Center for
European,
Governance and
Economic Development Research

Discussion Papers

Number 410 – December 2020

WHAT IS SO SPECIAL ABOUT ROBOTS AND TRADE?

Maite Alguacil
Alessia Lo Turco
Inmaculada Martinez Zarzoso

Georg-August-Universität Göttingen

ISSN: 1439-2305

What is so special about robots and trade?

Maite Alguacil*

Alessia Lo Turco†

Inmaculada Martinez Zarzoso‡

Abstract

We estimate the effect of the introduction of robots on the intensive and extensive margins of exports using a sample of Spanish manufacturing firms over the period 1994-2014. The empirical strategy used to identify the causal impact of robot adoption on the firm level export performance consists on combining propensity score matching (PSM) and difference in differences (DID) techniques. The results show that firms that start to use robots experience a sharp increase in their export probability, export sales and share of exports in total output and this result is robust to a wide array of checks. Robot adoption not only helps firms to start exporting and moves their specialisation towards intermediate products, but also favours export survival and export sales of exporting firms. The main results are driven by firms active in non-comparative advantage industries facing higher export sunk costs and market penetration costs and by those specialised in the production of intermediates, which can explain the increasing participation of Spain in global value chains. Inspection of the transmission channels suggests that the positive impact of robot adoption on exports could be driven by its positive effect on firm TFP and import probability.

KEYWORDS: robots; firm; exports; imports; intensive margin; extensive margin; PSM; DID
JEL CLASSIFICATION: F14; O14; O33

*Universitat Jaume I, Instituto de Economía Internacional and Dep. d'Economia, Av. Vicent Sos Baynat, s/n 12071 Castellón de la Plana, Spain. E-mail:*alguacil@uji.es*

†Università Politecnica delle Marche - Department of Economics and Social Sciences, Piazzale Martelli 8, 60121 Ancona - Italy. Tel.+39-0712207250 Fax +39-0712207102 E-mail:*a.loturco@univpm.it*

‡University of Goettingen and Universitat Jaume I, Dep. d'Economia, Av. Vicent Sos Baynat, s/n 12071 Castellón de la Plana, Spain. E-mail:*martinei@uji.es*

1 Introduction

In an integrated global economy, the implementation of new technologies can have important implications for relative production costs, international specialization and trade (Eaton and Kortum, 2012). The new technological developments, with the integration of artificial intelligence and the rapid diffusion of industrial robots adoption, have led to important changes in the world distribution of economic activities and in the organisation of global value chains (GVCs) (Atkinson, 2019). In Europe there were 14% more robots installations in 2018 than in 2017 and the majority of robots was employed in manufacturing to provide handling and welding operations (IFR, 2019). Differently from other machineries, due to their autonomy, adaptability and motion possibilities, robots are the best candidates to perform specific labour tasks and to deliver huge productivity increases through reduced production times and higher operational precision. Robot adoption, therefore, encompasses important changes in the relative advantages of the global division of labour. Thus, the increasing automation of firms in developed economies, together with the recent rise in labour costs in many developing countries, generate opportunities of bringing production back home (De Backer, DeStefano, Menon and Suh, 2018; Krenz, Prettner and Strulik, 2018; Faber, 2020). Moreover, with the widespread use of digital devices and increasing preferences for personalized products, firm competitiveness hangs more on the ability to efficiently provide customized high quality goods, rather than on the scale of production. Hence, automation could play a prominent role in promoting firms' competitiveness in the international markets and their GVC participation through exports (Zeng, 2017).

In this paper, to the best of our knowledge, we study for the first time the impact of robot adoption on firms' exports. In addition, we investigate the channels through which the use of robots fosters firms' export activities at the extensive - probability to export - and intensive - level of international sales - margins. With this aim, we use a representative sample of Spanish firms over the period 1994 to 2014 and identify the causal impact of robot adoption on firm level trade by considering robot adoption as a treatment and relying on the propensity score matching (PSM) approach combined with the difference in differences (DID) technique. Hence, we match treated (robot adopters) with untreated firms (never users) that share very similar characteristics and control for unobserved heterogeneous effects to identify causal effects. In examining the firm level export effects of robot adoption, we also analyse to what extent the incorporation of robots alters the global organization of firm activities by changing the geographical composition of exports. Finally, we explore five transmission channels through which firm's robot adoption may affect exports. In particular, we focus on whether robotization increases TFP and the probability to introduce new products, favours price reductions and labour cost saving and whether it promotes firm imports.

The analysis of the impact of robots on exports in the context of the Spanish economy is of particular importance, given the concurring increasing robotisation of production and export exposure by Spanish firms, which couple with their increasing involvement in GVCs. It is a relevant issue to understand to what extent the technological shift represented by robots can be one of the engines driving the country's success as intermediate supplier in the European industrial supply chains.

The main results indicate that robot adoption increases the extensive and the intensive margin of exports, that is, the probability to export and also the average value exported. Concerning the geographical composition of exports, we find no evidence that the share of exports from non-OECD changes due the adoption of this technology. When digging into the baseline evidence, we find that robot adoption especially enhances the export entry of non-exporting firms and sustains the export activity of exporters and of firms active in non comparative advantage industries. Robot adoption eases export sunk costs when they are expectedly higher. Also, we find that robot adoption especially matters for firms producing intermediate inputs. We interpret this findings in terms of robotization of production being one of the main drivers of the increasing involvement of Spanish firms in the GVCs as exporters of intermediates. Turning to the potential channels at work, we find that robot adoption increases firm TFP, reduces firm prices, causes the contraction of the firm labour force and fosters the introduction of new products. Furthermore, robot adoption help firms to start importing and increases the value and weight of imports in total sales, reducing however the relative importance of non-OECD economies as sources for foreign purchases. When we compute the mediated effect of robot adoption through each of the previous potential channels we find that the main active ones seem to be TFP and the probability to import.

We therefore contribute to the recent yet burgeoning strand of literature that investigates the economic consequences of robots adoption. Especially, we add evidence to incipient work that extends the study of the nexus between technology adoption and trade by looking at the trade effects of robotization at the firm level and the mechanisms of this connection. Most of the previous literature, including contributions by Artuc, Bastos and Rijkers (2018); De Backer *et al.*

(2018); Krenz *et al.* (2018), focuses on the effects of robots on trade flows between developed and developing countries revealing a clear impact of automation on the global division of production through offshoring and reshoring activities. According to Carbonero, Ernst and Weber (2018), the reverse process of reshoring production from developing to developed economies that emerges from this automation has led indeed to a reduction in employment in emerging countries by 5% between 2005 and 2014. From a firm level approach, Stapleton and Webb (2020) find however that the use of robots for Spanish firms actually had a positive impact on their imports from less developed countries and on the number of affiliates located there. As in Stapleton and Webb (2020), we focus on firm level robot adoption in the Spanish economy and inspect whether robot adoption alters the importance of non-OECD economies as source of imports. Nevertheless, we depart from the above-mentioned literature by explicitly focusing on the study of a firm propensity to participate in the international market via exports and by identifying the channels at work in promoting the firm international activity that go beyond productivity improvements.

The paper is organised as follows: Section 2 reviews the literature closely related to our analysis; Section 3 describes the data sources and the empirical strategy; Section 4 presents the baseline results and the robustness checks and Section 6 concludes.

2 Background

A growing body of the literature reveals that robotization has important implications on employment, productivity and the world distribution of production activities. In Table A1 in Appendix A we present a comprehensive overview of the existing academic papers that cover empirical applications for a number of countries in the world economy.

Focusing on the United States, Acemoglu and Restrepo (2020); Borjas and Freeman (2019) show a negative impact of robots on employment in manufacturing sectors. This displacement effect of labour for robot use is also found by Aghion, Antonin and Bunel (2019) for France and by Chiacchio, Petropoulos and Pichler (2018) for a set of European countries, showing moreover a particularly significant reduction in employment for non-educated workers. Nevertheless, there is also partial evidence supporting that robot adoption has a positive impact on total employment, although with an unclear effect for certain workers, mainly low-skilled ones (Klenert, Fernandez-Macias, Anton *et al.*, 2020; Dixon, Hong and Wu, 2020; Koch, Manuylov and Smolka, 2019; Dauth, Findeisen, Suedekum, Woessner *et al.*, 2018). In some cases, results also point to an increase in the wage premium of the skilled workers (Dauth *et al.*, 2018) or even gains in job stability (Dauth *et al.*, 2018; Dottori, 2020).

While the literature indicates that the influence of robot adoption on workers is ambiguous and mainly depends on the type of tasks they perform, an unambiguous effect on reducing cost of production and increasing labour productivity has been found in empirical studies (Graetz and Michaels, 2018; Dauth *et al.*, 2018). Besides, according to some studies, a higher exposure to robots rises significantly productivity and markups in those firms with high starting levels, while having a non-relevant impact for firms with initially low productivity and markups in the same industry. This leads to an increasing productivity divergence reinforcing the superstar phenomenon (Stiebale, Suedekum and Woessner, 2020). From a micro-level perspective, the incorporation of robots into the firms is also shown as a clear mechanism for improving firm' productivity in Dinlersoz, Wolf *et al.* (2018); Acemoglu, Lelarge and Restrepo (2020); Dixon *et al.* (2020); Stapleton and Webb (2020).

The impact of the rising prominence of robots on the international division of production and trade has been also recently analysed from a theoretical and empirical perspective by a few authors. Artuc *et al.* (2018) rely on a task-based Ricardian two-stage production and trade model to examine the implications of robotization for North-South trade. Although robots can reshape comparative advantages and substitute imports from less developed countries, the efficiency gains promoted by robots foster an increase both in North-South exports and imports. Empirically, in fact, they obtain a significant positive effect of the use of robots on imports from less developed economies, and an even greater impact on exports to these economies. On a slightly different note, some papers try to highlight the nexus between robot adoption and reshoring by looking at how robots affect imported input sourcing. In this direction, Krenz *et al.* (2018) theoretically model and empirically show that automation induces reshoring and is associated with an increasing skill premium. Within manufacturing sectors, an increase by one robot per 1000 workers would be associated with a 3.5% increase of reshoring activity. Along the same lines, De Backer *et al.* (2018) find a negative impact of automation in highly developed countries on the purchases of intermediates from foreign providers. A 10% increase in robot stock is associated with a 0.5% reduction in the growth of offshoring activities. On a similar vein, Faber (2020) states that, consistently with the reshoring hypothesis, the negative impact of robot adoption in the US on employment in Mexican local labor markets between 1990 and 2015 is mirrored in similarly large reductions in Mexican export-producing plants and exports to the US. The author complements the model by Acemoglu *et al.* (2020) with an export-producing sector to identify the effect of foreign robots on local employment.

Regarding the findings for Spanish firms, three recent works that focus on robots' adoption also rely on the database used in this paper. In particular, Koch *et al.* (2019) - applying a propensity score re-weighting estimator to data over the period 1990-2016- show that firms adopting robots experiment around 20 to 25 percent output gains in a time frame of four years, accompanied by net job creation and a reduction in the labour share of around 10 percent. Likewise, Stapleton and Webb (2020), using an instrumental variable identification strategy, also find that adoption of robots and related technologies is linked to a lower labour share and to an increase in the productivity of robot adopters. In addition, they also examine the effect on imports and found that the use of robots cause an increase in import intensity from less developed countries. This latter outcome suggests the mentioned relocation of previously outsourced tasks. Finally, Ballestar, Diaz-Chao, Sainz and Torrent-Sellens (2020) estimate a structural equation model to show a positive impact of robotization on labour productivity, when focusing on small and medium-sized firms. This study is more limited in scope that the other two, given that it employs data for only two years representing the recession and the recovery period. Compared to previous literature, we enlarge the view to explore the effects of robot adoption on trade by facing the unanswered question of how robots affect export activities of firms and through which channels. Thus, our research is also related to the recent burgeoning work on the effects of robots on labor market and firm performance.

3 Empirical Strategy

3.1 Data Sources

In this study we use representative data on Spanish manufacturing firms sourced from the Encuesta sobre Estrategias Empresariales (ESEE, or Survey on Business Strategies) started in 1990 by the SEPI foundation. Since that time, about 1,800 firms are surveyed every year using a questionnaire with 107 questions and more than 500 specific fields, which also includes information on the firms' balance sheet together with their profit and loss statements. The nice feature of these data is that it contains firm level information on robot adoption as well as a relevant bunch of firm characteristics. For firm robot adoption, our variable of interest, the data availability is on a four-year basis, therefore we observe firms in seven waves (1990-1994-1998-2002-2006-2010-2014). The before/after comparison in outcomes between robot adopters and never users will lead us to lose 1990 and 2014 for which we do not respectively observe the before and the after robot adoption period. Also the estimation of the initial capital stock by means of the perpetual inventory method for the computation of total factor productivity according to Levinsohn and Petrin (2003) leads us to lose the 1994 wave too, as for TFP we can only observe the before/after comparison starting from 1998. In any case, we are left with a sufficient number of firms and time periods to conduct our study. It is worth highlighting that, given the availability of four-year intervals, our DID estimates will mostly subsume long term changes in the outcomes of interest.

3.2 Stylized Facts and Main Variables

We start this section by comparing the use of robots in Spain and in two other selected European countries to grasp the importance of robot usage in the Spanish economy[1]. Figure 1 shows that in Spain the number of robot installations increases along the nineties and steadily decreases in the 2000s showing a very similar evolution as in France. However, robots installations steadily increased in Germany until the mid 2000s and the drop observed in France and Spain is less noticeable for Germany. Focusing now on the Spanish economy, a similar pattern can be observed when robot intensity is considered - instead of the absolute number of robots. Figure 2 shows a steady increase in the 1990s, followed by a drop after 2002 and a sudden increase after the recent crisis in 2008. The same holds for the export and import shares - right hand axis -, nonetheless the higher export and import orientation of the country already emerges in the second half of the 90s. For exports especially, it can be noticed an increase in export exposure of the Spanish economy that can be related to the growing interconnection of Spanish firms with the activity of global value chains. Indeed, some recent evidence reports the increasingly active role of Spain in the European global value chains in the period under analysis (Diaz-Mora, Juste and Gonzalez-Diaz, 2020). The country has experienced an increasing dependence on imported inputs and a contemporaneous growing role as an international provider of parts and components for the main industrial partners in the European Union. This feature is confirmed by Figure 3 where a

[1]Notice that the source of this data is IFR.

Table 1: Share of Robot Users by Industry and Year

Industry/year	1990	1994	1998	2002	2006	2010	2014	Total
Food, Beverages & Tobacco	0.11	0.14	0.22	0.28	0.27	0.33	0.35	0.24
Textile, Apparel & Footwear	0.08	0.08	0.1	0.11	0.17	0.15	0.1	0.11
Wood and Furniture	0.08	0.1	0.17	0.22	0.18	0.25	0.25	0.18
Paper and Printing	0.06	0.1	0.13	0.17	0.22	0.23	0.22	0.16
Chemicals, Plastic and Non Metal Min. Products	0.17	0.24	0.32	0.31	0.31	0.34	0.39	0.29
Metals and Metal Products	0.15	0.17	0.24	0.31	0.29	0.36	0.36	0.28
Machineries	0.12	0.2	0.26	0.25	0.28	0.34	0.35	0.25
Electrical Machineries and Eq	0.29	0.38	0.45	0.42	0.36	0.41	0.4	0.38
Automotive	0.32	0.41	0.48	0.54	0.58	0.62	0.68	0.51
Other Manuf.	0.12	0.19	0.21	0.21	0.18	0.22	0.23	0.19
Total	0.15	0.19	0.25	0.28	0.28	0.33	0.34	0.26

Source: SEPI. Own calculations.
The table shows the share of firms belonging to an industry and declaring to use robots in the specific year.

revealed comparative advantage index has been calculated by comparing the share of parts and components in Spanish exports to the share of the same set of exports for the world. We compare the index calculation for exports directed to the world to the index calculated when exports are directed to OECD and non-OECD destination markets and we find that the emerging and increasing specialisation in parts and components of the Spanish economy in our sample period is driven by its linkages with the OECD economies.

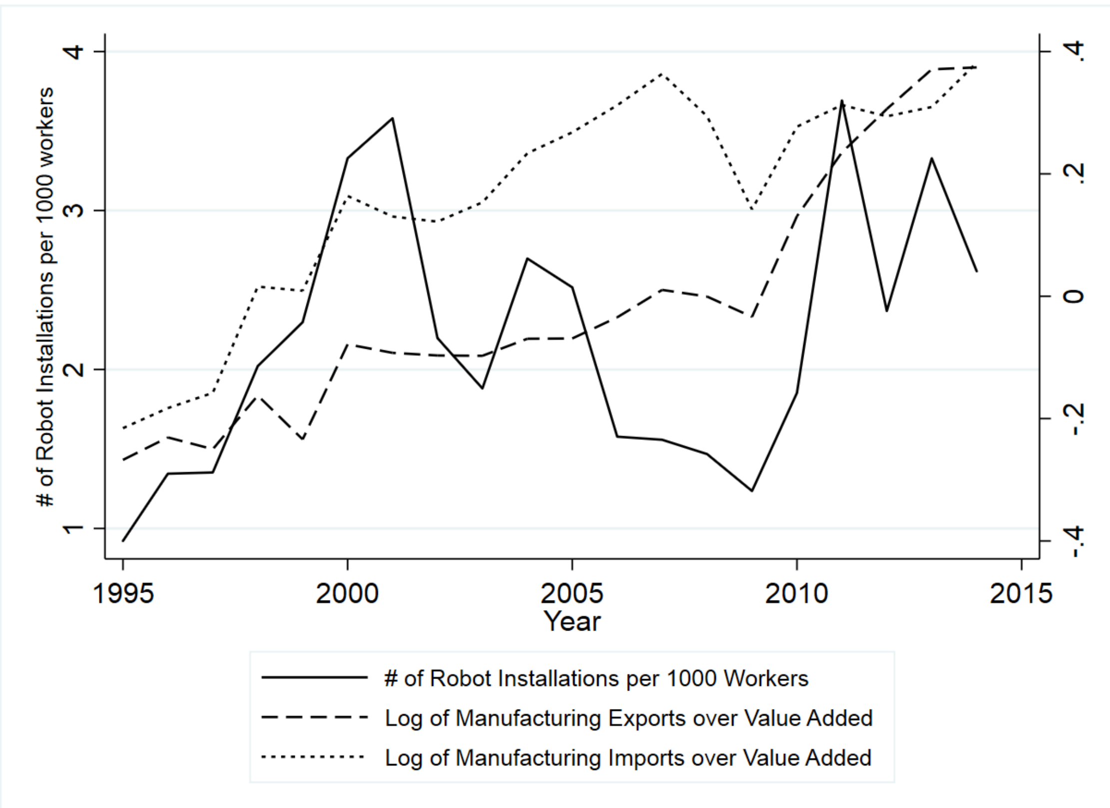
Turning to the firm level information on robot adoption in Spain, our database contains a dummy variable that takes value 1 for firms declaring to use robots and 0 otherwise. Table 1 shows the evolution over time of the share of firms declaring to use robots by industry. The figures in the table show a great extent of heterogeneity, with the Automotive sector recording the highest share of firms using robots, reaching almost 70 percent in 2014 and the Textile and Apparel recording the lowest percentage (10 percent in 2014). Turning to the evolution of robot adoption over time, the table reveals that over the period considered, the percent of firms using robots increased threefold in Food, Beverages & Tobacco, Wood & Furniture, Paper & Printing and Machinery and doubled in Automotive, Chemicals, Plastics & Non Metal Minerals and Metals & Metal Products. Non surprisingly, the percent of firms using robots remained low in Textile, Apparel & Footwear and in Other Manufactures.

In the rest of the paper, we will estimate the causal impact of robot adoption on the firm level extensive and intensive margins of exports using as identification strategy the propensity score matching (PSM) approach in combination with a DID estimation. We will also investigate whether robot adoption affects the composition of export in terms of destinations and of imports in terms of origin. Moreover, to inspect the channels through which robot adoption can affect

Figure 1: Log of Installations of Robots in Manufacturing- A cross country comparison

Source: IFR. Own calculations.

Figure 2: Spain: Evolution of Robots Adoption and Trade Exposure



Source: IFR, UNIDO2018 and WDI2019. Own calculations.

Figure 3: Spain: Revealed Comparative Advantage in Parts and Components

Source: WITS-Comtrade, Own calculations.
Exports of Parts and Components are flows recorded in the BEC codes 42 and 53. The Figure shows three different calculations of the Revealed Comparative Advantage Index: World (OECD/Non-OECD) refers to the ratio of share of Spanish exports of parts and components in total exports directed to the world (OECD/Non-OECD economies) over the share of world exports of parts and components in total exports directed to the world (OECD/Non-OECD economies).

exports we will analyse whether robot adoption leads to higher TFP and to infer the cost saving effects from robots we will further focus on its effect on the level and composition of firm employment. We will explore if robot adoption shapes a firm production structure by facilitating the introduction of new products and increasing the share of intermediates in firm sales, therefore increasing the share of firms able to hook GVCs as input providers. Finally, we will inspect the impact of robot adoption on firm import activity in terms of import probability, level and share under the hypothesis supported by the existing literature of a direct positive effect of importing on exporting.

Table 2 presents the evolution over time of our main outcome variables. The figures in the first columns confirm the increasing export orientation of firms in the Spanish economy, which has also been highlighted by studies focused on the post-crisis period (Almunia, Antràs, Lopez Rodriguez and Morales, 2018), and is rooted in the 90s. A similar picture emerges for the import activity of firms until 2006, as shown in the last three columns of the table. However, after the 2008 crisis, exports, the percentage of exporters and the export shares increased more rapidly than imports. The table further shows that the average size of firms declines and that the portion of firms with a share of intermediate goods in sales higher than 50% increases, while no particular pattern can be noticed for TFP and for the probability to introduce new products. Finally, Table A2 in Appendix A focuses on the sample of firms that are observed over the 1994-2014 period, and shows that robot users outperform non-users in terms of trade activities, TFP, size and innovation activities regardless of the inclusion of industry and region dummies. However, the difference between the two groups of firms dramatically shrinks when we control for firm size.

Table 2: Evolution over Time of the Main Outcome Variables

year	Pr(Exp)	Log(Exp)	Exp^{sh}	TFP	Log(Empl)	Pr(NewProd)	Pr(Interm)	Pr(Imp)	Log(Imp)	Imp^{sh}
1990	0.48	6.59	0.10	.	4.16	0.16	0.49	0.5	6.67	0.06
1994	0.57	8.30	0.16	2.85	4.25	0.27	0.52	0.59	8.1	0.09
1998	0.65	9.52	0.19	2.81	4.24	0.27	0.55	0.64	8.94	0.1
2002	0.65	9.67	0.2	2.77	4.3	0.23	0.56	0.66	9.26	0.1
2006	0.62	9.04	0.18	2.77	4.16	0.19	0.56	0.63	8.83	0.1
2010	0.65	9.55	0.21	2.75	4.01	0.2	0.59	0.62	8.67	0.09
2014	0.73	10.77	0.27	2.82	4.04	0.16	0.58	0.69	9.63	0.11
Total	0.61	8.95	0.18	2.8	4.17	0.21	0.55	0.61	8.51	0.09

Source: SEPI. Own calculations.
Pr(Exp) is a dummy taking value 1 if a firm exports and 0 otherwise. *Log(Exp)* is the log of the export value declared by the firm, 0 flows have been replaced by 1s. Exp^{sh} is the ratio of exports over the firm output. *TFP* is the firm total factor productivity estimated according to Levinsohn and Petrin (2003), *Log(Empl)* is the log of firm employment, *Pr(NewProd)* is a dummy taking value 1 if a firm introduces a new product and 0 otherwise, *Pr(Interm)* is a dummy taking value 1 if the weight of intermediate in firm sales is higher than 50% and in 0 otherwise. *Pr(Imp)* is a dummy taking value 1 if a firm imports and 0 otherwise. *Log(Imp)* is the log of the import value declared by the firm, 0 flows have been replaced by 1s. Imp^{sh} is the ratio of imports over the firm output.

To accomplish with the task of estimating the causal impact of robot adoption on the firm level export activity, we define starting to adopt robots as our treatment. A robot starter is a firm that uses robots in t and did not do it in the previous period, i.e. $t-1$, which in this particular database refers to four years before. According to this definition and to the combination of PSM with the DID estimator we are able to use four different waves - years 1998, 2002, 2006 and 2010 - of robot starters as for the wave of 2014 we are not able to observe the post-treatment period while, as previously mentioned, for 1994 we cannot observe the pre-treatment one for TFP.

Table A3 in the Appendix A shows the number of starters and never robot users by wave for which we have non missing observations concerning the main variables of interest that will be used in the empirical analysis. We have in total 515 starters and 2,377 never robot users that can potentially be used to match starters in the PSM and therefore serve as controls.

3.3 PSM implementation

We present in this subsection the Propensity Score Matching approach used to compute the Average Treatment effect on the Treated (ATT) for the treatment defined as robot adoption:

$$\gamma_{1,0}^{PSM} = E(Y_{post}^{1}|S=1) - E(Y_{post}^{0}|S=1) \tag{1}$$

where Y_{post} is the outcome after the treatment and S represents the status of the firm in terms of the two treatments, 1 for treated, 0 for the untreated. The parameter in 1 denotes the expected (average) effect of the treatment relative to the controls for a participant drawn randomly from the population of firms undergoing the treatment.

To account for the possibility that selection into the treatment rests on time invariant unobservable characteristics that are not captured by the matching procedure we combine the latter with the DID estimator (Blundell and Costa Dias, 2000, 2009):

$$\gamma_{1,0}^{PSM-DID} = [E(Y_{post}^{1}|S=1) - E(Y_{pre}^{1}|S=1)] - [E(Y_{post}^{0}|S=1) - E(Y_{pre}^{0}|S=1)] \tag{2}$$

where Y_{pre} denotes the outcome before the treatment. As $E(Y_{post}^{0}|S=1)$ is not actually observable, the missing counterfactual situation after the treatment is proxied by the outcome of the matched controls, selected from the population of firms in the comparative status 0, that is in the population of never robot users.

Then, we estimate a probit model of the start of robot adoption. In the model specification, we include the first lag of the dummy variables measuring the statuses of exporter, importer, product innovator, user of flexible systems, of machineries and computer assisted design tools. To account for common pre-trends we further include the firm growth between t and $t-1$ in size (log of employment), value added per worker, turnover, the change in the shares of exports and imports to and from OECD economies and the change in the share of R&D expenditures in total purchases.[2] Finally, we include region-sector dummies to account for local specificities in the industrial structure.[3]

Using the estimated propensity scores, we then apply the "Nearest Neighbours" (NN) matching with replacement on the "common support", that consists of matching a starter with the one or more controls having the most similar propensity scores. Due to the limited size of our starting sample we select the five nearest neighbours to calculate the matched outcome.[4] The matching is implemented for each cross-section, thus each treated is compared with five control units in the same year. For each treatment we will present ATT coefficients and analytical standard errors (Lechner, 2001). For completeness, we will also present bootstrapped standard errors based on 250 replications (Caliendo and Kopeinig, 2008), although in the context of NN matching their performance has been considered questionable by the literature (Abadie and Imbens, 2006, 2008).

Sincen PSM techniques have been developed to identify causal treatment effects in non-experimental data, the credibility of this approach relies on a rigorous control group selection on the basis of observable variables. Therefore, after matching, any difference between treated and controls in the probability to undergo the treatment is random. The use of the matching estimator in combination with a DID approach can drastically improve the quality of results

[2] It is worth mentioning that the baseline results show below are unaffected when we use TFP growth instead of the growth of value added per worker. Nevertheless, the lower number of firms for which the initial capital stock could be estimated and subsequently TFP could be computed led us to drop this variable for the propensity score computation. Results are available upon request.

[3] We have combined the 20 NACE-2 digit industries into two main aggregates subsuming traditional and advanced industries and we have interacted the dummies for these two aggregates with seventeen NUTS2 region dummies, ending up with thirty-four different fixed effects to include in the baseline specification.

[4] Also, the matching is applied "with replacement": the same control firm may be used as a match more than once. Nevertheless, once we use a matched control in a wave we do not match it again in subsequent waves to avoid the overlapping of the estimations periods.

from non-experimental settings, as it accounts for time invariant unobservables driving selection into the treatment (Blundell and Costa Dias, 2000). This feature further strengthens the interpretation of ATTs as causal effects. In this respect, the implementation and assessment of PSM diagnostics becomes fundamental. The standard testing procedures confirm the validity of our matching strategy. In particular, Table A4 A shows that the matching quality is satisfactory for our treated group: we obtain a relevant drop in the mean and median standardised bias and the share of treated firms out of common support is very low. Furthermore, Table A5 in in Appendix A shows the probit estimates for retrieving the propensity score and both the coefficient significance level and the standard test statistics at the bottom of the table, reveal the expected relevant drop in the explanatory power of the model on the sample made up of treated and matched controls.

This overall picture is rather consistent with evidence of balancing property being satisfied for all of the variables in most pairs. In addition, as shown in Figure B1 in Appendix B, the Propensity Score distributions of treated and controls almost perfectly overlap after matching. All in all, from the 515 potential treated we are able to match 508 firms - 7 treated firms remain out of the common support - for which we have information on the right hand side variables with 1,612 control firms.

4 Results

The main results obtained after combining PSM with DID estimations, as explained in the methodology section, are shown in Table 3. The table contains ATT estimates and the corresponding analytical and bootstrapped standard errors, which are shown in brackets below the corresponding coefficients. Although both sets of standard errors are fairly similar, we rely on the former for the reasons indicated above (Abadie and Imbens, 2006, 2008). The estimated coefficients indicate that the adoption of robots has a positive, significant and sizeable effect on the export activity of Spanish firms. The adoption of robots fosters firm exports both at the extensive and intensive margins. The before/after comparison of starters and never robot users reveals that robots increase a firm probability of exporting by around by 6.5 percentage points (Column [1]). Robot adoption also causes a sharp increase in the level of exports (Column [2]), which turns to be around 75% higher than before robot adoption, and in addition increases the weight of exports in total output (Column [3]), with adopters having a 4% higher export share compared to the pre-adoption period. On the contrary, no effect is found of robot adoption on the composition of exports in terms of destinations, as the share of exports to non-OECD economies is not affected. It is important to remark that the size of the effects refers to eight-year differences in the data and this is why the estimated effects are large.

In Panel A of Table 4 we further inspect our baseline findings on the relevance of robot adoption for firms' export entry and sales by comparing the DID estimates on the sup-sample of domestic firms, that is, firms whose sales in $t-1$ are exclusively made up by sales in the domestic market, to the DID estimates on the sub-sample of exporting firms. We find that robot adoption especially enhances the export entry probability of domestic firms which, consequently, experience an increase of their export share. It also helps exporters to maintain their export status, to increase their export share and to expand the level of their export sales. In all cases, no effect emerges on export destinations.

To support the relevance of robot adoption for firm export activity, in Panel B of Table 4 we compare the DID estimates obtained for the sup-sample of firms that belong to industries with a Comparative Disadvantage with the one of those belonging to industries with a Comparative Advantage.[5] The effect of robots appears to be driven by the former sub-group of firms and to a

[5]To define the set of comparative advantage industries we refer to the revealed comparative advantage (RCA) index computed for industries in the Spanish economy in 1990 by WITS-COMTRADE online software. As usual, we define comparative advantage industries those ones for which the RCA index is

minor extent by the latter.

Next, in order to inspect to what extent robots have favoured the participation of Spanish firms into global value chains as input providers we examine whether there exists a difference in the impact of robots on trade of intermediate and final goods. With this purpose we re-run the whole analysis on the sub-sample of producers of intermediate goods[6] The results, shown in Table 5, indicate that the effects of robot adoption on the export activities seem to be driven by firms that mainly produce intermediate products (upper panel in the table). Differently, the effects of robot adoption on export activities are not statistically significant for the remaining firms, as shown in the second part of the table. There is no evidence that firms that predominantly produce other types of goods export more or increase their export share vis-à-vis their controls. This piece of evidence, together with the above descriptive evidence on the increasing specialisation of Spanish manufacturing in exports of parts and components of final goods, suggests that robot adoption may be a driver of this export patterns for the country's manufacturing firms. These specific results could be driven by a potential lower need for intermediates to be customised according to the specificities of the foreign destination market. On the one hand, despite of the rising importance of customized intermediates, the large share of intermediate goods traded internationally are generic and standardised (Sturgeon and Memedovic, 2011). On the other hand, robot adoption can highly favour product modularisation, which is a relevant feature of production within GVCs (Van Assche, 2008).[7]

Finally, we inspect whether robot adoption favours an increase of a firm's probability to sell intermediate goods for an amount equal or above the 50% of the total sales of the firm. In Table 6 we show that this hypothesis is only corroborated for firms that were only active in the domestic market before robot adoption. Hence, robot adoption favours these firms' export entry and their

higher than 1 in 1990. Accordingly, the list of comparative advantage industries is as follows: food, leather and footwear, rubber and plastic products, metals, metal products, motor vehicles and other transport equipment.

[6]We divide the sample according to the type of products that are predominant in the firm sales. The database include a categorical variable that classifies firms according to the most prominent good typology in their sales. For instance, if initially - in $t-1$ - more than 50 percent of the products are intermediates the firm is classified as producer of these products.

[7]When a product is non-modular, components need to be specifically adjusted to one another in order to fully elicit the performance of the final product. On the contrary, modular products consist of loosely coupled components that interact with one another through well defined and codified architectural standards. Compared to usual machineries, a single robot can take on multiple functions. This kind of reconfigurable design is at the heart of modular products and can be done by robots. The ability to redesign modules in response to different purposes is particularly important in industries that build, design, or manufacture a wide array of products, such as the automotive, electronics, and chemical manufacturing industries.

Table 3: Results DID-PSM 5 Nearest Neighbours - Baseline Results

	[1] Pr(Exp)	[2] Log(Exp)	[3] Exp^{sh}	[4] $Exp^{sh}_{NonOECD}$
$Robot_{Start}$	0.065	0.754	0.038	1.221
ASE	[0.027]**	[0.338]**	[0.013]***	[1.308]
BSE	[0.031]**	[0.405]*	[0.018]**	[1.605]
Observations	977	975	967	977
Starters	373	371	369	373
Controls	604	604	598	604

Source: ESE-SEPI. Own calculations. Standard errors in brackets. ASE refers to analytic standard errors, BSE refers to bootstrapped standard errors. *** p<0.01, ** p<0.05, * p<0.1.

specialisation in the production of intermediates.

4.1 Robustness Checks

To validate the main result of Table 3 on the positive effect of robot adoption on the export activity of Spanish firms, we engage in a number of robustness checks that consist on presenting alternative model specifications and different ways of constructing the counterfactual in the PSM approach. The first variation consists on using levels of the continuous variables instead of the differences in the propensity score estimation. The results show that the estimated ATT are practically unchanged (see the upper-left part of Table A6 in Appendix A).

The second robustness check consist on using just three instead of five neighbours in the PSM (see upper-right part of Table A6 in Appendix A). Third, we modify the PSM strategy by alternatively adopting the Kernel and the Radius matching with a caliper of 0.5%. The results in the lower part of Table A6 show that our baseline results on the impact of robot adoption on firm exports hold in both cases (left and right panels for kernel and Radius matching, respectively). Figure B2 shows the propensity score distributions of treated and controls before and after the matching in all of these four alternative PSM procedures.[8]

As further robustness check, we exclude the 2010 wave from the sample in order to validate that our results are not exclusively driven by the increasing export orientation of firms in the Spanish economy in the post-crisis period. As a reaction to the reduction in domestic demand caused by the Great Recession in Spain, Almunia *et al.* (2018) have found a within-firm robust negative causal relationship between demand-driven changes in domestic sales and export flows over the

[8]Also results are robust when we run the PSM procedure by cross-section and firm industry (advanced versus traditional). Results are not shown for the sake of brevity, but they are available upon request.

Table 4: Results DID-PSM 5 Nearest Neighbours - Export Exposure of Firms

Panel A	Domestic Firms				Exporters			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Pr(Exp)	Log(Exp)	Exp^{sh}	$\text{Exp}^{sh}_{NonOECD}$	Pr(Exp)	Log(Exp)	Exp^{sh}	$\text{Exp}^{sh}_{NonOECD}$
Robot_{Start}	0.124	-	0.033	-1.619	0.062	0.550	0.037	2.193
ASE	[0.059]**	-	[0.018]*	[1.552]	[0.024]**	[0.303]*	[0.017]**	[1.836]
BSE	[0.065]*	-	[0.019]*	[1.785]	[0.030]**	[0.375]	[0.022]*	[2.090]
Observations	372	372	372	372	605	603	595	605
Starters	97	97	97	97	276	274	272	276
Controls	275	275	275	275	329	329	323	329

Panel B	Non-Comparative Advantage				Comparative Advantage			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Pr(Exp)	Log(Exp)	Exp^{sh}	$\text{Exp}^{sh}_{NonOECD}$	Pr(Exp)	Log(Exp)	Exp^{sh}	$\text{Exp}^{sh}_{NonOECD}$
Robot_{Start}	0.085	1.009	0.039	0.074	0.041	0.429	0.036	2.447
ASE	[0.041]**	[0.505]**	[0.019]**	[1.952]	[0.036]	[0.445]	[0.018]**	[1.713]
BSE	[0.042]**	[0.515]**	[0.022]*	[2.102]	[0.049]	[0.645]	[0.028]	[2.843]
Observations	563	562	559	563	414	413	408	414
Starters	194	193	192	194	179	178	177	179
Controls	369	369	367	369	235	235	231	235

Source: ESE-SEPI. Own calculations. Standard errors in brackets. ASE refers to analytic standard errors, BSE refers to bootstrapped standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Results DID-PSM 5 Nearest Neighbours - Intermediate and Non-Intermediate Goods Producers

	Intermediate Producers			
	[1]	[2]	[3]	[4]
	Pr(Exp)	Log(Exp)	Exp^{sh}	$\text{Exp}^{sh}_{NonOECD}$
Robot_{Start}	0.095	1.253	0.05	2.766
ASE	[0.043]**	[0.520]**	[0.020]**	[1.733]
BSE	[0.043]**	[0.544]**	[0.023]**	[2.016]
Observations	523	521	518	523
Starters	193	191	190	193
Controls	330	330	328	330
	Non-Intermediate Producers			
	[1]	[2]	[3]	[4]
	Pr(Exp)	Log(Exp)	Exp^{sh}	$\text{Exp}^{sh}_{NonOECD}$
Robot_{Start}	0.025	0.032	0.022	-0.393
ASE	[0.034]	[0.426]	[0.017]	[1.987]
BSE	[0.047]	[0.644]	[0.028]	[2.652]
Observations	449	449	444	449
Starters	177	177	176	177
Controls	272	272	268	272

Source: ESE-SEPI. Own calculations. Standard errors in brackets. ASE refers to analytic standard errors, BSE refers to bootstrapped standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Results DID-PSM 5 Nearest Neighbours - Probability of intermediate sales $\geq 50\%$

	All Firms	**Domestic**	**Exporters**	**Non-CA industries**	**CA industries**
	[1]	[2]	[3]	[4]	[5]
Robot_{Start}	0.034	0.096	0.009	0.01	0.056
ASE	[0.028]	[0.049]**	[0.033]	[0.039]	[0.039]
BSE	[0.033]	[0.056]*	[0.040]	[0.045]	[0.046]
Observations	972	369	603	560	412
Starters	370	96	274	193	177
Controls	602	273	329	367	235

Source: ESE-SEPI. Own calculations. Standard errors in brackets. ASE refers to analytic standard errors, BSE refers to bootstrapped standard errors. *** p<0.01, ** p<0.05, * p<0.1.

period 2009-13. This of course, would represent a competing explanation to the results shown above especially if robot adopters are more sensitive than non adopters to the slow-downs in domestic demand. Results that are reported in Table A7 in Appendix A actually corroborate our baseline findings on the positive impact of robots on firm export outcomes.

As a final robustness exercise, we define our treatment using new technologies that, although being similar, are different from robot adoption. We have selected adoption of flexible systems and adoption of machineries and include lagged robot adoption as a regressor in the estimation of the propensity score. The results shown in Table A8 in Appendix A indicate that there is no evidence of an effect of adoption of these technologies on firm level exports, thus ruling out potential confounding effects.

5 Inspecting the Channels

The results presented above imply that robot adoption by Spanish firms causes an improvement in their competitiveness. In this section, we explore which channels could be at work in mediating the effect of robot adoption on firms' export entry and sales. Hence, we proceed by inspecting the impact of robot adoption on a number of outcomes, which are expected to exert a role in driving firms' export entry and sales. We start by inspecting the impact of robot adoption on firm TFP, since this variable has been depicted - both by the trade theory and empirics - as the main driver of firm export entry and sales (Bernard and Jensen, 1999; Melitz, 2003; Bernard and Jensen, 2004; ISGEP, 2008). As expected, Column [1] of Table 7 shows a significant and sizeable effect of robot adoption on firm TFP. We proceed by inspecting the potential cost saving effects of robots by testing the impact of their adoption on the number of employees in a firm.[9] The implicit assumption is that robots substitute some of the workforce within the firm by performing similar tasks at a lower costs. Also, we inspect whether robot adoption favours an upgrading of the labour force in the firms by testing its impact on the share of $R\&D$ workers. Finally, to infer the extent to which robot adoption favours cost saving, we test its impact on the sale price of the products. Corresponding results are shown in Columns [2]-[4]. We find a negative impact of robot adoption on firm employment, although the estimated coefficient is only statistically significant at the 10 percent level. In particular, firms adopting robots employ 6.8 percent less workers. No significant effect emerges on the structure of employment in terms of the $R\&D$ employment share.[10]. When, we test for the effect of robot adoption on product prices we find that it favours a relevant price decline. Hence, all in all robot adoption seems to favour competitiveness through cost and price reductions.

A wide array of papers have shown a direct positive causal impact of innovation on exporting in the context of both developed and developing economies (Kumar and Siddharthan, 1994; Wakelin, 1998; Sterlacchini, 2001; Basile, 2001; Lo Turco and Maggioni, 2015). The important and direct role of product innovation for firm export probability has been also confirmed for the Spanish economy (Caldera, 2010; Cassiman, Golovko and Martínez-Ros, 2010; Cassiman and Golovko, 2011). Hence, we also test whether starting to use robots favours the introduction of new products by firms as a potential driver of firm export performance. In Column [5] we show that indeed robot adoption significantly and positively affects a firm's probability to add new

[9] Unfortunately, we have no direct information on the cost of labour.

[10] This evidence is unchanged in terms of the share of graduated workers.

products to the product mix. A firm's probability to introduce new products increased by around 8% due to robot adoption.

A vast literature has highlighted a relevant role for imports in enhancing a firm's export activity. First, importing new and more advanced goods relaxes some constraints in the production processes, thus, positively affecting the firm productivity (Halpern, Koren and Szeidl, 2015). As a consequence, higher productivity firms may face the export sunk costs and/or adapt or create new goods for the foreign customers (Kasahara and Lapham, 2012). Second, a direct linkage can exist between imports and exports, as imports may favour cost saving and technological upgrading of intermediate inputs (Bernard, Jensen, Redding and Schott, 2007; Turco and Maggioni, 2013; Bas and Strauss-Kahn, 2014; Feng, Li and Swenson, 2016; Navas, Serti and Tomasi, 2020). Hence, we test the impact of robot adoption on Spanish firms' import activities as we consider them a potential channel through which their export activity can be favoured. Columns [7]-[10] actually reveal that robot adopters experience a significant increase in their import probability of firms, in the level of their import purchases and in the share of imports in output. Hence, robot adoption seems to foster the entry in the import market for import purchases, however our results point in the direction of a declining firm involvement with Non-OECD partners therefore hinting at a possible substitution of inputs from low labour cost countries in favour of possibly higher quality/technology intensive inputs from high income economies. In comparison to the existent literature for the Spanish case, our results agree with Stapleton and Webb (2020) findings concerning the reduction in employment and the increase in total factor productivity. Otherwise, our outcomes are in contrast to Koch *et al.* (2019) who show a positive effect on employment and output for robot adopters. They found however that an increase in robot density at industry level has a negative impact in firms that do not adopt robots.[11]

As a final exercise, we show some back of the envelope calculations of the direct and indirect importance of the potential channels as drivers of the impact of robot adoption on the export activity of firms. this is done by following the principles of the mediation analysis (Sobel, 1982,

[11]We had also explored the impact of robot adoption on firm level output, but we find that, ceteris paribus, robot adoption does not seem to foster the scale of production. These results are available upon request from the authors. Also, exploration of the channels for intermediate and non intermediate producers reveal that robots use cause intermediate goods producers to upgrade their labour force by increasing the share of workers employed in R&D. The results also indicate that thanks to robot adoption this group of firms has a higher probability to become a product innovator. Differently, the effects of robot adoption on employment in the remaining group of firms is negative. Furthermore, these firms seem to drive the baseline finding on the import origin switch as they significantly reduce the share of imports from non-OECD economies after introducing robots.

Table 7: Results DID-PSM 5 Nearest Neighbours - Channels

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
	TFP	Log(Empl)	R&D Empl ^{sh}	P	Pr(NewProd)	Pr(Imp)	Log(Imp)	Imp^{sh}	Imp$^{sh}_{NonOECD}$
Robot$_{Start}$	0.040	-0.068	0.004	-0.440	0.079	0.963	0.018	-4.462	
ASE	[0.014]***	[0.040]*	[0.003]	[0.243]**	[0.037]**	[0.029]***	[0.345]***	[0.008]**	[1.448]***
BSE	[0.024]*	[0.040]*	[0.004]	[0.254]**	[0.043]*	[0.031]***	[0.384]**	[0.011]*	[1.967]**
Observations	549	958	965	953	968	977	972	972	975
Starters	254	371	364	359	369	373	371	371	372
Controls	295	587	601	594	599	604	601	601	603

Source: ESE-SEPI. Own calculations. Standard errors in brackets. ASE refers to analytic standard errors, BSE refers to bootstrapped standard errors. *** p<0.01, ** p<0.05, * p<0.1.

1986), which help shedding light on the underlying - indirect - determinants of observed direct relationship among economic phenomena (Heckman, Pinto and Savelyev, 2013; Heckman and Pinto, 2015). We, then, estimate a system with equations where, together with replication of the models in Table 7, we simultaneously estimate an equation for the before/after change in the export outcome as dependent on the before/after change of all of the above mentioned channels. It is worth highlighting that the low number of observations in the regressions follows from the inclusion of TFP among the variables in the model and suggests that the overall results should be taken with caution and interpreted just as descritpive. In Table 8 we do not report results for the seven channels equations, which would mimic results in Table 7. Instead, in Column [1] we present results for the export equation to grasp the role of each channel as potential driver of the effect of robot adoption on export performance and in Column [2] we present the corresponding mediated effect, $\beta^{Mediated}_{Channel\_j} = \frac{\partial Channel_j}{\partial Robot_{Start}} * \frac{\partial Export\ Outcome}{\partial Channel_j}$. For the sake of brevity, we only show estimates for the export probability and we use import probability as the main import channel together with the import geographical composition. These results suggests that across all the considered factors, TFP and imports emerge as the most significant drivers of the effect of robot adoption on export entry. Interestingly, when we include robot adoption among the right hand side regressors of the export equation in Column [3] of Table 8, the mediated effects of robot adoption lose significance (Column [4]), implying therefore that the effect of robot adoption is indeed working through the afore mentioned channels.

6 Conclusion

In this paper we have investigated the effect of adopting robots on firm exports for a representative sample of Spanish firms. PSM in combination with DID estimations has allowed us to identify the causal effect of robot adoption on the firm export probability, sales and share and also on a number of outcomes potentially driving the effect of robot adoption on exports. The main results indicate that robot adoption increases the probability of exporting and both, the level of exports and the firm export share, while it does not affect the export composition in terms of destination markets. These results are robust to a wide array of checks meant to prove the robustness of our PSM-DID empirical strategy, sample composition and treatment definition.

When further inspecting the baseline evidence, we find that it is driven by firms facing heavy export entry sunk costs and by those facing a difficult market penetration, such as non-exporters

Table 8: Results Seemingly Unrelated Regressions - Channels

	[1]	[2]	[3]	[4]
	Effect of Robot Adoption on Pr(Exp):			
		Mediated	Direct	Mediated
TFP	0.566***	0.023**	0.239**	0.010*
	[0.105]	[0.010]	[0.106]	[0.006]
Log(Empl)	-0.032	0.002	0.072**	-0.005
	[0.036]	[0.003]	[0.036]	[0.004]
R&D Empl ^{sh}	-0.462	0.000	-0.54	0
	[0.440]	[0.002]	[0.440]	[0.002]
P	-0.007	0.005	0.001	0.000
	[0.005]	[0.004]	[0.005]	[0.003]
Pr(NewProd)	0.065**	0.003	0.041	0.002
	[0.031]	[0.003]	[0.031]	[0.002]
Pr(Imp)	0.124***	0.013**	0.033	0.003
	[0.043]	[0.006]	[0.043]	[0.005]
$\text{Imp}^{sh}_{NonOECD}$	0.000	0.001	0.000	-0.001
	[0.001]	[0.002]	[0.001]	[0.002]
Robot_{Start}			0.038	
			[0.035]	
Observations	512	512	512	512

Source: ESE-SEPI. Own calculations. Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

and firms active in non-comparative advantage industries. Moreover, we show that robot adoption may have played a role in the increasing Spanish firms' participation to GVC as intermediate inputs providers. In fact, the main results on the export activity enhancing effects of robots are driven by the sub-sample of firms specialised in exporting intermediates. For instance, the adoption of robots spurs the production of intermediate goods by domestic firms who, indeed, experience a higher probability to start exporting due to robots. The investigation of the potential channels has revealed that robot adoption increases a firm TFP, can favour cost saving through employment reduction, reduces the prices at which the products are sold, fosters product innovation and has a positive impact of firm import activities. Finally, the results of back of the envelope computations of the mediated effect of robot adoption on exports suggest that TFP and importing may have acted as the main mechanism at work.
Conditioned to data availability, further work should be devoted to assess the impact of robot adoption on the product upgrading in terms of quality and complexity of the firm output mix.

A Additional Tables

Table A1: Empirical literature on the economic effects of using robots

Author/s (year)	Scope	Main data sources	Empirical approach	Main target variable/s	Remarks
			INDUSTRY LEVEL STUDIES		
Country case studies					
Acemoglu and Restrepo (2020)	- US - 772 community zones (CZs) - 13 manufacturing industries and 6 non-manufacturing sectors - Time span: 1990-2007	International Federation of Robotics (IFR), and EU-KLEMS database. Census and American Community Survey. US County Business Pattern CBP and NBER-CES data set	IV regressions on the exposure to robots. IV: robot adoption among industries in nine European economies	Employment and wages	• (-) Total employment • (-) Average wages

Dauth, Findeisen, Suedekum and Woessner (2017)	- Germany - 53 manufacturing industries and 19 non-manufacturing industries - Time span: 1994-2014	IFR, Institute for Employment Research (IAB) at the German Federal Employment Agency, Establishment History Panel (BHP) by the IAB, Federal Statistical Office. The Integrated Employment Biographies (IEB)	IV regressions on the local robot exposure for region. IVs: Robot installations across industries in other high-income countries (as in AR, 2020)	Employment and productivity	• (?) Total employment – Negative impact on manufacturing employment that is offset by additional jobs in service sector • (?) Wages – (+) for high-skilled workers – (-) for medium-skilled workers • (-) Labour income share • (+) Job stability • (+) Labour productivity
Borjas and Freeman (2019)	- US - 26 industries- Time span: 2004-2016	IFR and American Community Survey (ACS)	IV regression on the stock of robots shipped over the preceding 12 years. IV: number of robots shipped in the same industry and year in Japan and Germany	Employment and wages	• (-) Total employment • (-) Wages – Particularly in low-skilled and immigrant workers

Aghion, Antonin and Bunel (2019)	- France - Employment zones at industry level - Time span: 2014-1994	IFR and EU-KLEMS database. French administrative database	IV regression on exposure to robots. IV: robot exposure to other countries (as in AR, 2020)	Employment	• (-) Employment at the zone industry level – Non-educated workers more negatively affected than educated workers
Dottori (2020)	- Italy - Time span: 1991-2016	IFR and OECD database. Italian Social Security Institute	IV regressions. IV: robot use in other advanced European countries	Employment and wages	• (?) Total employment • (?) Average wages – For workers leaving the original employment: * (-) Employment * (?) Wages – For workers remaining in the original industry * (+) Wage * (+) Job stability

Faber (2020)	- Mexico (CZs level) - 20 manufacturing and non-manufacturing industries - Time span: 1995-2015	IFR CEPAL and Mexican censuses	IV regressions on exposure to foreign (US) robots. IVs for increased robot density and the share of Mexican imports: robot penetration in the rest of the world and an index of offshoring, respectively	Employment and wages	• (-) Employment – Stronger for low-skilled machine operators and technicians in highly robotized industries • (-) Exports to US and exports-producing firms
Multi-country studies					
Stiebale, Südekum and Woessner (2020)	- 6 European countries - 14 Manufacturing sectors - Time span: 2004-2013	IFR, Amadeus database and EU-KLEMS database	IV panel regression on stocks of robots: IV: sectoral adoption of robots in the US and the UK (as in AR, 2020)	Productivity and markups	• (+) TFP for the 20 per cent of firms with the highest initial productivity • (+) Markups for the top 10 per cent of firms with the highest initial markups • (-) Aggregate labour share in more productive and profitable firms
Klener, Fernández-Macías and Antón (2020)	- 28 EU countries - 10 Manufacturing sectors - Time span: 1995-2015	IFR, European Labour Force Survey (EU-LFS) and EU-KLEMS database	Fixed effects PD regressions	Employment	• (+) Aggregate employment • (?) Low-skill employment

Chiacchio, Petropoulos and Pichler (2018)	- 6 EU countries - 116 regions (NUTS2) - 15 manufacturing sectors and 3 non-manufacturing sectors - 18 demographic groups (considering gender, education and age categories) - Time span: 1995-2007	IFR and EU-KLEMS. European Community Household Panel (ECHP) and the European Union Statistics on Income and Living Conditions (EU-SILC). UN Comtrade database	IV regression on average robots' adoption. IVs: i) sectoral adoption of robots in similar advanced economies (as in AR, 2020) and ii) the country-specific intensity of Employment Protection Legislation (OECD) in its baseline 1990 level or its change between 1985 and 2007	Employment and wages	• (-) Employment – The displacement effect is particularly significant for medium-educated workers, for the youngest cohorts, and for men • (?) Wage growth
Graetz and Michaels (2018)	- 17 advanced EU countries - 14 industries (mainly manufacturing, but also agriculture and utilities) - Time span: 1993-2007	IFR and EU-KLEMS	IV PD regression on the use of robots. IVs: i) The fraction of each industry's hours worked performed by occupations that could have been replaced by robots and ii) the share of occupations requiring reaching-and-handly tasks compared to other tasks	Productivity and employment	• (+) Labour productivity • (+) TFP • (+) Average wages • (?) Total employment • (-) Share of low-skilled employment

Carbonero, Ernst and Weber (2018)	- 41 countries - 20 manufacturing sectors - Time span: 2000-2014	IFR	IV panel regression on robot automation: IV: the index of technical progress	Employment and offshoring activities	• (-) Employment at the global level – More pronounced in developing countries • (-) Offshoring activities in developed countries • (-) Employment in emerging countries
Krenz, Pretter and Strulik (2018)	- 43 countries (included all EU member countries) - 9 manufacturing industries - Time span: 2000-2014	IFR, World Input Output Database (WIOD) and Eurostat	PD regression on robot use. Measure of reshoring: The increase of domestic inputs relative to foreign inputs compared to the previous year	Trade and reshoring activities	• (+) Reshoring activities within countries and within manufacturing sectors – Reshoring activities positively associated with wages and employment for high-skilled labor

Artuc, Bastos, and Rijkers (2018).	- 24 OECD countries - 16 manufacturing and non-manufacturing industries - Time span: 1995-2015	IFR, EU-KLEMS and BACI	IV regression of trade between OECD countries and non-OECD countries. IVs for robot exposure: i) triple interaction between the country's initial income per capita, the share of workers engaged in replaceable tasks and global stock of robots, and ii) industry-level trends in robot adoption in countries with similar income level.	Trade	• (+) Imports from less developed countries (LDCs) • (+) Exports to LDCs – Mainly explained by trade in intermediate goods
De Backer, DeStefano,Menon, Ran Suh (2018)	- 40 highly developed countries (HDCs) and less developed countries - Time span: 2000-2014	IFR, WIOD, UNIDO and PATSTAT databases	PD regression. Measure of offshoring: Purchases of intermediate goods and from foreign providers. Measure of reshoring: Share of domestic demand served by foreign products	Trade and reshoring activities	• (-) Offshoring activities in HDCs • (?) Offshoring activities in LDCs • (?) Reshoring activities to developed home countries

DeStefano, De Backer and Ran Suh (2019)	- 33 HDCs, 16 industries (time span: 1993-2015) - 16 LDCs and 16 sectors (time span: 2000-2014)	IFR, WIOD, OECD databases	PD regression on growth of robot stock	Export / Import quality	• (+) Export quality of individual products in HDCs and LDCs • (+) Import quality of individual products (intermediates) in HDCs • (+) Compositional changes in export quality in LDCs • (?) Compositional changes in import quality (of intermediates)
FIRM LEVEL STUDIES					
Dinlersoz and Wolf (2018)	- US - Manufacturing firms (5 major 2-digit SIC manufacturing industries) - Time: 1991	US Census Bureau's 1991 Survey of Manufacturing Technology.	Semi-parametric cross-section estimation of a CES production function with endogenous technology choice	Employment and productivity	• (-) Labour share (both across plans and over time) • (+) Plant-level TFP • (+) Capital share • (-) Production workers with high wages

Acemoglu, Lelarge and Restrepo (2020)	- France - Manufacturing firms - Time span: 2010-2015	Survey by the French Ministry of Industry	PD regression	Employment, wages and productivity	• (-) Total employment
					  – (+) Employment in firms adopting robots
					  – (-) Employment in competitors (non-robots adopters' firms)
					• (+) Productivity
					• (-) Labour share
					• (-) Production workers share

Dixon, Hong and Wu (2020)	- Canada - Manufacturing firms - Time span: 2000-2015	Canadian Border Services Agency, the National Accounts Longitudinal Microdata File and the Workplace and Employee Survey	PD regression	Employment and productivity	• (+) Total employment – But robots displace managerial work • (+) Productivity
Koch, Manuylov and Smolka (2019)	- Spain - Manufacturing firms - Time span: 4-yearly period from 1990 to 2016	Encuesta Sobre Estrategias Empresariales, ESEE (SEPI Foundation in conjunction with the Spanish Ministry of Industry) and Instituto Nacional de Estadística	Two approaches: i) PD regression. Control variables: Four-year lag and four-year forward of firm characteristics. ii) Propensity score weighting estimator combined with difference-in-differences approach	Production, employment and labour cost	• (+) Employment for robot adopters • (+) Output for robot adopters

Stapleton and Webb (2020)	- Spain - Manufacturing firms - Time span: 1990-2016	ESEE	IV PD regression of the four-year difference on the use of robots (binary variable). IV: triple interaction between the ex-ante 'exposure' of industry-region pairs to robotisation use based upon their 1980s employment composition, baseline firm sales and changes in the global stock of robots	Production, employment, productivity and imports	• (-) Employment for firms using robots • (?) Output growth • (-) Labour share • (+) Labour productivity and TFP • (+) Probability of importing from LDCs • (+) The share of imports from LDCS • (+) The value of imports from LDCs
Ballestar, Díaz-Chao, Sainz and Torrent-Sellens (2020)	- Spain - Manufacturing firms - Time span: 2008 and 2015	ESEE	Structural Equation Model (SEM)	Labour productivity	• (+) Labour productivity in SMEs firms in 2015

Table A2: OLS - Difference between robot users and non-users - 1994-2014

Outcome	Robot Usage		Log(Empl)		Log(Output)		Obs.	R2	FEs	Industry	Region	Year
	0.258***	[0.010]					10,712	0.066		no	no	yes
Pr(Exp)	0.216***	[0.010]					10,712	0.134		yes	yes	yes
	0.034***	[0.010]	0.160***	[0.003]			10,521	0.303		yes	yes	yes
	5.089***	[0.152]					10,697	0.104		no	no	yes
Log(Exp)	4.227***	[0.149]					10,697	0.187		yes	yes	yes
	0.634***	[0.131]	3.116***	[0.042]			10,506	0.459		yes	yes	yes
	0.131***	[0.006]					10,623	0.063		no	no	yes
Exp^{sh}	0.098***	[0.006]					10,623	0.155		yes	yes	yes
	0.017***	[0.006]	0.070***	[0.002]			10,434	0.257		yes	yes	yes
	0.033***	[0.011]					10,613	0.004		no	no	yes
Pr(Interm)	-0.025**	[0.010]					10,613	0.2		yes	yes	yes
	-0.012	[0.011]	-0.006*	[0.004]			10,429	0.205		yes	yes	yes
	0.348***	[0.010]					6,788	0.157		no	no	yes
TFP	0.306***	[0.010]					6,788	0.211		yes	yes	yes
	0.022***	[0.006]	0.237***	[0.002]			6,665	0.761		yes	yes	yes
	1.249***	[0.028]					10,521	0.16		no	no	yes
Log(Empl)	1.108***	[0.028]					10,521	0.223		yes	yes	yes
	0.130***	[0.012]			0.675***	[0.003]	10,490	0.869		yes	yes	yes
	0.154***	[0.009]					10,571	0.036		no	no	yes
Pr(NewProd)	0.130***	[0.009]					10,571	0.075		yes	yes	yes
	0.055***	[0.010]	0.065***	[0.003]			10,397	0.111		yes	yes	yes
	0.260***	[0.010]					10,712	0.062		no	no	yes
Pr(Imp)	0.229***	[0.010]					10,712	0.121		yes	yes	yes
	0.037***	[0.010]	0.168***	[0.003]			10,521	0.307		yes	yes	yes
	4.835***	[0.147]					10,658	0.096		no	no	yes
Log(Imp)	4.179***	[0.146]					10,658	0.169		yes	yes	yes
	0.596***	[0.126]	3.115***	[0.041]			10,472	0.461		yes	yes	yes
	0.064***	[0.003]					10,626	0.041		no	no	yes
Imp^{sh}	0.052***	[0.003]					10,626	0.105		yes	yes	yes
	0.009***	[0.003]	0.036***	[0.001]			10,441	0.192		yes	yes	yes

Source: ESE-SEPI. Own calculations. Standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Potential Starters and Controls by Wave

Wave	Robot starters	Percent	Cum.	Never users	Percent	Cum.
1998	141	27.38	27.38	615	25.87	25.87
2002	115	22.33	49.71	649	27.30	53.18
2006	120	23.30	73.01	507	21.33	74.51
2010	139	26.99	100	606	25.49	100
Total	515	100		2,377	100	

Source: SEPI. Own calculations.

Table A4: Balancing Test

	Treated Firms	Control Firms	% Firms Out of Support	Mean Bias Before	Mean Bias After	Median Bias Before	Median Bias After
Robot Starters/Never Users	515	1,612	0.33	10.4	2.7	7.1	2.4

The covariate balancing tests for the PSM is shown in the Table. Treated firms are in the common support if their propensity score is lower than the maximum and higher than the minimum score of the control units. In the columns 4 and 5 we display the median bias across all the covariates included in the probit estimation before and after the matching.

Table A5: Probit for the propensity score estimation on the unmatched and matched sample

	Unmatched	Matched
	Pr(rob)	
$Size$	0.03	-0.033
	[0.024]	[0.056]
$Labour\ Productivity$	0.007	0.014
	[0.015]	[0.034]
$Turnover$	0.044**	-0.022
	[0.021]	[0.049]
Exp^{sh}_{OECD}	0.000	-0.001
	[0.000]	[0.001]
Imp^{sh}_{OECD}	0.000	0.001
	[0.000]	[0.001]
$Pr(Exp)_{t-1}$	0.088***	-0.011
	[0.017]	[0.041]
$Pr(Imp)_{t-1}$	0.069***	0.053
	[0.016]	[0.040]
$R\&D\ Purchases^{sh}$	-0.127	-0.001
	[0.226]	[0.489]
$Pr(NewProd)_{t-1}$	0.074***	0.004
	[0.019]	[0.038]
$Flexible\ System\ User_{t-1}$	0.073***	-0.014
	[0.020]	[0.039]
$Machinery\ User_{t-1}$	0.078***	-0.014
	[0.016]	[0.034]
$CAD\ User_{t-1}$	-0.012	0.011
	[0.016]	[0.038]
Observations	2,892	1,414
Pseudo-R2	0.12	0.014
Wald Chi2	315.994	21.679
p>chi2	0	1
Correctly Predicted %	81.95	

All continuous variables are measured as the change between t and $t-1$. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Results - Other Matching Methods

	NN Matching - Variables in Levels				NN Matching - 3 Neighbours			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Pr(Exp)	Log(Exp)	Exp^{sh}	$\text{Exp}^{sh}_{NonOECD}$	Pr(Exp)	Log(Exp)	Exp^{sh}	$\text{Exp}^{sh}_{NonOECD}$
Robot_{Start}	0.047	0.874	0.035	1.181	0.053	0.652	0.044	0.716
ASE	[0.028]*	[0.351]**	[0.014]**	[1.405]	[0.028]*	[0.347]*	[0.014]***	[1.337]
BSE	[0.031]	[0.414]**	[0.019]*	[1.708]	[0.032]*	[0.411]	[0.019]**	[1.666]
Observations	904	902	895	904	637	635	630	637
Starters	382	380	378	382	373	371	369	373
Controls	522	522	517	522	264	264	261	264

	Kernel Matching				Radius Matching			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Pr(Exp)	Log(Exp)	Exp^{sh}	$\text{Exp}^{sh}_{NonOECD}$	Pr(Exp)	Log(Exp)	Exp^{sh}	$\text{Exp}^{sh}_{NonOECD}$
Robot_{Start}	0.065	0.828	0.029	0.966	0.068	0.958	0.034	0.487
ASE	[0.027]**	[0.329]**	[0.013]**	[1.301]	[0.030]**	[0.367]***	[0.014]**	[1.364]
BSE	[0.026]**	[0.333]**	[0.016]*	[1.276]	[0.030]**	[0.378]**	[0.018]*	[1.548]
Observations	1,195	1,193	1,185	1,195	1,100	1,099	1,091	1,100
Starters	379	377	375	379	327	326	324	327
Controls	816	816	810	816	773	773	767	773

Source: ESE-SEPI. Own calculations. Standard errors in brackets. ASE refers to analytic standard errors, BSE refers to bootstrapped standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Results DID-PSM 5 Nearest Neighbours - Exclusion of the 2010 crisis wave

	[1] Pr(Exp)	[2] Log(Exp)	[3] Exp^{sh}	[4] $Exp^{sh}_{NonOECD}$
$Robot_{Start}$	0.067	0.868	0.035	0.94
ASE	[0.032]**	[0.395]**	[0.015]**	[1.621]
BSE	[0.037]*	[0.472]*	[0.019]*	[1.902]
Observations	734	732	725	734
Starters	273	271	269	273
Controls	461	461	456	461

Source: ESE-SEPI. Own calculations. Standard errors in brackets. ASE refers to analytic standard errors, BSE refers to bootstrapped standard errors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

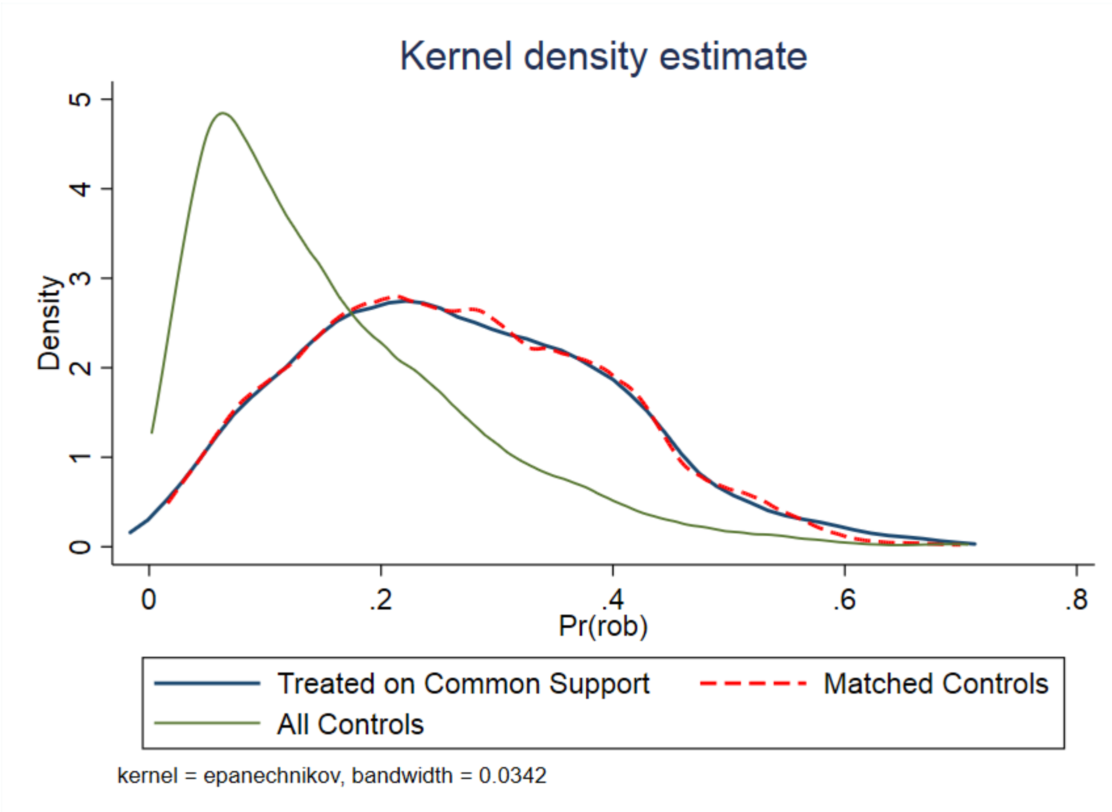
Table A8: Results DID-PSM 5 Nearest Neighbours - Other Competing Technology Adoption

	[1] Pr(Exp)	[2] Log(Exp)	[3] Exp^{sh}	[4] $\text{Exp}^{sh}_{NonOECD}$
	Treatment: $Flexible\ Systems$			
Start	0.019	0.346	0.006	1.565
ASE	[0.029]	[0.342]	[0.013]	[1.188]
BSE	[0.032]	[0.396]	[0.020]	[1.592]
Observations	873	873	870	873
Starters	392	392	392	392
Controls	481	481	478	481
	Treatment: $Machinery$			
Start	0.036	0.253	-0.011	0.248
ASE	[0.031]	[0.370]	[0.014]	[1.327]
BSE	[0.032]	[0.399]	[0.017]	[1.550]
Observations	812	811	808	812
Starters	434	433	430	434
Controls	378	378	378	378

Source: ESE-SEPI. Own calculations. Standard errors in brackets. ASE refers to analytic standard errors, BSE refers to bootstrapped standard errors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

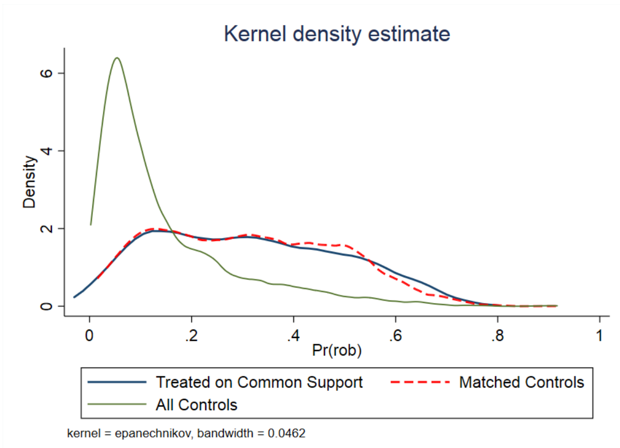
B Additional Figures

Figure B1: Propensity Score Distribution of Treated and Controls - Five Nearest Neighbours

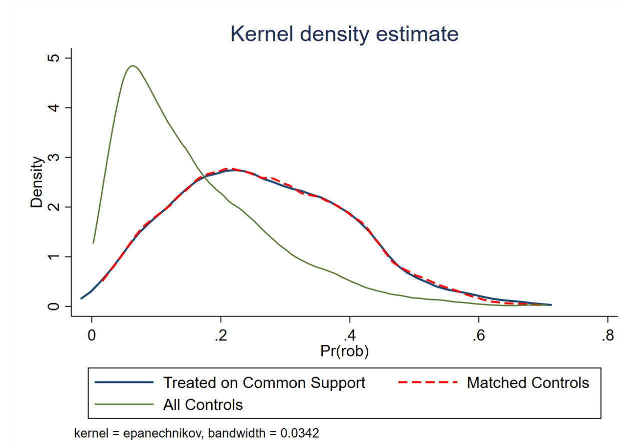


Source: ESE-SEPI. Own calculations.

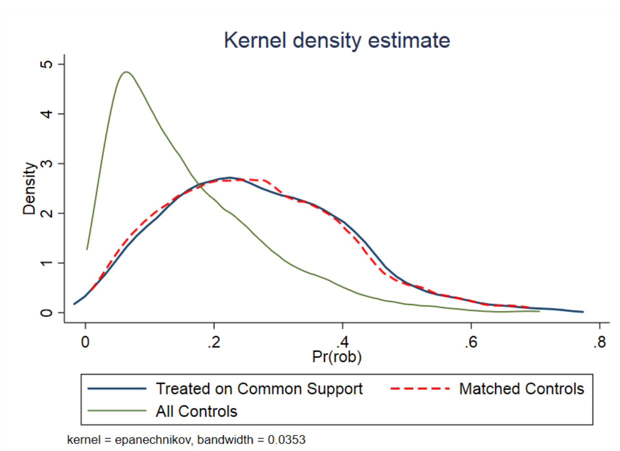
Figure B2: Propensity Score Distribution of Treated and Controls - Other Matching Algorythms



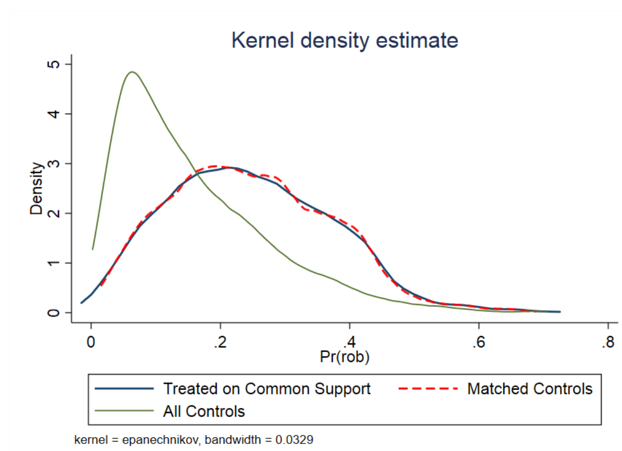
(a) NNmatching-VariablesinLevels



(b) NNmatching-ThreeNeighbours



(c) KernelMatching



(d) RadiusMatching

Source: ESE-SEPI. Own calculations.

References

Abadie, A. and Imbens, G.W. (2006). 'Large sample properties of matching estimators for average treatment effects', *Econometrica*, vol. 74(1), pp. 235–267.

Abadie, A. and Imbens, G.W. (2008). 'On the failure of the bootstrap for matching estimators', *Econometrica*, vol. 67(6), pp. 1537–1557.

Acemoglu, D., Lelarge, C. and Restrepo, P. (2020). 'Competing with robots: Firm-level', .

Acemoglu, D. and Restrepo, P. (2020). 'Robots and Jobs: Evidence from US Labor Markets', *Journal of Political Economy*, vol. 128(6), pp. 2188–2244.

Aghion, P., Antonin, C. and Bunel, S. (2019). 'Artificial intelligence, growth and employment: The role of policy', *Economie et Statistique*, vol. 510(1), pp. 149–164.

Almunia, M., Antràs, P., Lopez Rodriguez, D. and Morales, E. (2018). 'Venting out: Exports during a domestic slump', .

Artuc, E., Bastos, P.S.R. and Rijkers, B. (2018). 'Robots, Tasks and Trade', The World Bank.

Atkinson, R.D. (2019). 'Robotics and the future of production and work', Information Technology and Innovation Foundation.

Ballestar, M.T., Diaz-Chao, A., Sainz, J. and Torrent-Sellens, J. (2020). 'Knowledge, robots and productivity in SMEs: Explaining the second digital wave', *Journal of Business Research*, vol. 108, pp. 119–131.

Bas, M. and Strauss-Kahn, V. (2014). 'Does importing more inputs raise exports? firm-level evidence from france', *Review of World Economics*, vol. 150, pp. 241–275.

Basile, R. (2001). 'Export behaviour of Italian manufacturing firms over the nineties: the role of innovation', *Research Policy*, vol. 30(8), pp. 1185–1201.

Bernard, A.B. and Jensen, B.J. (1999). 'Exceptional exporter performance: cause, effect, or both?', *Journal of International Economics*, vol. 47(1), pp. 1–25.

Bernard, A.B. and Jensen, B.J. (2004). 'Why some firms export', *The Review of Economics and Statistics*, (86), pp. 561–569.

Bernard, A.B., Jensen, J.B., Redding, S.J. and Schott, P.K. (2007). ‘Firms in international trade’, *Journal of Economic Perspectives*, vol. 21(3), pp. 105–130.

Blundell, R. and Costa Dias, M. (2000). ‘Evaluation methods for non-experimental data’, *Fiscal Studies*, vol. 21(4), pp. 427–468.

Blundell, R. and Costa Dias, M. (2009). ‘Alternative approaches to evaluation in empirical microeconomics’, *Journal of Human Resources*, vol. 44(3), pp. 565–640.

Borjas, G.J. and Freeman, R.B. (2019). ‘From immigrants to robots: The changing locus of substitutes for workers’, *RSF: The Russell Sage Foundation Journal of the Social Sciences*, vol. 5(5), pp. 22–42.

Caldera, A. (2010). ‘Innovation and exporting: evidence from $s$panish manufacturing firms’, *Review of World Economics (Weltwirtschaftliches Archiv)*, vol. 146(4), pp. 657–689.

Caliendo, M. and Kopeinig, S. (2008). ‘Some practical guidance for the implementation of propensity score matching’, *Journal of Economic Surveys*, vol. 22(1), pp. 31–72.

Carbonero, F., Ernst, E. and Weber, E. (2018). ‘Robots worldwide the impact of automation on employment and trade’, International Labour Organization.

Cassiman, B. and Golovko, E. (2011). ‘Innovation and internationalization through exports’, *Journal of International Business Studies*, vol. 42(1), pp. 56–75.

Cassiman, B., Golovko, E. and Martínez-Ros, E. (2010). ‘Innovation, exports and productivity’, *International Journal of Industrial Organization*, vol. 28(4), pp. 372–376.

Chiacchio, F., Petropoulos, G. and Pichler, D. (2018). ‘The impact of industrial robots on EU employment and wages- A local labour market approach’, Bruegel.

Dauth, W., Findeisen, S., Suedekum, J., Woessner, N. *et al.* (2018). ‘Adjusting to robots: Worker-level evidence’, *Unpublished manuscript, Julius-Maximilians-Universität Würzburg*.

De Backer, K., DeStefano, T., Menon, C. and Suh, J.R. (2018). ‘Industrial robotics and the global organisation of production’, *OECD Science, Technology and Industry Working Papers*, (3).

Diaz-Mora, C., Juste, R.G. and Gonzalez-Diaz, B. (2020). ‘El momento de las cadenas regionales de valor: La integracion comercial en la peninsula iberica’, ICE Cuadernos Economicos.

Dinlersoz, E., Wolf, Z. *et al.* (2018). 'Automation, labor share, and productivity: Plant-level evidence from us manufacturing', US Census Bureau Center for Economic Studies.

Dixon, J., Hong, B. and Wu, L. (2020). 'The robot revolution: Managerial and employment consequences for firms', NYU Stern School of Business.

Dottori, D. (2020). 'Robots and employment: evidence from italy', *Bank of Italy Occasional Paper*, (572).

Eaton, J. and Kortum, S. (2012). 'Putting ricardo to work', *Journal of Economic Perspectives*, vol. 26(2), pp. 65–90.

Faber, M. (2020). 'Robots and reshoring: Evidence from mexican labor markets', *Journal of International Economics*, vol. 127, pp. 103–384.

Feng, L., Li, Z. and Swenson, D.L. (2016). 'The connection between imported intermediate inputs and exports: Evidence from chinese firms', *Journal of International Economics*, vol. 101, pp. 86 – 101.

Graetz, G. and Michaels, G. (2018). 'Robots at work', *The Review of Economics and Statistics*, vol. 100(5), pp. 753–768.

Halpern, L., Koren, M. and Szeidl, A. (2015). 'Imported inputs and productivity', .

Heckman, J., Pinto, R. and Savelyev, P. (2013). 'Understanding the mechanisms through which an influential early childhood program boosted adult outcomes', *American Economic Review*, vol. 103(6), pp. 2052–86.

Heckman, J.J. and Pinto, R. (2015). 'Econometric mediation analyses: Identifying the sources of treatment effects from experimentally estimated production technologies with unmeasured and mismeasured inputs', *Econometric Reviews*, vol. 34(1-2), pp. 6–31.

IFR (2019). 'World robotics - industrial robots', International Federation of Robotics.

ISGEP (2008). 'Understanding cross-country diffences in exporter premia: Comparable evidence for 14 countries', *Review of World Economics (Weltwirtschaftliches Archiv)*, vol. 144(4), pp. 596–635.

Kasahara, H. and Lapham, B. (2012). ‘Productivity and the decision to import and export: Theory and evidence’, *Journal of International Economics*, (DOI 10.1016/j.jinteco.2012.08.005).

Klenert, D., Fernandez-Macias, E., Anton, J.I. *et al.* (2020). ‘Do robots really destroy jobs? evidence from europe’, Joint Research Centre (Seville site).

Koch, M., Manuylov, I. and Smolka, M. (2019). ‘Robots and Firms’, Department of Economics and Business Economics, Aarhus University.

Krenz, A., Prettner, K. and Strulik, H. (2018). ‘Robots, reshoring, and the lot of low-skilled workers’, *Center for European Governance and Economic Development Research (CEGE)*, (351).

Kumar, N. and Siddharthan, N. (1994). ‘Technology, firm size and export behaviour in developing countries: The case of Indian enterprises’, *Journal of Development Studies*, vol. 31(2), pp. 289–309.

Lechner, M. (2001). ‘Identification and estimation of causal effects of multiple treatments under the conditional independence assumption’, in (M. Lechner and F. Pfeiffer, eds.), *Econometric Evaluation of Labour Market Policies*, pp. 1 – 18, Physica-Verlag, Heidelberg.

Levinsohn, J. and Petrin, A. (2003). ‘Estimating production functions using inputs to control for unobservables’, *Review of Economic Studies*, vol. 70(2), pp. 317–341.

Lo Turco, A. and Maggioni, D. (2015). ‘Dissecting the impact of innovation on exporting in Turkey’, *Economics of Innovation and New Technology*, vol. 24(4), pp. 309–338.

Melitz, M.J. (2003). ‘The impact of trade on intra-industry reallocations and aggregate industry productivity’, *Econometrica*, vol. 71(6), pp. 1695–1725.

Navas, A., Serti, F. and Tomasi, C. (2020). ‘The role of the gravity forces on firms’ trade’, *The Canadian Journal of Economics*, vol. 53(3), pp. 1059 – 1097.

Sobel, M. (1982). ‘Asymptotic confidence intervals for indirect effects in structural equation models’, *Sociological Methodology*, vol. 13, pp. 290–312.

Sobel, M. (1986). ‘Some new results on indirect effects and their standard errors in covariance structure models’, *Sociological Methodology*, vol. 16, pp. 159–186.

Stapleton, K. and Webb, M. (2020). 'Automation, trade and multinational activity. Micro evidence from Spain', University of Oxford.

Sterlacchini, A. (2001). 'The determinants of export performance: A firm-level study of Italian manufacturing', *Review of World Economics (Weltwirtschaftliches Archiv)*, vol. 137(3), pp. 450–472.

Stiebale, J., Suedekum, J. and Woessner, N. (2020). 'Robots and the rise of european superstar firms', .

Sturgeon, T. and Memedovic, O. (2011). 'Mapping global value chains: Intermediate goods trade and structural change in the world economy', UNIDO Development Policy and Strategic Research Branch.

Turco, A.L. and Maggioni, D. (2013). 'On the role of imports in enhancing manufacturing exports', *The World Economy*, vol. 36(1), pp. 93–120.

Van Assche, A. (2008). 'Modularity and the organization of international production', *Japan and the World Economy*, vol. 20(3), pp. 353 – 368.

Wakelin, K. (1998). 'Innovation and export behaviour at the firm level', *Research Policy*, vol. 26(7-8), pp. 829–841.

Zeng, D.Z. (2017). 'Measuring the effectiveness of the Chinese innovation system: A global value chain approach', *International Journal of Innovation Studies*, vol. 1(1), pp. 57–71.