manufacturing nec; repair and installation of machinery and equipment
All other non-manufacturing branches	D31T33: Manufacturing nec; repair and installation of machinery and equipment
Electricity, gas, water supply	D35T39: Electricity, gas, water supply, sewerage, waste and remediation services
Construction	D41T43: Construction

Table A2: TRAED indicator statistics among economic sectors

Sector	**Mean**	**SD**	**p50**	**Min**	**Max**
D01T03	0.6757567	0.5079043	0.6910621	0.0169006	1.658163
D05T09	1.900035	0.9959935	2.148016	0	3.989504
D10T12	4.6464	0.8577306	4.662709	2.313164	6.219182
D13T15	3.388786	0.3678649	3.498498	2.123282	4.02737
D16	5.648199	0.2753295	5.649137	4.988023	6.12007
D17T18	3.601499	0.5629145	3.638733	2.150225	4.799051
D19TD20	0.4807417	0.694381	0	0	2.302366
D21	3.262909	2.649779	4.348192	0	6.916811
D22	4.078481	3.225952	5.95226	0	7.647594
D23	5.127626	0.5367926	5.194301	3.501414	5.998357
D24	5.535183	0.3332425	5.551691	4.562799	6.314025
D25	5.612494	0.4634903	5.552483	4.506002	6.645398
D26	5.162432	1.093738	5.301649	2.017534	7.095385
D27	5.258816	0.6176682	5.377066	3.268099	6.17011
D28	5.087703	0.5950501	5.207024	2.818625	6.170329
D29	6.773282	1.710798	7.549074	2.632556	8.882624
D30	5.035353	0.5683227	5.065981	3.59664	5.977674
D31T33	4.723168	0.2766377	4.723446	4.053992	5.489874
D35T39	0.9930088	0.6344654	1.062679	0	2.115421
D41T43	0.8656387	0.4891277	0.896636	0.0166976	1.771202

Table A3: First stage IV regression

Variables	(1)	(2)
Japan RD	0.153**	0.0530**
	(0.0139)	(0.00544)
Value Added Deflator		-0.000151
		(0.000362)
Labour Cost		0.00121
		(0.00140)
Constant	0.878**	-0.156*
	(0.225)	(0.0699)
Sector/Country FE		YES
Observations	11,040	7,999
R-squared	0.412	0.958

Notes: Standard errors in parentheses are clustered at the country-industry level. Year dummies included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

Table A4: Dependent var: change in Workers Embodied in Exports

	High-Income Countries			*Low-Income Countries*		
Variables	(OLS)	(FE)	(IV)	(OLS)	(FE)	(IV)
TRAED Index	3.651**	4.120**	4.032	16.19***	16.19***	17.08***
	(1.712)	(1.755)	(2.621)	(4.610)	(4.788)	(6.248)
Value Added Deflator	0.267***	0.343***	0.269***	-0.0390	-0.00309	-0.0128
	(0.0734)	(0.0865)	(0.0746)	(0.0547)	(0.0524)	(0.0466)
Labour Cost	-0.204	-0.522*	-0.206	1.867**	1.727	1.833**
	(0.202)	(0.274)	(0.200)	(0.750)	(1.232)	(0.783)
Constant	72.54***	73.13***	64.91***	66.09***	77.57***	61.97***
	(11.30)	(10.25)	(9.991)	(18.52)	(11.23)	(19.26)
Observations	3,428	3,428	3,428	4,571	4,571	4,571
R-squared	0.491	0.133	0.491	0.277	0.172	0.280
Kleibergen-Paap F-stat.			95.649			47.689

Notes: Standard errors in parentheses are clustered at the country-industry level. Year dummies included in all models. Controls include GDP; EU membership and cost of labor. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

Table A5: Dependent var: Various Employment Outcomes

	Emp. Change		*Work. embodied in Exp.*		*Work. in Interm. Input*		*Work. in Final Input*	
Variables	(OLS)	(FE)	(OLS)	(FE)	(OLS)	(FE)	(OLS)	(FE)
Robot Density	-0.0252	-0.0213	-0.200	-0.164	-0.347	-0.979	-0.611	-0.532
	(0.322)	(0.301)	(0.478)	(0.445)	(1.100)	(1.008)	(0.738)	(0.525)
Constant	64.41***	87.80***	73.85***	89.42***	1.989	80.77***	45.82	104.4***
	(10.03)	(7.044)	(11.97)	(10.95)	(67.96)	(27.56)	(40.04)	(13.99)
Observations	7,999	7,999	7,999	7,999	7,975	7,975	7,975	7,975
R-squared	0.406	0.117	0.259	0.122	0.281	0.076	0.285	0.084

Notes: Standard errors in parentheses are clustered at the country-industry level. Year, sector and country fixed effects included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

Table A6: Interaction analysis

	Change in Employment		*Change in Work. Embod. in Exp.*	
Variables	(OLS)	(FE)	(OLS)	(FE)
TRAED Index	4.650**	4.583*	12.16*	13.43**
	(1.303)	(1.271)	(3.087)	(3.047)
Robot Density	-2.272*	-4.046**	-4.270**	-6.195***
	(1.316)	(1.619)	(2.074)	(2.356)
TRAED*RD	0.280	0.488**	0.503*	0.694**
	(0.199)	(0.216)	(0.292)	(0.292)
Value Added Deflator	0.0713*	0.0771*	0.0538	0.0621
	(0.0399)	(0.0450)	(0.0529)	(0.0586)
Labour Cost	0.362	1.075**	0.103	0.362
	(0.262)	(0.485)	(0.370)	(0.690)
Constant	64.46**	80.95*	54.71*	69.32**
	(11.59)	(7.402)	(16.87)	(12.06)
Observations	7,999	7,999	7,999	7,999
R-squared	0.414	0.140	0.277	0.146

Notes: Standard errors in parentheses are clustered at the country-industry level. Year, sector and country fixed effects included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

Table A7: Direct impact of robotization on the change in hours worked by sector

	High-Income Countries		Low-Income Countries	
Variables	(OLS)	(FE)	(OLS)	(FE)
Robot Density	-0.422**	-0.464**	4.747**	3.282**
	(0.166)	(0.192)	(0.965)	(0.711)
Value Added Deflator	0.143**	0.188***	0.0190	0.0133
	(0.0595)	(0.0667)	(0.0285)	(0.0313)
Labour Cost	0.261	0.0859	-0.330	0.177
	(0.262)	(0.299)	(0.557)	(0.692)
Constant	93.30**	81.57*	66.10*	98.67**
	(9.103)	(11.89)	(9.764)	(6.267)
Observations	3,212	3,212	2,963	2,963
R-squared	0.412	0.133	0.472	0.190

Notes: Standard errors in parentheses are clustered at the country-industry level. Year, sector and country fixed effects included in all models. Regressions are weighted by the number of workers in 1995. ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

Figure A1: correlation between the TRAED Index and the Change in workers embodied in Exports compared to 1995

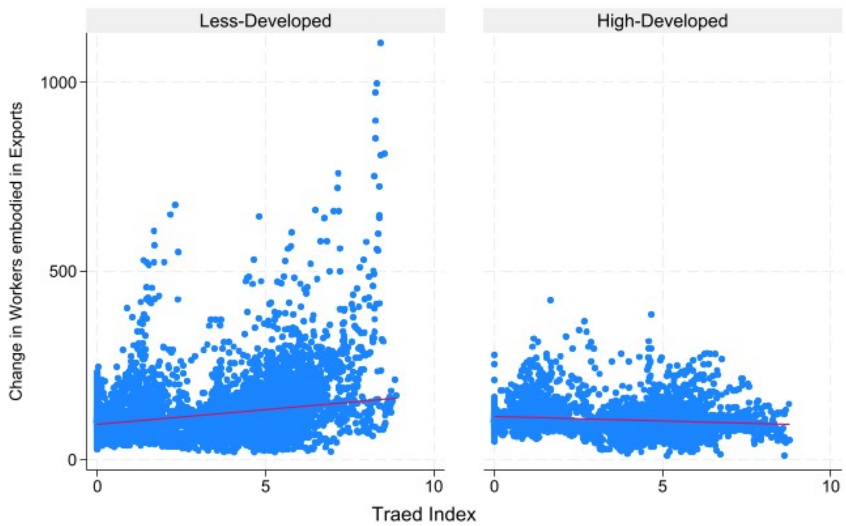


Figure A2: time trend of the operational robot stock for Japan and the top 5 European countries

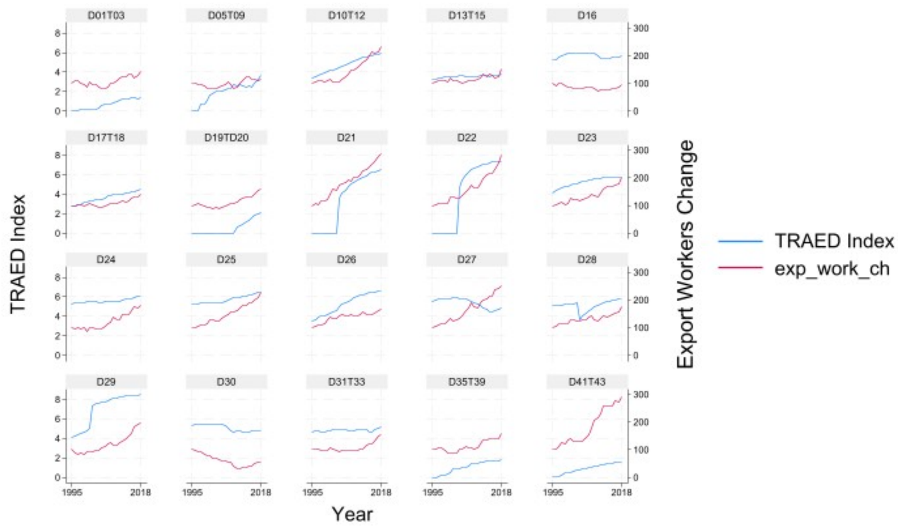
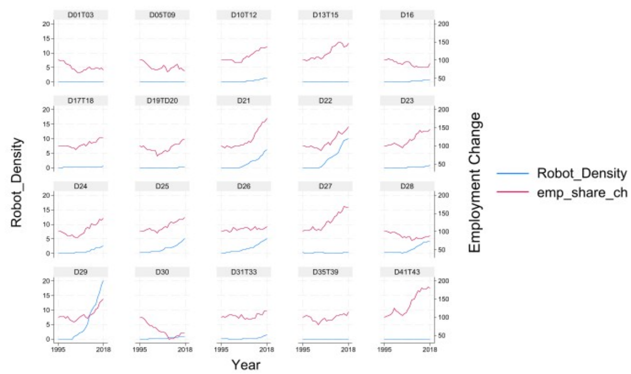
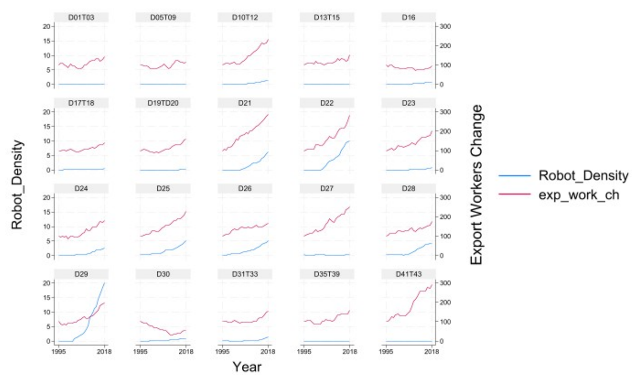


Figure A3: Association between the robot density of the 23 countries and changes in employment and export workers

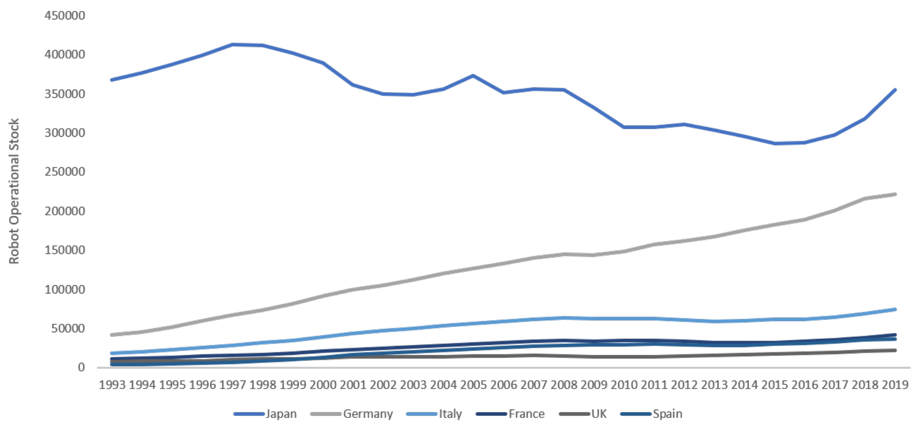


(a) Panel A



(b) Panel B

Figure A4: time trend of the operational robot stock for Japan and the top 5 European countries



Note: The data pertains to the operational stocks of all economic sectors in both Japan and the top five European countries.