Institut de Recerca en Economia Aplicada Regional i Pública
Research Institute of Applied Economics

Document de Treball 2012/14, 32 pàg.
Working Paper 2012/14, 32 pag.

Grup de Recerca Anàlisi Quantitativa Regional
Regional Quantitative Analysis Research Group

Document de Treball 2012/07, 32 pàg.
Working Paper 2012/07 32 pag.

"Do intra- and inter-industry spillovers matter? CDM model estimates for Spain"

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Abstract

This paper uses a structural model to analyse the impact of innovation activities, including intra- and inter-industry externalities, on the productivity of Spanish firms. To the best of our knowledge, no previous paper has examined spillover effects by adopting such an approach. Here, therefore, we seek to determine the extent to which the innovations carried out by others affect a firm's productivity. Additionally, firm's technology level is taken into account in order to ascertain whether there are any differences in this regard between high-tech and low-tech firms both in industrial and service sectors. The database used is the Technological Innovation Panel (PITEC) which includes 8,611 firms for the year 2009. We find that low-tech firms make the most of a range of factors, including funding and belonging to a group, to increase their investment in R&D. As expected, R&D intensity has a positive impact on the probability of achieving both product and, more especially, process innovations. Finally, innovation output has a positive impact on firm's productivity, being greater in more advanced firms in the case of process innovations. Both intra- and inter-industry spillovers have a positive impact on firm's productivity, but this varies with the firm's level of technology. Thus, innovations made by firms from the same sector are more important for low-tech firms than they are for their high-tech counterparts, while innovations made by the rest of the sectors have a greater impact on high-tech firms.

JEL classification: D24, O33.
Keywords: Productivity, innovation, industry spillovers.

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Acknowledgements:

The authors are grateful for the funding obtained from the Ministry of Education and Science for the project entitled "Determinants for the spread of innovation and their effects on productivity", ECO2009-12678/ECON, 2010-2012.
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Esther Vayá is grateful for the funding obtained from the Ministry of Education and Science for the project entitled "Regional economic growth and inequality in Spain", ECO2010-16006/ ECON, 2011-2013.

1. Introduction

Since the pioneering work of Griliches (1979, 1986), the relationship between innovation and productivity has been widely studied by many authors on both national and sectoral as well as firm levels. The Cobb-Douglas production function adopted in these empirical analyses has enabled the traditional inputs of physical capital and labour to be extended to include innovation expenditures. The results reported have tended to vary depending on the geographical area being analysed, and on the particular database and methodology being used. However, overall the evidence points to a positive and significant relationship between innovation and productivity on firm level (see Mairesse and Sassenou, 1991, for a detailed study, and also – to name just a few – Hall and Mairesse, 1995, for France; Harhoff, 1998, for Germany; Lotti and Santarelli, 2001, for a comparative study of Germany and Italy; and Parisi et al., 2006, for Italy).

Nevertheless since the publication of Crépon, Duguet and Mairesse (1998) the approach taken in this line of literature has shifted, moving from an input definition of innovation activities to an output definition. The authors estimate a structural model (henceforth the CDM model) involving three steps: (i) the firm's decision whether or not to engage in R&D, and the intensity of its investment, (ii) the effective innovation obtained from R&D expenditures and (iii) the relationship between innovation output and firm's productivity. In this way, the structural model enables an analysis to be undertaken not solely of the relationship between innovation input and productivity, but of the whole process (the firm's decision to innovate, innovation input intensity, production of innovation output and the impact of this "successful" innovation on the firm's productivity).

Due to the increasing availability of innovation survey data at the micro level, many authors rely on the CDM model to analyse the impact of innovation on the productivity of firms (see Hall and Mairesse, 2006 for a survey, as well as Janz et al., 2004 for Germany and Sweden; Lööf, 2005 and Lööf and Heshmati, 2006 for Sweden; Benavente, 2006 for Chile; Jefferson et al., 2006 for China; Mohnen et al., 2006 for seven European countries; Griffith et al., 2006, who carry out a comparative study of France, Germany, Spain and the United Kingdom; Masso and Vahter, 2008 for Estonia; Raffo et al., 2008 for a comparison across European and Latin American countries and Hall et al., 2009 for Italy, to name a few). In the case of Spain only a few papers have attempted to apply the structural model and then, in some instances, the sample has been restricted to the manufacturing firms using the dataset "Encuesta sobre Estrategias Empresariales" (ESEE)[1] (Huergo and Moreno, 2004; 2011). Other papers have sought to

[1] The ESEE is a firm-level survey of Spanish manufacturing which has collected information on a yearly basis since 1990.

overcome this limitation and study both manufacturing and service sectors; yet here the geographical area of analysis has been more limited (see for example, Segarra-Blasco, 2010 and Segarra-Blasco and Teruel, 2011 for Catalonia).

However, the impact of innovation on firm's productivity will vary depending on a number of factors, including the level of technology operated by the firm. While there are many articles that deal with this issue from the production function perspective (see for instance, Verspagen, 1995; Tsai and Wang, 2004 and Ortega-Argilés, 2010; 2011), there is much less evidence in papers that apply the CDM model. Thus, as Segarra-Blasco (2010) notes, the innovation indicators differ considerably according to the level of technological intensity. Likewise, Hall et al. (2009) show that high-tech firms can benefit more from product innovation than is the case of their low-tech counterparts.

It should be borne in mind, moreover, that the benefits derived from a firm's (or sector's) innovation are likely to spill over, given the firm's inability to channel all the benefits obtained from its investment. Therefore, when examining the impact of innovation on productivity, the diffusion of the innovation and any externalities need to be taken into account. Although there are numerous studies that report a positive relationship (see Griliches, 1992), other more recent papers arrive at different conclusions (Los and Verspagen, 2000, for American firms; Harhoff, 2000, for Germany; and Wakelin, 2001, for the United Kingdom, among others). Clearly, the results depend to a large extent on the variable used to quantify the externality (R&D expenditures, information on patents, surveys on innovation, etc.), as well as on the sector or country under analysis and the transmission mechanism used to weight the relationships between sectors. The literature examining the effect of spillovers on productivity is quite limited in Spain. Some articles, such as those by López-Pueyo and Sanaú (1999) and Gumbau-Albert and Maudos (2006), report externalities as being positive and significant in explaining productivity. However, other authors obtain different results depending on the firm's economic sector or technology level and no consensus exists in this area. Beneito (2001) analyses the impact of externalities on productivity in Spanish firms distinguishing according to technology level, while Segarra-Blasco (2007) analyses the impact of intra- and inter-industry externalities on Catalan firms. However, none of these studies has adopted the CDM approach.

Taking the above discussion into account, the aim of this paper is twofold. First, using the CDM model, we wish to analyse the extent to which the technology level affects the return that firms obtain from their investment in innovation. Given the small body of literature concerned with this aspect and its lack of consensus, the first goal of this study is to clarify this issue for the Spanish case. The study is conducted using the Technological Innovation Panel (PITEC) database and examines a sample of 8,611 Spanish firms belonging to both the industrial and service sectors in 2009. It should be stressed that the study breaks new ground, since as well as focusing on both the industrial and service sectors, it also examines the situation for the whole country. Thereby it aims to overcome a severe limitation given that, as we have already seen, most studies in this area focus only on the manufacturing sector or cover only a specific region. The second and main goal of this paper is to analyse the benefits that firms obtain from the innovations carried out by others (i.e., either all the other firms in the same sector or those in all other sectors). To the best of our knowledge, the assessment of the impact of these external sources of knowledge on the productivity of firms has not been dealt with in any country by applying the CDM model.

The rest of the paper is structured as follows. Section II presents the theoretical model, section III describes the database, section IV presents the empirical implementation, as well as, the results obtained, and finally the conclusions are drawn in Section V.

2. Model

The model adopted to estimate the relationship between innovation and productivity is a modified version of the CDM model. In line with other studies, we seek to improve the original specification by considering both product and process innovation. Likewise, we extend the original model by introducing measures of externalities in the productivity equation.

Following Griffith et al. (2006) the model can be formalized in four sequential equations:

(i) The research equations:

This first block is concerned with a firm's research activities, modelling the process that leads the firm to decide whether or not to undertake these research projects, and how much to invest in them. However, the intensity of R&D investment can be observed if, and only if, firms actually choose to spend on R&D. So, the first equation is a selection equation indicating whether the firm performs R&D activities or not, and can be specified as:

$$RD_i = \begin{cases} 1 & if \quad RD^* = w_i\alpha + \varepsilon_i > \bar{c} \\ 0 & if \quad RD^* = w_i\alpha + \varepsilon_i \leq \bar{c} \end{cases} \quad (1)$$

where RD_i is an (observable) indicator function that takes the value 1 if firm i has positive R&D expenditures, RD_i^* is a latent indicator variable whereby firm i incurs R&D expenditures if these are above given a threshold $\bar{c}$, wi is a set of explanatory variables and ε_i an error term.

The second equation is the innovation intensity that can be specified as:

$$RDI_i = \begin{cases} RDI^* = z_i\beta + e_i & if \quad RD_i = 1 \\ 0 & if \quad RD_i = 0 \end{cases} \tag{2}$$

where RDI_i^* is the unobserved latent variable accounting for firm's innovative effort measured as the logarithm of R&D expenditure per employee, z_i is a set of determinants of innovation expenditures and e_i is an error term.

(ii) The innovation equations (innovation production function):

This step links the research activities above to innovation output measures. Thus, the third equation is the innovation production function:

$$I_i = RDI_i^*\gamma + x_i^{'}\delta + u_i \tag{3}$$

where I_i is innovation output proxied by both product and process innovation indicators, and where the latent innovation effort RDI^* is an explanatory variable, x_i is a vector of other determinants of knowledge production and u_i is an error term.

(iii) The productivity equation (production function):

This last step is modelled by an augmented Cobb-Douglas production function:

$$y_i = \pi_1 k_i + \pi_2 I_i + v_i \tag{4}$$

where y_i is labour productivity, k_i is physical capital per employee, I_i is innovation output and v_i is the error term.

However, in our analysis, we propose two modifications of expression (4). First, we use an augmented Cobb-Douglas production function which in addition to including physical capital, labour and innovation, also incorporates human capital (h_i). Human capital is included because as the workers become more highly trained and acquire more skills they are able to carry out their tasks more efficiently. The literature emphasises the significance of human capital on a firm's productivity so that the more qualified workers the firm has, the more productive it tends to be[2].

Second, and as a key feature of this study, we include industry spillovers in the last equation. Thus, on the assumption that an external effect exists because of the public nature of knowledge, two types of externality are considered: intra-industry externalities (S_i^{INTRA}), which includes the innovation effort made by all other firms in the same sector, and inter-industry externalities (S_i^{INTER}), understood as the innovation effort made by all the firms in all the other sectors. Here, it should be borne in mind that knowledge transfer between firms can occur in a variety of ways: learning what other firms do either via the movement of workers between firms or through the reading of journal articles, the attending of conferences, the disclosure of patents, etc. The result, however, is the same: one firm uses the knowledge generated by another without having to pay for it directly.

To the best of our knowledge, none of the empirical articles that analyses the relationship between innovation and productivity using the CDM model has considered externalities. Bearing in mind that, in general, spillovers have a positive impact on a firm's productivity (Griliches, 1992 and Nadiri, 1993), it is interesting to determine the extent to which externalities might also appear when a structural model is used.

Consequently, we propose a new expression of equation (4):

$$y_i = \pi_1 k_i + \pi_2 g_i + \pi_3 h_i + \pi_4 S_i^{INTRA} + \pi_5 S_i^{INTER} + v_i \qquad (5)$$

3. Data: Technology Innovation Panel

The database used is the Technological Innovation Panel (PITEC), which provides information on the technological innovation activities of Spanish firms for the period 2003-2009. The National Institute of Statistics (INE), in consultation with a research group and with the sponsorship of the Spanish Foundation for Science and Technology (FECYT) and the Foundation for Technological Innovation (COTEC), is responsible for building up this database. PITEC is based on the Spanish Innovation Survey carried out by the INE, which in turn is based on the Community Innovation

[2] See, for example, Black and Lynch (1996) and Haltiwanger *et al*. (1999) for the United States; Turcotte and Rennison (2004) for Canada; Arvanitis and Loukis (2009) for Greece and Switzerland; Yang, Lin, Ma (2010) for China, and Lee (2011) for Malaysia.

Survey (CIS) which follows the guidelines laid down by the OECD's Oslo Manual and, through the use of a standardized questionnaire, enables comparisons to be made across countries.

PITEC is a data panel based on a representative selection of firms, which makes it possible to carry out repeated observations of the economic units included over time and, thereby, to develop much more precise estimations of the evolution of R+D+I activities in the business sector (innovation expenditures, composition of the samples, etc.), to determine the impact of innovation (different effects on productivity) and to identify the various strategies in the decisions adopted by firms when introducing innovations into their business (for instance, the different composition of internal and external R&D expenditures as a part of total expenditures). The panel comprises four non-excludable samples: (i) firms with 200 or more employees, (ii) firms with internal R&D expenditures, (iii) firms with fewer than 200 employees with external R&D expenditures but which carry out no internal R&D, and (iv) firms with fewer than 200 employees with no innovation expenditures.

A filtering process[3] was used in treating the data excluding primary sector and construction firms and leaving just those that belong to the industrial and service sectors. Similarly, only firms with ten or more employees were considered[4]. Note that the influence of extreme outliers was treated (see appendix A). Thus, the final sample consisted of 8,611 observations in 2009.

The PITEC provides information on innovation activities, such as types of innovation, cooperation between firms and number of patents, together with information on individual firm characteristics such as sales, volume of exports, workers and their level of education, the market in which the firm operates, funding sources, etc.

Based on our previous work with this database, we identify two advantages. First, the fact that it provides information on both the industrial and service sectors means that the serious limitation of most studies in this area (namely, that they focus solely on the manufacturing sector employing the dataset ESEE) are avoided. And second, it contains a high level of sectoral information broken down into details covering 44 industrial and service sectors in 2009. This level of detail enables a rich study to be undertaken examining differences in behaviour between sectors with different technology levels and, in turn, facilitates our study of sectoral externalities.

[3] This filtering process also involved eliminating observations that included some kind of incident (problems of confidentiality or takeovers and mergers, etc.) and those with an obvious anomaly (such as null sales).
[4] The population area considered here is as defined in the Spanish Innovation Survey on which the PITEC is based.

In line with the aim of this paper, and in order to determine whether the effects of innovation and externalities on productivity vary with the technology level, the sample of 8,611 firms was split by the technology level of the sector in which the firm operates. To do this, we used the Eurostat classification and grouped the firms by sector as follows (see appendix B):

- Low and medium-low tech industries (LTI)
- Medium-high and high tech industries (HTI)
- Non-knowledge-intensive services (NKIS)
- Knowledge-intensive services (KIS)

4. Empirical implementation

4.1. Empirical model

Below we present the variables and methodology used in estimating each part of the model described in the section above.

In the first step, we estimate equations (1) and (2) using a generalized Tobit model by maximum likelihood; thus, it is assumed that the correlated errors ε_i and e_i are joint normally distributed. Unfortunately, not all firms are requested to answer all the survey questions, while firms that engage in innovation activities have to complete a larger number of items. For this reason more information is available in the case of equation (2), while we only have limited information for equation (1).

The determinants of a firm's engagement in R&D activities (w_i) in 2009 are: firm size, belonging to a group, human capital, investment intensity per employee, dummy variables indicating whether the firm received public funding for R&D activities in the period 2007-09, a dummy variable equal to 1 if the firm protected its innovations during the period 2007-09, a set of dummy variables for factors hampering innovations in 2007-09, and a dummy variable equal to 1 if the market firm was international in the period 2007-09. The explanatory variables of R&D intensity - equation (2) - are the same as in w_i, with the exception of the international competition indicator[5]. We also add[6] a

[5] We select this variable as an exclusion restriction to provide more robust estimations. It is thought that this variable is correlated with the probability of engaging in R&D activities, but not necessarily with R&D intensity.
[6] This information is only available for innovative firms, which is why we have been unable to include it in equation (1).

set of dummy variables for the different sources of information used between 2007 and 2009 and a dummy variable indicating whether a firm cooperated in the period 2007-09.

In the case of equation (3), we distinguish two kinds of innovation output: process and product innovation. Each is measured by a dummy variable equal to 1 if the firm introduced at least one process (product) innovation in the period 2007-09. Thus, the innovation production function is estimated using a bivariate probit by maximum likelihood assuming both variables to be highly correlated[7]. As determinants we include the predicted value of R&D intensity obtained in equation (2) as a proxy for innovative effort, and a set of variables (x_i): firm size, protection methods used during the period 2007-09, sources of information and investment intensity (but only for process innovation since such innovation involves changes in the production line and so it might require the acquisition of new machinery and equipment).

In the final step, equation (5) is estimated using instrumental variables. Labour productivity depends on innovation output (process and product innovation) predicted in equation (3), investment intensity, firm size, human capital and intra- and inter-industry spillovers.

Apart from this, we control for unobserved industry characteristics in all the equations except the last one, given that sectoral externalities are included. We also control for firm size in all the equations. On the other hand, the estimates are made for all firms, not just those that innovate, since it is believed that all firms engage in some innovative effort, albeit that all report it.

As for problems related to the econometric analysis, it should be stressed that the CDM approach enables us to deal with two basic issues: biases of selectivity and endogeneity. Failing to take these into consideration would lead to potentially inconsistent and biased estimates of the parameters of interest. In the case of selectivity, it would be inappropriate to consider innovative firms alone because the firms are not randomly drawn from the population and a selection bias may thus arise. The CDM model takes this situation into account by including a selection equation in the first step. In the case of endogeneity, using predicted values instead of the realized values is a way of dealing with this potential bias in the various stages of the process. It is possible that unobservable firm characteristics can affect both their innovative effort (R&D expenditures) and their efficiency in producing innovations (see for instance, Griffith et al., 2006 and Hall et al., 2009, to name just a few).

[7] In this regard, we do not follow Griffith et al. (2006) who use two separate probits. However, a bivariate probit has been used by other authors, including, Hall et al. (2009), Masso and Vather (2008) and Antonetti and Cainelli (2011).

Given the many different ways in which spillovers can appear, measuring them is a complex task. We have considered several possible definitions, but have opted for the one that best fits the CDM approach. In other words, the CDM model explains productivity in terms of innovation output as opposed to innovation input. Thus, here, externalities also need to be in line with this idea. As a result, the definition of externalities presented below seeks to capture not only the knowledge current in the sector, but also the fact that firms obtain a successful innovation (product or process) thanks to this knowledge.

First, the 2009 intra-industry externality corresponding to firm i belonging to sector s is defined as the total R&D expenditures incurred by all the other firms in the same sector in 2007 provided that they have made a successful innovation during the period 2007-09:

$$S_{i,s}^{INTRA} = \sum_{j \neq i} \left(\ln \left(RD_{j,s}^{07} \right) \cdot I_{j,s}^{07-09} \right)$$

where $\ln\left(RD_{j,s}^{07}\right)$ is the logarithm of R&D expenditure carried out by the rest of the firms in its sector in 2007 and $I_{j,s}^{07-09}$ is an indicator variable equal to 1 if the firm j has achieved successful innovation results (product or process innovation) during the period 2007-09, or 0 otherwise. By using this definition we are able to capture the technological effort of the sector in which the firm is located, bearing in mind that the firms not reporting any effective innovation results are not included in the calculation of the spillover variable[8].

Second, the inter-industry externality corresponding to firm i belonging to sector s is defined as the weighted sum of all R&D expenditures incurred by the firms in all the other sectors provided that these firms have achieved a process or product innovation during the period 2007-09:

$$S_{i,s}^{INTER} = \sum_{\substack{j \neq i \\ m \neq s}} w_{sm} \cdot \left(\ln \left(RD_{j,m}^{07} \right) \cdot I_{j,m}^{07-09} \right)$$

where $\ln\left(RD_{j,m}^{07}\right)$ is the logarithm of R&D expenditure carried out by the rest of the sectors in 2007 and $I_{j,m}^{07-09}$ is an indicator variable equal to 1 if the firm j belonging to sector m has achieved an innovation output. Weighted w_{sm} is defined as the quotient between the intermediate purchase

[8] Obviously, not all the R&D expenditure incurred by all the other firms will benefit firm *i,* but it will serve as an indicator of the magnitude of the effective technological knowledge current in the sector.

by sector s of goods and services supplied by sector m and the total sum of intermediate purchase of sector s. Thus, the influence of the R&D expenditure incurred by firms in sector m (if they are capable of making a process or product innovation on their own) on the productivity of firm i in sector s is based on the relative importance that sector m has as a supplier to sector s. To construct the w_{sm} weights, we used the symmetric input-output table for Spain for 2005 (the latest year available), and for this an exercise of correspondence had to be carried out between the branches of business activity by which the PITEC data are classified and those used in the input-output table.

4.2. Descriptive statistics

Table 1 shows the descriptive statistics for the main variables in the model across the different technology sectors (see appendix C for the definition of the variables).

First, it can be seen that labour productivity is higher in high-tech industries than it is in low-tech industries. However, the opposite is the case in the services sector with the non-knowledge-intensive services presenting a higher labour productivity ratio than the knowledge-intensive services. Investment intensity is greater in more advanced firms, both in the industry and service sectors. Not surprisingly manufacturing firms invest more than service firms. In the case of human capital, the average percentage of qualified employees is much higher in more advanced firms. In particular, in knowledge-intensive services approximately 48% of workers have higher education.

High-tech firms are the most likely to engage in R&D activities with around 74% of high-tech industries choosing to undertake R&D projects. The intensity of this investment is also greater in high-tech than it is in low-tech firms. Thus, the more advanced a firm is, the greater its R&D effort. For example, knowledge-intensive services present the highest spending on R&D activities per employee (8.3 thousand euros). Similarly, the proportion of firms reporting a successful process or product innovation (or both) is higher in advanced firms than it is in low-tech firms, with the difference being most marked in product innovation (76% vs. 56% in industry, and 59% vs. 26% in services). Interestingly, the proportion of firms achieving innovation output is higher than that which report investing in R&D activities at all technology levels. This might be accounted for by the fact that the decision to engage in R&D activities was made in 2009 while innovation output would capture any innovation made in the period 2007-09. Another possible explanation might be the unrecognised importance of informal innovation.

Table 1: Descriptive statistics

	LTI	**HTI**	**NKIS**	**KIS**
Labour productivity [a, d]	136.528	150.764	99.307	72.997
Investment intensity [a, d]	1.268	1.592	0.204	0.801
Human capital [a]	12.110	21.123	14.457	48.167
Knowledge / Innovation				
R&D engagement [a]	0.507	0.739	0.210	0.551
R&D intensity [b, d]	2.150	4.708	2.547	8.298
Innovator (product or process) [a]	0.758	0.868	0.455	0.749
Process innovation [a]	0.650	0.672	0.375	0.592
Product innovation [a]	0.562	0.760	0.258	0.589
Protection [a]	0.238	0.298	0.144	0.275
Cooperation [c]	0.310	0.376	0.279	0.467
International competition [a]	0.564	0.719	0.202	0.249
Public support [a]				
Local funding	0.185	0.254	0.073	0.269
National funding	0.166	0.275	0.064	0.290
European funding	0.022	0.036	0.017	0.102
Sources of information [c]				
Internal sources	0.544	0.637	0.498	0.619
Market sources	0.432	0.505	0.440	0.497
Institutional sources	0.143	0.142	0.088	0.196
Other sources	0.141	0.179	0.124	0.222
Factors hampering innovations [a]				
Cost factors	0.513	0.535	0.307	0.491
Knowledge factors	0.234	0.228	0.171	0.219
Market factors	0.329	0.366	0.199	0.295
Non-innovative reasons	0.104	0.063	0.255	0.110
Firm size [a]				
Small	0.459	0.493	0.268	0.458
Medium	0.347	0.316	0.208	0.232
Large	0.195	0.191	0.523	0.310
Observations	2896	2018	1699	1998

Notes: LTI (low and medium-low tech industries), HTI (medium-high and high tech industries), NKIS (non-knowledge-intensive services), KIS (knowledge-intensive services). All variables cover the period 2007-09 except labour productivity, investment intensity, human capital, R&D engagement, R&D intensity and size which are for 2009. [a] Variables computed for total sample. [b] Variable computed for R&D performers sub-sample. [c] Variables computed for innovative sub-sample. [d] Median in thousands of euros.

As for the protection methods employed, it seems that this factor is equally important across the technology levels, with the exception of the non-knowledge-intensive services. Thus, the proportion of firms who opt to protect their innovations (through patents, trademarks, copyrights, etc.) in less advanced services is not as high as in the remaining technological levels. Once a firm has achieved innovative output (product or process), the proportion who decide to cooperate with other firms in further innovative activity is higher in the group of more advanced firms, especially in the services sector (47%). Note, moreover, that a large proportion of manufacturing firms operate in an international market, above all the high-tech industries (72%), while this percentage is considerably lower in the services sector. As for public funding, the number of firms that receive government support is much higher in high-tech sectors. Firms providing non knowledge-intensive services are the ones that receive the least public support, while knowledge-intensive services are the ones that benefit most from government funding. Internal sources of information, followed by market sources, are the most relevant for innovation activities across all technology levels. Among the factors that hamper innovation the most common are cost factors, such as the lack of funding.

As for firm size, Table 1 indicates that the industry sector adheres to a clear pattern dominated first by small firms, followed by medium and, finally, large firms. However, in the services sector, the structure varies according to the level of technology. Thus, in non-knowledge- intensive services approximately 52% of firms are large; while in knowledge-intensive services around 46% of firms are small, 31% large and 23% medium-sized.

4.3. Results

(i) Research equations:

Table 2 presents the results for equations (1) and (2). The first four columns show the estimates of the determinants of whether a firm engages in R&D activities. The right hand side of Table 2 (columns 5 - 8) then shows the intensity of R&D investment, conditional on a firm engaging in R&D. The results are presented for each technology sector in order to highlight any differences. The numbers reported are marginal effects evaluated at the sample means. Most of the variables are dummies (except human capital and investment intensity); thus, the coefficients show the effect of changing the dummy variable from 0 to 1.

First, firm size has a positive impact among the manufacturing sector: the larger the firm is, the more likely it is to engage in R&D activities. However, in the service sector firm size is not significant (and even negative in non-knowledge-intensive services). This result is in line with Lööf (2005) who also reports that the probability of engaging in R&D increases with firm size only in the case of manufacturing firms. However, firm size has a negative impact on the amount of R&D investment (again in agreement with Lööf, 2005 and Janz et al., 2004) since it is now scaled in relation to the number of employees (size).

Group membership does not seem to influence the decision to engage in R&D activities, but it is a significant factor in terms of investment intensity, especially in less advanced firms. This result is also in line with the previous literature (see, for instance, Janz et al., 2004 and Raffo et al., 2008).

Table 2: Research equation

(Dep var)	**Engage in R&D**				**R&D intensity**			
	LTI (1)	**HTI (2)**	**NKIS (3)**	**KIS (4)**	**LTI (5)**	**HTI (6)**	**NKIS (7)**	**KIS (8)**
Size:								
- *Medium*	0.148***	0.079***	0.0034	-0.0082	-0.678***	-0.426***	-0.321*	-0.686***
	(0.025)	(0.0207)	(0.0245)	(0.0243)	(0.0668)	(0.0628)	(0.165)	(0.0824)
- *Large*	0.148***	0.105***	-0.0589***	-0.041	-1.266***	-0.632***	-2.238***	-1.887***
	(0.0329)	(0.0245)	(0.0226)	(0.0261)	(0.0882)	(0.0893)	(0.193)	(0.121)
Group	0.003	-0.022	0.026	-0.047**	0.207***	0.185***	0.288**	0.213***
	(0.0255)	(0.0222)	(0.0187)	(0.0209)	(0.0637)	(0.0613)	(0.144)	(0.078)
Funding:								
- *Local*	0.350***	0.149***	0.325***	0.199***	0.289***	0.219***	0.386***	0.364***
	(0.0243)	(0.018)	(0.06)	(0.0169)	(0.0617)	(0.0593)	(0.145)	(0.0846)
- *National*	0.382***	0.209***	0.286***	0.232***	0.698***	0.539***	0.768***	0.549***
	(0.0259)	(0.0171)	(0.0642)	(0.0178)	(0.064)	(0.0577)	(0.164)	(0.0812)
- *EU*	0.274***	-0.0508	0.227	0.0577	0.0684	0.420***	0.641**	0.719***
	(0.072)	(0.0798)	(0.145)	(0.0502)	(0.128)	(0.127)	(0.307)	(0.107)
Protection	0.204***	0.135***	0.0602**	0.0669***	0.059	0.0968*	0.0298	0.277***
	(0.0244)	(0.0182)	(0.0289	(0.0193)	(0.0601)	(0.0559)	(0.14)	(0.0751)
Human capital	0.004***	0.0015***	0.0019***	0.0011***	0.012***	0.015***	0.018***	0.004***
	(0.0008)	(0.00058)	(0.00039)	(0.0003)	(0.0021)	(0.0014)	(0.0028)	(0.0013)
Investment intensity	0.007***	0.0051***	0.005***	0.005***	0.008**	0.012***	0.0078	0.0122***
	(0.001)	(0.00081)	(0.00081)	(0.00085)	(0.0032)	(0.00286)	(0.00667)	(0.00396)
Cooperation	--	--	--	--	0.237***	0.0723	0.119	0.131
					(0.0623)	(0.0587)	(0.147)	(0.0823)
International competition	0.122***	0.0965***	0.0765***	0.0587***	--	--	--	--
	(0.0227)	(0.0214)	(0.025)	(0.0201)				
Wald test:								
-Industry	0.1483	0.000	0.2477	0.000	0.000	0.000	0.024	0.000
-Hamper	0.000	0.000	0.000	0.000	0.399	0.307	0.118	0.022
-Sources	--	--	--	--	0.000	0.002	0.414	0.096
N	2,896	2,018	1,699	1,998	1,467	1,491	356	1,101
Wald test indep. (*)					0.164	0.013	0.613	0.033

Notes: LTI (low and medium-low tech industries), HTI (medium-high and high tech industries), NKIS (non-knowledge-intensive services), KIS (knowledge-intensive services). Reported marginal effects (at the sample means) are for the probability of engaging in R&D and for the expected value of R&D intensity conditional on performing R&D. Standard errors in parentheses are robust. Dependent variable "engaging in R&D activities" is a dummy variable.

Industry dummies, factors hampering innovation and sources of information are included in the R&D equation (Wald test reports de p-value of a test of joint significance).

(*) Wald test of independence of the selection equation and intensity equation (Ho: rho=0). The statistic has a $\chi^2(1)$ distribution.

*** Significant at 1%, ** significant at 5%, * significant at 10%.

As expected, public funding for innovation activities is a strong determinant at all levels of technology. Receiving government financial support during the period 2007-09 increased the probability of engaging in R&D activities in 2009, above all among firms in the low-tech sector. For instance, low-tech industries that received local funding were 35% more likely to engage in R&D than firms that did not receive local subsides. National funding has the greatest impact across all sectors (as reported also by Griffith et al., 2006), except in non-knowledge-intensive services where local funding is more relevant. Public funding, especially national and European funding, also has a marked influence on R&D intensity. It seems that less advanced firms spend more on R&D if they receive local or national funding, whilst European subsides are more relevant for high-tech firms.

Our results show that protecting innovative output is associated with a higher probability of engaging in R&D activities. This is true, above all, among manufacturing firms, where if a firm employed any type of protection method during the period 2007-09, the probability of it investing in R&D in 2009 rose by around 20% (13%) in low-tech (high-tech) industries. Yet, once a firm has decided to engage in R&D activities, its R&D effort is affected by protection methods only in high-tech sectors. This is particularly true of firms in the knowledge-intensive sectors who benefit most from protecting their inventions. Interestingly, for these firms protection is not particularly influential in their decision to engage in R&D activities, but once they undertake innovative activities the use of protection methods results in a higher R&D intensity. This result is in line with Griffith et al., (2006) who show that protection has an important impact on the decision as to whether or not to engage in R&D activities, while it has no impact on the amount of R&D undertaken in Spain.

Our findings in relation to the variables of human capital and investment intensity present a somewhat small yet positive impact on the decision to engage in R&D or not, as well as on the intensity of the innovative activities.

In the case of cooperation, only low-tech industries increased their R&D investment as a result of having cooperated with another firm during the period 2007-09[9].

Finally, we found that international competition[10] has a positive and significant impact, which means that firms that operate in international markets are more likely to engage in R&D activities, especially in low-tech industries.

[9] As explained in section IV.1, cooperation was not included in equation (1) since information for this variable is only available for innovative firms.

(ii) Innovation equations:

Table 3 reports the estimates of the knowledge production function. The first four columns show the results for process innovation and the last four columns those for product innovation. The numbers reported are marginal effects evaluated at the sample means. Most of the variables are dummies (except R&D intensity and investment intensity); thus, the coefficients show the effect of changing the dummy variable from 0 to 1.

It should be borne in mind that the Wald test confirms the use of a bivariate probit as opposed to two separate probits given the correlation between the two equations.

As expected, the R&D intensity predicted by equation (2) has a positive and significant impact on the likelihood of a firm's achieving product and process innovation. According to the literature (see Griffith et al., 2006; Masso and Vather, 2008; Hall et al., 2009 or Antonetti and Cainelli, 2011), this effect is higher for product innovation than it is for process innovation, a finding confirmed for all four subsamples.

If we analyse the differences between technology levels, we observe that in the manufacturing sectors, low-tech firms are more likely than high-tech firms to report a successful innovation (both process and product) given their R&D intensity (a finding in line with Hall et al., 2009). For instance, a unit increase in the logarithm of R&D intensity results in a 0.16% increase in the probability of achieving a process innovation. While it is true that low-tech firms have lower R&D expenditures, Table 3 shows that their R&D effort leads to a higher probability of producing an innovation output. As Hall et al. (2009) point out, this might be because innovating in less advanced sectors requires less R&D effort given that the innovation output is linked to changes in the organizational process, which will not be so strongly linked to technology.

In the case of the services sector, the same conclusion can be reached in relation to process innovations, although the difference between the two levels of technology is not so great. By contrast, the result for product innovation is just the opposite. Thus, the R&D intensity of firms that operate in knowledge-intensive services has a greater impact on the probability of achieving product innovation.

[10] As we mentioned above, we exclude international competition indicator in the intensity equation, but if we include it in the estimation it is insignificant. So, operate in international market is a determinant in the decision whether to engage in R&D activities, but it has not impact on the amount of R&D expenditure carried out.

In line with previous studies, the larger the firm, the greater is its probability of achieving product or process innovations. Likewise, in agreement with the literature, investment intensity has a significant and positive impact on the probability of introducing process innovations across all sectors, albeit that the coefficient value is lower.

Table 3: Innovation output equation

(Dep. var)	**Process innovation**				**Product innovation**			
	LTI	**HTI**	**NKIS**	**KIS**	**LTI**	**HTI**	**NKIS**	**KIS**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Predicted R&D intensity	0.157***	0.0437*	0.0754***	0.0581**	0.259***	0.110***	0.134***	0.219***
	(0.0274)	(0.0253)	(0.027)	(0.0249)	(0.0262)	(0.0192)	(0.0195)	(0.0246)
Size:								
- *Medium*	0.119***	0.0623**	0.0523	0.0630*	0.200***	0.0470**	-0.044	0.0850**
	(0.0253)	(0.0254)	(0.0442)	(0.0325)	(0.0256)	(0.0206)	(0.0283)	(0.0338)
- *Large*	0.206***	0.144***	0.157**	0.145***	0.319***	0.108***	0.182***	0.260***
	(0.0295)	(0.0292)	(0.0729)	(0.0498)	(0.0285)	(0.0217)	(0.0498)	(0.0454)
Investment intensity	0.00387***	0.00275**	0.00575***	0.00652***	--	--	--	--
	(0.00091)	(0.00114)	(0.00119)	(0.00122)				
Protection	0.0406*	0.0821***	0.0092	0.0121	0.147***	0.149***	0.120***	0.0049
	(0.0241)	(0.0241)	(0.0442)	(0.0314)	(0.024)	(0.0184)	(0.0356)	(0.0318)
Sources of information								
- *Internal*	0.204***	0.141***	0.398***	0.197***	0.208***	0.133***	0.218***	0.205***
	(0.0201)	(0.0232)	(0.0328)	(0.0247)	(0.0214)	(0.0202)	(0.031)	(0.0257)
- *Market*	0.178***	0.0757***	0.349***	0.185***	0.0886***	0.134***	0.148***	0.184***
	(0.021)	(0.0227)	(0.0376)	(0.0252)	(0.0235)	(0.0189)	(0.0325)	(0.0261)
- *Institutional*	-0.0671*	-0.0319	0.0187	0.00353	-0.00497	-0.00965	0.0294	-0.0379
	(0.0371)	(0.0365)	(0.0792)	(0.0385)	(0.0363)	(0.0336)	(0.0567)	(0.04)
- *Others*	0.122***	0.0660**	-0.0413	0.0529	0.103***	0.0612**	0.0779	0.131***
	(0.0317)	(0.030)	(0.0679)	(0.0346)	(0.0349)	(0.0263)	(0.056)	(0.0348)
Wald								
- Industry	0.000	0.029	0.001	0.002	0.000	0.000	0.000	0.000
- Sources	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	2,896	2,018	1,699	1,998	2,896	2,018	1,699	1,998
Pseudo R2	0.200	0.086	0.292	0.142	0.192	0.195	0.271	0.244
Wald test (*)					0.000	0.000	0.000	0.000

Notes: LTI (low and medium-low tech industries), HTI (medium-high and high tech industries), NKIS (non-knowledge-intensive services), KIS (knowledge-intensive services). Reported marginal effects (at the sample means) are for the bivariate probit. Standard errors in parentheses are robust. Both dependent variables are dummies.
Industry dummies and sources of information are included. Wald test reports the p-value of a test of joint significance.
(*) Wald test of correlation between the two errors terms to check if a univariate probit can be used instead of a bivariate probit (Ho: rho=0). The statistic has a $\chi^2(1)$ distribution.
*** Significant at 1%, ** significant at 5%, * significant at 10%.

According to the literature (see Griffith et al., 2006, and Masso and Vather, 2008), protection methods are more influential in obtaining a product innovation than they are in developing a process innovation. This might occur because process innovations are more difficult to patent than product innovations. Protecting an invention only increases the probability of obtaining a process innovation for manufacturing firms. However, it is also a relevant factor for non-knowledge-intensive services in relation to their likelihood of achieving a product innovation. Yet, in knowledge-intensive services the probability of obtaining a product or process innovation is not influenced by the use or otherwise of these protection methods.

The most important sources of information for both types of innovation are those from within the firm or group (internal). Their impact is more marked among less advanced firms than it is among their more advanced counterparts. Market sources (suppliers, customers, etc.) also have a positive impact on both kinds of innovation. However, their effect is greatest among more advanced firms in the case of their product innovations. The one source of information that is found not to be at all relevant for either process or product innovations is the institutional source.

(iii) Productivity equation:

Table 4 shows the estimates of the production function equation. As mentioned above, there is a high correlation between process and product innovations. This correlation is much higher when the predicted values are used[11]. This gives rise to unexpected results when both variables are included in the model, due to high levels of multicollinearity. For this reason, we chose to estimate process and product innovation separately, so as to analyse their respective impacts on labour productivity[12]. Other authors have encountered the same problem (see, for example, Raffo et al., 2008, who performed separate estimations to mitigate collinearity problems). Thus, the first four columns report the results when the predicted values of process innovation are included, while the last four columns show the results for product innovation.

We find that both types of innovation have a positive and sizeable effect on productivity. However, the coefficients vary considerably depending on the type of innovation included and across technology levels. Hence, process innovation increases productivity much more than in the case with a product innovation. Specifically, high-tech firms enhance their productivity considerably more than low-tech firms as the result of a process innovation. For instance, a high-tech industry (service) that introduces a process innovation reports a rise in productivity of around 60% (41%) compared to that of 37% (34%) for low-tech firms. On the other hand, a product innovation only increases productivity in low-tech industries and knowledge-intensive services, where its effect is around 25% for both cases.

[11] The correlation between predicted process innovation and predicted process innovation is around 0.62 on average.

[12] We have also studied the case where a single variable captures both innovations. The results are similar to those presented here, although the coefficients are a little lower than those reported when process innovation is included.

Investment intensity[13] and human capital both have a positive effect on productivity across all sectors except the knowledge-intensive services. Moreover, it seems that firms who operate in low-tech sectors benefit slightly more from an increase in these variables.

In general, and in line with Raffo et al. (2008) and Antonetti and Cainelli (2011), the larger the firm, the more productive it is, except in non-knowledge-intensive services.

Table 4: Productivity equation

(Dep. var.)	**Labour Productivity**							
	LTI (1)	**HTI** (2)	**NKIS** (3)	**KIS** (4)	**LTI** (5)	**HTI** (6)	**NKIS** (7)	**KIS** (8)
Predicted Process innov	0.369***	0.598**	0.340***	0.407**				
	(0,0878)	(0,244)	(0,105)	(0,161)				
Predicted Product innov					0.251***	0,157	0,277	0.246**
					(0,0713)	(0,125)	(0,189)	(0,12)
Investment intensity	0.0081***	0.0063***	0.0068***	-0,0019	0.0099***	0.0089***	0.0085***	0,0004
	(0,0016)	(0,0018)	(0,0026)	(0,00319	(0,0014)	(0,0017)	(0,0026)	(0,0027)
Human capital	0.0078***	0.0051***	0.0117***	-0,0002	0.0074***	0.0047***	0.0114***	-0,0005
	(0,0013)	(0,0011)	(0,0017)	(0,0008)	(0,0013)	(0,0011)	(0,0018)	(0,0009)
Size								
- *Medium*	0.239***	0.231***	0,0618	0.138**	0.241***	0.269***	0,0827	0.155**
	(0,033)	(0,0421)	(0,0756)	(0,0653)	(0,0323)	(0,0359)	(0,077)	(0,0642)
- *Large*	0.409***	0.443***	-0.114*	0.366***	0.411***	0.520***	-0,099	0.399***
	(0,0417)	(0,0644)	(0,068)	(0,0654)	(0,0416)	(0,0462)	(0,074)	(0,0656)
Spillovers								
- *Intra*	0.160***	-0,0462	0.616***	0.0534***	0.168***	-0,0343	0.617***	0.0544***
	(0,0148)	(0,0316)	(0,0319)	(0,0205)	(0,0146)	(0,0314)	(0,0323)	(0,0204)
- *Inter*	0.0239***	0.105***	-0.152***	0.0804***	0.0257***	0.116***	-0.146***	0.0835***
	(0,0067)	(0,0107)	(0,0232)	(0,0111)	(0,0066)	(0,0094)	(0,0233)	(0,011)
Constant	7.954***	9.773***	3.903***	7.823***	7.871***	9.555***	3.812***	7.815***
	(0,295)	(0,65)	(0,411)	(0,454)	(0,295)	(0,672)	(0,427)	(0,451)
N	2.822	1.952	1.578	1.868	2.822	1.952	1.578	1.868
R^2 adjusted	0,139	0,0895	0,339	0,0799	0,162	0,194	0,337	0,0915

Notes: LTI (low and medium-low tech industries), HTI (medium-high and high tech industries), NKIS (non-knowledge-intensive services), KIS (knowledge-intensive services). Reported coefficients are from an instrumental variable regression. Standard errors in parentheses are robust.
*** Significant at 1%, ** significant at 5%, * significant at 10%.

In the specific case of intra-industry externalities, our results show that the R&D expenditures incurred by firms in the same sector have a positive impact on productivity provided they achieve an output innovation. This effect is more marked for those firms belonging to low-tech sectors. Thus, the more advanced the firm is, the less benefit it obtains from an external knowledge

[13] The magnitude of the coefficient is quite low. As Lööf (2005) mentions, this could occur because investment intensity is a flux variable and it is a proxy for physical capital (stock).

current in its sector. This result is in line with findings reported by Segarra-Blasco (2007), who showed that low-tech industries benefit more than high-tech firms from intra-industry externalities. This suggests that there is a “technological threshold” beyond which firms do not benefit so greatly from the innovation expenditures made by other firms in the same sector. Here, we should mention the capacity of non-knowledge-intensive services to absorb this external knowledge. More specifically, if the rest of the firms in its sector increase their R&D expenditures and obtain an innovation, then non knowledge-intensive services would raise their productivity by 0.62%.

By contrast, high-tech firms seem to benefit most from inter-industry externalities. Thus, the R&D expenditure incurred carried out by the rest of the sectors - provided that this investment achieves an effective (product or process) innovation - has a greater impact on the productivity of more advanced firms. This result is consistent with the “absorption capacity” hypothesis forwarded by Cohen and Levinthal (1989), which suggests that the degree to which firms benefit from external innovation is heavily dependent on their own investment in research. Thus, firms with greater technological capital are the ones that benefit most from externalities. By contrast, non-knowledge-intensive services report a negative coefficient, which is unexpected and counterintuitive, since logically if all other sectors innovate then the firm should either derive some benefit or none at all, but in no circumstances does it appear plausible that the firm would be harmed by this innovation.

Moreover, we find that the magnitude of the intra-industry externality is greater than that of the inter-industry externality in low-tech firms. This result is particularly apposite for non-knowledge-intensive services since such firms do not increase their productivity as a result of product innovation. Thus, they need to absorb the knowledge current in their sector in order to raise their productivity. By contrast, the magnitude of the inter-industry externality is greater than that of the intra-industry externality in high-tech firms. This suggests that productivity in these firms increases more as a result of the innovations made in all the other sectors than as a result of the innovations carried out by all the other firms in the same sector.

5. Conclusions

This paper has analysed the impact of innovation activities on a firm’s productivity using a CDM model. The first goal has been to determine the extent to which the firm’s level of technology affects the relationship between innovation and its productivity, focusing not solely on the last step in this process but on the whole series of actions (from the firm’s initial decision to engage in R&D

activities to the impact of the output on productivity). The second and main goal of this paper has been to assess the benefit that firms derive from the innovation carried out by others, taking into account both intra- and inter-industry externalities. For this, we use the PITEC database and divide the sample of 8,611 Spanish firms into four subsamples according to their level of technology. Thus, the first objective is to shed some light on the importance of a firm's technological level, given that most of the literature employing the CDM model is not expressly concerned with this issue (being more typically interested in conducting cross-country comparisons). Similarly, and to the best of our knowledge, the second goal has not been dealt with at all for any country by adopting a CDM perspective. Thus, here we have sought to provide an initial attempt at examining the impact of external innovation on a firm's productivity.

The structural model has enabled us to demonstrate that innovation input (R&D intensity) affects innovation output (product and process) and that, in turn, this output has a positive impact on a firm's productivity.

Based on our results reported herein, and in line with previous studies, the main determinants of engagement in R&D activities are public funding (especially national and local support), the use of protection methods and the fact that a firm operates in an international market. Moreover, each of these factors has a greater impact on low-tech firms than they do on their high-tech counterparts. Thus, less advanced firms exploit these factors in reaching their decision to engage in R&D activities. A firm's size is also important in the case of manufacturing firms: the larger the firm is, the more likely it is to engage in R&D activities. Size however is irrelevant in the case of firms in the services sector. Additionally, human capital and investment intensity have a positive impact, albeit not so great, on the decision to engage in R&D activities.

Once a firm has decided to engage in R&D projects, the intensity of these activities depends significantly on public funding (national and European) and membership of a group, above all in low-tech sectors. According to the literature, a firm's size has a negative effect since R&D intensity is scaled in relation to the number of employees. Additionally, human capital and investment intensity have a positive impact on the amount of R&D investment undertaken.

Predicted rates of R&D intensity have a clearly positive impact on the probability of achieving process or product innovations. However, in line with previous studies, the impact is greater in relation to product innovation than it is to process innovation. Examining the sample by technology level reveals a number of patterns. Thus, for example, low-tech industries are always more likely than high-tech industries to obtain both product and process innovations. In the service sector, the same conclusion holds for process innovations, but the opposite is found in relation to product innovations, where more advanced firms have a higher probability of making product innovations. However, the use of protection methods results in a greater likelihood of achieving product as opposed to process innovations. A firm's size clearly has a positive impact on both product and process innovation.

As for productivity, the results show that obtaining a product or process innovation has a positive and sizeable impact. Nevertheless, in line with the literature, process innovation has a greater influence than product innovation on productivity. Besides, high-tech sectors are the ones that benefit most from process innovation.

In the case of externalities, our results clearly differ depending on the firm's level of technology. Hence, the R&D expenditures incurred by firms in the same sector (intra-industry externalities) have a positive impact on productivity, provided that an output innovation (either product or process) is achieved, and this effect is higher for low-tech firms. As discussed in the previous section, this might indicate that there is a "technological threshold" beyond which firms do not benefit so greatly from the innovation made by other firms in the same sector. However, the R&D expenditures carried out by the rest of the sectors (inter-industry externalities) have a greater impact on the productivity of high-tech firms. This result is in line with the "absorption capacity" hypothesis (Cohen and Levinthal, 1989), according to which the more technological capital available to a firm, the greater its ability to absorb external knowledge. In general terms, low-tech sectors benefit more from intra-industry externalities while more advanced firms are able to increase their productivity more thanks to inter-industry externalities.

APPENDIXES

Appendix A: Treatment of extreme values

The table below reports the number of firms with more than double the volume of sales by technological level. These observations have been replaced by the double of sales.

Table 5: Outliers

More than 2 Sales*	**HTI**	**LTI**	**NKIS**	**KIS**
Investment intensity	7	0	10	19
R&D intensity	1	4	3	57

Appendix B: Correspondence between branches of business activity

Table 6. Correspondence between PITEC and NACE-Rev. 2 classification.

Branches of business activity PITEC	**NACE Rev. 2**
Low-tech manufacturing industries	
Manufacture of food products, beverages and tobacco products	10, 11, 12
Textile industry	13
Wearing apparel	14
Leather and related products	15
Wood and products of wood	16
Paper and paper products	17
Printing and reproduction of recoded media	18
Manufacture of furniture	31
Other manufacturing	32
Medium-low-tech manufacturing industries	
Manufacture of rubber and plastic products	22
Manufacture of other non-metallic mineral products	23
Manufacture of basic metals	24
Manufactured of fabricated metal products	25
Building of ships and boats	301
Repair and installation of machinery and equipment	33
Medium-high-tech manufacturing industries	
Manufacture of chemical and chemical products	20
Manufacture of electrical equipment	27
Manufacture of machinery and equipment	28
Manufacture of motor vehicles, trailers and semitrailers	29
Manufacture of other transport equipment	30 (exc. 301, 303)
High-tech manufacturing industries	
Manufacture of pharmaceutical products and preparations	21
Manufacture of computer, electronic and optical products	26
Manufacture of air and spacecraft and related machinery	303
Non-knowledge-intensive services	
Trade	45,46,47
Transport and warehousing	49,50,51,52,53
Food service activities	55,56
Real estate activities	68
Administrative activities and auxiliary services	77,78,79,80,81,82
Other services	95,96
Knowledge-intensive services	
Telecommunications	61
Programming and broadcasting activities	62
Other information and communication services	58,59,60,63
Financial and insurance activities	64,65,66
Scientific research and development	72
Other activities	69,70,71,73,74,75
Education	85 (exc.854)
Human health and social work activities	86,87,88
Arts, entertainment and recreation	90,91,92,93

Source: PITEC and Eurostat.

Appendix C: Variable Definitions

Firms' characteristics:

Labour productivity: Sales per employee in 2009 (in logs).

Investment intensity: Gross investment in tangible goods in 2009 (in logs).

Human capital: percentage of employees with higher education.

Size: dummy variables according to the number of employees. Categories are: small (10-49), medium (50-199) and large (200 or more).

Industry: set of industry dummies according to the main branch of business activity (NACE-Rev.2) See appendix C for details.

Innovation:

R&D engagement: dummy variable that takes the value 1 if the firm has a positive R&D expenditure.

R&D intensity: internal and external R&D expenditure per employee in 2009 (in logs).

Process innovation: dummy variable which takes the value 1 if the firm reports having introduced a new or significantly improved production process during the period 2007-09.

Product innovation: dummy variable which takes the value 1 if the firm reports having introduced a new or significantly improved product during the period 2007-09.

Protection: dummy variable which takes the value 1 if the firm uses patents, a design pattern, trademarks or copyright to protect inventions or innovations during the period 2007-09.

Cooperation: dummy variable which takes the value 1 if the firm cooperates with other firms on innovation activities during the period 2007-09.

International competition: dummy variables that takes the value 1 if the firm trades in an international market during the period 2007-09.

Public funding:

Local funding: dummy variable which takes the value 1 if the firm receives local or regional funding for innovation activities during the period 2007-09.

National funding: dummy variable which takes the value 1 if the firm receives funding for innovation activities from the national government during the period 2007-09.

European funding: dummy variable which takes the value 1 if the firm receives EU funding for innovation activities during the period 2007-09.

Sources of information:

Internal sources of information: dummy variable which takes the value 1 if information from sources within the firm or group has high importance during the period 2007-09.

Market sources of information: dummy variable which takes the value 1 if information from suppliers, clients, competitors or private R&D institutions has high importance during the period 2007-09.

Institutional sources of information: dummy variable which takes the value 1 if information from universities, public research organization or technology centres has high importance during the period 2007-09.

Institutional sources of information: dummy variable which takes the value 1 if information from conferences, scientific reviews or professional associations has high importance during the period 2007-09.

Factors hampering innovations:

Cost factors: dummy variable which takes the value 1 if the lack of funding (internal and external) is an important factor or innovation costs are too high during the period 2007-09.

Knowledge factors: dummy variable which takes the value 1 if the lack of qualified personnel, lack of information on technology, lack of information on markets or difficulty in finding cooperation partner for innovation has high importance during the period 2007-09.

Market factors: dummy variable which takes the value 1 if market rigidities or uncertain demand levels has high importance during the period 2007-09.

Non-innovative reason: dummy variable which takes the value 1 if innovation is not necessary due to previous innovations or there is no demand during the period 2007-09.

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