# Robotization in Spanish firms:

## The impact of automation

Master's in Economics: Empirical Applications and Policies

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Bilbao, July 21st, 2023

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**Abstract:**

Based on the studies conducted by Acemoglu, Lelarge, and Restrepo (2020) and Koch, Manuylov, and Smolka (2021), this article aims to assess the short-term impact of robot adoption on the performance of Spanish manufacturing firms. Our findings suggest that robot adoption has a significant impact on firms' total costs and total employment. On average, total costs rise 11.1% and total employment 8.6%.



**Abstract:** robotization, causal inference, Spanish firms.



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# 1. Introduction

## 1. 1. The automation dilemma

The use of technical improvements, such as the robotization, in production processes has been a concern since Adam Smith's “Wealth of Nations” (Smith, 2019). However, David Ricardo was one of the first classic authors to address the dilemma of factory automation and employment in “On the Principles of Political Economy and Taxation” (2003). The author dispels his previous belief that the introduction of machines usually only brings benefits, for he recognized that good appears in capitalists and landlords, but not in workers. This is because, in addition to other cost savings, owners of the means of production have a greater opportunity to reduce labor through the introduction of new technologies.

Yet, today we know that, while accurate, this consequence interpretation of technological improvement is still limited. Ricardo and Smith had just survived the first industrial revolution and could not yet comprehend the extent to which new technologies were introduced into the production process, as is the case with the fourth revolution now taking place. Thus, we moved from the invention of the steam engine in the first industrial revolution to a series of physical megatrends in the fourth industrial revolution listed as four central points by Schwab (2016): i) autonomous vehicles, ii) 3D printing, iii) use of new materials, and iv) advanced robotics.

These advances have led to new political, social, and economic readings, as they are essentially transformative elements, just as the steam engine in the 18th century and the rest of the advances of the industrial revolutions changed the working environment and lifestyle of societies. However, because of the nature of this paper, it is necessary to limit ourselves to one of the megatrends described by Schwab (2016), specifically the last of these, robotization.

Robotization is a process in which the labor force is replaced by capital that is able to replicate the work of humans (Acemoglu, LeLarge, & Restrepo, 2020), that is, the automation of production processes mentioned by Ricardo (2003). Due to this advance, it is possible to observe extensive literature trying to understand the possible effects of robots, as well as the potential impact they may have on human welfare.  For instance, Leon-Lorente (2020), summarizes the transformations driven by robotization under 4 precepts: i) opportunity, alluding to generational change and the new skills of this new offspring; ii) uncertainty, referring to the accelerated and dynamic movements in the economy, in terms of prices, inputs or job destruction; iii) risk, bringing up especially the demographic challenge together with the desire to maintain competitiveness; and, finally, iv) talent, focusing on the educational key of the new context.

Authors have two different positions with respect to robotics and technological progress. One position can be described as technological optimism, as is the case of Arduengo and Sentis (2021), who argue that negative effects are the precedent of greater welfare. The second position is more pessimistic, as for instance Inzunza et al. (2020) who suggests that robot adoption generates job destruction.

On the positive side, Torrejón Perez et al. (2020) argue that the use of robots in the EU has quadrupled since 1995 to 2015 and exposed beneficial consequences on the European economy.

However, there are concerns about the uneven distribution of automation processes among different European industries and countries, which might limit the development of the EU. Cséfalvay (2020, p.1539) reports a wide variation in robot use across many European countries over the 1995-2015 period.

Currently, different studies dedicated to the analysis of robotization in some countries can be found, such as the case of Acemoglu, LeLarge, & Restrepo (2020), in which the case of France is exposed. However, empirical studies on the subject as well as the variety of approaches and methodologies are still limited. A review of the literature related to the study of the phenomenon is carried out in the next section.

Thus, this study focuses on understanding the impact of automation in one of these countries: Spain. A country in southwestern Europe that in 2022, in addition to being the fourth largest robot market, it also stands fourteenth globally, with a 1% increase in 2021 (IFR Statistical Services, 2022). The following sections present an empirical analysis of the effects of the implementation of automation in the Spanish manufacturing sector.

## 1. 2. Related literature

As already mentioned, the issue of the automation of production processes has been a recurring theme in economic history. However, scientific research on this topic has a much shorter history. Although quantitative and experimental research on the impact of robotization has significantly increased in recent decades.

However, it is no surprise that the dilemma of the positive or negative impact of robotics remains an issue. Karabarbounis and Neiman (2013) found that the fall in relative prices, due to technological improvement, incentivized a shift away from employment towards capital in the United States. Thus, other researchers, such as Frey and Osborne (2017), have estimated that 47% of US jobs are at risk of being automated in the next two decades. Likewise, Acemoglu and Restrepo (2017) found that the increased use of robots in the U.S. labor market between 1990 and 2007 had a negative effect on wages, with a decrease from 0.25% to 0.5% for the adoption of one robot.

This phenomenon is clearly evidenced in the analysis of Autor et al. (2001), who demonstrate that a decline in the price of computer capital negatively affects the demand and wages of workers performing routine labor, and positively those of more educated labor. The question remains whether the impact of robotics relative to employment is necessarily negative.

Acemoglu and Restrepo (2019) presents a new scenario caused by robotization, where two new notions are introduced: the displacement and reinstallation effect. The former alludes to the substitution of labor by capital, while the latter refers to the introduction of new tasks in which labor has a comparative advantage. Then, in the face of these two opposing effects, the authors show how the later more than compensates the former effect, so that the demand for labor is not negatively affected.

In fact, according to Acemoglu and Restrepo (2017), it is evident that the aforementioned negative impact does not uniformly affect the entire population. These authors highlighted the relevance of the characteristics of both employees and their jobs. According to their study, workers with lower educational levels experience a significantly greater negative impact owing to the manual and highly replicable nature of their tasks.

Furthermore, Acemoglu, Lelarge and Restrepo (2020) thoroughly examined the impact of robotization in France between 2010 and 2015, exploring its effects on both the firm- and industry-level.

They find that the impact labor share is greater at the overall level than at the firm level, given that firms adopting robots tend to be larger in size and experience faster growth than their competitors. However, the most striking aspect of the impact of robotization is its effect on employment. Acemoglu, Lelarge and Restrepo (2020) find a positive effect at the firm level, but a negative effect at the industry level. The explanation behind this lies in the fact that the growth of firms adopting robotization occurs at the expense of their competitors, resulting in significant drops both in terms of value added and employment for the latter.

Positive employment effects due to robotization have also been observed using Spanish data. Koch, Manuylov, and Smolka (2021) find a positive impact not only on employment but also on productivity. In addition, they analyze the relationship between firm characteristics and their propensity to adopt robots, revealing that larger firms have a greater tendency to robotize. The most salient results of their study revealed that robotization led to a notable increase in productivity of around 20-25%. This, in turn, resulted in a 5-7% decrease in labor cost share, which brought about a 10% increase in net employment in firms that adopted robotization. By contrast, companies that did not adopt this technology experienced reductions in headcount.

Koch et al. (2021) provide a very important starting point, as they use the same database as in our research: *Encuesta Sobre Estrategias Empresariales* (ESEE) conducted by Fundación SEPI. Hence, the primary focus of this study revolves around the notable contributions made by Acemoglu et al. (2020) and Koch et al. (2021), particularly regarding their estimates of the impact of robotization on employment.

## 1. 3. Objetives

The primary goal of this study is to investigate the influence of the robotization process on the performance of Spanish manufacturing firms. To achieve this, we draw upon a recent and relevant study conducted by Acemoglu, LeLarge, and Restrepo (2020) on French companies, which shares a similar timeframe. While the French study examined the impact from 2010 to 2015, our research specifically focused on the disparities observed between 2010 and 2016.

Notably, our approach offers a distinct perspective from that of Acemoglu et al. (2020). Our methodology employs the difference-in-differences method of causal inference and incorporates inverse probability weighting to address the potential biases arising from covariate imbalance.

The objective of this research is to determine whether the findings of Acemoglu et al. (2021) are observable in data collected from Spanish companies. Furthermore, we also consider the study conducted by Koch, Manuylov, and Smolka (2021) that uses the same data source but encompass a broader timeframe, resulting in a more historical analysis. By contrast, our research focuses on a specific framework marked by the critical period of the 2008 global crisis, which particularly impacted Spain in 2012.

Therefore, the central question of this research can be formulated as follows: "What differences in outcomes do robotized firms exhibit compared to non-robotized firms in the short term?" We aim to shed light on the effect of robotization on firms' outcomes such as added value, production, costs, wages, and employment. Moreover, we endeavor to delve deeper into the investigation by addressing the question: "Is the introduction of robots the cause of these observed differences?".

# 2. Data

## 2. 1. Encuesta Sobre Estrategias Empresariales (ESEE)

As mentioned above, the database used for this empirical analysis is the Encuesta Sobre Estrategias Empresariales (ESEE) prepared by Fundación SEPI (Sociedad Estatal de Participaciones Industriales). A project that attempts to include information on manufacturing companies with 10 or more employees since 1990, with the specific goal of tracking the crucial decisions of these companies using a panel data structure (Fundación SEPI, 2013).

The database includes yearly responses from 1990 to 2018, although we focus the analysis from 2010 to 2016. As of 2016, the database has 5840 firms registered, including active firms (those currently in the sample) and inactive companies (those not currently included in the sample).

The survey includes a bank of questions which not only deal with intra-firm issues such as accounting and descriptive data, prices, costs, and employment, but also addresses questions about strategic decisions, innovation, and productive infrastructure. Some of these questions are collected at a lower frequency, every four years. The central question of our research, whether firms use robots or not, is recorded every four years. Our data set includes firm data for 2010 and 2014, thus allowing us to identify firms that did not use robots in 2010 and did so in 2014. Firm outcomes, on which the effect of robotization is to be measured, are recorded in 2014 as well as 2016.

## 2. 2. Description of firms by robotization

This section aims at drawing a picture of Spanish manufacturing firms in the face of robotization before discerning a causal relationship. However, since our objective is to analyze the effect of robotization between 2010 and 2014, this descriptive analysis only considers those firms that did not use robots in 2010, so that the sample size is reduced from 5840 observations to 966, 825 of which did not adopt robots between 2010 and 2014, and 141 did. Thus, in the following pages, we describe the observable characteristics of these companies.

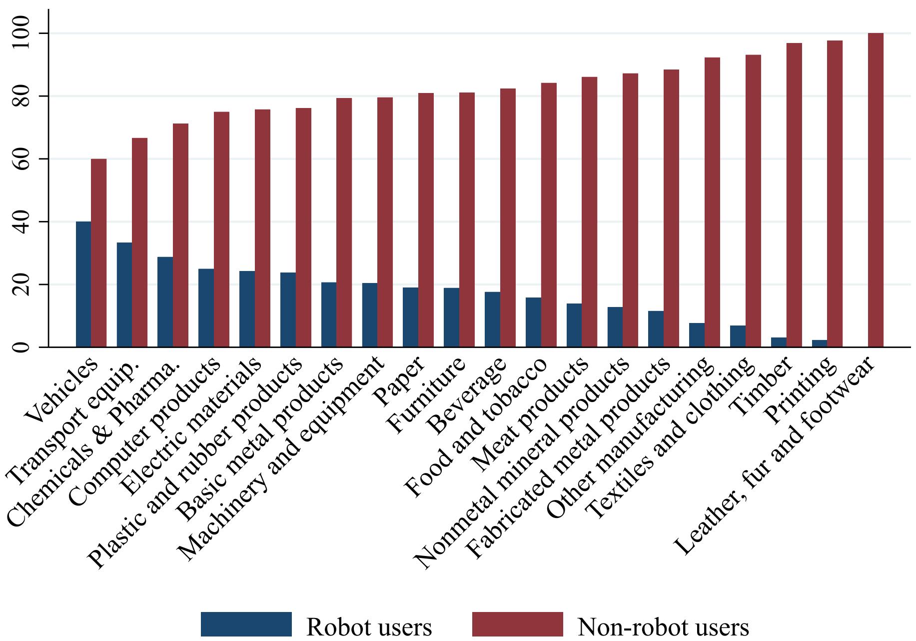
The following subsections describe how robot utilization is distributed across industries, by the type of production system, and whether firms export or not.

### 2. 2. 1. Use of robots by industries

Figure 1 displays the proportions of robotized and non-robotized companies within each industry in 2010. As can be seen, the representation of robotization varies greatly between industries, as for example in the case of companies dedicated to "leather, leather and footwear" in which robot users are nonexistent, while in other industries such as vehicles and transportation equipment where around 40% of companies do employ them. Thus, it is possible to observe how, together with the leather industry, the textile, timber, and printing industries do not even reach 10% of robotized companies within their categories, while the transport equipment, chemical-pharmaceutical, computer, and electrical materials industries, together with the automobile industry, are above 20% each.

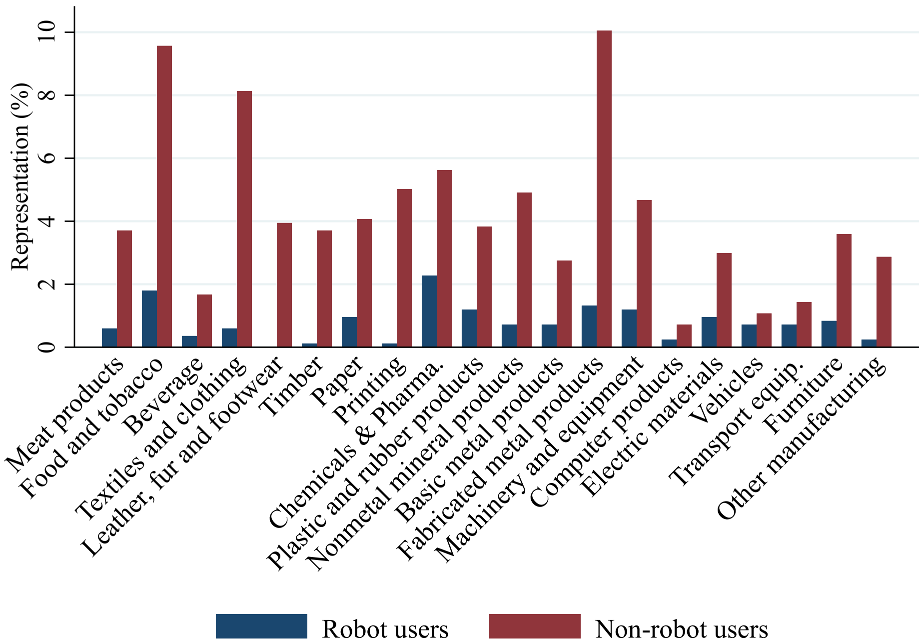
Therefore, it can be observed that industries related to more electronic issues, such as the vehicle and transport or computer product industries, show a higher level of robotization. Additionally, Figure 2 displays the proportions relative to the total, indicating that the sum of all the bars (red and blue) accounts for 100% of the observations. It is noteworthy that, apart from the asymmetries in the distribution of robotics, there exists a substantial disparity in the representation of each category within the sample.

*Figure 1. Proportion of robot usage by industry in 2010.*




*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

*Figure 2. Proportion of total robot use by industry in 2010.*

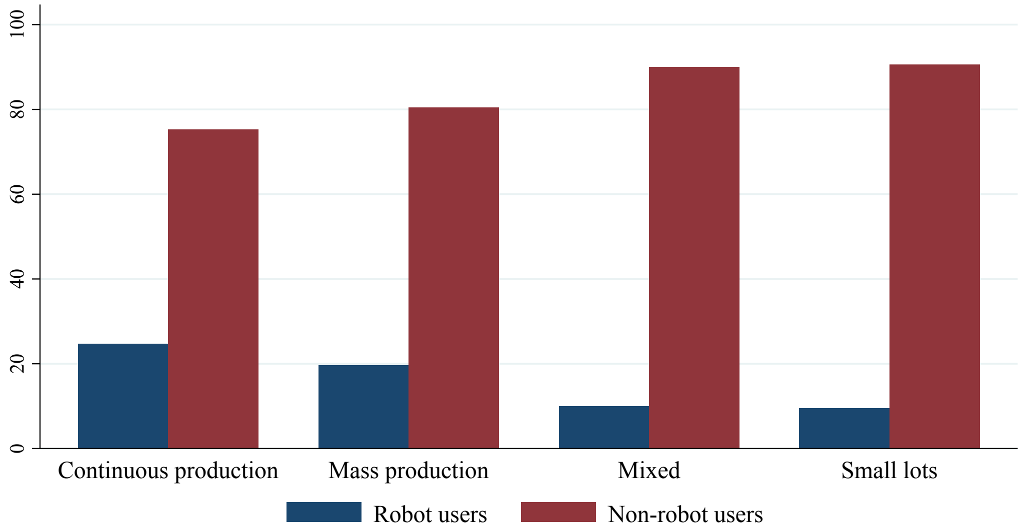



*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

### 2. 2. 2. Use of robots based on production system

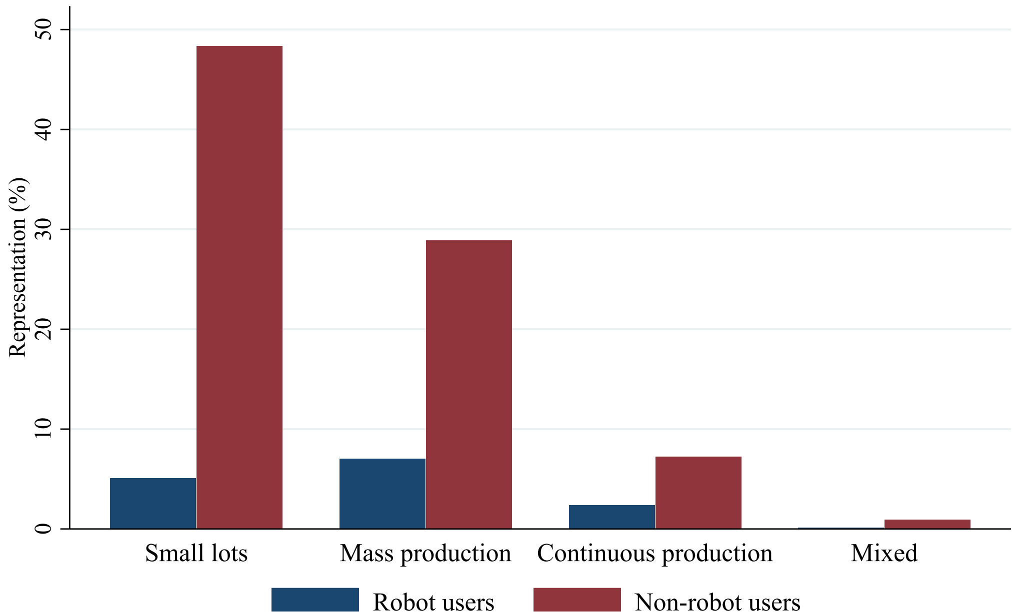
Firms in the sample are classified according to their production system in X groups: (i) continuous production, mass production, mixed, and small lots. The production system is another characteristic that exhibits notable variations in terms of user and non-user distribution. As shown in Figure 3, continuous production exhibits a 24.73% of recent robot users within its own category. Those firms that carry out smaller productions show a fewer number of firms belonging to the group of newly robotized companies. Even though, in Figure 4, which shows the proportions relative to the total, where the sum of all the bars (red and blue) is 100% of the observations, manufacturing companies that mass-produce are the most represented on the use of robots. It should also be noted that the category with the largest number of companies, small production, shows a large difference between new users and non-users of robots, whereas the aforementioned mass production shows a much smaller difference. Therefore, the distinctions that emerge from these production systems must be considered when estimating result in terms of causality.

*Figure 3. Proportion of robot use by production system in 2010.*




*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

*Figure 4. Proportion of total robot usage by production system in 2010.*

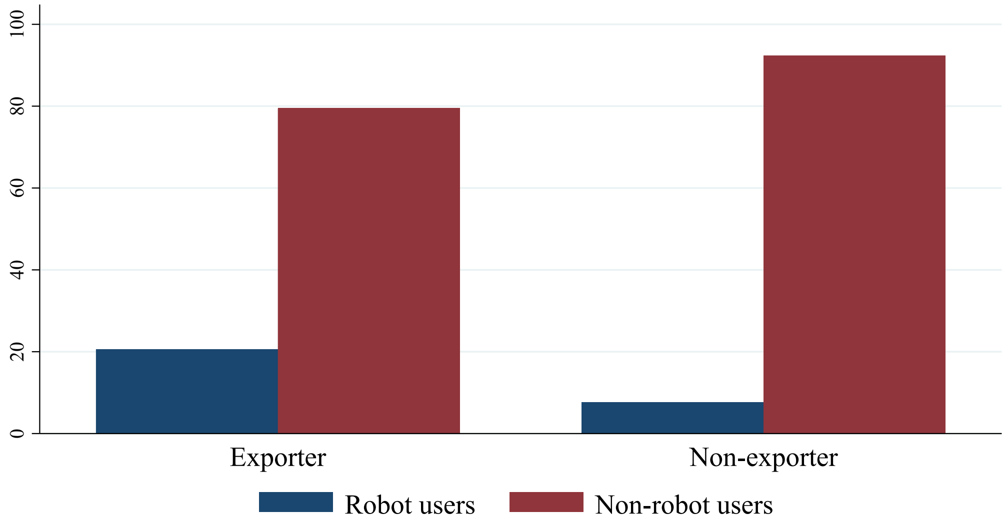



*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

### 2. 2. 3. Use of robots based on exporter status

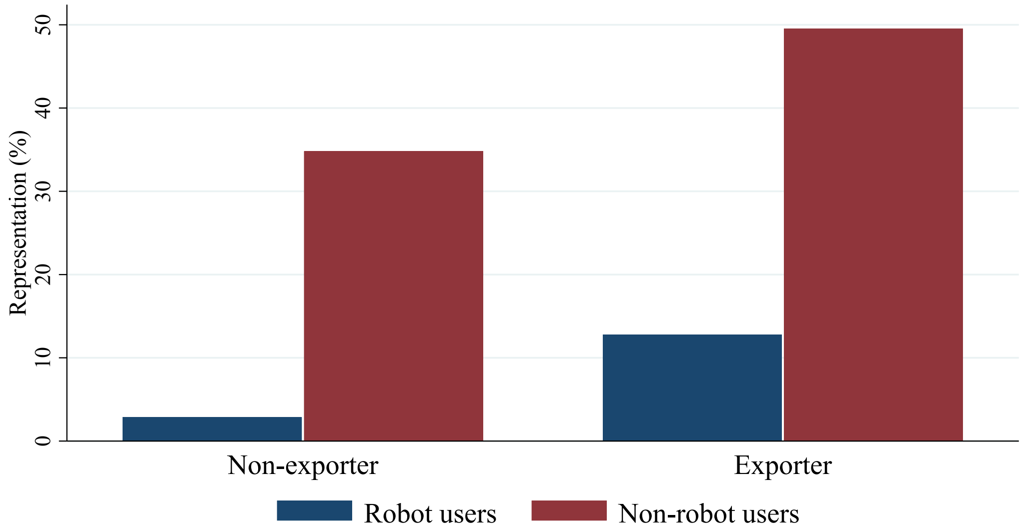
Figure 5 classifies exporting and non-exporting companies based on the condition of using robots. Here, as in the previous sections, there is a considerable difference between the groups because 20.54% of the new robot users are exporters while only 7.62% of the robot users are exporters. At the same time, Figure 6 shows the proportions relative to the total, meaning that the combined bars (red and blue) represent 100% of the observations. It should be noted that Figure 6 shows a greater accumulation of exporters, since they almost reach 65% of the companies in the sample, while non-exporters represent less than 40%. Thus, in this second table, the imbalance between the robot users of exporting companies and those who do not export is even more evident.

*Figure 5. Proportion of robot use by exporter status in 2010*




*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

*Figure 6. Proportion of total robot usage by exporter status in 2010*




*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

### 2. 2. 4. Outcomes based on robot use

In addition to taking into consideration the differences between the groups in terms of their characteristics, we also considered their differences in terms of outcomes in the pre-treatment period (Table 1) and post-treatment period (Table 2).

Table 1 shows the selected outcomes in the 2010 period by their treatment status stablished between period 2010 and 2014. As can be seen from the descriptive statistics, the differences in these variables were already more than evident before considering the use of the robot. In 2010, robot users had more employees, incurred higher costs, and generated more production. In short, these firms were already larger prior to treatment, which indicates that the sample is already biased and precludes direct comparison of the effect of robot use across treatment groups.

*Table 1. Outcomes of 2014 robot users and non-users in 2010.*

| | Use of robots | Mean | Std. Error | Min | Max | Obs. |
|---|---|---|---|---|---|---|
| Clerical workers per worker | Users | 1.455 | 6.676 | 0.00 | 67.8 | 131 |
| | No users | .634 | .892 | 0.00 | 9.7 | 704 |
| Labor costs | Users | 8.239 | 14.529 | .19 | 131.1 | 131 |
| | No users | 4.561 | 29.161 | .04 | 637.9 | 705 |
| Total costs | Users | 56.523 | 151.436 | .41 | 1437.5 | 131 |
| | No users | 31.969 | 188.791 | .06 | 3009.6 | 705 |
| Net costs per employee | Users | 34.702 | 10.972 | 12.50 | 69.5 | 131 |
| | No users | 30.809 | 11.266 | 7.10 | 72.1 | 705 |
| Average total employment | Users | 194.717 | 281.204 | 7.00 | 2456.0 | 131 |
| | No users | 104.219 | 544.799 | 4.00 | 11973.0 | 705 |
| Added value | Users | 12.396 | 22.193 | .17 | 169.8 | 131 |
| | No users | 6.612 | 36.689 | .02 | 814.6 | 705 |
| Productivity per worker | Users | 55.732 | 39.271 | 10.40 | 314.2 | 131 |
| | No users | 45.627 | 35.118 | 4.00 | 337.7 | 705 |

*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

Similarly, in Table 2, which shows the outcomes in the 2014 period, it is possible to observe that the differences between the two groups are still maintained and even increased, despite the fact that the variable indicating the proportion of white-collar workers over blue-collar workers has decreased. On the other hand, it should be noted that all the outcomes of the users increased from 2010 to 2014, except for the total average employment, which decreased, but not as much as that of the non-users, who show a much more pronounced drop.

*Table 2. Outcomes of 2014 robot users and non-users in 2014.*

| | Use of robots | Mean | Std. Error | Min | Max | Obs. |
|---|---|---|---|---|---|---|
| Clerical workers per worker | Users | 1.100 | 5.1485 | 0 | 60.50 | 140 |
| | No users | .666 | 1.2326 | 0 | 27 | 822 |
| Labor costs | Users | 8.522 | 14.2792 | .110 | 123.68 | 141 |
| | No users | 4.328 | 29.3247 | .018 | 712.68 | 825 |
| Total costs | Users | 60.927 | 145.6233 | .264 | 1382.48 | 141 |
| | No users | 31.712 | 196.1385 | .054 | 3482.21 | 825 |
| Net costs per employee | Users | 36.643 | 11.8496 | 10.100 | 75.80 | 140 |
| | No users | 32.368 | 12.1782 | 7.400 | 80.60 | 825 |
| Average total employment | Users | 191.773 | 262.3275 | 6.000 | 2173.00 | 141 |
| | No users | 95.370 | 524.0101 | 1.000 | 12970.00 | 825 |
| Added value | Users | 12.996 | 21.7953 | .068 | 178.91 | 141 |
| | No users | 5.999 | 30.5608 | .003 | 658.40 | 825 |
| Productivity per worker | Users | 58.254 | 33.2991 | 3.000 | 204.60 | 141 |
| | No users | 47.578 | 37.7582 | .400 | 357.30 | 825 |

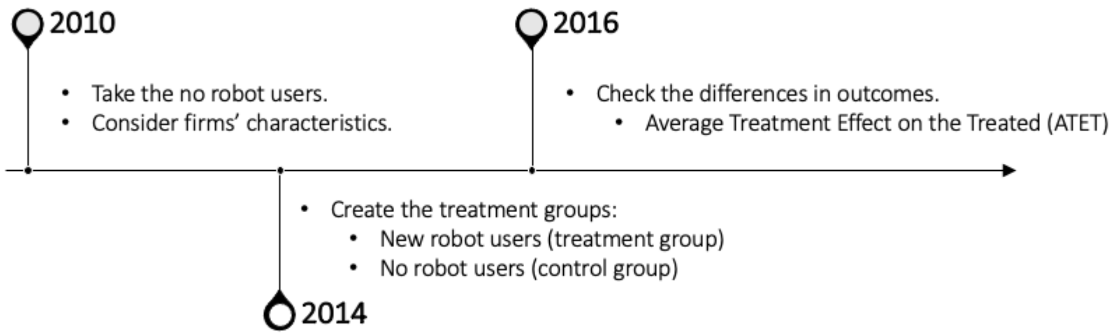
*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

## 2. 3. Methodology

This study aims at understanding the impact of robot adoption on firm's outcomes. To achieve this goal, we use causal inference methods, in particular, the semi-parametric difference in difference (SDID) method. The treatment is the use of robots in the manufacturing process, so that treated firms are those firms who adopt robots and the untreated firms unadopters.

As illustrated in the timeline shown in Figure 7, we eliminate all firms that already used robots in 2010, and therefore restrict the analysis to non-adopters as of 2010. Firm outcomes and treatment statuses are then measures in 2014. We define both treatment groups as follows. Treated firms are those that during 2010-2014 period have decided to introduce robots, while untreated firms have not. Accordingly, $D_{i1} = 0$, identifies the non-robotized firms and $D_{i1} = 1$ the robotized ones; notice that no firms are robotized in the pre-treatment period.

*Figure 7. Timeline of the research and the decisive points for the elaboration of the Difference in Difference methodology.*




*Source: Own elaboration.*

The observed outcome is $Y_{it}$, while $Y_{it}^1$ and $Y_{it}^0$ are the potential outcomes under treatment and under no treatment respectively, i.e., the outcome for individual i we would have observed had observation i been treated or untreated. Therefore, the observed and potential outcomes are related as follows:

$$Y_{i1} = Y_{i1}^0 + (Y_{i1}^1 - Y_{i1}^0)D_{i1}$$

An estimand of interest is the Average Treatment Effect (ATE), which is the mean difference between potential outcomes in the post-treatment period, i.e.:

$$ATE = E(Y_{i1}^1 - Y_{i0}^1)$$

However, this estimand is mainly used in randomized experiments, whereas our study is observational. Moreover, the interest of this study is not the mean effect on the whole population but on those treated. Thus, our main estimand of interest will be the Average Treatment Effect on the Treated (ATET), i.e.:

$$ATET = E(Y_{i1}^1 - Y_{i1}^0 \middle| D_{i1} = 1)$$

A necessary condition to be met in order to infer causation is that groups are comparable in terms of their characteristics. However, as observed in the descriptive section, the data do shows covariate imbalance, implying that the two groups have significant differences in terms of their characteristics in addition to treatment status. Therefore, in order to address covariate imbalance, we use the methodology proposed by Abadie (2005), which combines the difference-in-differences methodology with Inverse Probability Weighting (IPW). This technique weights up firms with underrepresented covariates among the untreated and weights down firms with overrepresented covariates among the untreated. In addition, and to avoid extrapolation outside the support of the covariates, we restrict the analysis to a common range of the propensity score in both groups in order to compare similar firms in terms of their likelihood of receiving the treatment. Therefore, the estimation of the Average Treatment Effect on the Treated (ATET) obtained has the following form according to Abadie (2005):

$$\frac{1}{N}\sum_{i=1}^{N}\left[(Y_{i1}-Y_{i0})\frac{D_{i1}-\hat{p}(D_{i1}=1|X_i)}{\hat{P}(D_{i1}=1)(1-\hat{p}(D_{i1}=1|X_i)}\right]$$

An estimate of this quantity is easily obtained using a weighted regression scheme, using as weights the weights from Inverse Probability Weighting. To implement this method, we run the following regression

$$\Delta Y_{it} = \alpha + \beta D_{i1} + u_{it}$$

where $\Delta Y_{it}$ represents the time difference from 2010 to 2014 or 2016 in the observed outcome (value added, wages, etc.) in natural log scale, and $u_{it}$ is a zero mean error term. Finally, the estimated $\beta$ is an estimate of the ATET. As the outcome is measured in first differences, firm-specific time-invariant confounding factors can be ruled out.

However, throughout the analysis, certain modifications were made for a correct and consistent estimation, among which we can find the omission of certain variables with excesses of zeroes. This has been done, because to carry out the weighting it is necessary to start from a logit with the covariates of the pre-treatment period selected and thus obtain the propensity scores. However, with the introduction of these variables, bias generated the elimination of a significant number of observations, which made it impossible to correctly estimate the effects of robotization on company outcomes.

On the other hand, it is worth mentioning that all continuous variables are measured in logarithms, so the impact estimates are to be interpreted as percentage changes.

# 3. Analysis

The first step is to estimate a logistic model for the propensity score. The probability of robot adoption between 2010 and 2014 is assumed to depend on the covariates in 2010. Estimates of this model can be found in Table 4, which is shown in the appendix at the end of the document.  Market share, net cost per worker and product standardization are the most significant variables in predicting the probability of adopting robots. In addition, labor costs, sector classification, and geographical scope are marginally significant.

## 3. 1. Results

Table 3 displays the ATET estimates obtained using the semiparametric DID method. Columns (1) and (2) reports 2014 and 2016 impact estimates of robotization, respectively.

It can be observed that not all impact estimates are significant, as only two of them are significant at the10% and 5% significance levels: total costs, and total average employment.

Firstly, the impact of robot adoption on the 2016 total costs is statistically significant at 10%, an average increase of 11.1% from the original 2010 value. An increase that seems to be perceived significantly more in the long term, since in 2014 this effect is not significant at the 10% significance level.

Average total employment in 2014 shows a significant average increase of 8.6% from the original value of 2010 due to the robotization of companies. This increase, unlike the previous effect, only appears in 2014, since in 2016 there is no evidence of an impact on employment due to the automation of the company's production processes.

## 3. 2. Robustness check

As highlighted in Section 2.2, the descriptive statistics show that in the pre-treatment period, the manufacturing firms, which were robotized by 2014 and those that were not, had unequal conditions on average. For instance, one could observe unbalanced treatment groups across industries, or a clear difference between those exporting and non-exporting. Likewise, it was also observed that values such as total expenditure, value added, and productivity per worker were already higher prior to the introduction of the treatment in companies that, by 2014, would adopt robots in their production lines.

*Table 3. Estimations of logarithmic difference of the outcomes between 2014 and 2016 with respect to 2010.*

| | 2014 | | 2016 | |
|---|---|---|---|---|
| | Coefficients | Observations | Coefficients | Observations |
| Clerical workers per worker | -0.0651 | 705 | -0.0608 | 563 |
| | (0.112) | | (0.140) | |
| Labor costs | 0.0680 | 723 | 0.0580 | 606 |
| | (0.0457) | | (0.0500) | |
| Total costs | 0.0797 | 723 | 0.111* | 606 |
| | (0.0491) | | (0.0613) | |
| Net costs per employee | -0.0210 | 722 | | |
| | (0.0251) | | | |
| Average total employment | 0.0860** | 723 | 0.0600 | 606 |
| | (0.0402) | | (0.0466) | |
| Added value | 0.114 | 723 | 0.0193 | 606 |
| | (0.0755) | | (0.120) | |
| Productivity per worker | 0.0280 | 723 | -0.0403 | 606 |
| | (0.0673) | | (0.112) | |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

### 3. 2. 1. Checking covariate balance

Table 5 of the appendix reports covariate balance across treatment groups for raw (unweighted sample) and the weighted sample This table includes the Normalized Mean Difference (NMD) which should close to zero when covariates are balanced across treatment groups. It also reports the Variance Ratio (VR), which should be around one for comparable treatment groups.

Several covariates exhibit Normalized Mean Difference values within the (rule of thumb) acceptable range (-0.25,0.25). However, there are also some cases, such as the "geographic scope of the market", labor costs, total costs, and average total costs, that are far away from the recommended values.

On the other hand, when the sample is weighted according to the SDID weighting scheme, the observed NMV values are much closer to zero.

Likewise, the Variance Ratio (VR) for the unadjusted data is far from one in several cases for the unadjusted data, such as the case of "Technology cooperation agreements," which are three times higher than one. However, the VR for this covariate gets reduced from 3.33 to a more accurate value of 1.24, as do many other variables. It should also be noted, however, that, as in the Normalized Mean Difference (NMD), there are certain variables whose VR are still considerably far from one, as in the case of the proportion of workers labor costs, and total costs.

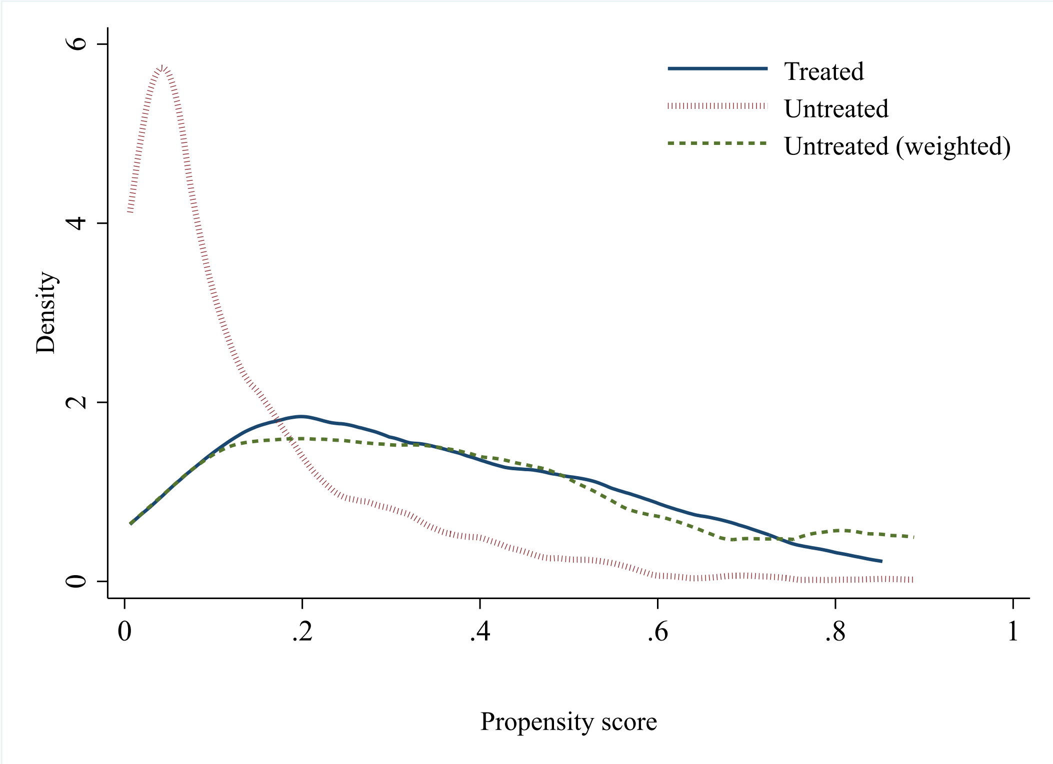
Although covariate balance is not perfect. However, using Inverse Probability Weighting (IPW) the two groups are more similar, thereby reducing the possibility that any observable cofounding factor confounds the estimation of the impact of robotization.

### 3. 2. 2. Checking common support

Figure 8 shows the distribution of the propensity score (the treatment probability). The red (dots) and blue (solid) lines indicate the probability of being treated for the treated and the untreated, respectively. That is to say that the distribution of the propensity score is very different across treatment groups, and thus they are not comparable. For this reason, we impose common support. Covariate balance improves for the weighted sample. we weight the untreated with the above weighting scheme, and the untreated are represented by the red line to the blue line. Thus, comparing the distribution of the treated (solid line) and untreated weights (dash line), the distribution is much more similar, showing two much more comparable groups.

However, certain deviations are evident along the x-axis between both lines, which could already be inferred from the differences mentioned in the previous subsection which examines covariate balance for each covariate individually. However, by employing Inverse Probability Weighting (IPW), the two groups become more alike and diminishes the likelihood of any observable cofounding factor affecting the estimation of the impact of robotization.

*Figure 8. Kernel density plot of the propensity scores.*




*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

# 4. Conclusions

After implementing causal inference techniques in the search for the impact of robotization on different outcomes of Spanish manufacturing companies, certain remarkable facts have become evident. The study focused on a short period of time (2010-2016), which includes a convulsive period such as the global financial crisis.

The data are obtained from the Encuesta Sobre Estrategias Empresariales (ESEE) and the main conclusions are that robotization has had a significant increase in costs and average employment.

Comparing our results with those obtained by Acemoglu et al. (2020) and Koch et al. (2021), there are some similarities and some differences.

Regarding the similarities, our findings indicate that robotization increases firms' average employment as of 2014in 8.6% on average with respect to their 2010 employment level.

Koch et al. (2021) find that robotization has a positive and significant impact on productivity, but our findings cannot corroborate theirs as we were not able to find a significant impact on productivity, perhaps due to the particularly harsh economic conditions at the time. Interestingly, Koch et al. (2021) highlight that the TFP of Spanish manufacturing firms in the post-crisis period behaved in the opposite way to what was expected, as non-robotic firms increased their levels while robot users decreased.

Another difference between our findings and previous ones entails the impact of robotization on total costs. None of the previous works reviewed find a significant impact on total costs, however, our estimates show an 11.1% significant increase in total costs in 2016 (as compared to 2010) due to robotization.

These differences in results may be due to different reasons, such as the use of a shorter period of analysis, or methodological differences, since Koch et al. (2021) make use different methods. Thus, it is advisable to use different estimation methods and time perspectives for a better understanding of the impact of robotization, so that a feasible future step in this line of research could be to enlarge the time range of the analysis. Similarly, it could be of interest to implement this form of estimation in other countries, perhaps less developed.

To conclude, it should be noted that in recent years, there have been significant advances beyond the robotization mentioned here, such as the case of Artificial Intelligence (AI), which is strongly linked to the development of robotization. This new element on the game board shows highly transformative elements that in the distant future, together with robotization, seem to have a strong impact on business performance around the globe.

# 5. Appendix

*Table 4. Estimations of the logistic regression of robot usage in 2014 and covariates.*

| VARIABLES | Robotization in 2014 |
|---|---|
| Technology cooperation agreements | 0.537 |
| | (0.610) |
| Age of the firm | -0.0249 |
| | (0.179) |
| $Age^2$ of the firm | 0.00861 |
| | (0.0169) |
| Unsuccessful search for external innovation funding | 0.325 |
| | (0.645) |
| Use of CAD | 0.0965 |
| | (0.312) |
| Market share | -0.0207** |
| | (0.00817) |
| Log(Net costs per employee) | -5.023** |
| | (2.020) |
| Log(Labor costs) | 3.794* |
| | (1.993) |
| Log(Total costs) | -1.959 |
| | (1.995) |
| Log(Clerical workers per worker ) | 0.0800 |
| | (0.350) |
| Log(Proportion of workers) | -0.237 |
| | (0.736) |
| Log(Average total employment) | -3.107 |
| | (1.934) |
| Log(Added value) | 2.037 |
| | (1.568) |
| Log(Added value over production) | -1.973 |
| | (2.177) |
| Andalucia | 0.676 |
| | (0.616) |
| Aragón | 1.223* |
| | (0.648) |
| Asturias | -1.211 |
| | (1.195) |
| Canarias | 1.552 |
| | (1.091) |
| Cantabria | -1.168 |
| | (1.269) |
| Castilla-La Mancha | 0.884 |
| | (0.646) |
| Castilla-León | 0.311 |
| | (0.660) |
| Cataluña | 0.590 |
| | (0.520) |

| | |
|---|---|
| C. Valenciana | 0.810 |
| | (0.555) |
| Extremadura | 0.280 |
| | (1.242) |
| Galicia | 0.400 |
| | (0.606) |
| Madrid | -0.0784 |
| | (0.580) |
| Murcia | -0.700 |
| | (1.083) |
| Navarra | 1.769** |
| | (0.750) |
| Meat products | -0.344 |
| | (1.014) |
| Food and tobacco | -0.298 |
| | (0.888) |
| Beverage | -0.398 |
| | (1.149) |
| Textiles and clothing | -1.173 |
| | (0.978) |
| Timber | -1.277 |
| | (1.384) |
| Paper | 0.126 |
| | (0.931) |
| Printing | -1.435 |
| | (1.330) |
| Chemicals and pharmaceuticals | 0.0393 |
| | (0.904) |
| Plastic and rubber products | 0.714 |
| | (0.914) |
| Nonmetal mineral products | -0.129 |
| | (0.976) |
| Basic metal products | 0.369 |
| | (1.061) |
| Fabricated metal products | 0.767 |
| | (0.899) |
| Machinery and equipment | 1.234 |
| | (0.934) |
| Computer products | 0.0781 |
| | (1.311) |
| Electric materials | 0.866 |
| | (0.966) |
| Vehicles | 1.869* |
| | (1.062) |
| Other transport equipment | 1.788* |
| | (1.074) |
| Furniture | 0.935 |
| | (0.942) |
| Small lots | -0.348 |
| | (1.202) |

| | |
|---|---|
| Mass production | 0.750 |
| | (1.193) |
| Continuous production | 0.620 |
| | (1.237) |
| Local (Geographical scope) | -0.764 |
| | (0.648) |
| Provincial (Geographical scope) | -0.418 |
| | (0.640) |
| Regional (Geographical scope) | -0.114 |
| | (0.497) |
| National (Geographical scope) | -0.109 |
| | (0.295) |
| International (Geographical scope) | -0.839* |
| | (0.467) |
| Does not perform, does not hire (R&D activity) | -0.199 |
| | (0.354) |
| Performs, does not hire (R&D activity) | -0.209 |
| | (0.420) |
| Does not perform, hires (R&D activity) | -0.923 |
| | (0.685) |
| Consumption (Type of good) | 0.430 |
| | (0.419) |
| Intermediate (Type of good) | 0.413 |
| | (0.331) |
| Low (Product standarization) | -0.595** |
| | (0.287) |
| Constant | 35.20* |
| | (17.98) |
| Observations | 752 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

*Table 5. Covariate balance with Normalized Mean Difference (NMD) and Variance Ratio (VR).*

| | UNWEIGHTED | | WEIGHTED | |
|---|---|---|---|---|
| | NMD | VR | NMD | VR |
| Technology cooperation agreements | 0.24 | 3.46 | 0.07 | 1.31 |
| Age of the firm | 0.17 | 1.17 | 0.06 | 1.14 |
| Age$^2$ of the firm | 0.13 | 0.82 | 0.06 | 0.89 |
| Unsuccessful search for external innovation funding | 0.11 | 1.89 | 0.07 | 1.46 |
| Use of CAD | 0.01 | 1.02 | -0.02 | 0.99 |
| Market share | 0.01 | 0.82 | 0.07 | 1.11 |
| Log(Net costs per employee) | 0.32 | 0.78 | -0.12 | 0.65 |
| Log(Labor costs) | 0.83 | 0.99 | -0.18 | 0.54 |
| Log(Total costs) | 0.80 | 0.93 | -0.20 | 0.51 |

| | | | | |
|---|---|---|---|---|
| Log(Clerical workers per worker ) | 0.14 | 1.33 | -0.05 | 1.12 |
| Log(Proportion of workers) | -0.15 | 2.54 | 0.02 | 1.77 |
| Log(Average total employment) | 0.87 | 1.05 | -0.17 | 0.56 |
| Log(Added value) | 0.84 | 0.92 | -0.20 | 0.54 |
| Log(Added value over production) | -0.27 | 1.00 | 0.12 | 0.67 |
| Andalucia | -0.04 | 0.90 | 0.10 | 1.44 |
| Aragón | 0.13 | 1.77 | 0.04 | 1.15 |
| Asturias | -0.16 | 0.28 | -0.00 | 0.97 |
| Baleares | . | . | . | . |
| Canarias | -0.01 | 0.91 | -0.03 | 0.82 |
| Cantabria | -0.03 | 0.72 | 0.01 | 1.19 |
| Castilla-La Mancha | 0.12 | 1.56 | -0.17 | 0.63 |
| Castilla-León | 0.02 | 1.09 | -0.04 | 0.86 |
| Cataluña | 0.01 | 1.02 | 0.05 | 1.08 |
| C. Valenciana | 0.05 | 1.11 | 0.00 | 1.01 |
| Extremadura | -0.09 | 0.46 | -0.01 | 0.95 |
| Galicia | -0.00 | 1.00 | 0.03 | 1.11 |
| Madrid | -0.15 | 0.70 | -0.06 | 0.85 |
| Murcia | -0.06 | 0.67 | -0.06 | 0.69 |
| Navarra | 0.16 | 2.43 | 0.06 | 1.31 |
| País Vasco | -0.04 | 0.89 | 0.07 | 1.27 |
| La Rioja | . | . | . | . |
| Meat products | -0.03 | 0.87 | 0.01 | 1.05 |
| Food and tobacco | 0.03 | 1.08 | 0.05 | 1.13 |
| Beverage | 0.04 | 1.36 | -0.01 | 0.97 |
| Textiles and clothing | -0.20 | 0.49 | -0.02 | 0.91 |
| Leather, fur and footwear | . | . | . | . |
| Timber | -0.18 | 0.25 | -0.01 | 0.93 |
| Paper | 0.04 | 1.17 | -0.01 | 0.96 |
| Printing | -0.28 | 0.15 | 0.00 | 1.03 |
| Chemicals and pharmaceuticals | 0.18 | 1.64 | -0.14 | 0.77 |
| Plastic and rubber products | 0.10 | 1.46 | 0.04 | 1.14 |
| Nonmetal mineral products | -0.06 | 0.77 | 0.03 | 1.16 |
| Basic metal products | 0.02 | 1.09 | 0.04 | 1.22 |
| Fabricated metal products | -0.12 | 0.74 | 0.00 | 1.01 |
| Machinery and equipment | 0.08 | 1.32 | 0.01 | 1.04 |
| Computer products | 0.06 | 1.66 | -0.06 | 0.68 |
| Electric materials | 0.07 | 1.38 | 0.06 | 1.31 |
| Vehicles | 0.16 | 2.71 | 0.05 | 1.26 |
| Other transport equipment | 0.12 | 2.04 | -0.03 | 0.89 |
| Furniture | 0.01 | 1.07 | 0.04 | 1.21 |

| | | | | |
|---|---|---|---|---|
| Other manufacturing | -0.12 | 0.46 | 0.02 | 1.14 |
| Small lots | -0.47 | 0.92 | -0.01 | 1.00 |
| Mass production | 0.34 | 1.13 | 0.15 | 1.03 |
| Continuous production | 0.20 | 1.64 | -0.18 | 0.74 |
| Mixed | -0.03 | 0.72 | 0.02 | 1.20 |
| Local (Geographical scope) | -0.17 | 0.50 | 0.02 | 1.11 |
| Provincial (Geographical scope) | -0.25 | 0.38 | 0.02 | 1.13 |
| Regional (Geographical scope) | -0.17 | 0.64 | 0.01 | 1.03 |
| National (Geographical scope) | 0.01 | 1.01 | 0.08 | 1.05 |
| International (Geographical scope) | 0.05 | 1.16 | 0.05 | 1.17 |
| Interior & Exterior (Geographical scope) | 0.28 | 1.27 | -0.13 | 0.96 |
| Does not perform, does not hire (R&D activity) | -0.47 | 1.27 | 0.06 | 1.01 |
| Performs, does not hire (R&D activity) | 0.11 | 1.34 | 0.02 | 1.07 |
| Does not perform, hires (R&D activity) | -0.02 | 0.91 | -0.00 | 0.99 |
| Perform, hires (R&D activity) | 0.46 | 1.81 | -0.08 | 0.96 |
| Consumption (Type of good) | -0.08 | 0.86 | 0.00 | 1.01 |
| Intermediate (Type of good) | 0.13 | 0.94 | -0.06 | 1.05 |
| Indefinite (Type of good) | -0.08 | 0.90 | 0.07 | 1.13 |
| Low (Product standarization) | -0.11 | 0.98 | 0.03 | 1.02 |
| High (Product standarization) | 0.11 | 0.98 | -0.03 | 1.02 |

*Source: Own elaboration based on data from Encuesta Sobre Estrategias Empresariales (ESEE).*

# References


Abadie, A. (2005). Semiparametric Difference-in-Differences Estimators. *The Review of Economic Studies, 72*(1), 1–19.

Acemoglu, D., & Restrepo, P. (2017, March). Robots and jobs: Evidence from us labor markets. *NBER Working Papers,* 23285. Retrieved from https://econpapers.repec.org/paper/nbrnberwo/23285.htm

Acemoglu, D., & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives, 33*(2), 3–30. Retrieved from https://doi.org/10.1257/jep.33.2.3

Acemoglu, D., LeLarge, C., & Restrepo, P. (2020). Competing with robots: firm-level evidence from France. *AEA Papers and Proceedings, 110*, 383-388.

Arduengo, M., & Sentis, L. (2021). The Robot Economy: Here It Comes. *International Journal of Social Robotics*(13), 937–947. Retrieved from https://doi.org/10.1007/s12369-020-00686-1

Autor, D., Levy, F., & Murnane, R. (2001). The Skill Content of Recent Technological Change: An Empirical Exploration. *NBER Working Paper Series, 8337*. Retrieved from https://www.nber.org/system/files/working_papers/w8337/w8337.pdf

Cséfalvay, Z. (2020). Robotization in Central and Eastern Europe: catching up or dependence? *European Planning Studies,, 28*(8), 1534-1553. Retrieved from https://doi.org/10.1080/09654313.2019.1694647

Frey, C., & Osborne, M. (2017, January). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting & Social Change, 114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Fundación SEPI. (2013, February 15). *Presentación*. Retrieved from Fundación SEPI: https://www.fundacionsepi.es/investigacion/esee/spresentacion.asp

Fundación SEPI. (2022, January 15). *Encuesta sobre Estrategias Empresariales (ESEE). Proyecto técnico.* Retrieved from Instituto Nacional de Estadística: https://ine.es/normativa/leyes/cse/proyecto_EncuestaEstrategiasEmpresariales.pdf

Fundación SEPI. (n.d.). *Datos y cuestionarios ESEE*. Retrieved June 20, 2023, from Fundación SEPI: https://www.fundacionsepi.es/investigacion/esee/svariables/disponibles.asp

Fundación SEPI. (n.d.). *Encuesta sobre Estrategias Empresariales. Ejercicio de 2014.* Retrieved June 20, 2023, from Fundación SEPI: https://www.fundacionsepi.es/investigacion/esee/svariables/cuestionarios/c-esee14.pdf

IFR Statistical Department. (2022). *World Robotics 2022 – Industrial Robots.* Frankfurt am Main, Germany: VDMA Services GmbH.

Jimeno, J. F. (2019). Fewer babies and more robots: economic growth in a new era of demographic and technological changes. *SERIEs, 10*, 93–114. Retrieved from https://doi.org/10.1007/s13209-019-0190-z

Karabarbounis, L., & Neiman, B. (2013). The global decline of the labor share. *NBER Working Paper Series*, 19136. Retrieved from https://www.nber.org/system/files/working_papers/w19136/w19136.pdf

Koch, M., Manuylov, I., & Smolka, M. (2021, August). Robots and firms. (N. Guner, Ed.) *The Economic Journal, 131*, 2553–2584. Retrieved from https://doi.org/10.1093/ej/ueab009

Leon-Llorente, C. (2020). Robotización, ¿sólo cambiará el empleo? *Revista empresa y humanismo, 23*(1), 9-33.

Inzunza, B. E., Wright, C., Ghys, T., & Cools, P. (2020). Imaginarios de la robotización: la automatización desde la perspectiva del empleado. Estudios Sociologicos, 38(113), 567-600. Retrieved from https://doi.org/10.24201/es.2020v38n113.1923

Ricardo, D. (2003). Sobre la maquinaria. In D. Ricardo, *Principios de Economía Política y Tributación* (pp. 313-321). Madrid: Ediciones Pirámide. Original work published in 1817.

Schwab, K. (2016). *La cuarta revolución industrial.* Madrid: Debate.

Smith, A. (2019). *La riqueza de las naciones* (Edición de Carlos Rodriguez Braun ed.). Original work published in 1776.

Torrejón Pérez, S., Klenert, D., Marschinski, R., Fernández-Macías, E., & González Vázquez, I. (2020, August 8). *The impact of industrial robots on the EU economy.* Retrieved from EU Science Hub: https://joint-research-centre.ec.europa.eu/system/files/2020-10/jrc121953_policy_brief_the_impact_of_industrial_robots_on_the_eu_economy.pdf