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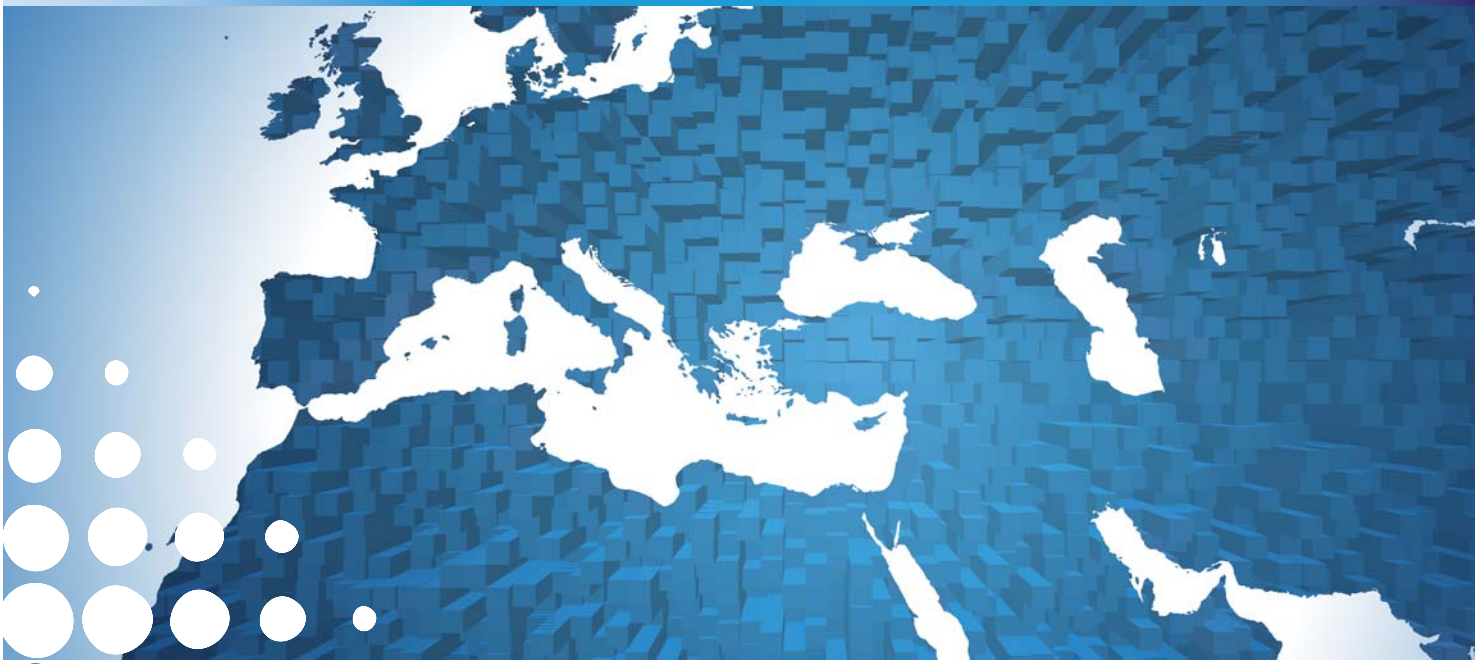

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# Do spillovers matter? CDM model estimates for Spain using panel data

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**Abstract**

This paper uses a structural model to analyse the impact of innovation activities and 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 external knowledge may affect both firms' behaviour (first stage of the model) and a firm's performance (last stage). 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 9,042 firms for the period 2004-2010. We find that the firm's decision whether to engage in R&D activities or not is influenced by what other firms do. In particular, the higher the number of firms undertaking R&D activities, the more likely to start R&D projects the firm is. Moreover, our results suggest that innovation carried out by other firms (intra- and inter-industry externalities) have a positive impact on firm's productivity. Finally, regarding the technology level, no clear pattern has been found.

**Keywords**
R&D, innovation, productivity spillovers

**JEL Classification**
D24, O33 J240

## 1. INTRODUCTION

The relationship between innovation and productivity has been widely studied for many decades and nowadays this topic still continues to generate great interest among the scientific community. How to increase firms' productivity is a key factor, not only at firm level, but also at national level especially in today's globalized world. That is why the study of its determinants has been the centre of attention of many researchers in the last years. Traditional literature relies on R&D expenditure as a proxy for innovation and it is introduced in the well-known Cobb-Douglas production function as an additional input. Nevertheless, since the seminal paper of Crépon, Duguet and Mairesse (1998) the way to deal with this relationship has changed. The authors proposed a structural model (also known as CDM model) where it is distinguished between two processes: (i) the generation of innovations from R&D expenditures and (ii) the impact of these innovations on firm's productivity.

One could think: the more a firm invests in R&D, the more its productivity increases. But unfortunately this is not true. Why? Because the firm has to be able to turn this investment into innovations strictly speaking and, as we can imagine, not all R&D expenditures result in successful innovations. Hence, if a firm wants to increase its productivity needs, not only invest in R&D activities, but also have the necessary mechanisms to transform this investment into innovations that indeed raise its productivity.

The general aim of this paper is to analyse the current relationship between innovation and productivity in Spain using the CDM model. It is worth mentioning that most of papers which rely on a structural model use cross-sectional data[1] and do not control for unobserved firm heterogeneity nor the time lag between firm's decisions whether to engage in R&D activities or not and the resulting innovation output, as well as, its effect on firm's productivity. In this regard, this study tries to shed some light analysing the case of Spain using the Technological Innovation Panel (PITEC) database from 2004 to 2010. Besides, this database enables us to study manufacturing and service firms, as well as, distinguish between technology levels. Given that, our main goal is to assess the extent to which the innovations carried out by others affect firm's behaviour and performance. It is well known 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. To the best of our knowledge, no previous paper has examined spillover effects by applying the CDM model and using panel data. Here, therefore, we seek to determine the extent to which external knowledge may have an impact along the structural model in the case of Spain. For this

[1] Some exceptions are Chudonovsky, et al. (2006) and Huergo and Moreno (2011).

reason we do not consider only its effect on the firm's productivity (last stage of the model) but also if the firm's decision to engage in R&D activities could be influenced by what other firms do (first stage). Particularly, this paper seeks to address the following questions: (i) Is the firm's decision whether to engage in R&D activities or not affected by what other firms in its sector do? (ii) Do Spanish firms benefit from innovation carried out by the rest of the firms in its sector? and in different sectors?

Indeed, our results suggest that external knowledge has an impact on both firm's behaviour and firm's performance. In particular, the greater the number of firms undertaking R&D activities the more likely to engage in R&D projects the firm is, suggesting the existence of what some articles have called "an incentive effect". In addition, innovations carried out by others firms (intra- and inter- industry externalities) have a positive impact on firm's productivity.

The rest of the paper is structured as follows. Section 2 presents the literature review, section 3 the empirical model, section 4 describes the database, variables and some descriptive statistics, section 5 presents the results, and finally the conclusions are drawn in Section 6.

## 2. LITERATURE REVIEW

There is a large volume of published studies analysing the impact of innovation on firm's productivity since the seminal papers of Griliches (1979, 1986) (for example Mairesse and Sassenou, 1991, for a detailed study; and also Hall and Mairesse, 1995, for France; Harhoff, 1998, for Germany; Lotti and Santarelli, 2001, for a comparative study of Germany and Italy; Parisi et al., 2006, for Italy; and Ortega-Argilés, 2010, 2011 and Goya et al., 2012 for Spain). Nevertheless from the publication of Crépon, Duguet and Mairesse in 1998 the approach taken in this line of literature has shifted, moving from an input definition of innovation activities[2] to an output definition. The authors estimate a structural model involving three steps[3]: (i) the firm's decision whether to engage in R&D activities or not, and the intensity of its investment, (ii) the realisation of innovations 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, its innovative effort, 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 firms' productivity (see Hall

[2] Usually it is proxied as R&D expenditures and included in the production function as an additional input.

[3] See Roberts and Vuong (2013) for an alternative framework.

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; Griffith et al., 2006a, 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; Hall et al., 2009 and Antonietti and Cainelli, 2011 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)[4] (Huergo and Moreno, 2004; 2011). Other papers have sought to 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).

As we mention previously, most of studies use cross-sectional data and only few of them have employed panel data. Some exceptions are Chudnovsky et al. (2006) who applies a CDM model to a balanced panel of Argentinian manufacturing firms for the period 1992-2001. Heshmati and Kim (2011) use a structural model for Korean firms from 1986 to 2002. Finally, Huergo and Moreno (2011) study the case of Spain using an unbalanced panel of 1,072 manufacturing firms (ESEE database) for 1990-2005[5]. In line with this, our study contributes to the scarce literature by using a panel structure with a CDM model. This enables us to control for both unobserved firm heterogeneity and the time lag along the whole process (from firm's decisions whether to engage in R&D activities or not to its impact on productivity through innovation output).

In addition, it is worth mentioning that there are other authors who also use panel data, however they focus on one part of the structural model. For instance, Artés (2009) studies the relationship between R&D and market concentration in Spain using data from ESEE. The author adopt a Heckam-type model to capture both the long-run decision (whether to conduct R&D activities or not) and the short-run decision (how much invest in these projects). Lhuillery (2011) also focus his attention on the first stage of the CDM model (the research equation) using the Swiss innovation panel to measure the importance of incoming external knowledge. On the other hand, Huergo (2006), Du et al. (2007) and Raymond et al. (2010) consider the innovation equation (the second stage of the CDM model) to analyse how R&D takes part in the process of generating innovations using panel data (for Spain, Ireland and the Netherlands respectively).

[4] The ESEE is a firm-level survey of Spanish manufacturing which has collected information on a yearly basis since 1990.
[5] In this case, the authors have focused their attention on the persistence in firms' behaviour.

As some evidence points out, the impact of innovation on firm's productivity depends on 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[6].

As we mention in the previous section, spillovers play an important role when the relationship between R&D, innovation and productivity is analysed. Numerous studies have studied the impact of spillovers on R&D expenditures (Harhoff, 2000) and productivity (Griliches, 1992; Los and Verspagen, 2000; Wakelin, 2001; Beneito, 2001; and Aiello and Cardamore, 2005, 2008, Griffith et al., 2006b; Goya et al., 2012; and Bloch, 2013). However, and as far as we know, no other paper has dealt with this issue in any country from a CDM model perspective. Some articles have attempted to explain part of this external knowledge in the first stage of the model by introducing dummy variables to capture how important are several sources of information - internal, competitors, suppliers, universities, and so on- in the firm's technological effort (Lööf and Heshmati, 2002; Griffith et al., 2006a; Masso and Vather, 2008; and Segarra-Blasco, 2010 among others). However, this variable is an ordinal measure and it is completely subjective. In addition, this information is only available for innovative firms, hence it can only be included to study R&D intensity, but not firm's decision whether to engage in R&D activities or not. One exception so far is Lhuillery (2011) who has information for all firms and is able to incorporate this variable in his analysis (which is focused on the first stage of the model). The author obtains a negative effect from rival's knowledge on the probability to engage in R&D activities, because according to the literature and as the author argues "incoming knowledge spillovers encourage firms to reduce their own production of knowledge by free-riding other firms". In addition, his results show that competitor's knowledge is not a relevant factor in firm's innovative effort. Apart from these attempts to include spillovers in the first stage of model, there is no other evidence using the CDM approach to the best of our knowledge.

Given this preliminary evidence, and as we mention in the previous section, our study aims to contribute to the existing (and short) literature as regards the use of panel data within a structural model framework. Our main challenge is to find out if external knowledge could have an impact on firm's decision whether to engage in R&D projects or not (first stage of the model) and/or on firm's productivity (last stage of the model) in Spain. Finally, it could be interesting assess which is the role played by technology in this process. Given the small body of literature

[6] 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 their low-tech counterparts. It is worth mentioning that both papers undertake a cross-sectional analysis.

concerned with this aspect using the CDM approach and its lack of consensus, we wish to clarify this issue for the Spanish case and we take it into account as a part of our analysis.

## 3. THE EMPIRICAL MODEL

The model adopted to estimate the relationship between innovation and productivity is a modified version of the CDM model (see Griffith et al., 2006a). Moreover, we extend the original model by introducing measures of external knowledge in two equations as it is showed below. The model, which consists of three stages, can be formalized in four sequential equations[7].

### (i) First stage: The research equations

This first stage of the model 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:

$$RD_{it} = \begin{cases} 1 \quad if \;\; RD^{*}_{it} = x^{(1)}_{it}\beta^{(1)} + \delta S^{j}_{t-1} + \alpha^{(1)}_{i} + \varepsilon^{(1)}_{it} > \overline{c} \\ 0 \quad if \;\; RD^{*}_{it} = x^{(1)}_{it}\beta^{(1)} + \delta S^{j}_{t-1} + \alpha^{(1)}_{i} + \varepsilon^{(1)}_{it} \leq \overline{c} \end{cases} \qquad (1)$$

where $i$ indexes the firm, $j$ indexes the firm's sector and $t$ indexes the year. $RD_{it}$ is an (observable) indicator function that takes the value 1 if the firm decides to undertake R&D activities, $RD^{*}_{it}$ is a latent indicator variable whereby the firm incurs R&D expenditures if these are above given a threshold $\overline{c}$, $x^{(1)}_{it}$ is a set of explanatory variables and $S^{j}_{t-1}$ is our measure of external knowledge lagged one year. Finally, $\alpha^{(1)}_{i}$ captures the unobserved firm heterogeneity and $\varepsilon^{(1)}_{it}$ is an error term.

According to our main goal, the most relevant variable is the spillover measure which tries to assess how firm decision to engage in R&D activities could be affected by what other firms do in the previous period. In particular, and assuming that firm *i* operates in sector *j*, we define this measure as the proportion of firms in the same sector *j* that undertake R&D activities the previous year[8]:

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[7] It is worth pointing out that we are working with a recursive model, hence feedback effects are not allow (Griffith, et al., 2006a).

[8] We have also tried take other definitions of spillovers into consideration (for example, based on intra-industry R&D expenditures), but they were no relevant.

$$S_t^j = \frac{n_t^j}{N_t^j} \cdot 100 \tag{2}$$

where $n_t^j$ is the number of firms undertaking R&D projects in the sector $j$ and $N_t^j$ is the total number of firms in sector $j$. There are two different consequences of knowledge spillovers. On the one hand, a positive effect could appear since an external pool of knowledge might have an incentive effect which could encourage firms to undertake R&D activities. This would be in line with the idea of absorptive capacity (Cohen and Levinthal, 1989), thus firms would be interested in investing in R&D to be able to benefit from external knowledge. Additionally, firms might decide take part in R&D projects because they want to improve their competitiveness. On the other hand, a negative effect is also plausible. In particular, a disincentive effect could appear since firms can see external knowledge as a substitute of their own production of knowledge. Thus, they prefer to have a free-riding behaviour instead of performing their own technological effort (in line with Lhuillery, 2011).

We estimate equation (1) using a random effects probit model given the panel structure and the binary character of the dependent variable (see Artés, 2009; Heshmati and Kim, 2011 and Lhiullery, 2011). This random effect structure has an important limitation since it relies on the assumption that the errors are not correlated with the regressors. In the case this assumption was not held, estimates would be inconsistent. To deal with this problem it is possible to parameterise the effect. To do so we augment the model by the Mundlak specification[9], or in other words, we include a vector of means of the time-variant regressors as a control variables to allow for some correlation between the random effect and the regressors (Mundlak, 1978).

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

$$RDI_{it} = \begin{cases} RDI_{it}^* = x_{it}^{(2)}\beta^{(2)} + \alpha_i^{(2)} + \varepsilon_{it}^{(2)} & if \quad RD_{it} = 1 \\ 0 & if \quad RD_{it} = 0 \end{cases} \tag{3}$$

where $RDI_{it}^*$ is the unobserved latent variable accounting for firm's innovative effort, $x_{it}^{(2)}$ is a set of determinants of innovation expenditures, $\alpha_i^{(2)}$ captures the unobserved firm heterogeneity and $\varepsilon_{it}^{(2)}$ is an error term. In this equation, we do not incorporate a spillovers measure, because we believe that the investment intensity depends much more on internal factors (such as, availability of funding) than on what others firms do[10]. However, we are going to take external knowledge from cooperation into consideration, as we explain in the next section.

[9] Allowing individual effects are correlated with the within-individual means of the regressors.
[10] Besides, as we have mention in the previous section, Lhuillery (2011) finds that knowledge spillovers coming from competitors were a factor to take into account in the first but not in the second equation.

This equation is estimated using the consistent estimator proposed by Wooldridge (1995)[11]. Thus, we estimate a pooled OLS including T inverse mills ratios (interacted with time dummies) obtained from estimate T probit models (one for each year).This enables us to account for the selection bias given that R&D intensity can be observed if, and only if, firms decide to undertake R&D activities (and hence have a positive R&D expenditure). In addition, as Wooldridge (2002) points out, we need to have an exclusion restriction in order to avoid multicollinearity problems, since inverse mills ratios have been incorporated in the second equation.

**(ii) Second stage: The innovation equation (innovation production function)**

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

$$I_{it} = \gamma RDI^{*}_{it-2} + x^{(3)}_{it}\beta^{(3)} + \alpha^{(3)}_{i} + \varepsilon^{(3)}_{it} \tag{4}$$

where $I_{it}$ is an innovation output indicator that takes the value 1 if the firm achieves an innovation, and where the latent innovation effort $RDI^{*}_{it}$ - predicted from equation (3) and lagged two periods- is an explanatory variable. $x^{(3)}_{it}$ is a vector of other determinants of the knowledge production, $\alpha^{(3)}_{i}$ captures the unobserved firm heterogeneity and $\varepsilon^{(3)}_{it}$ is an error term.

The innovation production function is estimated using a random effect probit model (see Huergo, 2006) including a vector of means of the time-variant regressors as control variables to allow individual effects being correlated with the within-individual means of the regressors (Mundlak, 1978).

**(iii) Third stage: The productivity equation (production function)**

This last step is modelled by an augmented Cobb-Douglas production function. Following Goya et al. (2012)[12] , we assume that firm's productivity depends on both own investment and external knowledge:

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[11] Given that Heckman type selection model (1979) is not available for panel data, we have decided to follow Wooldridge (1995) which takes into account the selection problem.

[12] The authors suppose that firm's technology depends on the innovation made by all the other firms $A_{ijt} = A \cdot \left(S^{intra}_{ijt}\right)^{\rho} \left(S^{inter}_{jt}\right)^{\pi}$ where $A$ is a constant to denote a common technology level for all the firms; $\mathrm{S}^{\mathrm{intra}}_{\mathrm{ijt}}$ and $\mathrm{S}^{\mathrm{inter}}_{\mathrm{jt}}$ are the intra-industry and inter-industry spillover respectively.

$$y_{it} = x_{it}^{(4)}\beta^{(4)} + \rho S_{it-1}^{j,intra} + \pi S_{t-1}^{j,inter} + \alpha_i^{(4)} + \varepsilon_{it}^{(4)} \qquad (5)$$

where $i$ indexes the firm, $j$ indexes the firm's sector and $t$ indexes the year. $y_{it}$ is labour productivity; $x_{it}^{(4)}$ is a set of explanatory variables (which include: labour, physical and human capital, and innovation output predicted from equation (4)); $S_{it-1}^{j,intra}$is the intra-industry externality lagged one period; and $S_{t-1}^{j,inter}$ is the inter-industry externality lagged one period. Last, $\alpha_i^{(4)}$ captures the unobserved firm heterogeneity and $\varepsilon_{it}^{(4)}$ is the error term.

As it can be seen in expression (5), and as a key feature of this study, industry spillovers are incorporated in the Cobb-Douglas production function. 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 $\left(S_{it}^{j,intra}\right)$ which includes the innovation effort made by all the other firms in the same sector, and inter-industry externalities $\left(S_t^{j,inter}\right)$, understood as the innovation effort made by the rest of the firms in the other sectors. Here, it should be borne in mind that knowledge transfer between firms can occur in a variety of ways (disclosure of patents, via the movement of workers between firms, reading of journal articles, and so on). The result, however, is the same: one firm uses the knowledge generated by another without having to pay for it directly. We have considered several possible definitions, but have opted for the one that best fits the CDM approach (following Beneito, 2001). 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 spillovers presented below seeks to capture not only the knowledge current in the sector, but also the fact that firms achieve a successful innovation output thanks to this knowledge.

Thus, intra-industry spillovers corresponding to firm *i* belonging to sector *j* at year *t* is defined:

$$S_{it}^{j,intra} = \sum_{k \neq i}\left(RD_{kt-2}^{j} * I_{k(t-2,t)}^{j}\right) \qquad (6)$$

where $RD_{kt-2}^{j}$ is R&D investment carried out by the rest of the firms in the same sector in the previous two years and $I_{k(t-2,t)}^{j}$ is an indicator variable equal to 1 if firms have achieved successful innovation output during the next three years, 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[13].

[13] 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.

Inter-industry spillovers corresponding to firm *i* belonging to sector *j* at year *t* is defined:

$$S_{it}^{j,inter} = \sum_{\substack{k \neq i \\ m \neq j}} w_{jm}\left(RD_{kt-2}^{m} * I_{k(t-2,t)}^{m}\right) \tag{7}$$

where $RD_{kt-2}^{m}$ is R&D expenditures carried out by the rest of the firms that operate in the rest of the sectors in the previous two years; $I_{k(t-2,t)}^{m}$ is an indicator variable equal to 1 if these firms have achieved successful innovation output during the next three years, or 0 otherwise; and $w_{jm}$ denotes the relative importance that sector *m* has as a supplier to sector *j*.

In line with previous equations, this final step is estimated by a random effects model.

To sum up, our model is made of equations (1), (3), (4), (5) which are estimated sequentially. 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.

## 4. DATA, VARIABLES AND DESCRIPTIVE STATISTICS

### 4.1. Data: Technology Innovation Panel (PITEC)

The database used is the Technological Innovation Panel (PITEC) elaborated by the National Institute of Statistics (INE)[14] and based on the Spanish Innovation Survey which in turn is based on the Community Innovation Survey (CIS). It follows the guidelines in Oslo Manual (OECD, 2005) and Frascati Manual (OECD, 2002) using a standardized questionnaire.

PITEC provides detailed information on the technological innovation activities of Spanish firms for the period 2003-2010. For instance, it offers information on different types of R&D expenditures, innovation outputs, number of patents, cooperation between firms, funding to undertake innovation activities, and so on. Many papers in important journals have used PITEC in recent years (see Molero and García, 2008; Vega-Jurado et al., 2009; García-Vega and Huergo, 2011; Montoro-Sánchez, et al., 2011; Santamaría et al., 2012; Trigo and Vence, 2012; Herrera and Sánchez-González, 2013; Trigo, 2013 to name a few).

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 we can overcome a severe limitation given that, as we have already seen, most studies in Spain focus only on the manufacturing sector (employing the dataset ESEE). In this regard, this paper tries to be a first attempt to study the service sector. Second, it contains a high level of sectoral information

[14] 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).

broken down into details covering 44 sectors (NACE Rev.1). 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 industry spillovers.

Our sample contains information for the period 2004-2010, since information in 2003 is limited. Influence of outliers was treated to avoid estimation problems (see Appendix A). We also eliminate observations that included some kind of incident (problems of confidentiality, takeovers, mergers, etc.) and those with an obvious anomaly (such as null sales). Primary sector and construction firms are excluded from the analysis, just those firms that belong to the industrial and service sectors are included in the study. Similarly, only firms with ten or more employees were considered[15]. Finally, in order to work with firms that are present in the three stages of the model, we keep those that remain at least three years in a row in the panel[16]. Thus, the final sample consisted of an unbalanced panel of 9,042 firms (57,379 observations).

The sample is split by the technology level of the sector in which the firm operates according to the Eurostat classification (see Appendix C) in order to determine whether the effects of innovation and externalities vary with this factor. Thus, firms are classified as: low and medium-low-tech industries (LTI), medium-high and high-tech industries (HTI), non-knowledge-intensive services (NKIS), knowledge-intensive services (KIS).

### 4.2. Variables

Below we present the variables used in estimating each part of the model described in the section above. A detailed definition of each variable can be found in Appendix D.

In equation (1), in the first stage of the model, our endogenous variable is proxied by a dummy variable that takes the value 1 if the firm has positive R&D expenditures. As determinants of firm's engagement in R&D activities we include firm size, measure as logarithm of number of workers - which reflects scale economies and access to finance-, physical capital stock per employee (using the perpetual inventory method, see Appendix E) and human capital, measure as the percentage of worker with high education. We also include a dummy variable that takes the value 1 if the firm belongs to a group – which could reflect not only access to finance, but also as Mohnen et al. (2006) points out, intra-group knowledge spillovers, or other synergies in different areas such as marketing or distribution-. We incorporate a dummy variable indicating whether the firm has operated in international market in the previous three years. As Ganotakis

[15] Following the population defined in the Spanish Innovation Survey (on which the PITEC is based).
[16] This last filter leads to a sample which is more than 90% of the whole unbalanced panel (63,615 observations). In Appendix B we can see that the properties of the sample are preserved after this last change.

and Love (2011) explain a strong competition in foreign markets encourage firms to invest in R&D in order to be competitive. Besides, a “learning by doing” effect could appear as well as a scale effect given that most of R&D costs are fixed, and exporting to new markets increases sales. We capture appropriability conditions through a dummy variable equal to 1 if the firm protected its innovations during the previous three years (here we take into account not only patents, but also copyrights, trademarks and so on). The idea is that the possibility to appropriate the benefits from innovation activities increases the likelihood of undertaking R&D projects. Three dummy variables indicating whether the firm received public funding for R&D activities in the previous three years are also include – those firms who receive these kind of subsides are expected to have a higher propensity to carry out R&D activities-. Finally, our variable of interest is the spillover measure. As we mention in the previous section, it is defined as the proportion of firms in the same sector than firm *i* undertaking R&D activities the previous year, and it is introduced in order to capture if firm’s decision is affected by what other firms in its sector do.

In equation (3) we define R&D intensity as the logarithm of R&D expenditures (intramural and extramural) per employee (in real terms). The explanatory variables in this case are the same than in equation (1) with the exception of firm size[17]. We also add a dummy variable indicating whether a firm cooperated with others to carry out their R&D projects in the previous three years. This variable would be capturing external knowledge share between firms who decide to collaborate. It worth pointing out that this information is only available for innovative firms, which is why we have been unable to include it in equation (1) [18].

In equation (4), innovation output is defined as process innovation. Actually, a firm can innovate in product or in process. However, product innovation is more related with product differentiation and creation of new markets, leading to an increase of firm’s sales, whereas process innovation improves production techniques, reduces costs, etc. leading to higher productivity performance. According to this, several papers has analysed solely the impact of process innovation on firm’s productivity (Vivero, 2002; Huergo and Jaumandreu, 2004b; Rochina-Barrachina et al., 2010 and Mañez et al., 2013)[19]. On the other hand, the questionnaire indicates that most of firms who obtain an innovation perform at least a process innovation, and

[17] According to the literature, we select this variable as an exclusion restriction to provide more robust estimations.

[18] 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 (3), while we only have limited information for equation (1).

[19] There are other authors who include both product and process innovations finding a greater impact of process innovation on firm’s productivity. For example, Huergo and Moreno (2011) show that product innovation present a lower coefficient than process innovation, and it even is not significant when dynamics are taken into account.

the proportion of firms that obtained only product innovation is particularly small[20]. This is completely logical, since, as it is point out in Vivero (2001), product innovation means a process innovation, because some enhancements in the production line need to be done in order to obtain a better or new product. Besides since we work also with the service sector, we think it is more appropriate considerate process rather than product innovation.

As explanatory variables in equation (4) we include the predicted value of R&D intensity obtained in equation (3) lagged to years as a proxy for innovative effort. Firm size, physical capital stock - since process innovation involves changes in the production line and so it might require the acquisition of new machinery and equipment-, and human capital are also included lagged two periods. We also incorporate a set of dummies variables such as belonging to a group (also lagged two years) and having used protection methods in the previous three years. Additionally, we include a dummy variable that takes the value 1 if the firm has performed R&D continuously (lagged two years). The idea is that investing in R&D continuously increases the probability of obtaining an innovation, unlike those firms who do it occasionally[21]. Moreover, we also add a dummy variable to indicate if the firm has operated in an international market in the previous three years. Finally, we introduce a dummy variable equal to 1 if the firm received European funding in the previous three years. It is believed that these kind of firms have to fulfil a set of demanding requirements, have a consolidate network, structural cohesion and so on in order to get this financial support. Thus it is thought that they have a higher propensity to achieve a process innovation.

In the final step of the model, equation (5), labour productivity is defined as logarithm of sales per employee. As explanatory variables we include the traditional inputs of labour, measure as the logarithm of number of workers, and physical capital, measure as the logarithm of physical capital stock per employee. Human capital, defined as the percentage of worker with high education, is also included in order to capture the fact that the more qualified workers, the more efficiently they carry out their tasks, and the more productive the firm tends to be. We also incorporate innovation output, proxied by process innovation predicted in equation (4). Finally, two measures of spillovers are included: (i) intra-industry externalities defined as the total R&D stock incurred by all the other firms in the same sector in the previous two years provided that they have made a process innovation in the next three years, and (ii) inter-industry externalities, defined as the weighted sum of the R&D stock incurred by the firms in all the other sectors provided that these firms have achieved a process innovation during in the next three years.

[20] In fact, 80% from the 70% of firm who declare to be innovators perform a process innovation or a product and process innovation. Only a 20% (of the 70%), get a product innovation exclusively.
[21] Continuity is a factor to take into consideration as pointed out by several authors (for instance, Huergo and Moreno, 2011) who study the persistence of innovation.

Both variables have been included in the equation lagged one year. Weighs, $w_{jm}$ in equation (5), are defined as the quotient between the intermediate purchase by sector *j* of goods and services supplied by sector *m* and the total sum of intermediate purchase of sector *j*. To construct them, we use the symmetric input-output table for Spain for 2005 (the latest year available)[22].

Apart from this, we control for time and industry effects[23]. On the other hand, and following Griffith et al. (2006a), 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.

### 4.3. Descriptive statistics

Table 1 shows the descriptive statistics for the main variables in the model across the different technology levels. First, it can be seen that labour productivity is slightly higher in high-tech industries than it is in low-tech industries unlike the situation that prevails in services. Not surprisingly, the average percentage of qualified employees is much higher in more advanced firms, especially in knowledge-intensive services. Regarding knowledge variables, we can see that high-tech firms (HTI and KIS) are more likely to engage in R&D activities, their intensity is greater and their investment in R&D is more continuous than low-tech firms (LTI and NKIS). Likewise, the proportion of firms reporting a process innovation is slightly higher in these kinds of firms. Moreover, high-tech firms protect their innovations and cooperate more than low-tech firms. Finally, the number of firms that receive government financial support is also higher in high-tech sectors. Therefore, given the differences presented it is worthy analysing each technology level separately.

Table 1: Descriptive statistics

| | | LTI | | HTI | | NKIS | | KIS | | TOTAL | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **mean** | **st dv** | **mean** | **st dv** | **mean** | **st dv** | **mean** | **st dv** | **mean** | **st dv** |
| Labour | overall | 11.985 | 0.839 | 12.037 | 0.736 | 12.041 | 1.102 | 11.184 | 1.156 | 11.788 | 1.018 |
| productivity [a, d] | between | | 0.796 | | 0.692 | | 1.063 | | 1.074 | | 0.968 |
| | within | | 0.297 | | 0.287 | | 0.282 | | 0.422 | | 0.332 |
| Number of | overall | 4.253 | 1.196 | 4.169 | 1.215 | 5.095 | 1.602 | 4.593 | 1.602 | 4.433 | 1.410 |
| employees [a, d] | between | | 1.182 | | 1.203 | | 1.599 | | 1.593 | | 1.400 |
| | within | | 0.193 | | 0.185 | | 0.197 | | 0.240 | | 0.205 |
| Physical | overall | 10.087 | 3.445 | 9.778 | 2.936 | 9.304 | 3.474 | 8.820 | 3.250 | 9.563 | 3.314 |
| capital [a, d] | between | | 3.230 | | 2.708 | | 3.137 | | 2.985 | | 3.065 |
| | within | | 1.442 | | 1.344 | | 1.577 | | 1.385 | | 1.421 |

[22] 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.

[23] Industry dummies capture technological opportunities and specific industry characteristic. We do not include them neither in the first nor the last equation given the inclusion of spillovers. We are aware that, especially in the last equation, spillovers might be capturing not only external knowledge but also specificities of the sector. Unfortunately, we cannot include industry dummies since there would be perfect multicollinearity with the inter-industry spillover variable.

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Human Capital [a] | overall | 12.136 | 13.538 | 20.882 | 18.457 | 13.762 | 19.817 | 42.157 | 33.358 | 22.722 | 25.600 |
| | between | | 11.603 | | 16.577 | | 17.438 | | 30.191 | | 23.770 |
| | within | | 7.139 | | 8.659 | | 9.835 | | 14.761 | | 10.407 |
| Group (0/1)[a] | overall | 0.362 | 0.481 | 0.421 | 0.494 | 0.510 | 0.500 | 0.402 | 0.490 | 0.407 | 0.491 |
| | between | | 0.450 | | 0.464 | | 0.468 | | 0.454 | | 0.459 |
| | within | | 0.163 | | 0.168 | | 0.177 | | 0.183 | | 0.172 |
| International Competition (0/1) [a] | overall | 0.583 | 0.493 | 0.718 | 0.450 | 0.283 | 0.451 | 0.215 | 0.411 | 0.479 | 0.500 |
| | between | | 0.418 | | 0.378 | | 0.375 | | 0.349 | | 0.434 |
| | within | | 0.264 | | 0.252 | | 0.252 | | 0.214 | | 0.247 |
| ***Knowledge / Innovation*** | | | | | | | | | | | |
| R&D engagement (0/1) [a] | overall | 0.578 | 0.494 | 0.782 | 0.413 | 0.256 | 0.437 | 0.535 | 0.499 | 0.576 | 0.494 |
| | between | | 0.391 | | 0.329 | | 0.367 | | 0.425 | | 0.412 |
| | within | | 0.303 | | 0.255 | | 0.242 | | 0.260 | | 0.273 |
| R&D intensity [b] | overall | 9.023 | 1.329 | 9.835 | 1.216 | 8.386 | 1.855 | 9.784 | 1.882 | 9.458 | 1.555 |
| | between | | 1.401 | | 1.270 | | 1.995 | | 2.039 | | 1.692 |
| | within | | 0.454 | | 0.342 | | 0.661 | | 0.498 | | 0.446 |
| Continuous R&D (0/1) [b] | overall | 0.678 | 0.467 | 0.786 | 0.410 | 0.607 | 0.489 | 0.779 | 0.415 | 0.737 | 0.441 |
| | between | | 0.408 | | 0.363 | | 0.441 | | 0.381 | | 0.398 |
| | within | | 0.292 | | 0.258 | | 0.266 | | 0.258 | | 0.271 |
| Process innovator (0/1) [a] | overall | 0.633 | 0.482 | 0.634 | 0.482 | 0.381 | 0.486 | 0.513 | 0.500 | 0.568 | 0.495 |
| | between | | 0.383 | | 0.385 | | 0.390 | | 0.398 | | 0.398 |
| | within | | 0.295 | | 0.295 | | 0.291 | | 0.304 | | 0.297 |
| Protection (0/1) [a] | overall | 0.273 | 0.446 | 0.337 | 0.473 | 0.183 | 0.386 | 0.249 | 0.432 | 0.271 | 0.445 |
| | between | | 0.339 | | 0.368 | | 0.292 | | 0.331 | | 0.342 |
| | within | | 0.287 | | 0.297 | | 0.256 | | 0.282 | | 0.285 |
| Cooperation (0/1) [c] | overall | 0.326 | 0.469 | 0.373 | 0.484 | 0.312 | 0.463 | 0.459 | 0.498 | 0.373 | 0.483 |
| | between | | 0.365 | | 0.382 | | 0.370 | | 0.408 | | 0.386 |
| | within | | 0.295 | | 0.298 | | 0.285 | | 0.294 | | 0.295 |
| ***Public support*** [a] | | | | | | | | | | | |
| Local funding (0/1) | overall | 0.216 | 0.411 | 0.262 | 0.440 | 0.080 | 0.272 | 0.240 | 0.427 | 0.217 | 0.412 |
| | between | | 0.293 | | 0.325 | | 0.200 | | 0.360 | | 0.316 |
| | within | | 0.289 | | 0.295 | | 0.189 | | 0.233 | | 0.265 |
| National funding (0/1) | overall | 0.170 | 0.376 | 0.256 | 0.436 | 0.065 | 0.247 | 0.250 | 0.433 | 0.200 | 0.400 |
| | between | | 0.272 | | 0.325 | | 0.179 | | 0.356 | | 0.309 |
| | within | | 0.259 | | 0.291 | | 0.172 | | 0.247 | | 0.255 |
| European funding (0/1) | overall | 0.029 | 0.169 | 0.041 | 0.199 | 0.020 | 0.140 | 0.100 | 0.299 | 0.050 | 0.218 |
| | between | | 0.109 | | 0.137 | | 0.100 | | 0.251 | | 0.168 |
| | within | | 0.129 | | 0.144 | | 0.099 | | 0.159 | | 0.138 |
| Firms | | 3126 | | 2272 | | 1140 | | 2504 | | 9042 | |
| | | (34.57%) | | (25.13%) | | (12.61%) | | (27.69%) | | (100%) | |
| Observations | | 19838 | | 14547 | | 7400 | | 15594 | | 57379 | |
| | | (34.57%) | | (25.35%) | | (12.90%) | | (27.18%) | | (100%) | |

Notes: LTI (low and medium-low tech industries), HTI (medium-high and high tech industries), NKIS (non-knowledge-intensive services), KIS (knowledge-intensive services). [a]Variables computed for total sample. [b]Variables computed for R&D performers sub-sample. [c]Variables computed for innovative sub-sample. [d]Mean in thousands of euros.

## 5. RESULTS

### (i) First stage: 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 using a random effects probit model. 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 by using the consistent estimator proposed by Wooldridge (1995) in order to account for the selection bias. The results are presented for each technology sector in order to highlight any differences. The numbers reported for columns 1-4 are marginal effects evaluated at the sample means. Most of the variables are dummies (except firm size, physical capital stock, human capital and the spillover); thus, the coefficients show the effect of changing the dummy variable from 0 to 1.

First of all, and according to the literature, firm size[24] has a positive impact among the manufacturing sector, thus the larger the firm, the more likely to engage in R&D activities (see for instance, Chudnovsky, 2006; Artés, 2009 and Lhuillery, 2011). However, in the service sector firm size is not significant (and even negative in non-knowledge-intensive services). Our findings in relation to the variables of physical and human capital 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. However, group membership seems to influence weakly the decision to engage in R&D activities, and only in less advanced sectors. Besides, it has a negative impact in terms of investment intensity. This could be explained because they benefit from innovation carried out within their group, so they need invest less money in R&D activities. As far as international competition is concerned, we find that it has a positive and significant impact, which means that firms operating in international markets are more likely to engage in R&D activities, especially in low-tech industries. This factor also increases the amount of R&D investment undertaken but only in manufacturing firms. This finding is in consonance with Artés (2009) and Huergo and Moreno (2011) who use exports to capture the importance of external markets and find that it influences positively the probability of engaging in R&D activities as well as its intensity. Our results show that protecting innovative output in the previous three years is associated with a higher probability of engaging in R&D activities. This is true, above all, among low-tech manufacturing firms and knowledge-intensive services. Yet, once a firm has decided to engage in R&D activities, its R&D effort is affected by protection methods only in manufacturing firms, and especially in low-tech sectors. Our results seem to be consistent with Lhuillery (2011) who shows that protection has an important impact on the decision whether to engage in R&D activities or not. However they are different in the second equation since the author finds that there is no impact of this variable on the amount of R&D undertaken.

[24]As we mentioned above, firm's size is taken as exclusion restriction.

Table 2. Research Equation

| (Dep var) | Engage in R&D activities (RE Probit) | | | | R&D intensity (Consistent estimator, Wooldridge1995) | | | |
|---|---|---|---|---|---|---|---|---|
| (Time period: 2004-2010) | **LTI** | **HTI** | **NKIS** | **KIS** | **LTI** | **HTI** | **NKIS** | **KIS** |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Firm size | 0.116*** | 0.0128*** | -0.00549* | -0.00158 | -- | -- | -- | -- |
| | (0.0151) | (0.00304) | (0.00307) | (0.0117) | | | | |
| Physical capital | 0.0217*** | 0.00217*** | 0.00701*** | 0.0177*** | 0.0410*** | 0.0477*** | 0.00520 | 0.0569*** |
| | (0.00419) | (0.000785) | (0.00195) | (0.00604) | (0.00602) | (0.00523) | (0.0209) | (0.00972) |
| Human capital | 0.0052*** | 0.0006*** | 0.00089*** | 0.0023*** | 0.00828*** | 0.00491*** | -0.00055 | -0.00103 |
| | (0.000887) | (0.000177) | (0.000237) | (0.000440) | (0.00169) | (0.00124) | (0.00322) | (0.00119) |
| Group | 0.0603* | 0.00159 | 0.0185* | 0.0293 | -0.110*** | -0.0616*** | -0.0989 | -0.102*** |
| | (0.0331) | (0.00419) | (0.00956) | (0.0297) | (0.0265) | (0.0202) | (0.0731) | (0.0355) |
| International competition | 0.136*** | 0.0204*** | 0.0229** | 0.0724** | 0.151*** | 0.116*** | 0.0588 | -0.0309 |
| | (0.0249) | (0.00591) | (0.0101) | (0.0314) | (0.0365) | (0.0354) | (0.0738) | (0.0363) |
| Protection | 0.163*** | 0.0147*** | 0.00939 | 0.130*** | 0.232*** | 0.107*** | 0.0467 | -0.0729 |
| | (0.0228) | (0.00368) | (0.0111) | (0.0241) | (0.0484) | (0.0382) | (0.110) | (0.0571) |
| Local Funding | 0.254*** | 0.0223*** | 0.0872*** | 0.306*** | 0.519*** | 0.202*** | 0.0673 | -0.0204 |
| | (0.0207) | (0.00466) | (0.0336) | (0.0247) | (0.0510) | (0.0404) | (0.158) | (0.0702) |
| National Funding | 0.280*** | 0.0210*** | 0.191*** | 0.304*** | 0.635*** | 0.247*** | -0.0514 | -0.107 |
| | (0.0202) | (0.00499) | (0.0584) | (0.0280) | (0.0531) | (0.0345) | (0.146) | (0.0683) |
| European Funding | 0.156*** | -0.00253 | 0.158 | 0.222*** | 0.115 | 0.0707 | -0.0776 | 0.0746 |
| | (0.0542) | (0.0136) | (0.131) | (0.0566) | (0.0889) | (0.0747) | (0.282) | (0.0747) |
| Spillover in t-1 | 0.00982*** | 0.00156*** | 0.00215*** | 0.0118*** | -- | -- | -- | -- |
| | (0.00179) | (0.000417) | (0.000432) | (0.000958) | | | | |
| Cooperation | -- | -- | -- | -- | 0.0700* | 0.0491 | -0.0565 | 0.151*** |
| | | | | | (0.0421) | (0.0361) | (0.115) | (0.0548) |
| IMR * Time dummies(1) | -- | -- | -- | -- | Yes*** | Yes*** | Yes*** | Yes*** |
| Means(2) | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** | Yes*** |
| Time dummies | Yes*** | Yes*** | Yes*** | Yes*** | No | No | No | No |
| Industry dummies | No | No | No | No | Yes*** | Yes*** | Yes*** | Yes*** |
| Observations | 16,712 | 12,275 | 6,26 | 13,09 | 9,111 | 9,36 | 1,468 | 6,701 |
| Number of groups | 3,126 | 2,272 | 1,14 | 2,504 | -- | -- | -- | -- |
| Rho (3) | 0.783 | 0.797 | 0.789 | 0.767 | -- | -- | -- | -- |
| Corrected predictions | 72.14% | 79.37% | 84.55% | 79.98% | -- | -- | -- | -- |
| Adjusted $R^2$ (4) | 0.1579 | 0.1608 | 0.1992 | 0.2411 | 0.225 | 0.335 | 0.416 | 0.459 |

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 (dummy variable). Bootstrapped standard errors are in brackets. (1) The interaction between IMR (inverse Mills ratio) and time dummies is significant at 1% confirming the inclusion of a selection equation. (2) We have incorporate only means of these variables that do not have a strong correlation with their within mean. We undertake this decision following Raymond et al. (2010, footnote 8), who assume that individual effects are not correlated with the regressors due to the lack of variation over time. (3) Rho is the percentage of total variance contributed by the panel-level variance component (if rho=0, the panel estimator is not different from the pooled estimator). (4) Adjusted McFadden's pseudo $R^2$ in Equation 1 and adjusted $R^2$ in Equation 2. *** 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 previous period increases the probability of engaging in R&D activities. Nevertheless there is no clear pattern according to the level of technology. As can be seen in Table 2, public funding has a much higher impact on low-tech industries than high-tech industries, unlike the situation that prevails in the service sector, where knowledge-intensive services increase their probability more than non-knowledge-intensive services[25]. National and local funding has the greatest impact across all sectors having also a marked influence on R&D intensity but only for manufacturing firms. Finally, only low-tech industries and knowledge-intensive services increase their R&D investment as a result of having cooperated with another firm during the previous period[26].

Regarding our main contribution at this stage of the model, the results presented in Table 2 show that the firm's decision whether to engage in R&D activities or not is influenced positively by the fact that the rest of the firms in its sector perform R&D in the previous period. This might reflect an incentive effect[27], since the greater the number of firms undertaking R&D activities in the same sector, the more likely to engage in R&D projects the firm is. Particularly, knowledge-intensive services increase their probability of engaging in R&D activities 1.18 percentage points if the proportion of firms of its sector who perform R&D increases 1 percentage point the previous year. It is worth pointing out that high-tech industries present the lowest coefficient value (0.15 percentage points).

Finally, Inverse Mills ratios obtained from equation (1) are clearly significant, showing the importance of taking the selection problem into consideration. In addition, control variables are statistically significant as well.

**(ii) Second stage: Innovation equation**

Table 3 reports the estimates of the knowledge production function. The numbers reported are marginal effects evaluated at the sample means. Most of the variables are dummies (except R&D intensity, firm size and physical capital stock); thus, the coefficients show the effect of changing the dummy variable from 0 to 1.

As expected, R&D intensity predicted by equation (2) lagged two years has a positive and significant impact on the likelihood of a firm's achieving process innovation. If we analyse the differences between technology levels, we observe that in manufacturing sectors, low-tech firms are more likely than high-tech firms to report a successful process innovation 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 an increase of 28 percentage points in the probability of achieving a

[25] In particular, it can be seen that high-tech industries are the ones that present the lowest coefficient. This could be explained by the fact that these kinds of companies engage in R&D activities in any case (given their profile and characteristics), so receiving public funding increases their probability but not to a great extent.

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

[27] As it has been explained in Section 3, this incentive effect could be due to two factors: i) the investment in R&D generates a pool of knowledge in the sector and allows firms to benefit from this information and expertise (through the absorptive capacity), ii) the fact that the rest of the firms undertake R&D projects could encourage firms to make an effort to improve their competitiveness in order not lose market share.

process innovation in low-tech firms vs. 5.7 percentage points in high-tech firms. 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 obtaining a process innovation. As Hall et al. (2009) points 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 addition, this result could also be suggesting that high-tech firms need a longer period of time to obtain an innovation. In fact, interviews carried out to Spanish firms show that R&D investment takes several years until it turns into an innovation.

Table 3. Innovation Equation

| (Dep var) | **Process innovation** (RE probit) | | | |
|---|---|---|---|---|
| (Time period: 2007-2010) | **LTI** (1) | **HTI** (2) | **NKIS** (3) | **KIS** (4) |
| Predicted R&D intensity in t-2 | 0.280*** | 0.0569** | 0.202** | 0.298*** |
| | (0.0555) | (0.0235) | (0.0826) | (0.0523) |
| Firm size in t-2 | 0.0587*** | 0.0566*** | 0.0453*** | 0.0837*** |
| | (0.0158) | (0.0165) | (0.0162) | (0.0259) |
| Physical capital in t-2 | -0.00518 | 0.00341 | 0.00719 | 0.0169* |
| | (0.00447) | (0.00295) | (0.00802) | (0.00876) |
| Group in t-2 | -0.0177 | 0.0103 | 0.114*** | 0.0383 |
| | (0.0194) | (0.0118) | (0.0429) | (0.0432) |
| Protection | 0.0507** | 0.0254** | 0.0430 | 0.109** |
| | (0.0203) | (0.0106) | (0.0507) | (0.0425) |
| Lack qualified personnel | 0.0216 | 0.0184 | 0.0865*** | 0.0758* |
| | (0.0173) | (0.0140) | (0.0310) | (0.0439) |
| Continuous R&D in t-2 | 0.0791*** | 0.0123 | 0.113* | 0.203*** |
| | (0.0187) | (0.0128) | (0.0664) | (0.0424) |
| International competition | 0.0311 | 0.00764 | 0.0214 | 0.0210 |
| | (0.0230) | (0.00983) | (0.0445) | (0.0441) |
| European Funding | 0.00862 | 0.0273*** | 0.181 | 0.0518 |
| | (0.0341) | (0.0102) | (0.257) | (0.0665) |
| Means [(1)] | Yes*** | Yes*** | Yes*** | Yes*** |
| Time dummies | Yes*** | Yes*** | Yes*** | Yes*** |
| Industry dummies | Yes*** | Yes*** | Yes*** | Yes*** |
| Observations | 10,460 | 7,731 | 3,980 | 8,082 |
| Number of groups | 3,003 | 2,167 | 1,109 | 2,340 |
| Rho [(2)] | 0.9135 | 0.9415 | 0.8998 | 0.8868 |
| Corrected predictions | 71.27% | 67.29% | 70.60% | 68.71% |
| Adjusted McFadden's pseudo R2 | 0.1012 | 0.0816 | 0.1518 | 0.1051 |

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 obtaining a process innovation (dummy variable). Bootstrapped standard errors are in brackets. [(1)] We have incorporate only means of these variables that do not have a strong correlation with their within mean. We undertake this decision following Raymond et al. (2010, footnote 8), who assume that individual effects are not correlated with the regressors due to the lack of variation over time. [(2)] Rho is the percentage of total variance contributed by the panel-level variance component (if rho=0, the panel estimator is not different from the pooled estimator). *** Significant at 1%, ** significant at 5%, * significant at 10%.

For instance, firms in the automotive sector or chemistry industry need at least 4 and 10 years respectively to materialise their R&D expenditures in an innovation output. However, in the case of the services sector the results are quite similar among firms. In line with previous studies, the larger the firm, the greater is its probability of achieving process innovations. On the other hand, physical capital has a positive impact (but only at 10%) on the probability of introducing process innovations only in knowledge-intensive services. As can be seen belonging to a group increases the likelihood of achieving process innovation in the case of those firms that belong to non-knowledge-intensive services exclusively. Even though it is recognized that protection methods are more influential in obtaining product innovation than they are in developing a process innovation (see Griffith et al., 2006, and Masso and Vather, 2008), the results from Table 3 show a positive effect. Thus, having protected an invention in the previous period increases the probability of obtaining a process innovation except for non-knowledge-intensive services. Contrary to our expectations, the lack of qualified personnel[28] has a positive effect on the probability of obtaining a process innovation in the service sector. However, this result is nothing new in the literature of obstacles to innovation (Baldwin and Lin, 2002). In fact, evidence points out that innovative firms are the ones who perceive this barrier[29]. As expected, in general continuous R&D has a positive and significant impact on the probability of achieving a process innovation. Thus, firms that perform continuous R&D have a greater probability of obtaining a process innovation than firms that invest occasionally. On the other hand, operating in an international market do not influence the probability of obtaining a process innovation (Harris et al. 2003 and Woetrer and Roper, 2010) and a similar result is found with respect to European funding since it is only relevant for high-tech industries.

**(iii) Third stage: Productivity equation**

Table 4 shows the estimates of the production function equation. According to the literature, we find that process innovation predicted in equation (4) has a positive and significant effect on productivity (Vivero, 2002; Huergo and Jamandreu, 2004b; Lee and Kang, 2007, Rochina-Barrachina et al., 2010 and Mañez et al., 2013). Although the coefficients vary across technology levels, they do not follow any specific pattern. Specifically, low-tech firms enhance their productivity slightly more (6.6%) than high-tech firms (4.1%) as the result of a process innovation. However, firms belonging to knowledge-intensive services that introduce a process innovation increase their productivity more (13%) than non-knowledge-intensive services (9.6%). In general, the larger the firm, the more productive it is in the case of high-tech industries. Nevertheless, the opposite is the case in the services sector. As expected, and in

[28] This variable has been used to proxy human capital because it was not significant, (probably because of multicollinearity problems). Thus, we define lack of qualified personnel as a dummy variable which takes the value 1 if the firm answers that the lack of qualified personal is a factor that hampers its innovation activity (see Appendix D for a detailed definition).
[29] Some studies have shown how the effect of obstacles turns into negative coefficient once it is taken into account only the sample of innovative firms instead of the whole sample. See Savignac (2008) and D'Este et al. (2008) for a more detailed analysis.

consonance with the literature, physical capital stock has a positive effect on productivity across all sectors. In addition, human capital has a positive impact on productivity, but this happens only in the manufacturing sector.

Table 4. Productivity Equation

| (Dep var) (Time period: 2007-2010) | Labour Productivity (RE) | | | |
|---|---|---|---|---|
| | **LTI** (1) | **HTI** (2) | **NKIS** (3) | **KIS** (4) |
| Predicted process innovation | 0.0666*** | 0.0414* | 0.0961*** | 0.1294*** |
| | (0.0184) | (0.0220) | (0.0284) | (0.0260) |
| Firm size | 0.0308 | 0.0875*** | -0.1799*** | -0.0516** |
| | (0.0234) | (0.0169) | (0.0299) | (0.0209) |
| Physical capital | 0.0556*** | 0.0481*** | 0.0353*** | 0.0983*** |
| | (0.0055) | (0.0065) | (0.0097) | (0.0138) |
| Human capital | 0.0021*** | 0.0019*** | 0.0007 | 0.0003 |
| | (0.0006) | (0.0005) | (0.0005) | (0.0004) |
| Intra-industry spillover in t-1 | 0.0006*** | 0.0002*** | 0.0000 | -0.0001*** |
| | (0.0001) | (0.0000) | (0.0000) | (0.0000) |
| Inter-industry spillover in t-1 | 0.0006*** | 0.0012*** | 0.0001 | -0.0003 |
| | (0.0001) | (0.0002) | (0.0001) | (0.0002) |
| Constant | 10.9927*** | 10.7566*** | 12.5816*** | 10.5774*** |
| | (0.1043) | (0.1090) | (0.1760) | (0.1577) |
| Time dummies | Yes*** | Yes*** | Yes*** | Yes*** |
| Industry dummies | No | No | No | No |
| Observations | 10,460 | 7,731 | 3,980 | 8,082 |
| Number of groups | 3,003 | 2,167 | 1,109 | 2,340 |
| $R^2$ within | 0.100 | 0.0833 | 0.0971 | 0.0299 |
| $R^2$ between | 0.140 | 0.180 | 0.0433 | 0.114 |
| $R^2$ overall | 0.148 | 0.175 | 0.0524 | 0.116 |

Notes: LTI (low and medium-low tech industries), HTI (medium-high and high tech industries), NKIS (non-knowledge-intensive services), KIS (knowledge-intensive services). Bootstrapped standard errors are in brackets. *** Significant at 1%, ** significant at 5%, * significant at 10%.

With respect to intra-industry externalities, our results show that, R&D expenditures incurred by firms in the same sector -provided that they achieve a process innovation- have a positive impact on manufacturing firms' productivity. For instance, if the rest of the firms in its sector increase their R&D expenditures in 1 million euros and obtain a process innovation, then low-tech (high-tech) industries would raise their productivity by 0.06% (0.02%). Contrary to our expectations, knowledge-intensive services present a negative coefficient. This last finding could be somehow reflecting a kind of competitive effect, in other words, a firm would reduce its productivity if the rest of the firms in the same sector increase their R&D expenditure and obtain an innovation. As far as inter-industry externalities are concerned, it can be seen that they are relevant only for manufacturing firms. In particular, if the rest of the firms in other sectors[30] increase their R&D expenditures in 1 million of euros - provided that this investment turn into a process innovation - then low-tech (high-tech) industries would raise their productivity by 0.06% (0.12%). However, the results in Table 4 suggest that firms in the service sector are not

[30] Here, we take into account those sectors that are suppliers of the sector in which the firm operates (according to the definition of spillover that we have considered in section 4).

influenced by what other firms in other sectors do. When the magnitude of the externalities are compared, one can observed that high-tech firms benefit more from innovation carried out by firms in other sectors than firms in the same sector.

On balance, the results of the first stage of the model suggest that the determinants of R&D intensity are different in the industry than in the services sector. Particularly, in the case of manufacturing firms: the higher the number of employees, physical and human capital, the more likely to engage in R&D activities a firm is and the greater its investment. Those firms who have operated in international markets, protected their innovations, and received public funding also present a higher likelihood to carry out R&D projects and invest more money in them. Finally, the greater the number of firms undertaking R&D activities in a sector in the previous period, the more likely a firm of this sector is to engage in R&D activities. Last of all, and regarding the level of technology operated by the firm, it seems that the effects are higher for low-tech than high-tech manufacturing firms. In the case of service sector, physical and human capital, have a positive impact on the probability of engage in R&D activities, while firm size is not important. Similar to the industry case, having operated in international markets, using protection methods and receiving public funding increase the likelihood of a firm's carrying out R&D projects. Moreover, our spillover measure is also important in the case of service firms (especially for knowledge-intensive services). Finally there is no clear pattern regarding the firm's technology level in the service sector neither in the first nor in the second equation. In particular, no variable is significant to explain R&D intensity in the case of non-knowledge intensive services, and only physical capital and belonging to a group for knowledge-intensive services.

Concerning the second stage of the model, our results show that the greater the R&D expenditures carried out two years ago and the fact that this investment has been done continuously, as well as, the larger firm and having used protection methods, the greater the probability of achieving a process innovation. However, physical capital, belonging to a group, operating in an international market or receiving European funding it does not seem influence the achievement of an innovation output. According to firm's technology level, no clear pattern can be established.

Last of all, in the last stage of the model we have seen that the results are different in the industry than in the services sector. Manufacturing firms increase their productivity with firm's size, human and physical capital, previous process innovation and R&D carried out by other firms (in the same sector or in other sectors). Even though, spillovers present a low coefficient, they are clearly significant. On the other hand, physical capital and previous innovation are also important for service firms' productivity. Nevertheless, the rest of variables, even spillovers, are not relevant generally speaking. Finally no distinct differences were found regarding the firm's technology level.

## 6. CONCLUSIONS

This paper has analysed the impact of innovation activities on a firm's productivity using a CDM model. Our main goal has been to assess the extent to which external knowledge may have an impact on firms' behaviour and firms' performance. To do so, we aim to answer the following questions: (i) Is the firm's decision whether to engage in R&D activities or not affected by what other firms do? (ii) Do Spanish firms benefit from innovation carried out by the rest of the firms in its sector? and in other sectors?

For this, we use a panel data of Spanish manufacturing and services firms (PITEC) from 2004-2010. We try to shed some light to the scarce literature that analyses this topic, since in general most of papers have used cross-sectional data. Working with a panel data enables us to control for both unobserved firm heterogeneity and the time lag along the whole process. To the best of our knowledge, no previous paper has dealt with spillover effect for any country by adopting a CDM perspective.

Returning to the hypothesis posed at the beginning of this study, the structural model has made possible to state that not only is R&D important in order to increase firm's productivity, but also the firm's ability to turn this investment into innovations strictly speaking (what some authors called "innovativity"). In fact, this study has shown how innovation input (R&D intensity) affects innovation output and that effectively this output has a positive impact on a firm's productivity. It is worth mentioning that, according to our results, manufacturing and service firms cannot be treated equally, since their behaviour is different along the process[31].

The following conclusions can be drawn from the present study. First of all, there is not a distinct difference regarding the technology level of the sector in which the firm operates along the model. An exception is the higher returns from the determinants of R&D decision for low-tech vs high-tech manufacturing firms. Secondly, and answering our first question, we have found that the firm's decision whether to engage in R&D activities or not is somehow influenced by what other firms do. The results show that the higher the number of firms undertaking R&D activities in the same sector, the more likely to engage in R&D projects the firm is. Therefore, an external pool of knowledge would encourage firms to carry out R&D

[31]In particular, our findings show that some variables that are relevant for manufacturing firms, they are not significant when the service sector is analysed. Thus, the results presented here need to be interpreted with caution as far as service sector is concerned. As we mention at the beginning of this paper, this is only a first attempt to study the service sector and a deeper analysis should be carried out to detect which factors would explain better the performance of these kinds of firms.

activities (both industrial and service sector). An implication of this is the possible existence of a “virtuous cycle”, since the fact that firms in a sector innovate stimulate the others to do the same, which has as a consequence that the rest of the firms decide to innovate too, and so on and so forth. As we have seen in Table 2, high-tech industries present the lowest coefficient. This could suggest that the decision made by these firms do not depend strongly on what other firms decided to do. Finally, and regarding our second question, our results suggest that there is a complementary between manufacturing firms (not service), both between firms in the same sector and firms operated in different sectors. Thus, R&D expenditures incurred by firms in the same sector (intra-industry externalities) or in other sectors (inter-industry externalities) - provided that a process innovation is achieved with their investment - have a positive impact on firm’s productivity. Furthermore, it has been shown that high-tech manufacturing firms increase more their productivity with R&D from other sectors (inter-industry externality) than from their own sector. A possible explanation for this might be that these firms face a higher rivalry which reduces the positive effect originated by the external R&D of firms in their same sector (intra-industry externality)[32].

In view of the findings of this study, it would be interesting design some policies to foster R&D investment from government and public institutions in order to increase productivity levels and become more competitive. First of all, we have seen that the more a firm invests in R&D and the fact that it is done continuously, the more likely to achieve an innovation, which increases its productivity. Given that public funding is a clear determinant not only in the innovative effort but also in the firm’s decision whether to engage in R&D activities or not, governments should maintain this financial support even though the current economic situation. It should be borne in mind that cut back public subsidies or any other funding will condition Spanish firms’ behaviour. Moreover, as we have seen innovate is a learning process being the probability of achieving an innovation greater when it is done continuously. For this reason, financial support should not be aimed at particular projects, but it ought to be addressed to promote R&D activities in a continuous way.

On the other hand, the more firms undertaking R&D projects, the better, since, as we have seen in the first stage of the model, this increases the probability of starting R&D activities. Moreover, the higher the R&D expenditures in a sector or in other sectors, the more a firm is going to increase its productivity (according to the results in the last stage of the model). Thereby, government support to help one particular firm would overtake the boundaries of this company, having a positive effect on both firm’s behaviour as well as firm’s productivity. In addition, firm size favour both firm decision whether to engage in R&D activities or not and the

[32] This result is in line with Goya et al. (2012) where the authors analyse spillovers in a production function framework using cross-section data for 2010.

probability of achieving a process innovation. However Spanish economy is made up of small and medium firms. For this reason, policies should seek cooperation between these firms in order to palliate their small size, as well as, promote enlargement or fusion of firms. Last of all, the results point out that operating in international markets is a factor which encourages firms to start R&D projects. Therefore, helps aimed at promoting internationalization are also important and governments should bear this in mind when they design their policies.

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## APPENDIXES

### Appendix A: Treatment of outliers

We consider as outliers those observations that are more than double the volume of sales according the level of technology operated by the firm. Observations have been replaced before deflating and calculating stock measures.

Table A1. Number of extreme values

| | LTI | HTI | NKIS | KIS | *Total* |
|---|---|---|---|---|---|
| Physical capital | 56 | 19 | 46 | 184 | *305* |
| R&D expenditure | 22 | 22 | 10 | 365 | *419* |
| *Observations* | *19838* | *14547* | *7400* | *15594* | *57379* |

Source: PITEC

### Appendix B: Descriptive statistics before filters

Table B1. Descriptive statistics

| | **LTI** | | **HTI** | | **NKIS** | | **KIS** | | **TOTAL** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **mean** | **st dv** | **mean** | **st dv** | **mean** | **st dv** | **mean** | **st dv** | **mean** | **st dv** |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Labour productivity [a, d] | overall | 11.978 | 0.851 | 12.038 | 0.756 | 11.999 | 1.112 | 11.140 | 1.181 | 11.756 | 1.048 |
| | between | | 0.812 | | 0.731 | | 1.080 | | 1.118 | | 1.015 |
| | within | | 0.312 | | 0.291 | | 0.305 | | 0.430 | | 0.344 |
| Number of employees [a, d] | overall | 4.253 | 1.213 | 4.179 | 1.243 | 5.107 | 1.614 | 4.634 | 1.663 | 4.456 | 1.452 |
| | between | | 1.212 | | 1.245 | | 1.626 | | 1.680 | | 1.463 |
| | within | | 0.212 | | 0.200 | | 0.220 | | 0.275 | | 0.230 |
| Physical capital [a, d] | overall | 10.087 | 3.445 | 9.778 | 2.936 | 9.304 | 3.474 | 8.820 | 3.250 | 9.563 | 3.314 |
| | between | | 3.230 | | 2.708 | | 3.137 | | 2.985 | | 3.065 |
| | within | | 1.442 | | 1.344 | | 1.577 | | 1.385 | | 1.421 |
| Human capital [a] | overall | 12.151 | 13.743 | 21.077 | 18.823 | 13.760 | 19.916 | 40.820 | 33.692 | 22.745 | 25.875 |
| | between | | 12.076 | | 17.405 | | 17.997 | | 30.866 | | 24.465 |
| | within | | 7.337 | | 8.845 | | 10.019 | | 14.810 | | 10.640 |
| Group (0/1) [a] | overall | 0.366 | 0.482 | 0.427 | 0.495 | 0.506 | 0.500 | 0.409 | 0.492 | 0.412 | 0.492 |
| | between | | 0.451 | | 0.466 | | 0.468 | | 0.458 | | 0.461 |
| | within | | 0.162 | | 0.169 | | 0.181 | | 0.181 | | 0.172 |
| International competition (0/1) [a] | overall | 0.575 | 0.494 | 0.714 | 0.452 | 0.284 | 0.451 | 0.205 | 0.404 | 0.465 | 0.499 |
| | between | | 0.423 | | 0.386 | | 0.380 | | 0.341 | | 0.436 |
| | within | | 0.264 | | 0.252 | | 0.250 | | 0.212 | | 0.245 |
| ***Knowledge / Innovation*** | | | | | | | | | | | |
| R&D engagement (0/1) [a] | overall | 0.570 | 0.495 | 0.777 | 0.416 | 0.254 | 0.435 | 0.516 | 0.500 | 0.564 | 0.496 |
| | between | | 0.395 | | 0.336 | | 0.370 | | 0.432 | | 0.418 |
| | within | | 0.304 | | 0.255 | | 0.240 | | 0.259 | | 0.272 |
| R&D intensity [b] | overall | 9.023 | 1.329 | 9.835 | 1.216 | 8.386 | 1.855 | 9.784 | 1.882 | 9.458 | 1.555 |
| | between | | 1.401 | | 1.270 | | 1.995 | | 2.039 | | 1.692 |
| | within | | 0.454 | | 0.342 | | 0.661 | | 0.498 | | 0.446 |
| Continuous R&D (0/1) [b] | overall | 0.678 | 0.467 | 0.786 | 0.410 | 0.607 | 0.489 | 0.779 | 0.415 | 0.737 | 0.441 |
| | between | | 0.408 | | 0.363 | | 0.441 | | 0.381 | | 0.398 |
| | within | | 0.292 | | 0.258 | | 0.266 | | 0.258 | | 0.271 |
| Process innovation (0/1) [a] | overall | 0.624 | 0.484 | 0.630 | 0.483 | 0.369 | 0.483 | 0.496 | 0.500 | 0.555 | 0.497 |
| | between | | 0.393 | | 0.392 | | 0.395 | | 0.408 | | 0.407 |
| | within | | 0.295 | | 0.294 | | 0.285 | | 0.301 | | 0.295 |
| Protection (0/1) [a] | overall | 0.271 | 0.445 | 0.337 | 0.473 | 0.181 | 0.385 | 0.242 | 0.428 | 0.267 | 0.442 |
| | between | | 0.343 | | 0.373 | | 0.292 | | 0.335 | | 0.345 |
| | within | | 0.286 | | 0.296 | | 0.256 | | 0.279 | | 0.283 |
| Cooperation (0/1) [c] | overall | 0.325 | 0.469 | 0.376 | 0.484 | 0.312 | 0.464 | 0.452 | 0.498 | 0.373 | 0.483 |
| | between | | 0.371 | | 0.388 | | 0.379 | | 0.415 | | 0.392 |
| | within | | 0.293 | | 0.296 | | 0.281 | | 0.292 | | 0.292 |
| ***Public support*** [a] | | | | | | | | | | | |
| Local funding (0/1) | overall | 0.213 | 0.409 | 0.260 | 0.439 | 0.080 | 0.271 | 0.230 | 0.421 | 0.212 | 0.409 |
| | between | | 0.296 | | 0.331 | | 0.202 | | 0.360 | | 0.320 |
| | within | | 0.287 | | 0.292 | | 0.189 | | 0.228 | | 0.261 |
| National funding (0/1) | overall | 0.170 | 0.375 | 0.258 | 0.438 | 0.066 | 0.248 | 0.238 | 0.426 | 0.197 | 0.398 |
| | between | | 0.276 | | 0.331 | | 0.186 | | 0.355 | | 0.312 |
| | within | | 0.257 | | 0.290 | | 0.170 | | 0.241 | | 0.252 |
| European funding (0/1) | overall | 0.030 | 0.170 | 0.043 | 0.202 | 0.020 | 0.140 | 0.095 | 0.293 | 0.050 | 0.218 |
| | between | | 0.114 | | 0.147 | | 0.105 | | 0.244 | | 0.172 |
| | within | | 0.130 | | 0.144 | | 0.096 | | 0.156 | | 0.138 |
| Firms | | 3581 | | 2610 | | 1404 | | 3275 | | 10870 | |
| % | | 32.94% | | 24.01% | | 12.92% | | 30.13% | | 100% | |
| Observations | | 21385 | | 15643 | | 8389 | | 18198 | | 63615 | |
| % | | 33.62% | | 24.59% | | 13.19% | | 28.61% | | 100% | |

Notes: LTI (low and medium-low tech industries), HTI (medium-high and high tech industries), NKIS (non-knowledge-intensive services), KIS (knowledge-intensive services). [a]Variables computed for total sample. [b]Variables computed for R&D performers sub-sample. [c]Variables computed for innovative sub-sample. [d]Mean in thousands of euros.

## Appendix C: Industry classification according to technological intensity

Table C1. Correspondence between PITEC and NACE Rev 1.1. classification

| Branches of business activity PITEC | NACE Rev 1.1 |
|---|---|
| ***Low-tech manufacturing industries*** | |
| Food products and beverages | 15 |
| Tobacco | 16 |
| Textile products | 17 |
| Clothing and furriers | 18 |
| Leather and leather products | 19 |
| Wood and wood products | 20 |
| Pulp, paper and paper products | 21 |
| Publishing and printing | 22 |
| Furniture | 361 |
| Games and toys | 365 |
| Other manufactures | 36 (exc. 361, 365) |
| Recycling | 37 |
| ***Medium-low-tech manufacturing industries*** | |
| Rubber and plastic products | 25 |
| Ceramic tiles and flags | 263 |
| Non-metallic mineral products (except tiles and flags) | 26 (exc. 263) |
| Ferrous metallurgic products | 271, 272, 273, 2751, 2752 |
| Non-ferrous metallurgic products | 274, 2753, 2754 |
| Metal products (except machinery and equipment) | 28 |
| Building and repairing of ships and boats | 351 |
| ***Medium-high-tech manufacturing industries*** | |
| Chemical products (except pharmaceuticals) | 24 (exc. 244) |
| Machinery and equipment | 29 |
| Electrical machinery and apparatus | 31 |
| Motor vehicles, trailer and semi-trailers | 34 |
| Other transport equipment | 35 (exc. 351, 353) |
| ***High-tech manufacturing industries*** | |
| Manufacture of pharmaceutical products | 244 |
| Office machinery and computers | 30 |
| Electronic components | 321 |
| Radio, TV and communication equipment and apparatus | 32 (exc. 321) |
| Medical, precision and optical instruments, watchs and clocks | 33 |
| Aircraft and spacecraft | 353 |
| ***Non-knowledge-intensive services*** | |
| Sales and repair of motor vehicles | 50 |
| Wholesale trade | 51 |
| Retail trade | 52 |
| Hotels and restaurants | 55 |
| Transport | 60, 61, 62 |
| Supporting and auxiliary transport activities, travel agencies | 63 |
| ***Knowledge-intensive services*** | |

| | |
|---|---|
| Post | 641 |
| Telecommunications | 642 |
| Financial intermediation | 65, 66, 67 |
| Real estate activities | 70 |
| Renting of machinery and equipment | 71 |
| Computer activities | 722 |
| Other related computer activities | 72 (exc.722) |
| Research and development | 73 |
| Architectural and engineering activities | 742 |
| Technical testing and analysis | 743 |
| Other business activities | 74 (exc. 742, 743) |
| Education | 80 (exc. 8030) |
| Motion picture, video and television programme production | 921 |
| Programming and broadcasting activities | 922 |
| Other human health and social activities | 85, 90, 91, 92 (exc. 921,922), 93 |

Source: PITEC and Eurostat

## Appendix D: Variable definition

Table D1. Variable definition

| | |
|---|---|
| *Firms' characteristics* | |
| Labour productivity | Sales per employee in t (in logs). |
| Size | Number of employees in t (in logs). |
| Physical capital stock | Physical capital stock calculated per employee in t (in logs). |
| Human capital | Percentage of employees with high education in t. |
| Lack of qualified personnel | Dummy variable which takes the value 1 if the lack of qualified personnel is a factor that prevents or hampers firm's innovation activity at any degree of importance (low, medium or high) during the period (t-2, t). |
| Group | Dummy variable that takes the value 1 if the firm belongs to a group in t. |
| International competition | Dummy variable that takes the value 1 if the firm trades in an international market during the period (t-2, t). |
| *Knowledge / Innovation* | |
| R&D engagement | Dummy variable that takes the value 1 if the firm has a positive R&D expenditure in t, and 0 otherwise. |
| R&D intensity | Intramural and extramural R&D expenditure per employee in t (in logs). |
| Continuous R&D | Dummy variable equal 1 if the firm performs R&D continuously, and 0 if it occasional or the firm does not perform any R&D. |
| 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 (t-2, t), and 0 otherwise. |
| 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 (t-2, t) and 0 otherwise. |
| Cooperation | Dummy variable which takes the value 1 if the firm cooperates with other firms on innovation activities during the period (t-2, t) and 0 otherwise. |

| | |
|---|---|
| *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 (t-2, t) and 0 otherwise. |
| National funding | Dummy variable which takes the value 1 if the firm receives funding for innovation activities from the national government during the period (t-2, t) and 0 otherwise. |
| European funding | Dummy variable which takes the value 1 if the firm receives EU funding for innovation activities during the period (t-2, t) and 0 otherwise. |

Source: PITEC. Note: Monetary variables are expressed in real terms.

**Appendix E: Stock of physical capital and R&D expenditure**

The well-known perpetual inventory method is used to accumulate physical and R&D flows:

$$K_t = K_{t-1} \cdot \left(1 - \delta_j^k\right) + C_t$$
$$K_0 = \frac{C_0}{g_s^k + \delta_j^k}$$

and

$$I_t = I_{t-1} \cdot \left(1 - \delta_j^i\right) + RD_t$$
$$I_0 = \frac{RD_0}{g_j^i + \delta_j^i}$$

with t = 2004, …, 2010   j = 1, 2, 3, 4   s = 1, ..., 44.

where $C_t$ is the real investment in material goods and $RD_t$ is the real R&D expenditure[33]. We applied different depreciation rates according to the technology level (j). Following Ortega-Argilés (2011), the more advanced the sector, the faster is the technological progress accelerating the obsolescence of its current physical capital and knowledge. Thus, we applied sectoral depreciation rates of 6% and 7% for physical capital ($\delta_j^k$) and 15% and 18% for innovation ($\delta_j^i$) to low-tech and high-tech sectors respectively. In the case of growth rates, if we use the initial periods for their computation, we would lose a considerable amount of information given that our panel has a short time dimension (2004-2010). Thus, we opted to calculate $g_s^c$ and $g_s^i$ as an average rate of change in real investment in material goods and real R&D expenditure in each sector(s) over the period 1995-2003[34]. We used the OECD's

[33] Both are expressed as constant values at 2010 base prices. Nominal values have been deflated using the GDP deflator.

[34] Note, however, that the choice of $g$ does not modify the results greatly. As Hall and Mairesse (1995) report: "In any case, the precise choice of growth rate affects only the initial stock, and declines in importance as time passes…".

ANBERD database to calculate physical capital growth rates ($g_s^c$) and the OECD's STAN database for innovation growth rates ($g_s^i$).

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