Journal of the Knowledge Economy
https://doi.org/10.1007/s13132-026-03261-7

Robots, Firms, and Regions: Explaining Spanish Manufacturing Firms' Productivity and Exports

Sebastiano Cattaruzzo[1] · **Carles Méndez-Ortega**[2,3] · **Joan Torrent-Sellens**[2,3]

Received: 10 September 2024 / Accepted: 24 March 2026

Abstract

This study investigates the impact of robot adoption on firm productivity and export, considering province-level factors. Analysing a large dataset of 4,767 Spanish manufacturing firms during the period 1990–2016, we find that robots enhance productivity, particularly for small and non-innovative firms. Regional influences such as intangible assets and localization economies shape export intensity and labour productivity. Our findings emphasize the need to tailor strategies taking into consideration firms' heterogeneity, for instance across size or innovation levels. Further, considering the firm- and regional level factors, this research provides insights and implications that can enhance digital transition policies in a comprehensive framework.

Keywords Robotization · Exports · Productivity · Firms · Regions

JEL codes O33 · O14 · D24 · F14 · R12

✉ Carles Méndez-Ortega
cmendezor@uoc.edu

Sebastiano Cattaruzzo
seba.cattaruzzo@unive.it

Joan Torrent-Sellens
jtorrent@uoc.edu

1 Department of Economics, Università Ca' Foscari Venezia, Venice 30123, Italy

2 Faculty of Economics and Business, Universitat Oberta de Catalunya, Rambla del Poblenou 154-156, Barcelona 08018, Spain

3 i2TIC-IA Lab, Research Centre UOC-DIGIT, Universitat Oberta de Catalunya, Barcelona, Spain

Published online: 11 April 2026

Introduction

As Europe continues to undergo rapid digital transformation, robotics and its associated automation technologies have become key drivers of productivity and efficiency across various industries, albeit with less disruptive labor impacts (Fernández-Macías et al., 2021; Antón et al., 2022). Spain, like many other countries, has witnessed a significant increase in the adoption of industrial robots by firms in recent years (Ballestar et al., 2020; Camiña et al., 2021b). This trend has prompted the need for a better understanding of the robotization impact on firm productivity and competitiveness, both domestically and in global markets. In fact, research in the field already accumulates a lot of evidence about industrial robotics as an internal factor of productivity and competitiveness (Koch et al., 2021; Duan et al., 2023). However, research into the external factors, particularly spatial and territorial characteristics, that interact with robotics in shaping firm productivity and competitiveness remains comparatively scarce (Jungmittag, 2021; Lamperti et al., 2023; Jestl, 2024, Fernández-Escobedo et al., 2024), specifically at fine-grained regional levels. This article aims to fill this research gap.

According to the International Federation of Robotics (IFR), an industrial robot is "an 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" (Müller, 2022, p. 30). During the last few years, the uses of industrial robots have grown significantly both in terms of their number and in terms of functionalities within industrial automation processes (Maslej et al., 2023). According to the most recent forecasts, by 2025 it is expected to reach a record number of 700,000 new installed units, with average growth over the next few years close to 6% (Müller, 2022). Despite the fact that more than 60% of the robots installed today are located mainly in five industries (electricity and electronics, automotive, metallurgy and machinery, chemicals and plastics, and food) as well as in five countries (China, Japan, the USA, South Korea and Germany), research in the field attributes to industrial robotics a moment of explosion linked to an exponential growth in its diversification and applicability (Pratt, 2015; Graetz & Michaels, 2018).

Up to four underlying expansive trends have been pointed out. First, the uses of industrial robotics will accelerate thanks to advances in robot compaction and usability determined by the introduction of new artificial intelligence (AI) and programming applications (Can et al., 2020; Dwivedi et al., 2021, 2023). In this context, the processes of technological convergence between robotics and AI are opening new and important trajectories of business innovation (Grashof & Kopka, 2023; Babina et al., 2024). Secondly, due to the growing collaboration between robots and humans, which allows the complementarity of tasks and a much more efficient joint work that is done separately (Dauth et al., 2021; Holm & Lorenz, 2022). Thirdly, due to the incorporation of SMEs into the world of robotics, which will allow, if consolidated, a very broad growth of its application base (Ballestar et al. 2020, 2021a; Li et al. 2024). And, fourthly, due to the improvements in economic and environmental efficiency that robotics induces, and that industrial activity should adopt to develop a cleaner and more sustainable production system, as well as an efficient one (Díaz-Chao et al., 2021; Torrent-Sellens et al., 2022, 2023).

What is the economic result of this robotic explosion? The new generations of robots would be contributing to generating more wealth through the traditional processes of creative destruction, innovation and productivity gains (Czarnitzki et al., 2023; Wang et al., 2023). Robots end up improving productivity when applied to tasks that are performed more efficiently by machines, and with a higher and more consistent level of quality than people (Acemoglu & Restrepo 2018a, b, 2019; Damioli et al. 2021). In fact, economic research already has a set of results that confirm the hypothesis of a positive effect, albeit uneven and with slight magnitudes, of robotics on aggregate (Graetz & Michaels, 2018; Cette et al., 2021; Jungmittag, 2021) and regional (Du & Lin, 2022) productivity, with recent meta-analytic evidence highlighting substancial heterogeneity across contexts, levels of analysis and complementary factors (Schneider, 2025). Regarding business research, recent work on samples of firms in several countries has validated the idea of positive selection or self-selection. Firms with the best previous performances are the most likely to use industrial robotics, at the same time that in these firms an important link between robotic use, digital technological convergence and intensity and labour or total factor productivity has been confirmed (Acemoglu et al. al., 2020; Koch et al., 2021; Bettiol et al., 2024), increasingly extending to firms' export performance and export sophistication through productivity-enhancing mechanisms (Cao et al., 2025; Hongsheng Zhang et al., 2025). This link is being strengthened as firms are able to establish complementarity relationships between the uses of robotics and investment and innovation in intangible assets, such as R&D activities, the redesign of business processes, changes organisational, or new competencies of managers and workers (Ballestar et al. 2021b; Brynjolfsson et al. 2021; Nakatani 2024). Likewise, the financial, political, and institutional environment also plays an important role in the consolidation of these effects (Schuelke-Leech, 2018).

With the aim of providing new evidence for the European sphere, in this article we analyse the role played by spatial effects (with a focus on province-level characteristics) in the relationship between the use of industrial robotics, and productivity and exports of manufacturing firms (Valentini et al., 2023). We analyse a rich dataset of Spanish manufacturing firms, combining information on robot adoption, value generating process, productivity, and exports with data on province-level characteristics such as ICT investment, stock, and agglomeration economies. We use panel fixed effects to estimate the role of robot adoption on firm labour productivity and exports, and we explore the channels through which province-level characteristics affect this relationship. Overall, this study aims to provide important insights into the effects of robotization on the Spanish economy and offer valuable policy implications for firms and regions seeking to optimise their productivity and competitiveness. By examining the impact of province-level characteristics on the relationship between robots and firm productivity, our study seeks to contribute to a better understanding of the complex dynamics between technology adoption and regional competitiveness in the digital age.

This study delves into the relationship between robotization, firm productivity, exports and innovation considering the influence of structural spatial variables. We find that robot adoption predominantly boosts productivity particularly for small and non-innovative firms, suggesting alternative automation technologies for innovative firms. Additionally, regional factors like intangible assets negatively impact exports for non-innovative firms, while localization economies positively influence export intensity and labour productivity for innovative firms. These findings emphasise the importance of considering industry sector and innovation levels when designing strategies for productivity growth, highlighting the need for nuanced policies and approaches.

The remainder of the paper is organized as follows. Sect. "Productivity, Export, and Robotization: Firm- and Regional-Level Theories and Evidence" gives an overview of the literature on productivity, export, and robotization both from a firm and a regional perspective. Sect. "Data and Methodology" introduces the analysed data sources, presents an exploratory data analysis, and unfold the methodological approach. Sect. "Result" reports and comments the empirical results, while Sect. "Concluding Remarks" concludes.

Productivity, Export, and Robotization: Firm-and Regional-Level Theories and Evidence

Firm-Level Determinants of Export and Productivity and Their Interrelation

Export and productivity are two crucial dimensions of firm performance that are closely interrelated. Empirical studies have demonstrated that firms that export are generally more productive than those that do not export (Bernard et al., 1995; Wagner, 2007; Melitz, 2003). This relationship is often referred to as the export-productivity nexus. While the relationship is well-established, the question of what determines the export and productivity of firms has been a topic of extensive research in recent years.

Several studies have found a positive relationship between firm size and export performance (e.g., Aitken & Harrison, 1999; Wagner, 2007). This can be attributed to the fact that larger firms have more resources to devote to exporting activities, such as marketing, logistics, and product adaptation. Firm size has also been found to be positively associated with productivity and export intensity (e.g., Diaz & Sánchez, 2008; Serrano & Myro, 2019). Larger firms are able to achieve economies of scale and scope, which can lead to higher productivity. Traditionally, the comparison between SMEs and large firms has been a common practice in economic research. However, this standard confrontation fails to capture the nuances within the SME category and overlooks the potential heterogeneity among small and micro enterprises. By introducing a new classification of small and micro versus medium and large enterprises, we can gain deeper insights into the factors that drive productivity growth and export intensity across a broader range of firm sizes. This choice acknowledges that small and micro enterprises may face distinct challenges (i.e., financing-, recruiting-, and marketing-wise) and exhibit unique characteristics compared to medium- and large-sized enterprises.[1]

Also, firms that invest in innovation are more likely to export (e.g., Aw et al., 2011; Serrano & Myro, 2019). Innovation can help firms develop new products that are more competitive in foreign markets or improve existing products to meet the needs of foreign customers. Innovation has also been found to be positively associated with productivity (e.g., Crepon et al., 1998; Ortega-Argilés et al., 2011). Innovation can lead to the adoption of new technologies, better management practices, and more efficient production processes, which can improve productivity. More generally, the innovative side of a firm, which is intrinsically multifaceted and represented by both input and output measures, impacts both firm-level productivity and export (Añón-Higón & Bonvin, 2022).

Relatedly, robotization, or the adoption of advanced automation technologies, is a determinant that could affect firms' export and productivity outcomes. More precisely, technology is factor-augmenting (Acemoglu & Autor, 2011) and it affects productivity positively. This increased productivity may then also be helpful in competing globally, increasing the firm's exports margin. In this line, Alguacil et al. (2022) found that robot adoption may indeed increase productivity and then, consequently exports. Generally, the majority of evidence suggests that robot increases productivity (Acemoglu et al., 2020).

Foreign ownership is another determinant that affects firms' export and productivity outcomes. For instance, Aitken & Harrison (1999) for Venezuela & Javorcik (2004) for Lithuania found that domestic firms benefit from direct foreign investment. Additionally, Keller (2004) developed a model that tracks the international technology diffusion phenomenon showing how indeed foreign sources of technologies, such as being subsidiaries of multinational enterprises are key for productivity growth. Firm age is an essential determinant of firms' export and productivity outcomes. This emerges for firms in several European countries in Segarra et al. (2022). Also, a study by Coad & Tamvada (2012) found that younger firms in India face significant barriers to growth, which could also affect their export and productivity performance. However, Haltiwanger et al. (2013) found that young firms in the US contribute significantly to job creation. Therefore, the relationship between firm age and export and productivity outcomes is complex and cannot be taken for granted. More generally, it is quite established that age may proxy for the accumulation of knowledge and experiences that may turn out to be particularly useful when facing non-domestic markets.

In summary, the literature suggests that firm size, age (as a proxy of cumulative knowledge), innovation-related variables and foreign ownership are important determinants of export and productivity.

[1] This is particularly true in the context of exporting firms and focusing on export intensity, where for instance, small and micro-firms thanks to their reduced sizes have more easiness in achieving higher ratios. More generally, there exists size-specific patterns that suggest how smaller firms behave significantly different from medium and larger counterparts (Hollenstein, 2005). Recent studies suggest the presence of these patterns also when looking at firm-level productivity (Yeo & Park, 2022).

Robots Use and its Relationship with Export and Productivity

The integration of robotics into firm operations has profound implications for labour productivity and export intensity. Studies indicate a positive correlation between robot adoption and labour productivity. Koch et al. (2019) found that robot adoption in Spanish manufacturing firms led to significant output gains and net job creation, with labour productivity increasing by 20–25% within four years of. Similarly, Graetz & Michaels (2018) conducted a comprehensive analysis across various industries in 17 countries and found that robot density, defined as the number of robots per thousand workers, is positively associated with productivity at the firm level. This association suggests that robots contribute to reducing labour costs and enhancing output quality and quantity, leading to higher productivity levels. Recent meta-analytic evidence further confirms this nexus, although highlighting differences in estimated effects stemming from methodological choices across studies (Schneider, 2025).

In terms of export intensity, another critical measure of firm performance, we see firms that adopt robotic technology having enhanced export intensity due to increased production efficiency and product quality, which are highly valued in international markets. Barajas et al., (2019) found that Spanish manufacturing firms that adopted robots were more likely to increase their export-to-sales ratio compared to non-adopters. This suggests that robotics can be a significant driver of competitive advantage in global markets.

The combined effects of robotics on productivity and exports are notably pronounced in firms that integrate advanced technologies with export activities. Ballestar et al., (2020) provide evidence from Spanish SMEs, showing that robotics, combined with knowledge-intensive activities, enhances productivity, which in turn supports higher export levels. More recent firm-level evidence for Spain confirms these effects, showing that robot adoption is associated with improvements in output and exporting performance (Shahin et al., 2024). Concluding, the evidence suggests that robot adoption at the firm level is a significant driver of labour productivity, which can enhance export intensity. However, the extent of these effects varies significantly across firm sizes and industries, highlighting the need for tailored approaches in technology integration for optimizing economic outputs.

Concluding, the literature suggests a synergistic relationship between robotics adoption, labour productivity, and export intensity. Robots enhance labour productivity and TFP by automating tasks, which allows firms to reallocate labour to more complex and productive activities, thus optimizing the overall input mix. This increase in productivity and efficiency makes firms more competitive on a global scale, enhancing their export capabilities. For example, a study by Koch et al. (2021) demonstrates that German firms employing robots could significantly reduce production costs and enhance product quality, leading to a higher propensity to export. Similarly, research in both the U.S. and Chinese manufacturing sector indicated that robot adoption not only increased productivity but also enabled firms to penetrate new international markets due to improved production capabilities (Acemoglu & Restrepo, 2020; Hongsheng Zhang et al., 2025).

The Productivity-Robotization-Territory Nexus

So far, most of the research on robotization has focused on employment, the initial research on the effects of robotics continued with the general postulates of jobless recovery (Brynjolfsson & McAffe, 2011, 2014) and with the idea of job skill-biases and polarisation in the digitised economy (Goos et al., 2014; Karabarbounis & Neiman, 2014; Michaels et al., 2014). During the recessions there was a destruction of low and medium-skilled jobs, normally linked to routine tasks, while during the recovery phases these displaced workers had great difficulties making the transition to other jobs, exacerbating structural problems of technological unemployment or precarious work. The first available evidence indicated that the digitisation, automation, and robotization of work was beginning to generate important substitution or displacement effects of employment, reducing its participation in national income and increasing inequality (Acemoglu et al., 2014; Autor & Salomons, 2018; Acemoglu & Restrepo, 2020). In fact, research in the field began to speak in terms of a race against the machines or "robocalypse" (Autor & Salomons, 2017; Berg et al., 2018; Acemoglu & Restrepo, 2019). But as the second wave of robotization and digitalisation has taken hold, research in the field has reached new common ground. This new available evidence ostensibly nuances both the utopias of robotic and artificial singularity as well as the most pessimistic visions of a robotic apocalypse (Fernández-Macías et al., 2021; Naudé, 2021; Klenert et al., 2023). Three main results have been highlighted. Firstly, industrial robotics has a clear trend towards replacing the employment of industrial workers in low and medium-skilled tasks (Frey & Osborne, 2017). Secondly, we are not advancing towards a generalised substitution of jobs, but towards a reassignment of tasks and a displacement of jobs (Dauth et al., 2021). In general, industrial robots replace some tasks, while they can also complement and augment human work, for example in other occupations or branches of activity, such as R&D activities or services (Waldman-Brown, 2020; Dottori, 2021; Kariel, 2021). And third, industrial robotization in particular and digitised automation in general are associated with increasing polarisation of employment structure and outcomes (Krzywdzinski, 2021; Reljic et al., 2021; Fierro et al., 2022).

In summary, robotization has positive effects on productivity and mixed effects, without falling into massive jobless, on employment (Graetz & Michaels, 2017; Gregory et al., 2022). Despite substituting low-skilled industrial employment, industrial robotics would generate spillover effects and externalities towards the job quality and the wages of resilient industrial employees with greater skills for the use of robots, and towards the quantity and quality of employment in the services. On the other hand, job polarisation would grow in favour of employees, firms, industries and territories with better jobs, productivity and wages associated with greater dynamic capabilities to interact with robotics (Dauth et al., 2021; Liu & Son, 2024; Montobbio et al., 2022). In business terms, all these findings indicate that robotics develops processes of creative destruction that make firms more efficient, although in terms of employment the results depend largely on the technological and knowledge intensity of their value generation process, as well as to the firm's relations with its economic environment.

It is precisely in this complementarity sense that recently literature has paid increasing attention to exports and their link with productivity and employment (Alguacil et al., 2020, 2022; Koch, 2021). The main thesis of these investigations is that industrial robotics would be associated with the reconfiguration of global value chains in the sense that some of the industrial relocation processes that would have occurred during the hyper-globalisation period would be reversing (Antràs, 2020). Firms that use industrial robots more intensively, with more automated and digitised production processes, are more likely to promote reshoring processes, and return part of their activity to their countries of origin, which would mean clear improvements in competitiveness and substantial effects on employment. On the one hand, increases in employment, job quality and wages for the most qualified workers and in more advanced occupations. On the other hand, it would also generate reductions in less qualified employment and in more routine occupations, encouraging polarisation (Krenz et al., 2021; Liu, 2023). On the other side of the coin, research has also highlighted the extent to which reshoring can be detrimental to developing economies, especially less-skilled manufacturing operators (Faber, 2020; Kugler et al., 2020).

However, despite this growing evidence, little is known about the role that space plays in the adoption, use and results of industrial robotics in firms. Some recent research has pointed to the importance of dynamic agglomeration economies, such as the intensity of use of robotics in the industry or in the area where the firm is located (robot hubs) (Brynjolfsson et al., 2023) or the extension of the uses of robotics to other non-industrial industries (Cséfalvay, 2023). In this context, research in the field has also found complementary relationships between robotic intensity, the size of cities, and the job quality of foreign employees (Chen & Tan, 2023) or between robotic intensity, skill change, structural transformation and the situation of the regions (Hu et al., 2023). In general, these results indicate that the regions or cities that invest more in R&D or have better levels of human capital are more capable of promoting complementarities between robots and the labour force, generating positive effects for both the quantity and the quality of employment (Valentini et al., 2023). This is also in line with contributions from the evolutionary theory (Dosi & Nelson, 2013).

Regarding productivity and exports, the little evidence available, practically confined to Chinese firms in their entirety, has obtained a link between the spatial effect, the use of industrial robots and the results of the firms. Du & Lin (2022) find that the relationship between industrial robotics adoption and TFP is different depending on the region where the robots are used: U-shaped in the area of use and inverted U-shaped in the neighbouring region. On the other hand, Zhang et al. (2023) obtain differentiated effects of the use of industrial robots on the entry and performance of exports depending on the markets and the density of competition. This effect is much more relevant for large firms, while adopting SMEs would see their market shares reduced and non-adopters could be expelled from the markets.

Given the existing evidence and the emerging relevant firm-level and spatial dimensions, this article answers to the following research questions:

RQ1: What roles do robotization and spatial effects play in explaining the productivity and exports of industrial firms?

RQ2: Is the mediating role of robotization and space homogenous across firm sizes? What about innovative and non-innovative firms?

RQ3: Does the technological level and socio-economic features of neighbouring regions affect firm-level export and productivity?

Data and Methodology

Micro-Data Source

The firm's working panel comes from the Encuesta sobre Estrategias Empresariales (Business Strategy Survey, ESEE) of the SEPI Foundation. The ESEE is a statistical operation with panel data that annually interviews some 1,800 Spanish industrial firms, the vast majority of which are SMEs. In this research, the ESEE annual series 1990–2016 was used[2]. The use of the ESEE database allows detailed data of the value process, competitive advantage and performance of the industrial firm. Further, the large availability of data and the effective sampling strategy allows also to test the robustness of the findings along different dimensions. For instance, firm sizes and innovative status are the two dimensions of interest for this paper and they have been implemented as follows. Regarding firm sizes, we split the sample between micro and small firms as opposed to medium and large firms. Regarding innovative status, we consider two possible variables one being patenting firms versus non-patenting ones, while the other consider firms that have been innovators versus those who have not. All large manufacturing firms are included in the sample, while for SMEs, a stratified, proportional and systematic sampling is used by industries and size of the firm (Camiña et al., 2020). With regard to data entry, ESEE provides detailed information for twenty economic sectors, which are representative of the Spanish industrial SMEs' fabric (Eppinger et al., 2018).

Regional Data Source

The regional data used in this paper, which consists of province-level data, was obtained from various sources. The Spanish statistical service provided data on population density and the number of tertiary educated people in each province. The localization economies variable was constructed using the ESEE dataset. In addition, other time-invariant variables used as controls, such as whether the province is an island, located on the coast, or in a big city, were created by the author. Finally, data on R&D and ICT investment was obtained from the Ivie (Instituto Valenciano de Investigaciones Económicas) databases. The use of these various sources allowed for a comprehensive collection of regional data at the province level, which is crucial for understanding the complex relationships between firm-level and regional-level variables.

[2] Given that the ESEE database consists of panel data, firms that exit the dataset do so primarily due to absorption or mergers. This aspect is controlled for in our analysis to ensure the robustness of our findings.

Both the ICT intangible investment map and the ICT intangible stock map depict a heterogeneous situation at the provincial level with regard to both values (Fig. 1). It is important to note that these values represent the median across the entire period of study. It can be observed that there is a certain degree of correlation between the values of intangible investment and intangible stock in certain Spanish provinces. However, there are cases such as Malaga, Alava, and Leon, which exhibit high levels of intangible investment in ICT but very low intangible stock. Conversely, provinces like Tarragona and Albacete show both low investment and stock values in ICT.

Descriptive Statistics

The table provides descriptive statistics for firm-level and regional-level variables in a sample of 4,767 firms observed for an average of 9.5 years (Table 1). The sample firms have an average export intensity of 20%, which indicates that, on average, firms in the sample generate 20% of their revenue from exports. Labour productivity is relatively high, suggesting that the sample firms are efficient in their production processes. In terms of age, the values of both the standard deviation and the interquartile range (IQR) suggest the presence of a huge variability around the mean value of 27 years. In terms of size, the situation is even more amplified with a standard deviation which is roughly three-fold the magnitude of the mean value. Indeed, all this variability and previous literature on the topic (Coad & Hölzl, 2009) makes of utmost importance the separated consideration of firms belonging to different size classes. In line with the previous evidence hinting at considerable heterogeneity, we note how also R&D expenditure follow a similar path.

The low level of robot use may suggest that the sample firms may not be fully exploiting the potential of automation, but an additional explanation lies in the adoption of a strict definition of robotization, excluding other more general and older automation technologies. The average level of foreign ownership is low, indicating that the sample firms are mostly domestically owned. At the regional level, on average the sample is characterized by high levels of intangible assets related to ICT, relatively

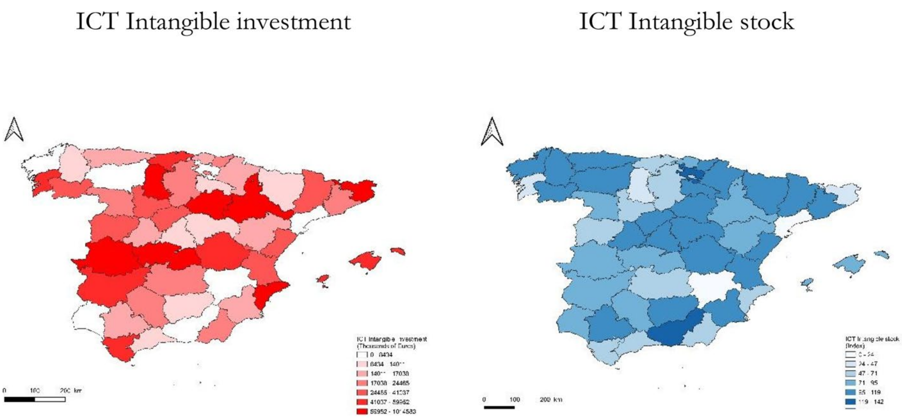

Fig. 1 Median values for ICT intangible investment and ICT intangible stock. Source: Own elaboration

Table 1 Descriptive statistics for the sample

Variable	Mean	SD	IQR	Skewness	Kurtosis
Export intensity	0.2	0.27	0.34	1.35	4.32
Labour productivity (th€/n)	1.47E+04	7.36E+04	1.17E+04	171.87	32928.39
Age (years)	27.06	21.4	24	1.99	10.6
Number of employees (n)	249.09	777.55	213	10.55	157.73
R&D expenditure (th€)	5.32E+04	7.41E+05	0	28.55	959.66
Robot use (1/0)	0.28	0.45	1	1	2
Foreign ownership (%)	17.24	36.44	0	1.73	4.09
Stock intangible assets ICT (%)	63.35	49.52	80.71	0.83	3.15
Investment intangible assets ICT (th€)	380435.9	787750.2	386460.8	4.02	22.59
Population density (n/km^2)	342.67	281.59	537.9	0.8	8.4

The number of firms observed is 4,767, which sums up to 41,157 total observations

high population density, and high investment in intangible assets, suggesting that the sample firms operate in regions with favourable conditions for innovation and knowledge-based activities.

In terms of time evolution (Fig. 2), we highlight how the general trend is trivially upward increasing, but this is subject to differences in magnitudes and trajectories according to the dimension along which we disaggregate. Overall, medium and large firms have been precursors in the adoption of robots, while smaller enterprises have been following and still have to catch up. Being an innovative firm seems to constitute a strong premium in terms of robot adoption, as the distribution shifts up by more than 10% points. Similarly, patenting firms are more likely to adopt robots and the more time passes, the more this effect enlarges.

We conclude the exploratory data analysis providing the kernel densities of the main variables of interest split by the categories used in this study, namely firm size, innovative and patenting status (Fig. 3). The graphics clearly indicate how the firms' behaviour differs significantly along the dimensions under study and how these are relevant for the disaggregated analysis.

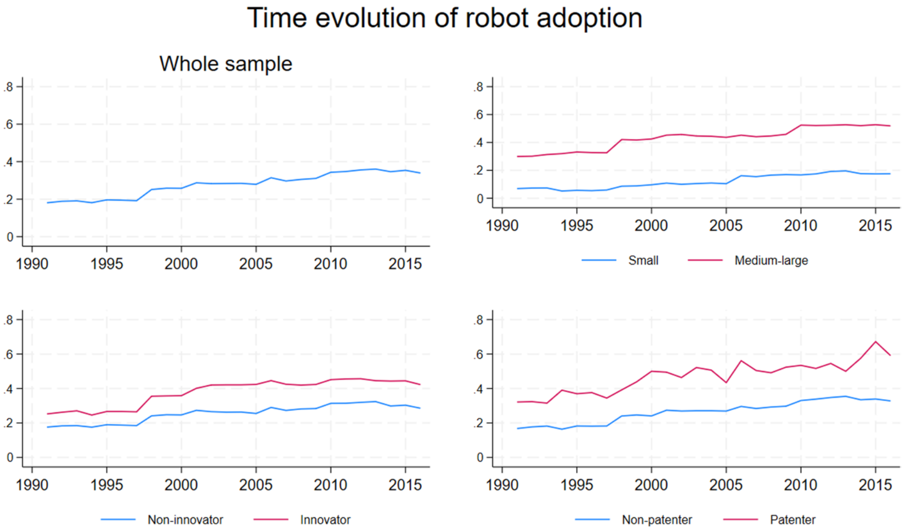

Fig. 2 Time evolution of robot adoption. Source: Own elaboration

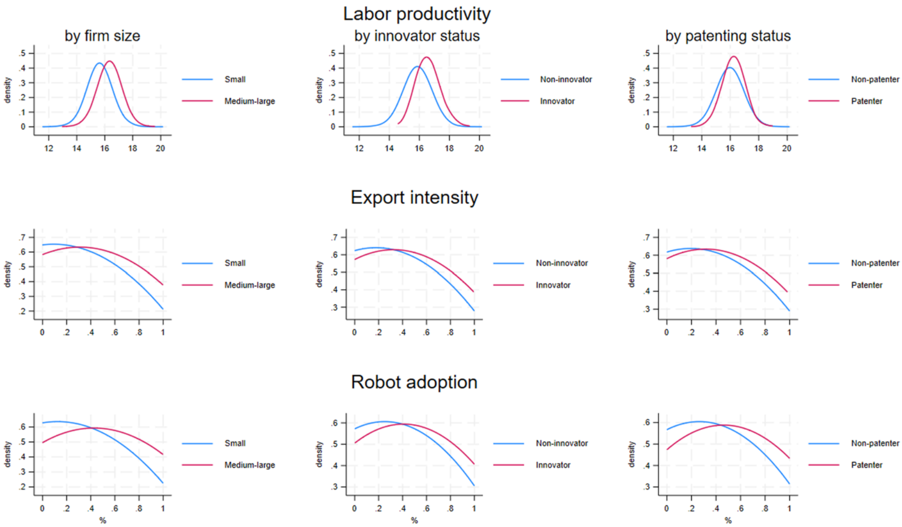

Fig. 3 Density value by type of firm. Source: Own elaboration

Estimation Approach

The methodology used in this paper involves a panel data econometric analysis to investigate the relationship between robotization and key firm-level variables such as productivity, defined either as value added per worker or TFP, and export intensity in the Spanish economy from 1990 to 2016. The model includes two dependent variables and several explanatory variables, including lagged values of the dependent variables, age of the firm, sector, a robotization variable,[3] employees, foreign ownership, and regional variables. The paper employs fixed effect models to control for time-invariant variables, reduce the possible biases derived from unobservable factors and estimate the effect of the explanatory variables on the dependent variables.

In addition, the model used includes a spatial lag approach, which captures the effect of neighbouring provinces on firms belonging to the province. This approach is used to account for the spatial dependence of economic variables, where the behaviour of one firm can affect the behaviour of firms in neighbouring regions. The spatial lag approach incorporates neighbouring regional variables, such as the number of firms in the same sector in neighbouring provinces, population density, and regional expenditure in R&D. These variables are included to capture the spatial spillover effects that may impact the productivity and export intensity of firms. The inclusion of a spatial lag approach is an important contribution to the methodology used in this study, as it allows for a more comprehensive understanding of the factors that influence firm-level and regional-level variables.

The model is as follows:

$$\begin{gathered} Y_{ijt} = X_{it-1} + X_{jt-1} + \\ X_j + WX_{jt-1} + WX_j + \epsilon_{it} \end{gathered}$$

where dependent variables, Yijt, represent the labour productivity, defined as output per worker, of the firm *i* and the export intensity, and are regressed against several explanatory variables.[4] The explanatory variables, Xit-1, capture the firm's characteristics in t-1, such as age, sector, robotization and digitalization variables, employees, and foreign ownership. The explanatory variables, Xjt, capture the province characteristics in t-1, such as population density, localization economies and regional expenditure in R&D. Additionally, the model includes province dummy variables, Xj, which are time-invariant. Furthermore, a spatial lag approach is included in the model, where WXjt-1 represents the neighbouring province characteristics in t-1 and WXj represents neighbouring province dummy variables, which are time-invariant[5]. Finally, as anticipated, we replicate the estimation procedure disaggregating along

[3] In this context, there exist several ways to define and numerically proxy for robotization at firm-level, with none of these that come without shortcomings. For instance, it could be interesting to study how the intensity of robotization or its cumulated years of use are associated with our dependent variables. Nevertheless, we argue that for the scope of the paper, which is to explain the how robots and territories relate with firm-level export intensity and productivity, the binary choice is a parsimonious, directly interpretable, and significant decision, also under an Occam's approach.

[4] Estimating separate firm-level regressions for labour productivity and export intensity using identical regressors—age, sector, robotization, digitalization, number of employees, and foreign ownership—is justified by the distinct influences these factors may exert on different aspects of firm performance. Further, the choice allows for a nuanced comparison of how these factors differently affect productivity and market expansion. This approach aligns with strategic management and international business research, suggesting varied impacts of firm characteristics on different performance metrics (Grant, 1991; Lu & Beamish, 2001).

[5] The analysis uses provinces as the territorial unit due to data availability constraints. Ideally, metropolitan areas or local labour markets would provide a more accurate representation of the spatial economic dynamics. However, the lack of accessible and comprehensive data at these finer spatial levels necessitates the use of provinces for this study.

firms' dimensions, such as firm size and innovative status. In terms of firm size consideration, we adopt a direct confrontation between micro/small firms and medium/large ones (following the EUROSTAT definition). This is slightly different from standard approaches in economics that tend to group together small and medium enterprises. Nevertheless, this traditional grouping is far from homogenous and the risk of mixing different mechanisms and dynamics may bias the results. Contrarily, we uncover distinct patterns and dynamics within the SME sector.

Spatial Dependency Tests

The selection of spatial variables for the model was done through a series of tests. Firstly, the variables were chosen based on their economic sense and the existing literature on the subject. Then, the variables were tested for significance in the non-spatial model to determine their relevance in explaining the dependent variables. Finally, the spatial autocorrelation of these variables across the provinces was tested using Moran's I and LISA. Moran's I measures the degree of spatial clustering of a variable, while LISA tests for local spatial autocorrelation. The use of these tests allowed for the selection of spatial variables that capture the spatial dependence of economic variables and their impact on firm-level and regional-level variables. The inclusion of relevant spatial variables in the model is crucial for understanding the complex relationships between firm-level and regional-level variables, and their impact on total factor productivity and export intensity.

Robustness Analysis

To control for different productivity measures and ensure the robustness of our estimates, we replicated the analysis using total factor productivity instead of labour productivity. Precisely, we employ the Levinsohn & Petrin (2003) methodology to estimate firm-level total factor productivity (TFP) based on output. This method is widely used in empirical studies, it has been shown to produce reliable estimates of firm-level productivity and it has been already successfully applied to the present dataset (for instance, in Torrent-Sellens et al., 2022). The Levinsohn and Petrin (LP) method involves estimating a production function that accounts for the unobserved heterogeneity among firms. Specifically, the method assumes that unobserved productivity is correlated with both the inputs and the outputs of the production process. This correlation allows for the estimation of a firm-specific TFP residual that captures the unobserved factors affecting productivity.

To implement the LP method, we first estimate a Cobb-Douglas production function using a panel of firm-level data. We then use the estimated parameters of the production function to compute the expected level of output for each firm. We then calculate the TFP residual as the difference between the actual and expected levels of output, adjusting for firm-specific characteristics. Further, to address potential issues of endogeneity and measurement error, we include lagged inputs and outputs as instruments in our estimations. We also test for the robustness of our results by using alternative specifications of the production function and alternative measures of inputs and outputs.

By doing so, we aimed to test if the results differ when using different approaches to measure firm productivity. The detailed estimations can be found in the annex of the paper. Other methodological precautions are related to multicollinearity diagnoses that have been addressed by testing the tolerance and variance inflation factor (VIF) among the explanatory variables and to the use of alternative TFP estimations, such as the Ackerbergerg, Caves & Frazer (2015) correction. The yielded estimates are untouched for what pertains to the significant variables. Finally, for the sake of additional robustness checks and alleviate possible endogeneity issues, we re-estimate the model using the Box-Cox (1964) transformation, instead of the standard log transformation, and also in this case, the results are robust. A final extension to the model consists of the inclusion of a time-variant dummy variable accounting for the exporter status in the productivity equation and yet again, the estimated coefficients are in line with what commented.

Results

Having established the framework that captures the interplay between productivity, export, robotization and space, we now turn our attention to the empirical findings. Through the application of a spatial lag approach, we have carefully examined the complex web of spatial dependencies that shape economic outcomes. Our estimation model incorporates an array of firm-level and province-level characteristics, alongside fixed effects to account for unobserved heterogeneity. By integrating these elements into our analysis, we are primed to uncover significant insights into the factors driving productivity and export intensity. In the following sections, we present the results and associated tables, illustrating the nuanced relationships and shedding light on the spatial spillover effects that influence economic dynamics at both the firm and regional levels.

Full Model

In this first sub-section, we present the estimations for the full sample and disaggregated by firm sizes. By exploring different firm categories, we uncover how spatial dependencies affect economic outcomes across small, medium, and large firms. This initial disaggregation offers valuable insights into the heterogeneous effects based on firm size. Additionally, we anticipate further disaggregation by distinguishing between innovator and non-innovator firms, as well as patenting and non-patenting firms. These subsequent analyses will provide a deeper understanding of how spatial spillover effects vary among firms with different innovation and patenting profiles. By considering these various dimensions, we aim to inform targeted policies for fostering innovation, enhancing productivity, and promoting regional economic development (Table 2).

The presence of firms in the same sector within the province has a positive impact on the export intensity of firms. When we split the sample, the positive effect remains for medium and large firms, but for small firms, this positive effect is only observed for productivity. This suggests that for small firms, which primarily operate in the

Table 2 Panel estimations of the empirical model – Fixed effects

	FULL SAMPLE		SMALL		MED-LARGE FIRMS	
VARIABLES	LAB.PROD	EXP.INT	LAB.PROD	EXP.INT	LAB.PROD	EXP.INT
Lagged dep. var	0.522***	0.517***	0.461***	0.489***	0.553***	0.545***
	(0.0221)	(0.0114)	(0.0164)	(0.0142)	(0.0259)	(0.0153)
LAB.PROD		0.280***		0.223***		0.114
		(0.0629)		(0.0752)		(0.0974)
AGE	0.0173	−0.338***	−0.0155	−0.561**	0.0234*	−0.179**
	(0.0119)	(0.106)	(0.0232)	(0.254)	(0.0131)	(0.0748)
AGE SQ.	−0.0174**	0.192***	0.00463	0.269**	−0.0192**	0.114**
	(0.00824)	(0.0616)	(0.0134)	(0.136)	(0.00922)	(0.0487)
EMPL.	−0.179***	0.378***				
	(0.0145)	(0.035)				
R&D	0.320***	−0.106	0.230*	−0.02	0.140***	0.186
	(0.0446)	(0.21)	(0.125)	(0.635)	(0.0392)	(0.229)
ROBOT USE	0.0159**	0.0191	0.0317***	0.127	0.000513	0.0054
	(0.0064)	(0.0323)	(0.0103)	(0.0823)	(0.00489)	(0.0309)
FOREIGN OWN	0.00187**	0.00705	0.00214	0.0314**	0.00145*	0.0028
	(0.00074)	(0.00465)	(0.0027)	(0.0153)	(0.00084)	(0.00427)
stock intang. assets ICT	0.0256**	−0.139***	0.0370**	−0.167	0.0474***	−0.163**
	(0.00996)	(0.0532)	(0.0155)	(0.12)	(0.0146)	(0.075)
investment in-tang. assets ICT	0.0456***	−0.0366	0.0333***	0.035	0.0178**	−0.00761
	(0.00717)	(0.0339)	(0.0101)	(0.0596)	(0.00887)	(0.0387)
POP.DEN	−0.0283	−0.26	−0.0974**	0.186	−0.013	−0.371**
	(0.031)	(0.162)	(0.0442)	(0.341)	(0.0297)	(0.157)
bordering POP. DEN	−0.113***	−0.0512	0.0399	−0.562	−0.129***	−0.00493
	(0.0297)	(0.129)	(0.0595)	(0.49)	(0.0323)	(0.117)
# firms same province	0.0365	0.349**	0.161**	−0.0365	0.0582**	0.431***
	(0.0256)	(0.163)	(0.0651)	(0.378)	(0.028)	(0.15)
# firms border-ing province	0.296***	0.261	0.167***	0.788**	0.331***	0.209
	(0.0289)	(0.186)	(0.0602)	(0.4)	(0.0264)	(0.169)
Constant	8.300***	−11.66***	8.091***	−10.93	5.300***	−4.956***
	(0.492)	(1.986)	(1.283)	(6.878)	(0.358)	(1.854)
Within R-squared	0.66	0.317	0.55	0.277	0.748	0.345
Observations	41,157	41,157	20,478	20,478	20,679	20,679
Number of firms	4,767		2,773		2,424	

Bootstrapped standard errors in parentheses - *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All variables are in log form. The estimated coefficients in the table have been adjusted for unobserved heterogeneity through the inclusion of fixed effects. The reported results have undergone robustness checks to verify the stability and consistency of the estimated coefficients (i.e., re-estimation using TFP for productivity, clustered standard errors at sectoral level and Box-Cox transformation instead of the log one).

domestic market, localization economies have a significant impact on productivity rather than export intensity. However, for large firms, localization economies have a positive impact on both productivity and export intensity, indicating that these firms benefit from localization economies using both variables. When we analyse the same effect for neighbouring regions, we find a positive impact, indicating that firms located within a province are influenced by the localization economies that occur in the neighbouring regions. This positive effect suggests that these neighbouring regions can also provide benefits to the firms located in the current province.

In summary, the findings indicate that localization economies play a crucial role in determining the performance of firms in certain industries. Specifically, the presence of firms in the same sector within a province has a positive impact on the export intensity of medium and large firms, while it affects the productivity of small firms. Moreover, the positive effect of localization economies extends to neighbouring regions, further emphasizing their importance for the performance of firms. These findings highlight the need for policymakers and business leaders to consider the impact of localization economies when making decisions related to firm location and regional development strategies.

The robustness of the findings and of their magnitudes is confirmed by the robustness checks (see Appendix) that show how even switching from labour productivity to total factor one, very few differences emerge and none of these affect the most significant results that we comment. This also suggests that the identification of the model is relatively stable.

Innovation-Based Split Samples

First, we confirm the stability of our estimates starting from the coefficients of the control variables. Then, regarding the main findings of our study, we find that robotization has a positive and significant effect on the productivity of both innovative and non-innovative firms. However, when we further split the sample into firms that register patents and those that do not, we observe that the positive effect of robot adoption is mainly driven by non-innovative firms (Table 3).

These findings suggest that firms that are able to patent technologies may rely on other automation technologies that are not captured by our robotization variable. This could be the case of manufacturing firms in traditional industries that are typically supplier-dominated. In contrast, science-based sectors may rely more on human capital and intangible assets, such as patents, rather than on physical capital, such as robots, to innovate and increase productivity.

Overall, our results highlight the heterogeneous effects of robotization on firm productivity and the importance of considering the context in which firms operate, such as the level of innovation and the industry sector, when designing policies and strategies aimed at promoting productivity growth, as also suggested by related recent evidence (Zhao et al., 2024).

Now we will further examine regional variables and their impact on export and productivity. Specifically, we will explore how these variables affect innovative, patented firms versus non-innovative, non-patented firms. The presence of intangible assets in the province, specifically ICT assets, has a negative impact on export for firms that do not patent or innovate within the province. This is logical since these firms are located in a region with high innovation and are thus negatively affected, causing them to lose market power.

When examining the impact of localization economies on innovative, patented firms versus non-innovative, non-patented firms, we found that localization economies have a positive and significant effect on export intensity, particularly for firms that innovate. Additionally, localization economies have a significant impact on labour productivity for innovative firms. However, the effect of localization economies on labour productivity and export intensity for patented firms is not entirely clear, as these firms are highly heterogeneous. While the effect appears to be positive, it is not statistically significant.

Concluding Remarks

In conclusion, this article has examined the role of robotization on firm productivity and export performance in Spain, with a focus on how province-level characteristics, such as investment in ICT, affect firm-level productivity. Our analysis has shown that robot adoption is positively associated with firm productivity in Spain, and that the effects of robotization are moderated by province-level characteristics, such as ICT investment and agglomeration economies.

In this study, we shed more light on the complex relationship between robotization, firm productivity, and innovation across different industry sectors. First, we show that not only robot adoption significantly enhances overall productivity, but also it is primarily non-innovative and small firms driving this positive effect. This suggests that innovative firms, especially those involved in patent registration, may rely on alternative automation technologies beyond the scope of our robotization variable. More generally, the diverse outcomes underline the importance of considering the specific industry sector and level of innovation when formulating strategies and policies aimed at promoting productivity growth.

Expanding our investigation to regional variables, we uncover intriguing insights into their impact on export performance and productivity. Remarkably, the presence of intangible assets, such as ICT assets, in a province negatively affects the export capabilities of non-innovative firms without patents. Conversely, localization economies demonstrate a pronounced positive effect on export intensity, particularly for firms engaged in innovation. Moreover, they also exhibit a significant influence on labour productivity for innovative firms. However, the implications of localization economies on labour productivity and export intensity for patented firms remain inconclusive, highlighting the substantial heterogeneity within this group. These findings emphasize the need for policymakers and strategists to account for the contextual nuances of firms' operations to effectively stimulate productivity growth.

Indeed, our findings have important implications for firms and regions seeking to optimize their productivity and competitiveness in an increasingly globalized world. Firstly, our results suggest that firms, especially small and non-innovative ones, should consider investing in robotics and automation to enhance their productivity and competitiveness and to avoid lagging behind. This aligns with Dosi et al.'s

Table 3 Panel estimations of the empirical model – Fixed effects – innovation-specific results

	PATENTER		NON-PATENTER		INNOVATOR		NON-INNOVATOR	
VARIABLES	LAB	EXP	LAB	EXP	LAB	EXP	LAB	EXP
	PROD	INT	PROD	INT	PROD	INT	PROD	INT
Lagged dep. var	0.545***	0.528***	0.516***	0.512***	0.627***	0.617***	0.502***	0.502***
	(0.0327)	(0.0617)	(0.0196)	(0.0124)	(0.0337)	(0.0288)	(0.0206)	(0.0127)
LAB.PROD		0.00919		0.293***		0.125		0.308***
		(0.13)		(0.0621)		(0.129)		(0.0874)
AGE	−0.0462	0.284	0.0200*	−0.373***	−0.00654	−0.586	0.0218*	−0.318***
	(0.0455)	(0.173)	(0.0115)	(0.13)	(0.0576)	(0.358)	(0.012)	(0.12)
AGE SQ.	0.0179	−0.256*	−0.0195**	0.215***	−0.00164	0.317*	−0.0209**	0.183***
	(0.0264)	(0.148)	(0.00797)	(0.0735)	(0.031)	(0.179)	(0.00871)	(0.071)
EMPL.	−0.140***	0.277*	−0.183***	0.379***	−0.115***	0.165	−0.189***	0.403***
	(0.0275)	(0.165)	(0.0153)	(0.0418)	(0.0315)	(0.105)	(0.0144)	(0.0456)
R&D	0.138	1.038**	0.330***	−0.158	0.204***	−0.726*	0.279***	0.213
	(0.0903)	(0.469)	(0.0366)	(0.27)	(0.0694)	(0.414)	(0.0516)	(0.5)
ROBOT USE	−0.0131	−0.00193	0.0178***	0.0125	0.0192**	0.0426	0.0142**	0.00843
	(0.0136)	(0.117)	(0.00562)	(0.035)	(0.00964)	(0.0481)	(0.00716)	(0.04)
FOREIGN OWN	0.00188	0.0257**	0.00197*	0.00696	0.00244**	0.00531	0.00161*	0.00747
	(0.00117)	(0.0108)	(0.00101)	(0.0048)	(0.00117)	(0.0066)	(0.00088)	(0.00584)
stock intang. assets ICT	0.0261	−0.0462	0.0242*	−0.140**	−0.00429	−0.00215	0.0332***	−0.175***
	(0.0344)	(0.215)	(0.0128)	(0.0559)	(0.0164)	(0.137)	(0.0098)	(0.0641)
investment intang. assets ICT	0.0376*	−0.0827	0.0473***	−0.0288	0.0174	−0.0105	0.0529***	−0.0459
	(0.0218)	(0.162)	(0.00772)	(0.0403)	(0.0127)	(0.0639)	(0.00732)	(0.035)
POP.DEN	−0.00353	−0.604	−0.0312	−0.251*	−0.0513	−0.32	−0.0305	−0.257
	(0.154)	(0.689)	(0.0332)	(0.139)	(0.0727)	(0.233)	(0.0348)	(0.178)
bordering POP.DEN	−0.0589	0.523	−0.115***	−0.0675	−0.0237	0.453	−0.122***	−0.111
	(0.135)	(0.754)	(0.0374)	(0.188)	(0.0739)	(0.286)	(0.033)	(0.182)
# firms same province	0.0286	0.903	0.038	0.329**	0.131*	0.687**	0.0233	0.320*
	(0.175)	(0.717)	(0.0327)	(0.148)	(0.0744)	(0.273)	(0.0322)	(0.175)

Table 3 (continued)

	PATENTER		NON-PATENTER		INNOVATOR		NON-INNOVATOR	
VARIABLES	LAB	EXP	LAB	EXP	LAB	EXP	LAB	EXP
	PROD	INT	PROD	INT	PROD	INT	PROD	INT
# firms bordering province	0.348**	−0.358	0.298***	0.280*	0.214***	−0.127	0.302***	0.341
	(0.171)	(0.743)	(0.0271)	(0.149)	(0.077)	(0.275)	(0.0361)	(0.217)
Constant	5.438***	−3.105	8.570***	−12.43***	2.884***	−4.145	9.061***	−9.479*
	(0.642)	(3.423)	(0.425)	(2.668)	(0.575)	(2.951)	(0.615)	(5.478)
Within R-squared	0.801	0.388	0.648	0.312	0.791	0.451	0.631	0.299
Observations	2,561		38,596		6,683		34,474	
Number of firms	877		4,708		591		4,176	

Bootstrapped standard errors in parentheses - *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All variables are in log form. The estimated coefficients in the table have been adjusted for unobserved heterogeneity through the inclusion of fixed effects. The reported results have undergone robustness checks to verify the stability and consistency of the estimated coefficients (i.e., re-estimation using TFP for productivity, clustered standard errors at sectoral level and Box-Cox transformation instead of the log one).

emphasis on the innovation-driven competition among firms, where those lagging in technology adoption may fall behind (Dosi et al., 2015). By providing financial incentives and establishing innovation hubs, governments can facilitate access to robotics technologies, especially in regions with lower productivity and innovation metrics.

Secondly, our study highlights the importance of province-level characteristics in shaping the relationship between robots and firm productivity, suggesting that policymakers should consider targeted interventions to enhance these characteristics in regions lagging behind in terms of productivity and innovation. Moreover, the segmentation between small/micro firms and medium-large ones constitutes an alignment to policy making interventions. Indeed, governments and policy actors often employ different measures to support small and micro enterprises compared to medium-sized firms. By focusing on this disaggregation, our analysis can provide more targeted policy recommendations to enhance productivity growth and export performance among these specific groups. Finally, small and micro enterprises constitute a significant portion of the business landscape in many economies. Ignoring this important segment of firms may lead to incomplete findings and an incomplete understanding of the overall economic dynamics.

Limitations and Future Directions

Purposedly, we did not enter neither into the self-selection versus learning-by-exporting debate in firm-level international trade nor into the possible self-selection of robot-adopting enterprises. On the one hand, we do not look at learning-by-exporting, which is a very complex phenomenon, and it shall be analysed in its singularity. On the other hand, self-selection is taken into consideration using the past productivity model in our empirical formulation of firm's export determinants, but we do not discuss it in its more detailed aspects. In this line, we also include in the export equation all the firms present in the sample, artificially adding to them 1 dollar of exported value.[6] Indeed, this standard practice does not significantly affect the distribution of interest, especially given the estimation technique, the long-observed time span, and the adoption of fixed effects and several robustness checks. Contrarily, this choice allows to have a uniform sample and thus, to control for the "robotization" effect on the same firms.

In terms of external validity, extrapolating these findings to other countries requires careful consideration due to varying economic, industrial, and technological landscapes. Firstly, the influence of robot adoption on productivity and export performance may vary significantly in countries with different levels of industrialization and technological integration. Spain, as a moderately industrialized country within the EU, provides a specific context where ICT investments and agglomeration economies could have distinct impacts compared to more or less industrialized nations.

[6] This adjustment is not the only one suggested in the vast literature on the topic of (log) transformations. For this reason, we also replicated the estimates using a Box-Cox (1964) transformation and all the significant results are not affected. We do not adopt the also suggested inverse hyperbolic sine transformation, as it has recently been shown that its outcome is directly related to the unit of measurement of the variables (Aihounton & Henningsen, 2021).

For example, in highly industrialized countries like Germany or Japan, the impact of robotics might be more pronounced due to higher levels of technology adoption and advanced manufacturing techniques, potentially leading to even greater productivity enhancements. Conversely, in less industrialized countries, the effects might be more subdued due to limited technological infrastructure and lower robot adoption rates, suggesting that the Spanish findings may not fully translate to these environments. Secondly, the particular emphasis on SMEs in the ESEE dataset highlights another aspect of external validity. While SMEs constitute a significant portion of the economy in many countries, the structure and challenges faced by SMEs can vary widely. For instance, SMEs in developing countries might not experience the same productivity gains from robotization seen in Spanish SMEs, owing to differences in access to capital, technology, and skilled labour. Moreover, the impact of localization economies and ICT assets on export capabilities and productivity noted in Spanish regions might not hold in regions where these factors differ markedly, such as in countries with less regional economic concentration or differing policies on technology and innovation.

Finally, considering future research, our study opens up several avenues for further investigation. One interesting direction would be to explore the impact of robotization on different types of SMEs, such as local or non-local firms and manufacturing and non-manufacturing firms, which may face different barriers to robot adoption as well as diverse trajectories of complementarity, results and connection with their spatial environment (Jestl, 2024) Another potential avenue for future research would be to examine the impact of robotization on employment and job polarization in Spain, which has important implications for social welfare and inequality (Valentini et al., 2023).

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s13132-026-03261-7.

Authors Contribution Sebastiano Cattaruzzo: Conceptualization; Methodology; Formal Analysis; Data Curation; Writing-original draft; Writing-review & editing. Carles Méndez-Ortega: Conceptualization; Methodology; Data Curation; Writing-original draft; Writing-review & editing. Joan Torrent-Sellens: Conceptualization; Writing-original draft; Writing-review & editing; Supervision; Funding acquisition.

Funding Open Access funding provided thanks to the CRUE-CSIC agreement with Springer Nature. This work was supported by the Next Generation EU - "GRINS - Growing Resilient, INclusive and Sustainable" project (PE0000018), National Recovery and Resilience Plan (NRRP) – PE9 - Mission 4, C2, Intervention 1.3". The authors thank Fundación SEPI for providing the firm data for the development of this research.

Data Availability The data that support the findings of this study are not publicly available as they were obtained under a commercial license from a third-party provider and are subject to access restrictions. Interested researchers may obtain access directly from the data provider under its terms and conditions. The authors are not permitted to share the data.

Declarations

Ethics statements This study does not involve human participants or animals. Ethics approval and informed consent are therefore not required.

Conflict of interest The authors declare that they have no competing interests.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2014). Return of the Solow paradox? IT, productivity, and employment in US manufacturing. *American Economic Review, 104*(5), 394–399.

Acemoglu, D., Lelarge, C., & Restrepo, P. (2020). Competing with robots: Firm-level evidence from France. *American Economic Review Papers & Proceedings*, *110*, 383–388.

Acemoglu, D., & Autor, D. H. (2011). Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics, 4*, 1043–1171.

Acemoglu, D., & Restrepo, P. (2018a). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, *108*(6), 1488–1542.

Acemoglu, D., & Restrepo, P. (2018b). Modelling automation. *American Economic Association Papers and Proceedings, 108*, 48–53.

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labour. *Journal of Economic Perspectives*, *33*(2), 3–30.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labour markets. *Journal of Political Economy*, *128*(6), 2188–2244.

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica, 83*(6), 2411–2451.

Aihounton, G. B., & Henningsen, A. (2021). Units of measurement and the inverse hyperbolic sine transformation. *Econometrics Journal, 24*(2), 334–351.

Aitken, B. J., & Harrison, A. E. (1999). Do domestic firms benefit from direct foreign investment? Evidence from Venezuela. *American Economic Review, 89*(3), 605–618.

Alguacil, M., Lo Turco, A., & Martínez-Zarzoso, I. (2020). What is so special about robots and trade? Available at SSRN *3756787*.

Alguacil, M., Turco, A. L., & Martínez-Zarzoso, I. (2022). Robot adoption and export performance: Firm-level evidence from Spain. *Economic Modelling, 114*, Article 105912.

Añón-Higón, D., & Bonvin, D. (2022). Information and communication technologies and firms' export performance. *Industrial and Corporate Change*, *31*(4), 955–979.

Antón, J. I., Klenert, D., Fernández-Macías, E., Urzì Brancati, M. C., & Alaveras, G. (2022). The labour market impact of robotisation in Europe. *European Journal of Industrial Relations, 28*(3), 317–339.

Antràs, P. (2020). De-globalisation? Global value chains in the post-COVID-19 age. *National Bureau of Economic Research Working Paper*, w28115.

Autor, D. H., & Salomons, A. (2017). Robocalypse now: Does productivity growth threaten employment. In: European Central Bank (Ed.). *Proceedings of the ECB forum on central banking: Investment and growth in advanced economy*. Frankfurt am Main, ECB, pp. 45–118.

Autor, D. H., & Salomons, A. (2018). Is automation labour share–displacing? Productivity growth, employment, and the labour share. *Brooking Papers on Economic Activity, Spring*, 1–63.

Aw, B. Y., Roberts, M. J., & Xu, D. Y. (2011). R&D investment, exporting, and productivity dynamics. *American Economic Review, 101*(4), 1312–1344.

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics, 151*, Article 103745.

Ballestar, M. T., Camiña, E., Díaz-Chao, A., & Torrent-Sellens, J. (2021b). Productivity and employment effects of digital complementarities. *Journal of Innovation & Knowledge*, *6*(3), 177–190.

Ballestar, M. T., Díaz-Chao, Á., Sainz, J., & Torrent-Sellens, J. (2020). Knowledge, robots and productivity in SMEs: Explaining the second digital wave. *Journal of Business Research, 108*, 119–131.
Ballestar, M. T., Díaz-Chao, Á., Sainz, J., & Torrent-Sellens, J. (2021a). Impact of robotics on manufacturing: A longitudinal machine learning perspective. *Technological Forecasting and Social Change*, *162*, 120348.
Barajas, A., Huergo, E., & Moreno, L. (2019). Robots and firm exporting. *Journal of International Economics*, *116*, 103–125.
Berg, A., Buffie, E. F., & Zanna, L. F. (2018). Should we fear the robot revolution? (The correct answer is yes). *Journal of Monetary Economics, 97*, 117–148.
Bernard, A. B., Jensen, J. B., & Lawrence, R. Z. (1995). Exporters, jobs, and wages in US manufacturing: 1976–1987. *Brookings papers on economic activity Microeconomics*, *1995*, 67–119.
Bettiol, M., Capestro, M., Di Maria, E., & Ganau, R. (2024). Is this time different? How Industry 4.0 affects firms' labor productivity. *Small Business Economics, 62*(4), 1449–1467.
Box, G. E., & Cox, D. R. (1964). An analysis of transformations. *Journal of the Royal Statistical Society. Series B, Statistical Methodology, 26*(2), 211–243.
Brynjolfsson, E., Buffington, C., Goldschlag, N., Li, J. F., Miranda, J., & Seamans, R. (2023). Robot hubs: The skewed distribution of robots in US manufacturing. *AEA Papers and Proceedings, 113*, 215–218.
Brynjolfsson, E., & McAfee, A. (2011). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*. Digital Frontier Press.
Brynjolfsson, E., & McAfee, A. (2014). *The second machine age. Work, progress, and prosperity in a time of brilliant technologies*. W.W. Norton & Company.
Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal, Macroeconomics, 13*(1), 333–372.
Camiña, E., Diaz-Chao, A., & Torrent-Sellens, J. (2020). Automation technologies: Long-term effects for Spanish industrial firms. *Technological Forecasting and Social Change, 151*, Article 119828.
Can, H., Minkovska, D., & Stoyanova, L. (2020, October). Estimation of energy performance classes of concrete structures with artificial intelligence models. In *2020 III International Conference on High Technology for Sustainable Development (HiTech)* (pp. 1–3). IEEE.
Cao, Y., Chen, S., & Tang, H. (2025). Robot adoption and firm export: Evidence from China. *Technological Forecasting and Social Change, 210*, Article 123878.
Cette, G., Devillard, A., & Spiezia, V. (2021). The contribution of robots to productivity growth in 30 OECD countries over 1975–2019. *Economics Letters, 200*, Article 109762.
Chen, B., & Tan, D. (2023). Industrial robots and the employment quality of migrant workers in the manufacturing industry. *Sustainability, 15*(10), Article 7998.
Coad, A., & Hölzl, W. (2009). On the autocorrelation of growth rates: Evidence for micro, small and large firms from the Austrian service industries, 1975–2004. *Journal of Industry, Competition, and Trade, 9*, 139–166.
Coad, A., & Tamvada, J. P. (2012). Firm growth and barriers to growth among small firms in India. *Small Business Economics, 39*, 383–400.
Crepon, B., Duguet, E., & Mairesse, J. (1998). Research, innovation and productivity: An econometric analysis at the firm level. *Economics of Innovation and New Technologies*, *7*, 115–158.
Cséfalvay, Z. (2023). As robots are moving out of the cages – Toward a geography of robotization. *Eurasian Geography and Economics, 64*(1), 89–119.
Czarnitzki, D., Fernández, G. P., & Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization, 211*, 188–205.
Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review, 11*, 1–25.
Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2021). The adjustment of labour markets to robots. *Journal of the European Economic Association*, *19*(6), 3104–3153.
Díaz-Chao, Á., Ficapal-Cusí, P., & Torrent-Sellens, J. (2021). Environmental assets, industry 4.0 technologies and firm performance in Spain: A dynamic capabilities path to reward sustainability. *Journal of Cleaner Production, 281*, Article 125264.
Diaz, M. A., & Sánchez, R. (2008). Firm size and productivity in Spain: A stochastic frontier analysis. *Small Business Economics, 30*, 315–323.
Dosi, G., Moschella, D., Pugliese, E., & Tamagni, F. (2015).Productivity, market selection, and corporategrowth:comparative evidence across US and Europe. *Small Business Economics*, *45*(3), 643–672.

Dosi, G., & Nelson, R. R. (2013). The evolution of technologies: An assessment of the state-of-the-art. *Eurasian Business Review, 3*, 3–46.

Dottori, D. (2021). Robots and employment: Evidence from Italy. *Economia Politica*, *38*, 739–795.

Duan, D., Chen, S., Feng, Z., & Li, J. (2023). Industrial robots and firm productivity. *Structural Change and Economic Dynamics*, *67*, 388–406.

Du, L., & Lin, W. (2022). Does the application of industrial robots overcome the Solow paradox? Evidence from China. *Technology in Society, 68*, Article 101932.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., & Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994.

Dwivedi, Y. K., Sharma, A., Rana, N. P., Giannakis, M., Goel, P., & Dutot, V. (2023). Evolution of artificial intelligence research in Technological Forecasting and Social Change: Research topics, trends, and future directions. *Technological Forecasting and Social Change, 192*, Article 122579.

Eppinger, P. S., Meythaler, N., Sindlinger, M. M., & Smolka, M. (2018). The great trade collapse and the Spanish export miracle: Firm-level evidence from the crisis. *World Economy, 41*(2), 457–493.

Escobedo, R. F., Peña, B. E., & Odriozola, L. A. (2024). Cluster mapping in Spain: Exploring correlation between industrial agglomeration and regional performance. *Investigaciones Regionales - Journal of Regional Research, 59*, 81–104.

Faber, M. (2020). Robots and reshoring: Evidence from Mexican labour markets. *Journal of International Economics, 127*, Article 103384.

Fernández-Macías, E., Klenert, D., & Anton, J. I. (2021). Not so disruptive yet? Characteristics, distribution and determinants of robots in Europe. *Structural Change and Economic Dynamics*, *58*, 76–89.

Fierro, L. E., Caiani, A., & Russo, A. (2022). Automation, job polarisation, and structural change. *Journal of Economic Behavior & Organization, 200*, 499–535.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280.

Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, *104*(8), 2509–2526.

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

Graetz, G., & Michaels, G. S. (2017). Is modern technology responsible for jobless recoveries? *American Economic Review, 107*(5), 168–173.

Grant, R. M. (1991). The resource-based theory of competitive advantage: Implications for strategy formulation. *California Management Review, 33*(3), 114–135.

Grashof, N., & Kopka, A. (2023). Artificial intelligence and radical innovation: An opportunity for all companies? *Small Business Economics*, *61*, 771–797.

Gregory, T., Salomons, A., & Zierahn, U. (2022). Racing with or against the machine? Evidence on the role of trade in Europe. *Journal of the European Economic Association, 20*(2), 869–906.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? Small versus large versus young. *Review of Economics and Statistics*, *95*(2), 347–361.

Hollenstein, H. (2005). Determinants of international activities: Are SMEs different? *Small Business Economics, 24*, 431–450.

Holm, J. R., & Lorenz, E. (2022). The impact of artificial intelligence on skills at work in Denmark. *New Technology, Work and Employment, 37*(1), 79–101.

Hu, S., Lin, K., Liu, B., & Wang, H. (2023). Does robotization improve the skill structure? The role of job displacement and structural transformation. *Applied Economics*. https://doi.org/10.1080/00036846.2023.2206623

Javorcik, B. S. (2004). Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages. *American Economic Review, 94*(3), 605–627.

Jestl, S. (2024). Industrial robots, and information and communication technology: The employment effects in EU labour markets. *Regional Studies*. https://doi.org/10.1080/00343404.2023.2292259

Jungmittag, A. (2021). Robotization of the manufacturing industries in the EU: Convergence or divergence? *Journal of Technology Transfer*, *46*(5), 1269–1290.

Karabarbounis, L., & Neiman, B. (2014). The global decline of the labour share. *Quarterly Journal of Economics*, *129*(1), 61–103.

Kariel, J. (2021). Job creators or job killers? Heterogeneous effects of industrial robots on UK employment. *Labour*, *35*(1), 52–78.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature, 42*(3), 752–782.

Klenert, D., Fernández-Macias, E., & Anton, J. I. (2023). Do robots really destroy jobs? Evidence from Europe. *Economic and Industrial Democracy*, *44*(1), 280–316.

Koch, M., Manuylov, I., & Smolka, M. (2021). Robots and firms. *Economic Journal*, *131*(638), 2553–2584.

Krenz, A., Prettner, K., & Strulik, H. (2021). Robots, reshoring, and the lot of low-skilled workers. *European Economic Review, 136*, Article 103744.

Krzywdzinski, M. (2021). Automation, digitalization, and changes in occupational structures in the automobile industry in Germany, Japan, and the United States: A brief history from the early 1990s until 2018. *Industrial and Corporate Change*, *30*(3), 499–535.

Kugler, A. D., Kugler, M., Ripani, L., & Rodrigo, R. (2020). US robots and their impacts in the tropics: Evidence from Colombian labour markets. *National Bureau of Economic Research Working Paper*, w28034.

Lamperti, F., Lavoratori, K., & Castellani, D. (2023). The unequal implications of Industry 4.0 adoption: Evidence on productivity growth and convergence across Europe. *Economics of Innovation and New Technology*. https://doi.org/10.1080/10438599.2023.2269089

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The review of economic studies*, *70*(2), 317–341.

Li, D., Jin, Y., & Cheng, M. (2024). Unleashing the power of industrial robotics on firm productivity: Evidence from China. *Journal of Economic Behavior & Organization*, *224*, 500–520.

Liu, D., & Son, S. (2024). Exploring the impact mechanism of collaborative robot on manufacturing firm performance: A dynamic capability perspective. *Sustainable Futures, 8*, Article 100262.

Liu, L. (2023). Job quality and automation: Do more automatable occupations have less job satisfaction and health? *Journal of Industrial Relations*, *65*(1), 72–87.

Lu, J. W., & Beamish, P. W. (2001). The internationalization and performance of SMEs. *Strategic Management Journal, 22*(6–7), 565–586.

Maslej, N., Fattorini, L., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Ngo, H., Niebles, J. C., Parli, V., Shoham, Y., Wald, R., Clark, J., & Perrault, R. (2023). *Artificial intelligence index report 2023*. Institute for Human-Centered AI, Stanford University. Available in: https://aiindex.stanford.edu/report/

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

Michaels, G., Natraj, A., & Van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. *Review of Economics & Statistics, 96*(1), 60–77.

Müller, C., & VDMA Services GmbH. Available in. (2022). *World robotics 2022. industrial robots*. IFR statistical department. https://ifr.org/img/worldrobotics/Contents_WR_Industrial_Robots_2022.pdf

Montobbio, F., Staccioli, J., Virgillito, M. E., & Vivarelli, M. (2022). Robots and the origin of their labour-saving impact. *Technological Forecasting and Social Change, 174*, Article 121122.

Nakatani, R. (2024). Multifactor productivity growth enhancers across industries and countries: Firm-level evidence. *Eurasian Business Review*, 1–46.

Naudé, W. (2021). Artificial intelligence: Neither utopian nor apocalyptic impacts soon. *Economics of Innovation and New Technology*, *30*(1), 1–23.

Ortega-Argilés, R., Potters, L., & Vivarelli, M. (2011). R&d and productivity: Testing sectoral peculiarities using micro data. *Empirical Economics, 41*, 817–839.

Pratt, G. A. (2015). Is a Cambrian explosion coming for robotics? *Journal of Economic Perspectives*, *29*(3), 51–60.

Reljic, J., Evangelista, R., & Pianta, M. (2021). Digital technologies, employment, and skills. *Industrial and Corporate Change*. https://doi.org/10.1093/icc/dtab059

Schneider, F. (2025). Do robots boost productivity? a quantitative meta-study. *Journal of Economic Surveys*

Schuelke-Leech, B.-A. (2018). A model for understanding the orders of magnitude of disruptive technologies. *Technological Forecasting and Social Change, 129*, 261–274.

Segarra-Blasco, A., Teruel, M., & Cattaruzzo, S. (2022). Innovation, productivity and learning induced by export across European manufacturing firms. *Economics of Innovation and New Technology*, *31*(5), 387–415.

Serrano, J., & Myro, R. (2019). From domestic to exporter, what happens? Evidence for Spanish manufacturing firms. *Structural Change and Economic Dynamics*, *51*, 380–392.

Shahin, T., Ballestar de las Heras, M. T., & Sanz, I. (2024). Robots in action. *The World Economy*, *47*(7), 2828–2854.

Torrent-Sellens, J., Díaz-Chao, Á., Miró-Pérez, A.-P., & Sainz, J. (2022). Towards the Tyrell corporation? Digitisation, firm-size and productivity divergence in Spain. *Journal of Innovation & Knowledge, 7*(2), Article 100185.

Torrent-Sellens, J., Ficapal-Cusí, P., & Enache-Zegheru, M. (2023). Boosting environmental management: The mediating role of Industry 4.0 between environmental assets and economic and social firm performance. *Business Strategy and the Environment, 32*(1), 753–768.

Valentini, E., Compagnucci, F., Gallegati, M., & Gentili, A. (2023). Robotization, employment, and income: Regional asymmetries and long-run policies in the Euro area. *Journal of Evolutionary Economics, 33*(3), 737–771.

Wagner, J. (2007). Exports and productivity: A survey of the evidence from firm-level data. *World Economy, 30*(1), 60–82.

Waldman-Brown, A. (2020). Redeployment or robocalypse? Workers and automation in Ohio manufacturing SMEs. *Cambridge Journal of Regions, Economy and Society, 13*(1), 99–115.

Wang, L., Zhou, Y., & Chiao, B. (2023). Robots and firm innovation: Evidence from Chinese manufacturing. *Journal of Business Research, 162*, Article 113878.

Yeo, Y., & Park, C. (2022). Does firm size matter? decomposing korean firms' productivity growth based on a stochastic frontier approach and its policy implications. *Asian Journal of Technology Innovation*(2). https://doi.org/10.1080/19761597.2022.2049975

Zhang, F., Zhang, Q., & Wu, H. (2023). Robot adoption and export performance: Evidence from Chinese industrial firms. *Journal of Manufacturing Technology Management*.

Zhang, H., Chen, Z., & Wei, Y. (2025). Robot adoption and export sophistication: Firm-level evidence from China. *Journal of Asian Economics, 98*, Article 101891.

Zhao, Y., Said, R., Ismail, N. W., & Hamzah, H. Z. (2024). Impact of industrial robot on labour productivity: Empirical study based on industry panel data. *Innovation and Green Development, 3*(2), Article 100148.