

*Research article*

## The involvement of the Spanish industrial sector in environmental sustainability and its impact on productivity

Alejandro García-Pozo<sup>1</sup>, Elena Lasso-Dela-Vega<sup>1,\*</sup>, Marina Marfil-Cotilla<sup>2</sup> and Juan Antonio Campos-Soria<sup>1</sup>

<sup>1</sup> Department of Applied Economy (Economic Structure), Faculty of Economics and Business Studies, University of Malaga, Spain

<sup>2</sup> Department of Applied Economy, Faculty of Economics, University of Valencia, Spain.

\* **Correspondence:** Email: [elenalasso@uma.es](mailto:elenalasso@uma.es).

**Abstract:** In recent years, developed economies have become aware of the importance of respecting the environment in the economic development of countries. As it is reflected in Sustainable Development Goals (SDGs) 8 and 9 of the 2030 United Nations' Agenda which promote sustainable growth and environmentally friendly industrialisation. Environmental impacts are more visible in the industrial sector than in all other productive sectors. In the case of Spain, 55.66% of companies in this industrial sector consider it important to invest in R&D with the aim of reducing such environmental impacts. This paper shows that the pursuit of this objective constitutes a fundamental element in the innovative process and describes its consequences on the productivity of industrial companies. Estimates of the relationships between R&D investment, innovation, and productivity were established using a CDM structural model applied to a sample of Spanish industrial companies included in the Technological Innovation Panel database. The results obtained confirm that business involvement in the reduction of environmental impact has positive and statistically significant effects on the decision to invest in R&D and the amount of effort involved, on the probability of conducting innovative activities, and on productivity, showing that productivity is 6.5% higher in industrial companies that attempt to reduce environmental impacts than in those that do not.

**Keywords:** Eco-innovation; productivity; CDM model; industrial sector; Spain

**JEL Codes:** Q01, D24, L00

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## 1. Introduction

In recent years, awareness has grown within developed economies of the relevance of the environment and its relationship with the economic development of countries. This phenomenon is evidenced by Sustainable Development Goals (SDGs) 8 and 9 of the United Nations 2030 Agenda, which propose a transition toward a model of sustainable economic growth and industrial development that respects the environment.

The industrial sector stands out from the rest of the economic sectors due to the high volume of waste it generates and the energy consumption involved in its production processes. In Spain, such energy consumption increased between 2017 and 2019 by 6.7 percentage points (INE, 2020). This issue has led developed economies—in this case, Spain—to establish environmental regulations that reduce the ecological impact of productive sectors such as the aforementioned industrial sector. Examples of these regulations are Law 9/2020 of 16 December to regulate the greenhouse gas emission rights trading scheme or Law 22/2011 of 28 July on waste and contaminated soils.

By virtue of complying with these regulations, companies are forced to make environmentally targeted modifications to their production processes. This aspect brings us to the concept of eco-investment, which is understood as the development of processes or modifications that address sustainable objectives and seek to reduce environmental damage (Beise & Rennings, 2005; De Marchi, 2012). The effects of such investments on business performance raise questions about the incentives for companies to engage in eco-innovation beyond simple compliance with established regulations.

Therefore, the aim of this paper was to analyse the investment decisions of eco-innovative industrial firms in terms of the probability of innovating, the type of innovation, and its intensity. We also investigate the impact on productivity of this type of environmental investment in the Spanish industrial sector. The novelty of this study lies mainly in the fact that, to the authors' knowledge, none of the previous literature has analysed environmental innovation decisions and the productivity of these eco-innovative firms in the industrial sector. Another innovative aspect of this study is that we highlight the differences in the labour productivity of Spanish industrial firms according to the region in which they conduct their main activity. The inclusion of regions in this study follows the criteria set out in the work of García-Pozo et al. (2021).

The rest of the paper is structured as follows: The next section presents a review of the literature; the third section describes the methodology applied; the fourth section presents a brief analysis of the database used; the fifth section presents and discusses the main econometric results; and the sixth and final section summarises the main conclusions drawn from this research.

## 2. Literature review

The aforementioned concept of eco-investment has given rise to an entire literature on the impact of such sustainable investments on company performance (e.g. see Kneller & Manderson, 2012; Yang et al., 2012; Chakraborty & Chatterje, 2017). These authors have found that investment in compliance with environmental regulations favours innovation rather than hindering it and generates positive impacts on firms' productivity. In this regard, there are well-known studies that have analysed incentives for eco-innovation, finding that a key factor is the establishment of environmental regulations (Doran & Ryan, 2012; Sierzchula et al., 2012; Triguero et al., 2015; Li et al., 2020; Hojnik et al., 2021). However, there is far less literature on the productivity effects of firms' incentives to

engage in environmental innovations: Wugan and Guangpei (2018) study the factors driving eco-innovation in China also observing its effect on company performance; García-Pozo et al. (2018a), García-Pozo et al. (2018b), and Amores et al. (2014) have studied Spanish services, the transport sector, and the metal sector, respectively, showing that the attempt to reduce environmental impacts has a positive effect on innovation and labour productivity.

It should be emphasised that the analysis of the effect of environmental innovation on business productivity stems from previous research on the effects of investments in R&D (environmental or non-environmental) on business performance, with the work of Griliches (1979, 1986) and Pakes & Griliches (1980) being seminal in this field. In this regard, most authors have conducted their studies in recent decades, mainly applying the methodology proposed by Crepon et al. (1998) (the CDM model), together with contributions from Griffith et al. (2006) to this model.

**Table 1.** Selected literature on innovation and productivity in the industrial sector.

Authors	Country	Period analysed	Main findings
Acosta et al. (2015) <sup>c,f,m</sup>	Spain	2008–2011	Innovation output and investment intensity influence productivity. Highlights the role of public funding in firms' likelihood to invest.
Bartelsman et al. (2017) <sup>b,e,l</sup>	European countries (14)	2001–2010	Innovative activity contributes to aggregate productivity, although the average firm-level effect is negligible.
Brown and Guzmán (2014) <sup>b,l</sup>	Mexico	2004–2006	Innovation, wages and capital intensity significantly influence productivity. At the same time, market shares and high-tech industries influence the propensity to innovate.
Bukstein et al. (2019) <sup>a,e,m</sup>	Uruguay	2004–2015	Barriers to innovation reduce the propensity to innovate but do not have a significant impact on labour productivity.
Castellacci (2011) <sup>a,d,m</sup>	Norway	1998–2000; 2002–2004; 2004–2006	Firms with greater market concentration have a higher propensity to innovate, but competitive firms that choose to invest in R&D generate higher productivity impacts.
Costa-Campi et al. (2014) <sup>c,f,l</sup>	Spain	2004–2010	R&D intensity is positively related to process innovation.
Duch-Brown et al. (2018) <sup>c,f,l</sup>	Spain	2004–2013	The relationship between innovation and productivity depends on the type of innovation and the chosen industry. In the ICT industry, product, process, and marketing innovations are closely related.
Frank et al. (2016) <sup>c,g,m</sup>	Brazil	2009–2011	Market orientation and internal and external R&D positively affect innovation output.
García-Pozo et al. (2018b) <sup>c,f,l</sup>	Spain	2003–2014	Reducing environmental impact has a positive effect on the innovation process and labour productivity.

*Continued on next page*

Authors	Country	Period analysed	Main findings
García-Pozo et al. (2021) <sup>a,f,l</sup>	Spain	2008–2016	There are regional differences in productivity according to the type of innovation conducted. In Andalusia and Madrid, productivity increases with product innovation, whereas in Catalonia it increases with process innovation.
Griliches (1986) <sup>b,i,n</sup>	USA	1957–1977	R&D investment contributes to productivity growth, which depends to a large extent on the intensity of innovative investment.
Gómez and Borrastero (2021) <sup>b,k,l</sup>	Argentina	2010–2012; 2014–2016	The innovation process links innovation to productivity regardless of prevailing macroeconomic and industrial conditions.
Gong and Wang (2022) <sup>c,j,l</sup>	China	2015–2017	Positive correlation between R&D investment and innovation output and the latter and business performance.
Mariev et al. (2022) <sup>a,h,l</sup>	Russia	2012–2014	Human capital is a relevant factor for business innovation. Such innovations accelerate productivity.
Okan and Oktay (2021) <sup>b,d,l</sup>	Turkey	2012–2014	Spending on innovation increases the likelihood of innovation and boosts productivity.
Ramadani et al. (2019) <sup>a,h,l</sup>	South East European countries	2013–2014	Product innovation has a positive effect on the performance of firms in transition countries. Human capital and foreign investment enhance product innovation.
Raymond et al. (2015) <sup>b,d,e,m</sup>	The Netherlands and France	1994–1996; 1998–2000; 2002–2004	Unidirectional causality from innovation to productivity. So, upstream productivity does not significantly affect product innovation.
Siedschlag and Zhang (2015) <sup>a,d,m</sup>	Ireland	2004–2008	International companies are more likely to invest in innovation and higher labour productivity, especially through process and organisational innovations.
Trachuk and Linder (2018) <sup>c,d,l</sup>	Russia	2012–2014	Industry-specific characteristics influence the relationship between innovation and productivity. Innovations in high-tech industries generate the greatest productivity impacts.
Vokoun (2016) <sup>b,d,l</sup>	Czech Republic	2001, 2003, 2006 y 2008	Innovation is an important determinant in boosting SME productivity.

Notes: Sectors: <sup>a</sup>all sectors, <sup>b</sup>manufacturing, <sup>c</sup>industry sector. Databases: <sup>d</sup>Community Innovation Survey (CIS), <sup>e</sup>Investment Statistics (IS) and Production Statistics (PS), <sup>f</sup>PITEC (Based on the Spanish Economy Survey), <sup>g</sup>Industrial Research of Technological Innovation (PINTEC), <sup>h</sup>Business Environment and Enterprises Survey (BEEPS), <sup>i</sup>National Science Foundation (NSF), <sup>j</sup>China Stock market and accounting research databases, <sup>k</sup>Argentina's National Survey on employment and innovation dynamics. Econometric model used: <sup>l</sup>CDM model, <sup>m</sup>Variant of CDM model, <sup>n</sup>Variant of Cobb-Douglas function production.

Following the work of García-Pozo et al. (2018a), Table 1 shows 20 studies within the industrial sector conducted in a wide variety of countries and periods. Each of these studies provides information on the author, country, period of study, production sector of interest, database used, econometric methodology applied, and main results. It can be seen that most of the studies used CDM models or variants of the same, making use of European Community innovation databases or, in some cases, homologous national databases that store information on innovation and productivity in the respective country.

Table 1 also shows that, firstly, these studies confirm the relationship between investment in innovation (R&D) and productivity gains. This relationship also holds for small and medium-sized enterprises (Vokoun, 2016). Secondly, Castellacci (2011) highlighted the level of market concentration as a determinant of the propensity to innovate, showing that competitive firms that choose to invest in R&D generate higher productivity impacts than firms with higher market concentration. Thirdly, it is established that the proven relationship between innovation and productivity may vary depending on the type of innovation and the industry referred to. For example, Trachuk & Linder (2018) found higher productivity impacts in high-tech industries. García-Pozo et al. (2021) pointed out regional discrepancies according to the type of innovation, showing that productivity increases along with product innovations in Andalusia and Madrid, whereas it increases along with process innovations in Catalonia. Ramadani et al. (2019) highlighted the relevance of product innovation for productivity improvement in transition economies. Finally, the origin of innovation also seems to exert a relevant effect on business performance. Thus, Frank et al. (2016) found that home-grown R&D is more conducive to innovation production than technology acquisition from abroad, while García-Pozo et al. (2018a, 2018b) highlighted the relevance of an environmental motive in innovation decisions.

All of these findings are indicative of the importance the economic literature has placed on the relationship between innovation and productivity. They also show the weight that environmental innovation has had on companies in recent decades. This aspect particularly holds true for the industrial sector, which stands out as a productive branch that is strongly regulated regarding environmental issues and that has great potential for process innovation. However, studies that have analysed incentives for environmental innovation and their effect on productivity in industrial companies are extremely scarce, if not non-existent. The present study was motivated by this bibliographical vacuum.

### 3. Methodology

We have used the CDM structural model (Crépon et al., 1998) in the analysis because of its ability to combine the different stages of the innovation process with its impact on firm productivity. The usefulness of the CDM model for analysing the relationships between R&D, innovation, and productivity has been widely corroborated by previous studies applied to the industrial sector (e.g. Acosta et al., 2015; García-Pozo et al., 2021; Hall et al., 2009; Lööf & Heshmati, 2002).

The CDM model is specified by a recursive nonlinear non-feedback system of equations structured in three stages. Following García-Pozo et al. (2018a) and Griffith et al. (2006)—in which the theoretical development of this analysis technique can be found—the CDM structural model has a very simple basic form: firstly, a firm decides whether or not to make some kind of investment in innovation and, if so, determines the amount of effort this will involve; secondly, as a result of such investment, innovation is produced; and, thirdly, production is conducted using this innovative knowledge with the collaboration of other productive factors. These three basic stages follow the

sequence of a firm's decisions in terms of innovation activities and results (Hall et al., 2009). In the present study, the stages are reflected in the econometric model by means of four equations that follow an extension to the approach proposed by Griffith et al. (2006). In line with these authors, the three basic stages can be expressed as described in the following subsections.

### 3.1. R&D Equations

The first two decisions a company faces are whether to invest in R&D or not and, if so, what amount of innovation effort will be required.

These decisions can be specified by means of two equations that indicate firms' willingness to invest in R&D or not and, if so, quantify the intensity of the firm's innovative effort.

Thus, assuming that  $i$  represents the number of firms, taking values from 1 to  $N$ , and that  $r_i^*$  shows the innovative effort of the firm (an unobservable latent variable):

$$r_i^* = z_i' \beta + e_i \quad (1)$$

where  $z_i$  represents the vector of those factors that determine the innovative effort,  $\beta$  shows the set of coefficients to be estimated, and  $e_i$  is the error term.

An undesired selection bias would occur using Equation (1), as it would only measure the intensity of the innovative effort of those firms that implement R&D investment. To avoid this situation, a selection equation is proposed that determines whether a firm performs R&D or not. Thus,

$$rd_i = \begin{cases} 1 & \text{if } rd_i^* = w_i' \alpha + \varepsilon_i > c \\ 0 & \text{if } rd_i^* = w_i' \alpha + \varepsilon_i \leq c \end{cases} \quad (2)$$

where  $rd_i$  represents a binary endogenous observed variable that takes the value 1 when the company invests in R&D and 0 otherwise. In addition,  $rd_i^*$  symbolises the latent variable corresponding to the decision to conduct innovation in such a way that the company will conduct R&D if this variable reaches a value higher than that marked by the constant  $c$ . On the other hand,  $w_i$ ,  $\alpha$ , and  $\varepsilon_i$ , represent the vector of variables that determine the decision to invest in R&D, the vector of coefficients to be estimated, and the error term, respectively.

The value of the intensity of the innovative effort made when investing in R&D can then be estimated using Equation (3), conditional on the firm's decision to engage in innovation activities:

$$r_i = \begin{cases} r_i^* = z_i' \beta + e_i & \text{if } rd_i = 1 \\ 0 & \text{if } rd_i = 0 \end{cases} \quad (3)$$

If it is assumed that the error terms  $e_i$  and  $\varepsilon_i$  follow a bivariate normal distribution of zero mean along with unit variances and the correlation coefficient of both errors  $\rho_{ee}$ , the system of Equations formed by (2) and (3) can be estimated by maximum likelihood<sup>1</sup>.

### 3.2. Knowledge production or innovation equations

As Hollen et al. (2013) pointed out, achieving the full benefits of innovation involves not only taking into account technological innovation but also management-related innovation. Therefore, regarding this

<sup>1</sup> Known as Heckman's (1979) maximum likelihood selection procedure or generalised Tobit type II model.

stage of the model, we present knowledge production equations for the three types of innovation (i.e. product, process, and organisational innovation). These equations have the following form:

$$g_{i,k} = r_i^* \gamma + x'_{i,k} \delta + u_{i,k} \quad (4)$$

where  $g_{i,k}$  represents a binary variable indicating the innovative process, which shows whether the company conducts some form of product, process, or organisational innovation<sup>2</sup>. The variable  $r_i^*$  shows the predicted value of the effort or investment made in R&D by each company as a result of the estimation of Equations (2) and (3) in the first part of the model,  $x_{i,k}$  represents the vector of determinants of each of the types of innovation,  $\gamma$  and  $\delta$  are the coefficients of interest to be estimated, and  $u_{i,k}$  shows an error term for each type of innovation.

To estimate Equation (4), we applied the simulation method of the trivariate probit model suggested by Cappellari & Jenkins (2003)<sup>3</sup>, assuming that  $u_{i,1}$ ,  $u_{i,2}$  and  $u_{i,3}$  have a multivariate normal distribution, each with zero mean and variance-covariance matrix  $V$ . Thus, as Hall et al. (2009) pointed out, including the predicted R&D effort in the innovation output equation takes into account the full sample of firms, while assuming that all of them make some kind of innovative effort even if only some of them invest in R&D and report it. Moreover, by using this predicted value instead of the value actually invested in the innovation production function, the problems of simultaneity and endogeneity between innovative effort in R&D investment and knowledge production can be solved, because  $w_i$  and  $z_i$  are independent of  $u_{i,k}$  in each of the equations.

### 3.3. Productivity equation

The last stage of this model shows the effect on labour productivity of the predicted probability of product, process, or organisational innovation. For this purpose, a Cobb-Douglas model is applied where the main inputs are innovation in the three types of innovation, capital, and labour. This effect on labour productivity can be represented, without showing the constant term, as follows:

$$y_i = k_i \alpha_1 + l_i (\beta_1 - 1) + g_{i,1} \pi_1 + g_{i,2} \pi_2 + g_{i,3} \pi_3 + o_i \omega + v_i \quad (5)$$

As indicated,  $y_i$  represents the productivity of labour taken in logarithms in this case,  $k_i$  shows the logarithm of physical capital,  $l_i$  the logarithm of employment,  $\alpha_1$  is the elasticity of output regarding physical capital, and  $\beta_1$  the elasticity of output regarding employment. On the other hand,  $g_{i,k}$  represent the three types of knowledge input (product, process, and organisational), which, by using their predicted probability values obtained from the innovation production equation, avoids the endogeneity problem of these explanatory variables. The semi-elasticities corresponding to each type of innovation are captured in the values of  $\pi_1, \pi_2, \pi_3$ . Additional control variables have also been included in the vector  $o_i$ , such that the vector  $\omega$  represents the semi-elasticities of output with respect to the rest of the explanatory variables in the model. Finally, the error term is captured in the variable  $v_i$ .

<sup>2</sup>  $k$  in Equation (4) takes the following values: 1 for product innovation, 2 for process innovation, and 3 for organisational innovation.

<sup>3</sup> These authors use the Geweke-Hajivassiliou-Keane (GHK) maximum likelihood simulation method.

#### 4. Database used

This study uses the database from the Panel on Technological Innovation (PITEC). As explained on the Spanish R+D+I Observatory website, PITEC is a panel-type database that monitors the technological innovation activities of Spanish companies. This database was jointly developed by the Spanish National Statistics Institute (INE) and the Spanish Foundation for Science and Technology (Fundación Española para la Ciencia y la Tecnología). Currently, the data available in this panel cover the period 2003 to 2016, and offers information on more than 460 variables corresponding to more than 12,000 companies from all productive sectors broken down into 43 activity groups. PITEC uses the methodological framework established for the creation of the Community Innovation Survey (CIS) developed by EUROSTAT and the innovation classification criteria included in the Oslo Manual (OECD, 2005), which facilitates the comparison of Spanish data with other European Union countries. To avoid inconsistencies due to methodological changes since 2008, the information available from that year until 2016 has been used. This decision was also supported by the fact that, at that time, the classification of economic activities based on CNAE-2009 was introduced in the PITEC database. In the Innovation Survey for 2018, there is also a break in the series due to methodological changes in the new version of the Oslo Manual. For this reason, the data are not comparable with those published for previous years. In addition, several groups of records were excluded: firstly, those of firms with no productivity data, with productivity data below unity, or records that were outside the interval defined for the sample by the  $\mu \pm 2\delta$  function, following a criterion similar to that established by Mohnen et al. (2006); secondly, those where a firm had fewer than three observations in the period analysed; and thirdly, those observations that were clearly anomalous, following a criterion similar to that established by Lööf & Heshmati (2006) and Raymond et al. (2010). After this cleaning process, the database used had an unbalanced sample of 42024 observations referring to the period 2008 to 2016. In the present study, we included the observations of industrial enterprises classified in PITEC activity groups 3 to 27, corresponding to the industrial activities included in the CNAE-2009 (National Classification of Economic Activities).

The variables used in the proposed model are presented and defined in Table A.1, together with their average values. Although it is true that these variables have traditionally been used in this type of analysis of the industrial sector, we would like to draw attention to some novel features. Firstly, a variable has been created that represents the importance a company places on reducing the environmental impact of its industrial activity as a consequence of its innovative process. This variable, included in the three stages of this model, takes the form of a dummy variable and is called environment. Secondly, all the variables related to income, expenditure, and investment used in this model were deflated (2008 euros) for each branch of activity, using as a deflator the data provided by the BD. MORES database<sup>4</sup> produced by the Spanish Ministry of Finance and Public Administrations. Klette & Griliches (1996) and Mairesse & Jaumandreu (2005), among others, have already pointed out the relevance of using industry-specific deflators when analysing production functions, as in the present case. Thirdly, a novel contribution of this work for firms in the industrial sector has been the use of the stock of physical capital deflated for each industrial sub-sector following the procedure and sectoral depreciation rates estimated by García et al. (1998) and by De Bustos et al. (2008).

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<sup>4</sup> See <http://www.sepg.pap.minhap.gob.es/sitios/sepg/es-ES/Presupuestos/Documentacion.aspx>.

The remaining variables used in the model will be discussed in relation to the results obtained at each stage of the model.

## 5. Results and Discussion

### 5.1. R&D equations

As indicated in the methodology section, Table 2 shows the estimates of the two equations of the first stage of the CDM model, in which we used Heckman's (1979) maximum likelihood selection model robust to heteroskedasticity. In this case, the first equation or selection equation takes the form of a binomial logit model which takes a value of 1 when the firm decides to invest in R&D and zero otherwise. In the second equation, depending on whether or not the company decides to conduct innovative activities, the innovative effort of the companies is estimated by means of a linear regression by ordinary least squares, where the dependent variable is the logarithm of the investment in R&D per employee. The use of this selection method is supported by the significance of the  $\rho$  statistic.

The main factors influencing the decision of Spanish industrial companies to invest in R&D are those related to the availability of national or local public funds to conduct these investments, with those related to the availability of European Union funds being a distant second. In addition, the importance that the company places on reducing the environmental impact of its activity also plays a significant role in this decision. Furthermore variables that capture firms' characteristics exert a positive influence on the decision to invest in R&D. On the other hand, the main problem encountered by companies when investing in R&D is the scarcity of external financing. It is also noteworthy that industrial firms located in the autonomous communities of Madrid and, above all, Catalonia, are more likely to invest in R&D than those in the rest of Spain. As Acosta et al. (2015) pointed out, the different regional innovation systems in Spain, both in terms of public and business policies, justify the introduction of these variables in the model.

The estimate of actual R&D investment in the second equation also shows that the availability of public funds, particularly national public funds (52.8%), to conduct these investments significantly determines their execution. The implementation of legal protection activities for innovation, cooperation with other companies to innovate, and the location of companies in Catalonia or Madrid also significantly increases the effective investment in R&D on the part of Spanish industrial companies.

Three groups of variables have been included in both equations in order to make the model more robust: the first group indicates the sources of information used by the firm to innovate; the second group indicates the industrial sub-sector in which the firm operates; and the third group includes the year of each observation. Table 2 shows the probabilities of the Wald tests of joint significance for each group of variables.

**Table 2.** Estimation of the R&D equations.

	Engage in R&D		R&D intensity	
	Marginal effect	s.e.	Marginal effect	s.e.
Size (in log)	0.204***	(0.009)		
Formal protection	0.258***	(0.021)	0.139***	(0.017)
Cooperation	0.109***	(0.020)	0.152***	(0.017)
International competition	0.147***	(0.026)	0.036	(0.027)
Environment	0.290***	(0.021)	0.044**	(0.021)
Age	-0.001	(0.000)	-0.006***	(0.000)
Lack of funding	0.005	(0.013)	0.006	(0.011)
Lack of external funding	0.034***	(0.012)	0.038***	(0.011)
Cost of innovation	-0.012	(0.011)	-0.013	(0.010)
Local funding	0.416***	(0.025)	0.328***	(0.019)
National funding	0.584***	(0.025)	0.528***	(0.018)
EU funding	0.181***	(0.051)	0.206***	(0.032)
Madrid <sup>b</sup>	0.073**	(0.032)	0.137***	(0.027)
Catalonia	0.116***	(0.021)	0.223***	(0.019)
Andalusia	-0.009	(0.040)	-0.273***	(0.038)
Constant	-2.944***	(0.070)	5.770***	(0.082)
Wald test: Sources of information <sup>a</sup>	0.000		0.000	
Wald test: Economic activities <sup>a,c</sup>	0.000		0.000	
Wald test: Time dummies <sup>a</sup>	0.005		0.000	
Wald Chi <sup>2</sup> (54)	6514.58***			
Log pseudolikelihood	-47680.89			
/athrho	0.518*** (0.029)			
/lnsigma	0.130*** (0.006)			
Rho ( $\rho$ )	0.474***			
LR test of indep. eqns. ( $\rho = 0$ )	chi <sup>2</sup> (1) = 210.48			
	Prob > chi <sup>2</sup> = 0.0000			
Observations	32155			
Censored Observations	9869			

Notes: Statistically significant at: \*10%, \*\*5%, and \*\*\*1%. Robust standard errors for heteroskedasticity are shown in parentheses. <sup>a</sup>The Wald joint significance tests include the probability values of the variables in each group. <sup>b</sup>The reference variable between location is “Other regions”. <sup>c</sup>The reference variable between economic activities is “Food industry”.

## 5.2. Innovation or knowledge production equations

Table 3 shows the estimates of the equations for the production of knowledge or innovation. These have been estimated using a trivariate probit model rather than by estimating independent equations for each type of innovation (i.e. product, process, and organisational innovation). This decision is supported by the estimated correlation coefficient of the error terms ( $\rho$ ), whose value is significantly different from zero in all three subsamples. Moreover, as Hall et al. (2009) pointed out, this correlation coefficient ( $\rho$ ) is always positive and significant when considering pairwise equations, confirming that

product, process, and organisational innovation are influenced by the same unobservable factors, but at different intensities.

**Table 3.** Estimation of the innovation production equations.

	Product innovation		Process innovation		Organizational innovation	
	Marginal effect	s.e.	Marginal effect	s.e.	Marginal effect	s.e.
Predicted R&D intensity	0.282***	(0.025)	0.136***	(0.024)	0.216***	(0.023)
Size (in log)	0.077***	(0.007)	0.149***	(0.007)	0.141***	(0.006)
Equipment cost	-0.000*	(0.000)	0.000***	(0.000)	0.000**	(0.000)
Training expenditure	0.000***	(0.000)	0.001***	(0.000)	0.000***	(0.000)
Formal protection	0.323***	(0.020)	0.066***	(0.019)	0.229***	(0.018)
Environment	0.082***	(0.020)	0.198***	(0.020)	0.286***	(0.019)
Internal	0.056***	(0.010)	0.033***	(0.010)	0.061***	(0.010)
Suppliers	-0.023**	(0.009)	0.187***	(0.009)	0.076***	(0.008)
Customers	0.149***	(0.010)	-0.042***	(0.010)	0.029***	(0.009)
Competitors	0.038***	(0.010)	-0.029***	(0.010)	-0.013	(0.009)
Universities	-0.062***	(0.010)	-0.033***	(0.010)	-0.052***	(0.009)
Trade fairs	0.076***	(0.010)	0.026***	(0.010)	0.085***	(0.009)
Madrid <sup>b</sup>	0.036	(0.028)	0.057***	(0.020)	0.022	(0.027)
Catalonia	0.084***	(0.018)	0.049***	(0.018)	-0.027	(0.017)
Andalusia	0.019	(0.037)	0.097***	(0.028)	0.057	(0.036)
Constant	-2.738***	(0.149)	-1.651	(0.144)	-2.886	(0.136)
Wald test: Economic activities <sup>a,c</sup>	0.000		0.000		0.000	
Wald test: Time dummies <sup>a</sup>	0.000		0.000		0.000	
Log pseudolikelihood	-55042.65					
Wald Chi <sup>2</sup> (147)	18571.44***					
$\rho$ (process-product innov.)	0.032***	(0.008)				
$\rho$ (product-organizational innov.)	0.104***	(0.009)				
$\rho$ (process-organizational innov.)	0.339***	(0.008)				
Likelihood ratio test	chi <sup>2</sup> (3) = 1527.48***					
of $\rho_{21} = \rho_{13} = \rho_{23} = 0$						
Observations	32155					

Notes: Statistically significant at: \*10%, \*\*5%, and \*\*\*1%. Robust standard errors for heteroskedasticity are shown in parentheses. <sup>a</sup>The Wald joint significance tests include the probability values of the variables in each group. <sup>b</sup>The reference variable between location is “Other regions”. <sup>c</sup>The reference variable between economic activities is “Food industry”.

As can be seen in Table 3, the variable that includes the predicted investment in R&D, obtained from the previous stage, shows high, positive, and statistically significant values in the three types of innovation. This result confirms the relevance of representing the willingness to conduct R&D and of

effectively implementing R&D investments in relation to the increased probability of generating innovations of the types analysed. This probability is also positively affected by making investments that legally protect the investments made in innovation through instruments such as patents.

The variable that reflects the environmental involvement of companies in innovative processes shows an estimate of coefficients that confirms the positive and significant impact of such eco-innovative involvement on the probability that industrial entities effectively develop product, process, and organisational innovation.

In addition, information on innovative processes coming from the company itself and from trade fairs shows a positive and statistically significant effect on the probability of conducting the three types of innovation. From a regional perspective, it seems that only the location of firms in the regions analysed has a positive and significant effect on the probability of firms conducting process innovation compared to those located in the rest of Spain.

It is important to note that the estimates made at this stage are consistent with those obtained by Acosta et al. (2015), García-Pozo et al. (2021, 2018b), and Griffith et al. (2006), although there are some differences in the sub-sectors analysed in these papers.

### 5.3. *Labour productivity equation*

This section presents the econometric results of the estimation of the third stage of the CDM model (i.e. the productivity equation).

Table 4 shows the coefficient estimates of the variables that affect variation in labour productivity measured as sales per employee expressed in logarithms. This being the case, they will provide elasticities or semi-elasticities depending on the terms used to express the independent variable in each case.

As shown in Table 4, the first relevant finding is that the coefficients of the predicted probabilities of the innovations analysed are positive and statistically significant *ceteris paribus*, implying that the implementation of these three types of innovation is conducive to increases in the labour productivity of industrial firms. These results are in line with those obtained by Acosta et al. (2015) and García-Pozo et al. (2018b) which, to the authors' knowledge, are the only papers addressing the three types of innovation in the industrial sector of the Spanish economy.

The second significant finding, which is related to one of the main objectives of this study, is that the semi-elasticity estimated for the variable representing involvement in eco-innovation shows that industrial companies that attempt to reduce environmental impacts when exercising their activity as a relevant objective of innovation obtain increases in labour productivity that are 6.5% higher than those of industrial companies that do not follow such a course.

Thirdly, positive and statistically significant semi-elasticities were found related to factors such as presence in international markets, belonging to a business group, foreign ownership of more than 50%, and the presence of workers with higher degrees (25.9%, 25.6%, 11.6% and 0.3%, respectively) (see Table 4). This finding confirms that the relationship with the business environment and the existence of greater human capital in Spanish industrial firms can improve their labour productivity.

Finally, the estimates made show that the location of the firm's headquarters also has an impact on labour productivity, confirming the existence of a regional factor that is a determinant of productivity regarding the firms analysed. Thus, a positive and statistically significant relationship was found between the coefficients obtained for Madrid (12.9%) and Catalonia (9.0%) and labour productivity, whereas in the case of Andalusia, the estimated semi-elasticity was lower than that of the

reference variable (i.e. the remaining Spanish regions as a whole) (−8.8%). However, the greater impact on labour productivity derived from firms being located in Madrid and/or Catalonia could be due to the fact that firms with higher productivity choose to locate there (FECYT, 2007). Obviously, such a strategy would be non-viable regarding the industrial development of the Andalusian economy.

**Table 4.** Estimation of the labour productivity equation.

	Coef.	s.e.
Predicted probability of product innovation	0.070***	(0.025)
Predicted probability of process innovation	0.138***	(0.026)
Predicted probability of organizational innovation	0.175***	(0.061)
Physical capital stock (log)	0.139***	(0.007)
Size (log)	−0.114***	(0.000)
Environment	0.065***	(0.015)
International competition	0.259***	(0.014)
Group	0.256***	(0.010)
Foreign capital	0.116***	(0.012)
Degree	0.003***	(0.000)
Madrid <sup>b</sup>	0.129***	(0.014)
Catalonia	0.090***	(0.009)
Andalusia	−0.088***	(0.022)
Constant	0.060***	(0.060)
Wald test: Economic activities <sup>a,c</sup>	0.000	
Wald test: Time dummies <sup>a</sup>	0.000	
F test (47, 31797)	303.69***	
Adjusted R <sup>2</sup>	0.3201	
Observations	31845	

Notes: Statistically significant at: \*10%, \*\*5%, and \*\*\*1%. Robust standard errors for heteroskedasticity are shown in parentheses. <sup>a</sup>The Wald joint significance tests include the probability values of the variables in each group. <sup>b</sup>The reference variable between location is “Other regions”. <sup>c</sup>The reference variable between economic activities is “Food industry”.

## 6. Summary and conclusions

This study used data from the Survey on Innovation in Enterprises (PITEC) to analyse the impact of elements that favour innovation on the labour productivity of industrial firms in Spain. Specifically, we estimated the influence on labour productivity of companies that consider the reduction of the environmental impact of their activity to be a relevant objective of innovation (i.e. those companies considered to be eco-innovative). We also analysed the impact of the regional location of firms on labour productivity. This was conducted by estimating a CDM structural model that establishes the relationships between the decision to implement internal R&D investment, the investment actually made, innovation output, and labour productivity.

The first conclusion that can be drawn from the estimates made is that reductions in the environmental impact of industrial companies as an objective of innovation is a decisive factor when deciding to invest in R&D, which will subsequently be transformed into the generation of knowledge that will reduce such environmental impacts. The eco-innovation generated and the greater environmental awareness in society will lead to more environmentally sustainable industrial production, which will also increase labour productivity. The empirical evidence shown in this study provides arguments in favour of expanding business investments aimed at obtaining eco-innovative measures that improve business performance.

Secondly, the results decisively show that the availability of public funding, basically from local and national institutions, is a key element when industrial companies are deciding to invest in R&D or not, and when deciding on the amount of effort to be made in this investment. It seems, therefore, that one of the objectives of Spanish public administrations should be to encourage companies' access to public funding schemes that improve the conditions for these companies to invest in R&D in order to generate innovative and eco-innovative knowledge. It is also the case that Spanish industrial companies must make an effort to access forms of financing offered by the European Union—the use of which was actually minimal in the period analysed—in order to achieve these innovation objectives.

Thirdly, the amount of innovative effort made by industrial companies was also found to be of key importance to them regarding the generation of innovative knowledge in the three areas analysed: products, processes, and organisation. Investment in R&D had the greatest impact in the areas of products and organisation.

Fourthly, regional differences in labour productivity have been found to exist as a result of the generation of innovative knowledge in Spanish industrial firms. The largest increases in labour productivity were found in Madrid and Catalonia compared to those in the rest of Spain. The results also show that productivity is lower in firms located in Andalusia compared to those located in the rest of Spain, which could be explained by the low per capita income in this region and the well-known relationship between productivity and wages.

Finally, this study has some limitations, such as the inability to incorporate unobserved factors that may affect the eco-innovation decision due to the limitations of the database used. Along these lines, it is important to highlight that, to date, the issue of eco-innovation and environmental sustainability has had little weight in the development of innovation databases in Spain and the European Union. The introduction of improvements in the design of questionnaires for the creation of databases aimed at obtaining better knowledge on these aspects, in relation to industrial and service companies, will enable more specific work to be conducted that will yield more accurate conclusions in the field of eco-innovation and environmental sustainability in the business sphere.

### **Use of AI tools declaration**

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

### **Author contributions**

All authors have contributed significantly to the development of this article, participating in the different stages of the research process.

## Conflict of interest

All authors declare no conflicts of interest in this paper

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