Essays on innovation, productivity and knowledge flows: evidence for Spanish firms

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To my family

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Chapter 1: General framework and outline of the thesis

1.1 Introduction and motivation

The relationship between innovation and productivity has been widely studied for many decades, and nowadays this topic continues to generate great interest among the scientific community. How to increase firms' performance is a key factor, not only at firm level, but also at a national level, especially in today's globalized world. This is why the study of its determinants has been at the centre of attention of many researchers over the past few years. As extensively acknowledged, innovation is an essential element and, as it will be seen below, its importance for productivity growth is undeniable.

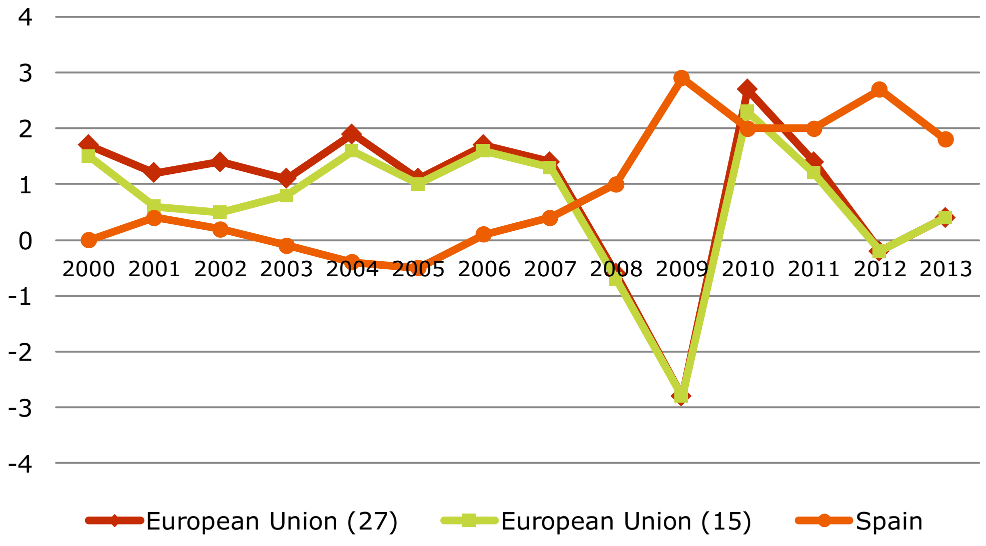
But what does innovation mean? Despite its relevance, the literature does not provide a clear and accurate definition of innovation. It is a wide and complex concept which can be understood in different ways and can be approximated using different variables. All in all, it seems plausible to assume that innovation is something new, not only for products, but also corresponding to a better ways of doing something, and the root of this "newness" is knowledge.

Interestingly, knowledge can be created inside firms, shared between different companies or simply spill over firm's boundaries. As first stated by Griliches (1979), the level of knowledge in one sector depends on own research efforts as well as external knowledge, or as the author puts it "knowledge borrow or stolen from other sector or industries". Thus, firm performance not only depends on its own knowledge, but also on the knowledge and experience generated by others that it is present in the society. The reason is that knowledge is a (quasi-) public good. In other words, it is non-rival -it can be consumed without depleting it, so its use by one firm does not impede others from doing the same- and (at least partially) non-excludable -(almost) no one can be excluded from using it.

Taking this into account, this dissertation aims to further understand the bond between innovation and firms' performance in Spain considering these knowledge flows. In this regard, two distinctions will be drawn in this study: i) depending on the "origin" of knowledge one can distinguish between *internal* knowledge (transfers within the firm) and *external* knowledge (coming from outside the company), and ii) depending on the "willingness", knowledge flows can be *voluntary* (for example, cooperation agreements) or *involuntary* (also known as spillovers).

The motivation to study Spain lays on the fact that even though productivity has increased in recent years (Figure 1.1), this growth is largely attributable to a drastic reduction in employment instead of an increase in production (Table 1.1).

Figure 1.1 Real labour productivity (annual growth rate)



Source: Eurostat; own representation.

Table 1.1 Real GDP and employment (annual growth rates)

	GDP growth			Employment growth		
	Spain	**EU 27**	**EU 15**	**Spain**	**EU 27**	**EU 15**
2000	5.0	3.9	3.9	5.1	2.2	2.4
2001	3.7	2.0	2.0	3.2	0.8	1.3
2002	2.7	1.3	1.2	2.5	-0.1	0.7
2003	3.1	1.5	1.3	3.2	0.4	0.5
2004	3.3	2.6	2.4	3.6	0.6	0.8
2005	3.6	2.2	2.0	4.1	1.0	1.0
2006	4.1	3.4	3.2	4.0	1.6	1.5
2007	3.5	3.2	3.0	3.0	1.8	1.6
2008	0.9	0.4	0.1	-0.1	1.0	0.8
2009	-3.8	-4.5	-4.6	-6.5	-1.8	-1.8
2010	-0.2	2.0	2.0	-2.2	-0.7	-0.3
2011	0.1	1.7	1.5	-1.9	0.3	0.3
2012	-1.6	-0.4	-0.5	-4.2	-0.2	-0.3
2013	-1.2	0.1	0.0	-3.0	-0.3	-0.4

Source: Eurostat.

As shown in Figure 1.1, up until 2007, Spanish firms presented lower rates of labour productivity growth than those recorded by their European counterparts (both EU-27 and EU-15). Since that date, however, Spain's growth rates have risen notably taking them to the top of Europe's rankings, with the exception of 2010. This might suggest successful adaptation to the economic crisis; but, the reality is quite different. As can be seen in Table 1.1, the fall in employment in Spain has been much greater than that recorded in the rest of the continent since 2008. As a result, Spanish firms have increased their productivity via the destruction of jobs, as opposed to a production growth. Actually, Spain's GDP growth rate has been lower than Europe's during the last years. This fact raises concern about the role played by innovation, since innovation is a key determinant for economic growth, as emphasized by numerous articles. For this reason, it becomes very interesting to obtain a better understanding of the situation in Spain during these recent years.

All in all, the main goal of this dissertation is to investigate the relationship between innovation and firm performance taking into account the impact of knowledge flows on firm's innovative behaviour and performance, as well as, on firm productivity. To this end, Spanish firms from both manufacturing and services sectors are considered. As it will be seen in next sections, the evidence for Spain is scant. There has been little discussion about involuntary knowledge flows, both external and internal. In addition, most studies are exclusively focused on the manufacturing sector, while little attention has been paid to the service sector. Therefore, this inquiry attempts to modestly contribute to the literature to some extent.

Escalating from a basic and traditional model towards a more complex structural model, each chapter attempts to improve and overcome the limitations encountered along the way. This gradual process has had as a result the following three pieces of research:

- Goya, E.; Vayá, E. and Suriñach, J. (2012) "Productivity and innovation spillovers: Micro evidence from Spain (2004-2009)"[1]. Submitted to *Journal of Productivity Analysis* (2nd round evaluation)
- Goya, E.; Vayá, E. and Suriñach, J. (2013) "Do spillovers matter? CDM model estimates for Spain using panel data"[2]. *SEARCH* working paper collection, WP4/28.

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[1] Presented at the *51th ERSA and 37th AECR Congress 2011*, Barcelona (Spain), August 2011, and *XV Spanish Applied Economics Meetings,* Coruña (Spain), June 2012.

[2] Presented at the *Workshop on Firm Growth and Innovation*, Tarragona (Spain), June 2012; *XVI Spanish Applied Economics Meetings,* Granada (Spain), June 2013*; 40th Annual Conference of the European Association for Research in Industrial Economics*, Évora (Portugal), August 2013; *XXVIII Industrial Economics Meetings*, Segovia (Spain), September 2013; and *XXXVIII Spanish Economic Association Meeting,* Santander (Spain), December2013.

- Goya, E. (2014) “How important are internal knowledge flows for innovative firm’s performance?”. *CIP* Discussion Paper No. 112, University of Reading. Submitted to *Journal of Technology Transfer*.

While it is true that each of the above is a separate paper, they all pursue the same goal: to have a better understanding of the impact of knowledge flows on innovation and productivity in Spain.

The rest of this introduction provides a brief overview of the relationship between innovation and productivity, followed by a basic review of some concepts regarding knowledge flows. Finally, the outline and research questions are summarized in the last section.

1.2 General background

According to the endogenous growth models (Lucas, 1988; Romer, 1986, 1990), economic growth is driven by investments in human capital and innovation, as well as knowledge spillovers. Therefore, both creation and diffusion of knowledge are key elements in economic development.

From an empirical point of view, numerous studies in the previous decades point out the importance of these factors as drivers of productivity. As for human capital, the literature shows its positive influence on productivity; as workers become better trained and acquire more skills, they can carry out tasks more efficiently (Black and Lynch, 1996; Haltiwanger et al., 1999 for the United States; Turcotte and Rennison, 2004 for Canada; Arvanitis and Loukis, 2009 for Greece and Switzerland; Yang, et al., 2010 for China; Lee 2011 for Malaysia).

As far as the purpose of this study is concerned, the relationship between innovation and productivity has been widely studied by many authors since the pioneering work of Griliches (1979, 1986). Investments in innovation activities lead to a higher stock of knowledge and technological capability having as a result new or improved goods and services and/or higher levels of efficiency in the production process. Thereby, innovation may have an impact on increasing sales and/or reducing costs of production; raising productivity consequently. The results obtained from empirical studies seem to depend on the geographical area analysed and the database and methodology used. Yet in general, the evidence certainly points to a positive and significant relationship between innovation and productivity at the firm level (see Chapter 3 for a review). Nonetheless, it is worthy bearing in mind the "file drawer" problem (Rosenthal, 1979). As argue by Tsai and Wang (2004), the empirical evidence could be "over-optimistic" as for the impact of innovation in productivity, since those papers that do not support such a positive effect have a higher probability of not being published.

As mentioned in the previous section, not all of the benefits derived from research efforts are fully appropriable by its producer. On the contrary, when a firm innovates, part of the knowledge generated spills over -being available for others to use it due to the firm's incapacity to keep it within its boundaries. According to Griliches (1979), there are two types of externalities: *rent spillovers* and *pure knowledge spillovers*. The former appears when the market transactions do not reflect the full quality of goods that are purchased at a lower price than their quality improvements, while the latter does not occur in relation to economic transactions but they basically capture flows of ideas and information. Although some studies argue that rent spillovers should not be considered spillovers since they arise from mis-measurements, other papers state the opposite. If a firm pays less than the cost to create the knowledge on its own, then it can be assumed to benefit from spillovers (Keller, 2004). In addition, as Belderbos and Mohnen (2013) point out, rent spillovers can include or be correlated with pure knowledge spillovers. For instance, even if the firm pays a price that reflects the technology embodied in the product, it might own some complementary technology that allows it to obtain a higher profit from the good purchased. Moreover, in order to buy and sell products, face-to-face meetings are sometimes necessary, which may have as a result knowledge flows. In any case, as pointed out by several authors, it is very difficult to distinguish between both types of spillovers empirically. For that reason, most articles employ the general notion of 'knowledge spillovers' [3] (Mohnen, 1996; Ornaghi, 2006; Bloch, 2013).

Another distinction that the literature undertakes is the difference between *explicit* and *tacit* knowledge (Polanyi, 1966). Explicit knowledge can be understood as knowledge which can be codified and which is easier to protect (for instance, in a book). On the other hand, tacit knowledge is embodied in people's abilities being difficult to write down or codify somehow. As Kaiser (2002) points out, tacit knowledge is transmitted involuntarily between firms and, as the author puts it "[it] is a main source of research spillovers".

As mentioned in the previous section, knowledge flows can be considered from different perspectives depending on their "origin" and "willingness". As for the "origin", here it will be distinguished between: i) *internal knowledge flows* (transfers within the firm) and *external knowledge flows* (information coming from outside the company). As regards the "willingness", a distinction will be made between: i) *voluntary* and ii)

[3] In this line, here it is also going to be used this broad concept to refer to any kind of externality related to research activities. For that reason, 'knowledge spillover', 'spillover', 'externality' or 'external knowledge flows' are going to be used interchangeably henceforth.

involuntary. Generally speaking spillovers are involuntary as it is supposed that the firm who innovates would like to appropriate of all the benefits from its investment; thus it is considered that knowledge which spills over firm's boundaries happens involuntarily. However, voluntary knowledge flows can occur if firms decide deliberately to cooperate in order to carry out innovation projects. Although cooperation between firms is beyond the scope of this study, voluntary knowledge flows are going to be taken under consideration when internal transfers are analysed, since the benefits from these internal collaborations are going to remain inside the company (see Chapter 5 for full details).

All in all, the diffusion of knowledge can come about in different ways: movements of workers between firms, scientific articles in journals, conferences, informal communications among scientists, disclosure of patents, reverse-engineering, etc. The result, however, is the same: one firm uses the knowledge generated by others without paying for it directly. Nonetheless, the acquisition of external knowledge is not always free. According to Cohen and Levinthal (1989), firms need to be able to recognize external information in order to absorb it and use it for their own benefit. Being exposed to external knowledge is not enough to acquire it. In their seminal article, the authors develop the notion of "*absorptive capacity*". This ability is acquired through its own investments in R&D, thus firms with greater technological capital are the ones who obtain the most benefit from external knowledge.

Finally, it should be borne in mind that, as knowledge can be transmitted through many different channels, measuring spillovers becomes a complicated task. Thus, despite their recognised importance, there is no established method to quantify them. In fact, several proxies have been used in empirical studies to approximate such effects, having a variety of different conclusions as a result (see Chapter 3 for a literature review). Therefore, although the impact of spillovers on firm productivity have been widely analysed, this topic still continues to catch researchers' attention in both innovation economics as well as industrial organization literature. Capturing knowledge flows and their impact on firms' performance, as well as firms' innovative performance is a challenge to be faced. That is why this dissertation will humbly try to shed some light on this issue.

1.3 Outline of the thesis and research questions

As discussed above, this thesis intends to provide a deeper understanding of the role played by knowledge flows on the relationship between innovation and productivity. Below is a summary of the content of each chapter, along with the research questions that this dissertation seeks to address.

First of all, Chapter 2 presents the data employed in this thesis. The Technological Innovation Panel (PITEC) is described in detail, highlighting its advantages. In addition, evidence for the period under analysis is presented.

Secondly, Chapter 3 analyses the impact that R&D expenditure and intra- and inter-industry externalities have on Spanish firms' performance. While there is an extensive literature analysing the relationship between innovation and productivity, there are far fewer studies in this particular area examining the importance of sectoral externalities, especially focused on Spain. One novelty of this study, conducted for the industrial and service sectors, is that it considers the technology level of the sector in which the firm operates. Following the literature on spillovers, an extended Cobb-Douglas production function is presented. The Olley and Pakes (1996) estimator is applied to control for both selection bias and simultaneity problems providing consistent estimates.

Research questions Chapter 3:

(i) Does the impact of innovation on firm performance differ according to a firm's technology level?

(ii) Are Spanish firms able to benefit from externalities?

(iii) If so, do these benefits vary according to a firm's technology level?

Thirdly, Chapter 4 improves and extends the previous chapter by using 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. This chapter, therefore, is intended to determine the extent to which external knowledge may affect both firms' behaviour (first stage of the model) and firms' performance (last stage). Additionally, the 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.

Research questions Chapter 4:

(i) Is the firm's decision to engage in R&D activities or not affected by what other firms in its sector do?

(ii) Do Spanish firms benefit from innovations carried out by the rest of the firms in its sector and in other sectors?

After having investigated the relevance of external knowledge flows, Chapter 5 aims to analyse the extent to which internal knowledge flows may have an impact on a firm's innovative performance. As most innovation literature has focused its attention on external knowledge transfers, internal knowledge flows have faded into the background.

However, the transference of information and experience within firms can improve their technological performance, impacting positively on their innovativeness and boosting its innovative sales. Voluntary and involuntary knowledge flows are taken under consideration in this chapter as well as firm's absorptive capacity.

Research questions Chapter 5:

(i) Are internal knowledge flows (voluntary and involuntary) important for firm's innovative performance?

(ii) Does this impact differ depending on a firm's absorptive capacity?

Finally, Chapter 6 summarises the main conclusions and draws some policy implications.

Chapter 2: Data

2.1 The Technological Innovation Panel (PITEC)

The dataset used is the Technology Innovation Panel (PITEC)[4], which provides information on the innovation activities of Spanish firms. The National Institute of Statistics (INE), in consultation with a group of experts and under 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 has a panel structure containing information on about 12,000 firms over time. This information comes from successive waves of the Spanish Innovation Survey which is based on the Community Innovation Survey (CIS) following the guidelines of the Oslo Manual (OECD, 2005) and Frascati Manual (OECD, 2002) using a standardized questionnaire. Although these surveys are carried out every two years in most European countries, it is conducted yearly in Spain. Participation in the Spanish Innovation Survey is mandatory. Firms receive the questionnaires via mail and they are requested to complete them in fifteen days. Since 2009 some companies have the option to perform the survey on the Internet.

CIS surveys carried out around Europe have proved to be a powerful tool to study innovation activities, and most papers analysing this topic employ CIS type data. In the case of Spain, PITEC has been used in pioneering innovation studies over the last years (see for instance, García-Vega and Huergo, 2011; Montoro-Sánchez, et al., 2011; Nieto and Rodriguez 2011; Santamaría et al., 2012; Trigo and Vence, 2012; Herrera and Sánchez-González, 2013; Trigo, 2013 to name a few). The reason is that it provides information on individual firm characteristics (employment, sales, exports,

[4] Available on the FECYT website: http://icono.fecyt.es/PITEC/Paginas/descarga_bbdd.aspx

the market in which the firm operates, industry sector, etc.), along with detailed information on innovation activities. For instance, it offers information on different types of innovation expenditures as well as innovation outputs, cooperation, barriers to innovation, public financial support to engage in innovation activities, etc.

PITEC is made up of 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. Although it is carried out since 2003, the information for that year has a severe limitation (only includes samples (i) and (ii)). The restriction was overcome next year incorporating the four samples mentioned above. For that reason, only data from 2004 is used in this thesis.

For the analysis carried out in the upcoming chapters, a filtering process is undertaken. In particular, those observations with any kind of incident (for instance, confidentiality problems, takeovers, mergers, employment incidents, etc.) are eliminated from the sample. Additionally, those observations containing obvious anomalies, such as, null sales are also deleted. Following the population defined in the Spanish Innovation Survey, only firms with ten or more employees are included in the analysis. Furthermore, the sample is restricted to firms belonging to the manufacturing and services sectors (as can be seen in Table 2.1), whereas the primary and construction sector are excluded from the analysis. Besides that, the influence of extreme values has been treated to avoid estimation problems. In particular, those observations of physical capital and innovation expenditures (including R&D) which are two times the volume of sales have been replaced with this value (see Table A.1 in Appendix). The eventual sample is different in each chapter according to the information available when the papers were written.

On the other hand, PITEC can be divided up according to different factors of interest. In the first two chapters of this thesis, the technology level of the sector in which the firm operates is considered. Following the Eurostat classification, firms can be group into the following categories: (i) low and medium-low tech manufacturing industries (LTMI), (ii) medium-high and high-tech manufacturing industries (HTMI), (iii) non-knowledge-intensive services (NKIS), and (iv) knowledge-intensive services (KIS). Table 2.1 provides the correspondence between PITEC and NACE classification by technology level.

Finally, PITEC has a triple advantage. Firstly, it is based on a standardised questionnaire, enabling comparisons with other studies. Secondly, it provides information on both the industrial and service sectors. As will be explained in the upcoming chapters, most studies in Spain focus solely on the manufacturing sector, generally using the dataset *Encuesta sobre Estrategias Empresariales (ESEE)*[5]. PITEC, however, makes possible to overcome this limitation including the service sector under analysis. Finally, it contains a high level of sectoral information covering 55 sectors (following NACE Rev 1.1). This level of detail enables a rich study to be undertaken, examining differences in behaviour between sectors with

[5] The ESEE is a firm-level survey of Spanish manufacturing which has been collecting annual information since 1990.

different technology levels and, in turn, making a more interesting study of inter-industry externalities possible (Chapters 3 and 4)[6].

Table 2.1 Industry classification according to technological intensity

Branches of business activity by 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)

To be continued on the next page

[6] It is worth mentioning that PITEC is representative at sectoral level, but not at regional level. For that reason, spatial analysis cannot be carried out.

Table 2.1 – *continued from the previous page*

Branches of business activity by PITEC	NACE Rev 1.1
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, watches 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.

2.2 Innovation and productivity

As mentioned previously, PITEC offers highly detailed information on innovation activities. It includes several indicators of innovation (from both the input and output sides) as well as of other related variables. In this section definitions of the main variables of interest related to innovation and productivity are presented (however, see each chapter for a detailed definition of all the variables used in the econometric analyses).

First of all, it is worth bearing in mind just how the questionnaire itself is organized. At the outset, firms are asked to answer a set of general questions: that is, to provide information about their business activity, ownership (public, private, etc.), year of creation, sales, exports, number of employees, distribution of employees by level of studies, geographical market in which the firm operates (local, national, European, etc.), innovation expenditures, personnel dedicated to R&D activities, financial support for conducting innovation activities, etc.[7].

Firms are then questioned about their innovation activities. They are specifically asked if they have introduced a product or process innovation or if they have undertaken an innovation project in the preceding three years (either one that is still in progress or that has subsequently been abandoned). These questions serve as a filter, so only those firms that have initiated an innovation project (regardless of its success and regardless of whether it remains incomplete or has been abandoned) go on to answer a

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[7] Unlike PITEC, in CIS questionnaires items related to innovation expenditures or public funding are asked only once firms have confirmed their engagement in innovation activities.

series of additional questions[8]. The additional questions are concerned with finding out about any cooperation agreements they might have signed in order to carry out innovation activities, sources from which firms can obtain information when undertaking or completing innovation projects and the different objectives pursued in their undertaking of innovation activities. Finally, all firms are requested to respond to an additional set of questions, some of which are related to innovation. Thus, for example, they are asked to identify factors hampering innovation activities[9] and about their use of different innovation protection methods. Other questions address non-technological innovations, including, organizational and marketing innovations.

2.2.1 How to measure innovation and productivity with PITEC

According to PITEC, innovation activities include all the scientific, technological, organizational, financial and marketing steps taken in developing or implementing innovations. For that reason, they are known as "innovation inputs" in the literature.

Although of these inputs, R&D investment is usually the most important, it constitutes just one of them. Table 2.2 outlines the different types of innovation expenditures and includes a corresponding brief description.

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[8] R&D expenditure is by definition an innovation activity. Therefore, R&D performers are considered to be firms with innovation activities and so are required to respond to the additional set of questions.

[9] The fact that this question is asked to the whole sample (not only to firms with innovation activities) has generated counter-intuitive results in the literature of obstacles to innovation using CIS type data. The reason is that, in general, innovative firms are the ones who perceive these barriers (see Savignac, 2008, and D'Este et al., 2008).

Table 2.2 Innovation activities

Innovation activities	**Definition**
In-house R&D	Creative work undertaken within the enterprise to increase the stock of knowledge for developing innovations.
External R&D	Same activities as above, but performed by other enterprises (including other enterprises or subsidiaries within the group) or by public or private research organizations and purchase by the firm.
Acquisition of machinery, equipment and software	Acquisition of advanced machinery, equipment (including computer hardware) or software to produce innovations.
Acquisition of external knowledge (not included in R&D)	Purchase or licensing of patents and non-patented inventions, know-how, and other types of knowledge from other enterprises or organizations for the development of innovations.
Training for innovative activities	Internal or external training for firm's personnel specifically for the development or introduction of innovations.
Market introduction of innovations	Activities for the market introduction of firm's innovation, including market research and launch advertising.
Design and others	Activities to design, improve or change the shape or appearance of innovations, and other activities to implement innovations (not included in the previous categories).

Source: PITEC and CIS.

The outcome of investment in innovation activities is an innovation, referred to as the "innovation output". Here, two types of innovation are considered: product and process innovations[10].

PITEC defines a product innovation as the market introduction of a new, or significantly improved, good or service, in terms of its basic characteristics, technical specifications, incorporated software or other components, or user friendliness. It can be originally developed by the firm or by others, but it has to be new to the firm in question, although not necessarily to the market. As such, a distinction can be drawn between product innovations that are new to the firm and the market (what some authors refer to as "radical" or

[10] PITEC also provides information about non-technological (organizational and marketing) innovations as well as about patents.

"true" innovations) and product innovations that are new only to the firm (or "incremental" innovations or "imitations"). Indeed, PITEC provides information about their respective economic impacts; that is, the percentage of total sales attributable to true innovations and the percentage attributable to incremental innovations.

A process innovation, by contrast, is defined as the implementation of a new, or significantly improved, production process, distribution method or supporting activity[11]. As with a product innovation, it may have been developed by the firm or by others and, while it has to be new to the firm, it does not have to be new to the market.

It is worth mentioning that while input innovation variables refer to the current period (*t*), innovation output indicators refer to the preceding three years [*t-2, t*].

The concept of productivity has been defined in many different ways in the literature, the definition depending basically on the availability of data. Here, the information available on PITEC allows us to compute labour productivity[12], a measure that has been widely used in the literature to approximate productivity, especially by those authors that use CIS data. Examples of studies adopting this approach include Harhoff (1998) for Germany; Los and Verspagen (2000) for the USA; Lotti and Santarelli (2001) for Germany and Italy; Wakelin (2001) for the UK; Vivero (2002) for Spain; Aiello and Cardamore (2005, 2008) for Italy; Ballot et al. (2006) for France and Sweden; Kafouros and Buckley (2008) for the UK; Mate

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[11] Purely organizational innovations are excluded.

[12] PITEC does not contain any data on intermediate inputs or any information from which to build input cost shares, which would be required to compute the total factor productivity (TFP).

and Rodriguez (2008) for Spain; Ortega-Argiles (2010, 2011) for Europe and Segarra-Blasco (2010) for Catalonia. Given that PITEC is the Spanish version of the CIS questionnaire, labour productivity – defined as firm sales per employee – is adopted here.

2.2.2 Evidence for the period 2004-2011

In this section the evolution taken by innovation and productivity is presented, along with evidence of the level of technology of the sector in which firms operate, to determine whether differences exist with regard to this factor.

Table 2.3 Evolution of innovation 2004-2011 (in %)

	2004	2005	2006	2007	2008	2009	2010	2011
Innovation input								
Firms with innovation activities	5128	6424	5988	5605	5202	4868	4473	4036
Share of firms with innovation activities	67.8	70.9	67.3	65.0	62.8	61.8	59.7	57.2
Share of firms with R&D expenditures[1]	64.7	64.4	58.9	56.8	54.9	52.7	51.1	49.9
Intensity of innovation activities[2]	1.31	1.55	1.49	1.54	1.71	1.66	1.73	1.58
Innovation Output								
Share of firms with an innovation output	65.1	72.1	72.3	70.7	71.6	73.8	74.9	63.0
Process innovation	50.0	55.9	57.4	54.6	56.7	60.1	61.7	48.6
Product innovation	50.4	55.0	54.4	52.2	54.3	57.0	58.3	46.2
New firm[3]	77.4	77.7	76.5	76.9	77.9	77.5	77.7	77.7
New market[3]	60.1	56.6	56.9	58.8	59.9	57.5	56.7	58.1

Notes: Input innovation variables refer to year *t*, while innovation output indicators refer to the period [*t*-2, *t*]. [(1)] It includes internal and external R&D. [(2)] Intensity is defined as total innovation expenditures over sales. [(3)] Share of product innovators with an innovation new only to the firm (market). Source: PITEC; own calculations.

As shown in Table 2.3, the share of firms reporting involvement in innovation activities has fallen since 2005 as has the share of firms investing in R&D. As can be seen, most firms engaging in innovation do so, at least, in R&D (but not exclusively), with only about 7% of firms engaging in innovation activities other than R&D. Interestingly, even though the proportion of innovative firms has decreased, the intensity of investment has risen. In particular, since 2008 the percentage of innovation expenditures over sales has presented a higher coefficient than in earlier years (for instance, total innovation expenditures represented 1.73% of sales in 2010). However, in 2011 this figure had fallen to levels comparable with those for 2007.

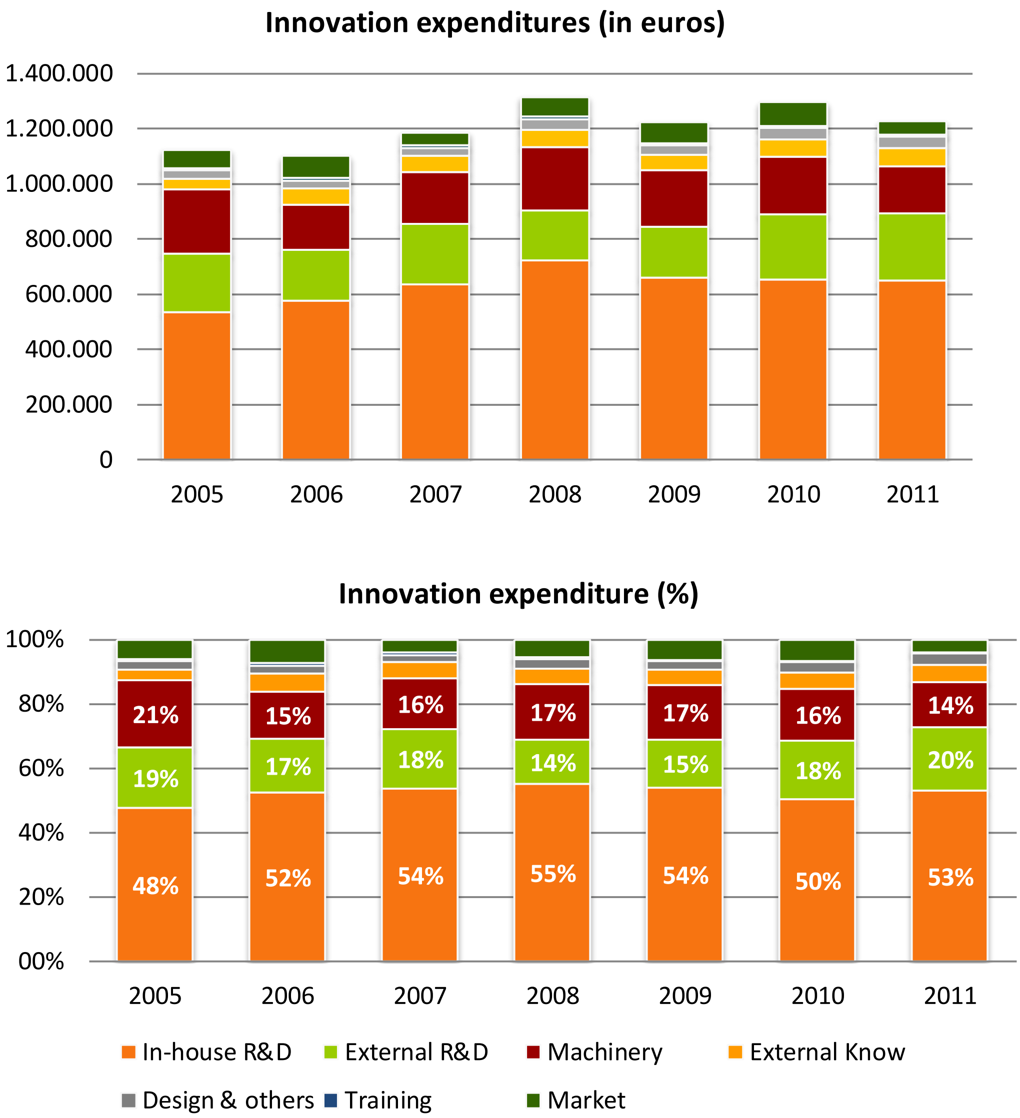
Figure 2.1 allows us to analyse the distribution of innovation expenditure and its intensity over the period 2005-2011[13]. The first graph indicates that, in real terms, innovation spending has risen, since the average innovation expenditure in 2011 was higher than that in 2005. The second graph shows that the distribution seems to have remained stable over time. Specifically, around three quarters of total innovation expenditure is dedicated to R&D (internal and external), some 17% to the acquisition of machinery, equipment and software, with the remaining being distributed among the other four categories. Finally, Figure 2.2 indicates that, in general, R&D (internal and external) accounts for a large proportion of the innovation intensity, followed by investment in machinery, equipment and software. In-house R&D intensity presented a positive trend up to 2008 before falling. Similar results can be found for investment in machinery, while the opposite is true for external R&D intensity, which has increased after 2008.

An examination of the innovation output measure (see Table 2.3) indicates that, on average, around 70% of firms have made at least one innovation in the period 2004-2011, the percentage being slightly higher for process than for product innovations. In terms of novelty, about 77% of product innovators have developed a product that was new to the firm (though not

[13] Information on training, market, design and other innovation activities is available from 2005 onward.

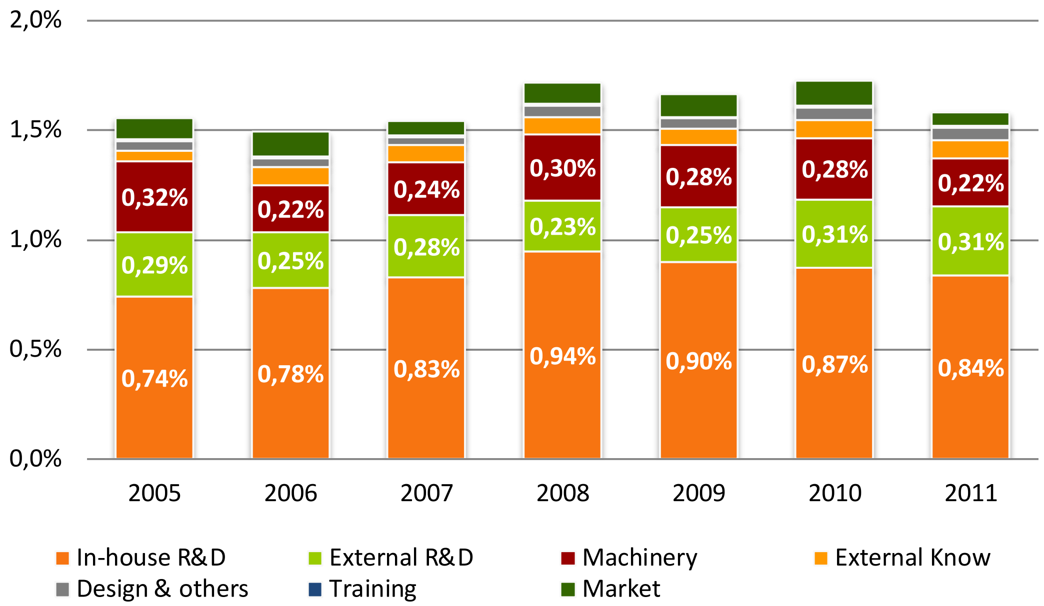
to the market), while this number fell to 58% when considering a "true" innovation.

Figure 2.1 Distribution of innovation activities. 2005-2011



Source: PITEC, own calculations.

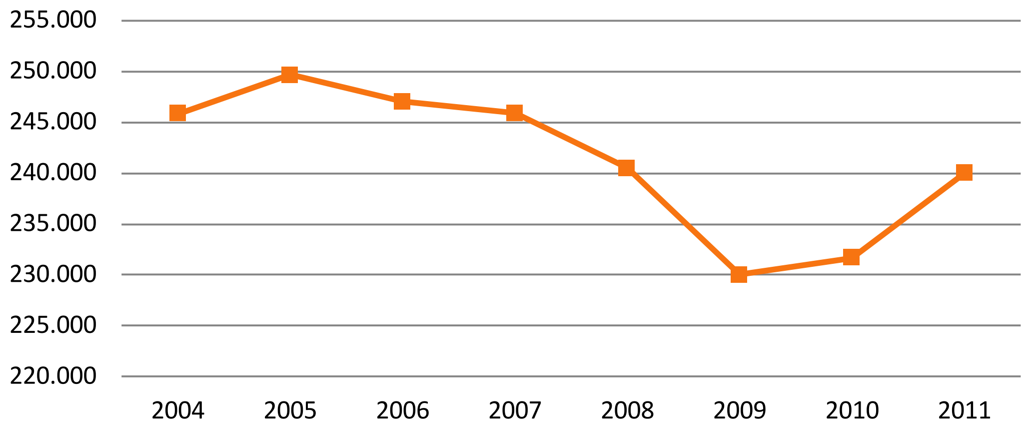
Figure 2.2 Innovation intensity. 2005-2011



Source: PITEC and own calculations.

Figure 2.3 shows a fall in productivity between 2005 and 2009, at which point it began to climb. As discussed in the first chapter, however, this ratio may have been affected by the evolution of employment. Specifically, the rise recorded in recent years could be due to a fall in the number of employees as opposed to an actual increase in sales. The information supplied by PITEC does not seem to capture this trend over the last few years (i.e., no reduction in employment); however, it should be borne in mind that these graphs show the sample aggregated. In other words, it is possible that in recent years some firms might have suffered the effects of the economic crisis and reduced the size of their workforce (and/or their sales), especially small and medium-sized firms, whereas large companies with huge workforces may not have experienced the same difficulties.

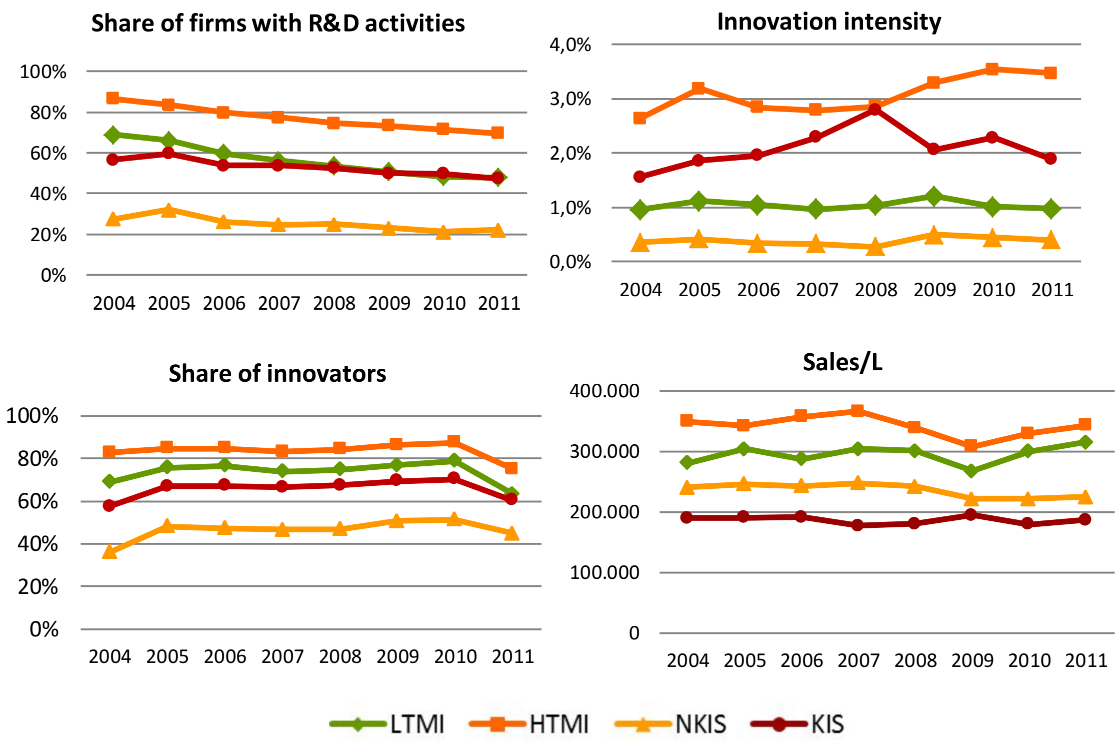
Figure 2.3 Productivity (Sales/Employment) 2004-2011



Source: PITEC; own calculations.

Finally, an examination is undertaken to determine whether there are differences according to the level of technology of the sector in which a firm operates. First of all, Figure 2.4 shows that high-tech manufacturing industry (HTMI) has the greatest share of firms engaged in R&D activities, while firms belonging to the non-knowledge intensive services (NKIS) have the lowest proportion. It can also be seen that the advanced sectors (HTMI and KIS) are those with the highest ratios of investment in innovation (over sales) and the ones that have recorded some growth during this period. For instance, high-tech manufacturing firms increased their innovation intensity from 2.64% in 2004 to 3.46% in 2011. In contrast, less advanced sectors (LTMI and NKIS) present the lowest levels of intensity and a constant ratio over the period. On the output side, it can be seen that the proportion of firms achieving an innovation (product or process) was, on average, 84% for high-tech manufacturing firms, 74% for low-tech manufacturing firms, 66% for knowledge intensive services and 46% for non-knowledge intensive services. As shown, up to 2010, there was a positive evolution, regardless of the level of technology; however, since that date, the percentage of innovators has fallen. Finally, overall productivity is highest in the manufacturing sector, while service firms, especially knowledge-intensive service firms, present the lowest values.

Figure 2.4 Evolution according technology level



Source: PITEC; own calculations.

In short, the results presented in this chapter highlight that there are, indeed, differences in both innovation input/output and in productivity with the level of technology employed by a firm. As a result, this factor is taken into consideration in the following chapters.

Chapter 3: R&D, firm performance and spillovers

3.1 Introduction

As discussed in the introduction of this dissertation, the decline in GDP highlights the importance of innovation as an economic growth factor. This raises a number of questions that need to be addressed: Does Spain suffer from a lack of innovation activity? Or is Spain unable to translate its investments into production growth? This last issue is critical, since it is widely acknowledged that if a firm can increase its productivity it is likely to gain in competitiveness, an essential attribute in today's globalized world.

In recent decades, the number of studies examining the relationship between innovation and firm productivity has increased (see following section for a literature review). In general, the findings stress the importance of R&D as a determinant of economic performance. According to the Frascati Manual (2002): "Research and experimental development (R&D) comprise creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society and the use of this stock of knowledge to devise new applications".

As stated by the *Lisbon Strategy,* all EU members were expected to be investing 3% of their GDP in R&D activities by 2010. Since most countries failed to reach the target, the *Europe 2020 Strategy*, approved in 2010, opted to maintain the same objective for the next ten years. Thus, the member states are expected to invest 3% of their GDP in R&D activities by 2020. Despite this, a number of countries have adopted their national R&D intensity targets, which is the case of Spain. Specifically, the Spanish government has set an R&D intensity target of 2% (0.8% of this investment to be made by the public sector[14] and 1.2% by the business sector).

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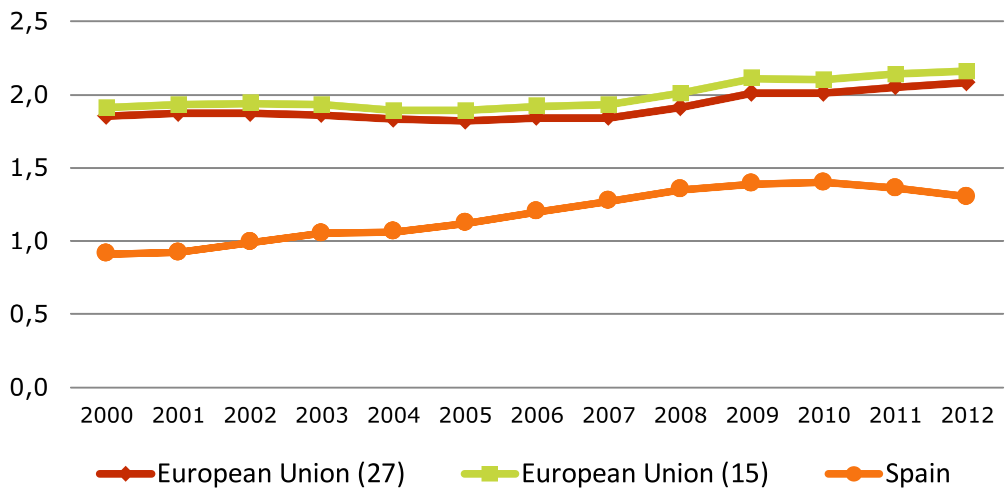
[14] Public sector includes the government and the higher-education sector.

As shown in Figure 3.1, up until 2009 Spain presented a positive evolution in its investment in R&D. The European Commission reported that Spanish R&D intensity increased with an annual average growth of 4.3% over the period 2000-2009, well above the European average. However, after that date, and contrary to the overall trend in Europe, Spanish R&D intensity has fallen reaching just 1.3% of GDP in 2012[15].

Figure 3.1 Gross domestic expenditure on R&D (% of GDP)

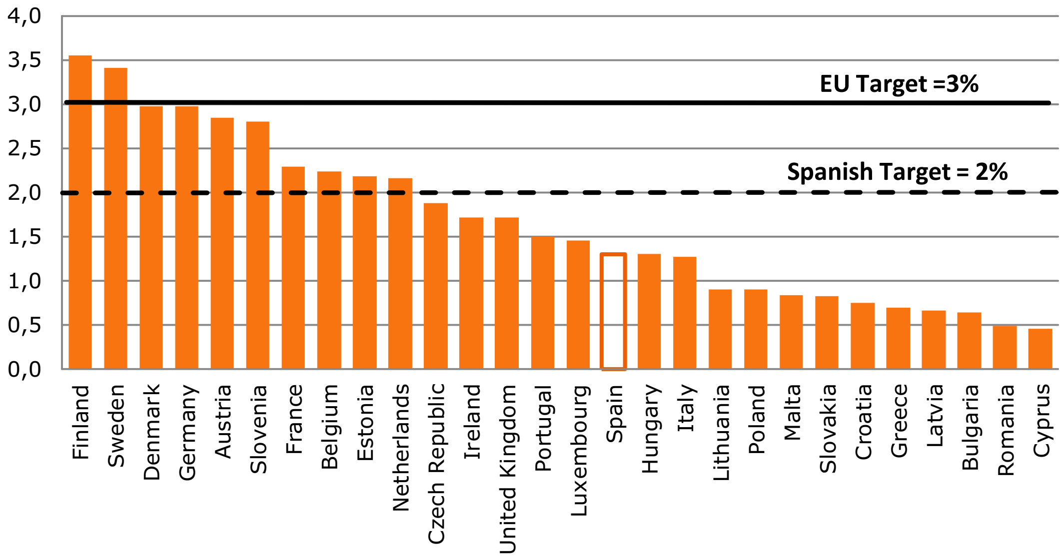


Source: Eurostat; own representation.

In general, R&D investment has grown substantially in Spain over the last decade. Nevertheless, despite this positive evolution, investment levels are still below European levels (2.08% for EU-27 and 2.16% for EU-15 in 2012) and fall well short of meeting the target set for 2020 (see Figure 3.2).

[15] This figure can be broken down according to the source of funding: 0.69% was invested by the business sector and 0.61% by the public sector (0.25% by the government and 0.36% by higher education) in 2012.

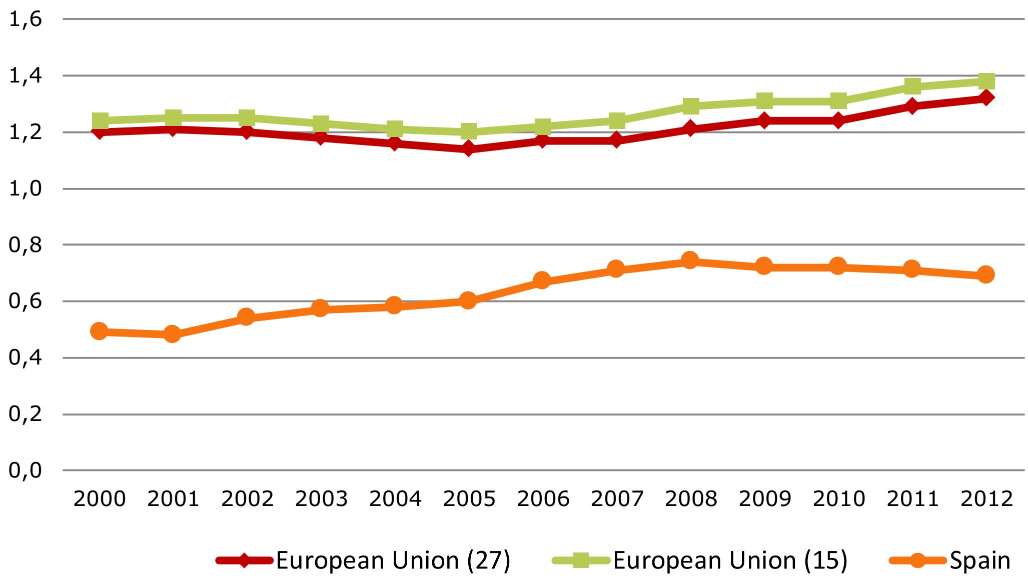
Figure 3.2 Gross domestic expenditure on R&D in 2012 (% of GDP). Cross-country comparison.



Source: Eurostat; own representation.

A considerable amount of this R&D investment is undertaken by the business sector. Specifically, roughly two thirds of the total R&D intensity should be carried out by the private sector. Figure 3.3 highlights two facts: first, Spain's business R&D to GDP ratio is much lower than that of the European Union and, second, private R&D investment has been affected by the economic crisis. Although, in general, Spain presents a positive evolution, since 2008, investment in R&D has gone into decline, unlike in the rest of Europe, where investments present a positive trend. Based on the national target, Spain faces a major challenge with the private sector having to increase its R&D intensity from 0.61 in 2012 to 1.20% in 2020.

Figure 3.3 Business sector expenditure on R&D (% of GDP)



Source: Eurostat; own representation.

On the basis of the previous discussion, it is essential to gain a better picture of Spain's R&D-productivity relationship if we are to further our understanding of it and if we hope to design policies that can raise productivity, especially in the current economic climate. For this reason, the primary goal of this chapter is to analyse the relationship between R&D and firm performance in Spain over the last few years. In the light of previous studies that report differences in the productivity gains attributable to innovation in accordance with a firm's level of technology, and given that few studies of the Spanish case take this factor into account, here we assess whether differences can be found between high- and low-tech firms.

Additionally, as explained in section 1.2, it should be borne in mind that the knowledge derived from a firm's investment in innovation is likely to spill over, given its inability to reap all the benefits from its investment. Therefore, when examining the impact of innovation on productivity, the diffusion of the innovation and any externalities generated also need to be taken into account. Several papers have analysed the importance of spillovers; however, there has been little discussion about this aspect from a sectoral perspective, particularly in Spain. Thus, the second goal of this chapter is to study the extent to which a firm's performance is influenced by the innovation carried out by other firms in the same sector (intra-industry externality) or by the innovation activities of firms in other sectors (inter-industry externality).

The study is conducted using PITEC (see Chapter 2 for a full description of the database) for the period 2004 to 2009. The Olley and Pakes (1996) estimator is adopted for the econometric analysis. By doing so, unobserved heterogeneity, simultaneity issues and selection biases can be accounted for. These are common problems that arise when a productivity analysis is carried out. However, by using this method, consistent and reliable coefficients can be obtained.

To sum up, the aim of this chapter is twofold. First, it seeks to analyse the extent to which the technology level of Spanish firms affects their returns from their investment in innovation. Second, it assesses how this factor influences potential knowledge flows from other firms' innovations, both intra- and inter-industry externalities. Thus, this chapter aims to answer the following questions: (i) Does the impact of innovation on firm performance differ according to a firm's level of technology? (ii) Are Spanish firms able to benefit from externalities? (iii) And if so, do these benefits vary according to a firm's technology level?

This chapter is organized as follows. Section 3.2 presents the literature review, section 3.3 the model, section 3.4 describes the variables used in the analysis, section 3.5 shows the results, section 3.6 presents some further explorations and finally the conclusions are drawn in section 3.7.

3.2 What do we know so far?

Since the pioneering work of Griliches (1979, 1986), the relationship between innovation and productivity has been widely studied by many authors at both national and sectoral levels as well as at the firm level. The well-known Cobb-Douglas production function is normally used to conduct the empirical analysis, with the traditional inputs of physical capital and labour being extended to include innovation expenditures. In general, the evidence reveals a positive and significant relationship between innovation and productivity at the firm level (see 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 Ballot et al., 2006 for France and Sweden; Ortega-Argilés et al., 2010 and 2011 for European firms). However, the results obtained seem to depend on the geographical area being analysed as well as on the nature of the database and methodology used.

It is worth mentioning that most of these articles undertake cross-country analyses, and pay scant attention to the impact that the sector in which a firm operates might have. As stressed in the previous section, the first goal in this chapter is to determine whether there are any differences in the impact of innovation on productivity depending on the level of technology of the firm's sector. Empirical evidence to date suggests that the impact of R&D expenditures on a firm's productivity is more marked in high-tech sectors than it is in their low-tech counterparts (see Verspagen, 1995 for nine OECD countries; Tsai and Wang, 2004 for Taiwan; Ortega-Argilés et al., 2010 and 2011 for European firms).

In addition, this chapter seeks to determine if the stock of knowledge available at the firm level is dependent on both the firm's own innovation and on externalities. As discussed above, the benefits derived from innovation in a firm (or sector) are likely to spill over because of the firm's inability to channel all of the benefits obtained from its investment effort. Thus, a firm's performance can be explained by its own knowledge as well as by the knowledge generated somewhere else which is in the public domain. For this reason, externalities need to be taken into consideration.

From an empirical perspective, most articles employ a production function where spillovers are included as an additional input (following Griliches, 1979). Although there has been a considerable number of studies that have analysed the impact of R&D spillovers on productivity, a general consensus has yet to be reached on just what that effect might be. Despite the positive impact reported by some authors (Griliches, 1992; Nadiri, 1993; Cincera, 2005 for a worldwide analysis; Wiese, 2005 who reviews various studies conducted in the '80s and '90s; Aiello and Cardamone, 2005 and 2008; Cardamore, 2012 for Italy and Bloch, 2013 for Denmark), others draw different conclusions. For example, Klette (1994), in an examination of the effect of R&D spillovers in Norway for the period 1975-1986, concludes that the impact depends on the technological level of the recipient firm. Thus, only high-tech industries are able to benefit from spillovers; low-tech firms, by contrast, present a negative coefficient. Similarly, Los and Verspagen (2000) study the impact of technological spillovers on the productivity of 7,000 American firms between 1977 and 1991. They consider four definitions of spillovers and offer different conclusions depending on technology level and the kind of estimation conducted (within or between). While within estimations present a positive impact of spillover regardless of the definition adopted, between estimations lead to positive, non-significant and negative results. Harhoff (2000) analyses 443 German firms for the period 1977-1989 and finds that the effect of spillovers is positive only for high-tech firms and that it is conditioned by the firm's own R&D intensity. However, negative elasticities are reported for firms in less sophisticated industries. Wakelin (2001) investigates the impact of intra- and inter-industry spillovers on the productivity of 170 UK manufacturing firms between 1988 and 1996. Although spillovers are not a relevant factor in the enhancement of productivity in general, when firms are separated according to their innovation history new evidence comes to light. Specifically, firms belonging to sectors defined as "net users of innovation" present a strong positive impact of intra-industry spillovers. Kafouros and Buckley (2008) using a balanced panel of 117 UK manufacturing firms for the period 1995-2002 analyse intra- and inter-industry externalities according to technology level and firm size. Their findings show that high-tech firms are able to benefit from the innovation of others; whereas low-tech firms present a negative coefficient. Firm size is also a relevant factor in this study, with small firms increasing their labour productivity with both types of externalities, unlike large firms which record a negative impact from intra-industry externalities. Finally, Medda and Piga (2014) study the impact of intra- and inter-industry spillovers on the TFP growth of 3,077 Italian firms from 1998 to 2000. While intra-industry spillovers present a clearly positive coefficient, inter-industry externalities show different effects. Specifically, spillovers originating from supply sectors have a positive impact whereas knowledge coming from customers presents a negative coefficient.

Overall, the evidence is unclear, with spillovers having an apparently heterogeneous effect (being positive, negative or not significant). Yet, it should be borne in mind that the results are conditioned by the sector or country under analysis and that they are highly dependent on the way in which externalities are quantified. In this regard, it seems that most papers opt to use a weighted sum of R&D as a measure of spillover. However, there is no general agreement on how these weights should be defined. The guiding idea is that the closer two firms are the more likely it is that spillovers will occur[16]. This proximity can be measured in different ways with technological similarity, geographical distance and commercial relations being the principal types considered in the literature. In the case of the former, technological proximity, most papers follow Jaffe (1986), who defines proximity between firms using patent data (Cincera, 2005). Others, however, employ a set of firm characteristics in their approximations (Aiello and Cardamore, 2008). The strand of the literature that uses geographical distance to formalise spillovers relies on the idea that the greater the spatial proximity the more firms can gain from each other's knowledge[17] (Bloch, 2013). Finally, some researchers adopt an input-output approach using trade flows to weight the external pool of knowledge; thus, the more commercial relationships a firm establishes, the more it will benefit from the research activities of these other firms (Medda and Piga, 2014). To sum up, although the importance of spillovers is beyond question, how they should be measured at the micro level and what their effect is on firm performance remain far from clear.

If we focus on the case of Spain, the relationship between innovation and productivity has been examined by a number of authors, who conclude that innovation has a positive impact on productivity. However, a general limitation of most of these studies is that their analyses are restricted to

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[16] Interestingly, Nooteboom et al. (2007) point out that being too far apart or too close is not beneficial for a firm. If two firms have very different knowledge bases there is less chance of knowledge flowing, whereas if there are overlaps because firms are very similar technologically then there are fewer learning opportunities or complementarities.

[17] Despite the importance of spatial proximity (see Audretsch and Feldman, 1996; Döring et al. 2006), its analysis lies beyond the scope of this study.

manufacturing firms based on the *ESEE* dataset. Among the most recent papers employing this database we find Vivero (2002), Huergo and Moreno (2004), Huergo and Jaumandreu (2004a), Maté-García and Rodríguez-Fernández (2002, 2008), Rodríguez-Fernández and Maté-García (2006), Rochina-Barrachina et al. (2010) and Casiman et al. (2010), to name but a few. By contrast, only a few papers have carried out a joint analysis of both manufacturing and service sectors, most notably Segarra-Blasco (2010) and Segarra-Blasco and Teruel (2011) who analyse the case of Catalonia using data from the fourth Community Innovation Survey (CIS4).

In the case of external knowledge, far too little attention has been paid to the effect of spillovers on the productivity of Spanish firms. Some articles, including Ornaghi (2006), argue that externalities are positive and significant in explaining productivity. In this study the impact of spillovers on productivity growth is examined in 3,151 manufacturing firms from 1990 to 1999. Spillovers are measured by taking into account firm size and the results indicate a positive impact of technological externalities on growth in productivity. However, the results in other studies differ according to the economic sector in which the firm operates and its level of technology. For instance, Beneito (2001) analyses the impact of intra-industry externalities on productivity for 501 Spanish manufacturing firms distinguishing them according to technology level during the period 1990-96. The author concludes that only firms using advanced technologies are able to benefit from the knowledge in their technological neighbourhood. In particular, the spillover effect depends on the intensity of R&D, with firms in the intermediate quartile being the ones that experience the largest productivity gains.

All in all, the question that still needs to be addressed is whether differences are to be found in the returns that Spanish firms obtain from their innovation investments in relation to their technology level. In addition, given the paucity of studies assessing the impact of spillovers in Spain, this chapter will examine if firms in the sample are able to benefit from the innovation carried out by others.

3.3 Model and estimation strategy

The model adopted to estimate the relationship between innovation and firm performance is the extended Cobb-Douglas production function, which apart from including conventional production factors (physical capital and labour) also incorporates human capital and innovation[18]. Human capital has been included in the Equation [3.1] given that the more qualified workers the firm has, the more effectively they are likely to perform their tasks and the more productive the firm is likely to be. Additionally, innovation, the variable of interest in this study, has been included as a production function input. Investment in innovation can reduce the costs of production or raise firm sales, thus increasing production.

$$Y_{ist} = A_{ist} \cdot K_{ist}^{\beta_1} \cdot L_{ist}^{\beta_2} \cdot H_{ist}^{\beta_3} \cdot RD_{ist}^{\beta_4} \qquad [3.1]$$

where Y_{ist} is the output of firm i belonging to sector s in year t, $A_{ist}$is the firm's technology level, $K_{ist}$is physical capital, $L_{ist}$is labour, $H_{ist}$is human capital, $RD_{ist}$is innovation and $\beta_1, \beta_2, \beta_3, \beta_4$, are the returns on each variable respectively.

[18] It should be pointed out that only a few microeconomic studies, especially for the case of Spain, have incorporated human capital and innovation as factors in the production function.

With respect to the technology level A_{ist} in Equation [3.1], in this chapter it is assumed that an external effect exists due to the public nature of knowledge. Hence one firm's level of technology is dependent on the innovation made by all the other firms:

$$A_{ist} = A \cdot \left(S_{ist}^{intra}\right)^{\phi_1} \cdot \left(S_{ist}^{inter}\right)^{\phi_2} \qquad [3.2]$$

where A is a constant denoting a common technology level for all the firms; S_{ist}^{intra} is the intra-industry externality of firm i in sector s capturing the innovative effort made by all the other firms in the same sector; and S_{ist}^{inter} is the inter-industry externality understood as the innovation made by the firms in the rest of the sectors.

Thus by combining Equations [3.1] and [3.2] it can be seen that a firm's output is explained in terms of its own investments (in physical capital, human capital and innovation) and of the knowledge generated outside the firm:

$$Y_{ist} = A \cdot K_{ist}^{\beta_1} \cdot L_{ist}^{\beta_2} \cdot H_{ist}^{\beta_3} \cdot RD_{ist}^{\beta_4} \cdot \left(S_{ist}^{intra}\right)^{\phi_1} \cdot \left(S_{ist}^{inter}\right)^{\phi_2} \qquad [3.3]$$

From Equation [3.3] it can be concluded that (under the assumption that $\phi_1 \neq 0$ and $\phi_2 \neq 0$), even though a firm does not invest in innovation, it can still benefit from the innovation carried out by all the other firms and, thereby, increase its performance.

Expressing [3.3] in log form the following empirical model is specified:

$$y_{ist} = \beta_0 + \beta_1 k_{ist} + \beta_2 l_{ist} + \beta_3 h_{ist} + \beta_4 rd_{ist} + \phi_1 S_{ist-2}^{intra} + \phi_2 S_{ist-2}^{inter} + controls + e_{ist} \qquad [3.4]$$

$$e_{ist} = \omega_{ist} + \eta_{ist} \qquad [3.5]$$

where ω_{ist} is a productivity shock and η_{ist} is the error term. Lower case letters indicates log-transformed variables (with the exception of human capital which is a percentage). See next section for a detailed definition.

As far as the estimation method is concerned, it is well known in the literature that estimates from a production function may suffer from simultaneity as well as selection bias. As such, OLS estimates are biased and inconsistent.

The former problem, simultaneity (first noted by Marschak and Andrews, 1944), arises because productivity shocks (ω_{ist}) are known to the firm but not to the econometrician. Thus, when the firm has to determine the usage of inputs its decision is influenced by its beliefs about productivity. Therefore, input choices will be correlated with productivity shocks. So if a firm faces a positive (negative) productivity shock, its use of inputs is going to increase (decrease) accordingly. Not taking this issue into consideration leads to biased and inconsistent estimates since the error term is correlated with the explanatory variables (breaking one of the basic hypotheses of OLS). The second problem, selection bias, manifests itself because of the exit of inefficient firms (not randomly). A firm with higher capital is expected to obtain higher profits in the future and so is more likely to stay in the market despite a negative productivity shock (given that in the future it is thought it will produce more) than a firm with a lower level of capital[19].

In order to deal with these problems and to ensure the reliability of the coefficients we use the estimator proposed by Olley and Pakes in 1996 (hereafter OP). Other methods are employed in the literature, but they only

[19] Even though the evidence suggests that simultaneity bias is more important than selection bias, the estimator used here controls for both.

address simultaneity bias[20]. In contrast, the OP estimator addresses both simultaneity as well as selection bias[21]. For this reason, this estimation method has been used by several authors who seek to analyse, for instance, the impact of trade and tariffs on firm productivity (see for example, Pavcnick, 2002; Schor, 2004; Amiti and Koungs, 2007; De Loecker, 2007; Loung, 2011; Van Beveren, 2012 and Arvas and Uyar, 2014). While it is true that it is not one of the most common approaches in the innovation literature, some papers have recently applied this estimator to obtain unbiased and consistent estimates of the production function (see Marrocu et al.; 2011 and Añón-Higón and Manjón-Antonlín, 2012).

3.3.1 Olley & Pakes (1996) estimator

Intuitively, the idea behind the OP method is to make "observable" the "unobservable"; in other words, to use an equation to proxy for the unobserved productivity shock. By doing so, the econometrician can control for the correlation between the error term and the inputs and obtain consistent results. Below, the main features of the OP approach are described (using the same notation as that employed by Olley and Pakes,

[20] As shown in the literature, simultaneity problems can be addressed by using instrumental variables or fixed effect estimators. However, given that the panel is short and instrumental variables use lagged values as instruments, their suitability is reduced (facing a problem of weak instruments). The fixed effects estimator, on the other hand, relies on the assumption that productivity shocks are constant over time, which is an excessively strong premise from our point of view, especially bearing in mind the economic situation in the period under analysis.

[21] Another option might be the Levinsohn and Petrin (2003) estimator, but intermediate inputs are needed in this case (and this information is not provided by PITEC). Thus, we strongly believe that the best option available is the OP estimator.

1996)[22]. After that, the changes introduced in order to adapt the method to our case are explained.

First of all, the authors base their analysis on the traditional Cobb-Douglas production function:

$$y_{it} = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + \beta_l l_{it} + e_{it} \qquad [3.6]$$

where the log of output (y_{it}) is explained by the age of the firm (a_{it}), the log of capital (k_{it}), the log of labour (l_{it}) and an error term (e_{it}) that is decomposed in two components: a productivity shock (ω_{it}) and a measurement error term (η_{it}). The former is observed by the firm but not by the econometrician and affects the firm's decision, while the latter is unobserved by both and does not affect firm's decision.

As for the inputs in the production function, the authors differentiate between variable factors (such as, l_{it}), which can be easily adjusted given a productivity shock, and fixed factors (also known as "state variables") which depend on information from the previous period and are costly to adjust with productivity shocks (k_{it} and a_{it}).

As explained by the authors, at the beginning of every period an incumbent firm has to decide whether to exit or to continue in the market. The firm remains in the market if its productivity is higher than a certain threshold (referred to as the "exit rule"). In that case, it has to choose a level of inputs (l_{it}) and a level of investment ("investment decision rule") according to ω_{it}, k_{it} and a_{it}: $i_t = i_t(\omega_t, k_t, a_t)$. Here, it is assumed that $i_t > 0$ and investment is increasing in productivity, conditional on the values of all

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[22] For a detailed explanation of the equations and estimation strategy see Olley and Pakes (1996).

observed state variables (positive productivity shocks will increase the investment in the next period). By doing so, the investment function can be inverted as follows: $\omega_t = h_t(\, i_t, k_t, a_t)$ where $h_t(\cdot) = i_t^{-1}(\cdot)$. As the authors put it "this expression allows us to express the unobservable productivity variable as a function of observables, and hence to control for ω_t in the estimation", thereby removing the simultaneity bias.

The production function can then be rewritten as:

$$y_{it} = \beta_l l_{it} + \phi_t(\, i_{it}, k_{it}, a_{it}) + \eta_{it} \qquad [3.7]$$

where $\phi_t(\, i_{it}, k_{it}, a_{it}) = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + h_t(\, i_{it}, k_{it}, a_{it})$.

This semi-parametric regression model identifies β_l but not β_a or β_k. To do so, estimates of the survival probabilities (P) are needed; that is, the probability of the firm surviving in the market. Using a probit model and the exit rule mentioned earlier these probabilities are computed. By doing so, the model accounts for selection bias. Finally, estimated coefficients of capital and age are obtained running non-linear least squares using $\hat{\beta}_l$, $\hat{\phi}$ and $\hat{P}$.

To summarize, OP methodology comprises three stages. The first one controls for unobserved productivity shocks including the inverse of the investment demand function in the estimation. Thus, as the error term is no longer correlated with the inputs, the simultaneity bias can be removed. The second estimates the survival probabilities in order to address selection bias. The third and final stage obtains the coefficients of the state variables (β_a and β_k) by including the survival probabilities and the inputs estimates computed in the previous steps.

We modify this method slightly to adapt it to our specific requirements. First of all, age is not included in the analysis since this information is not available for all firms[23]. Second, R&D expenditures are incorporated in the analysis. We follow Amiti and Koungs (2007)[24] and include R&D stock as a state variable since treating it as exogenous is inappropriate. As with physical capital, we assume that the decision to invest in R&D is taken in *t-1*. Thus, the investment demand function depends on: $i_t = i_t(\ \omega_t, k_t, rd_t)$. The rest of the procedure is the same as described above, apart from the fact that we include rd_t as state variable instead of a_t.

3.4 Data and variables

The data used in this chapter consist of an unbalanced panel of 9,115 firms (50,349 observations) for the period 2004-2009. For estimation purposes, only firms that remain at least three years in the panel are included in the study since some variables are lagged two periods[25]. This filter leads to a sample which is around 91% of the whole sample (55,303 observations). Table A.2 in the Appendix shows that the sample preserves the properties after applying this filter and that it does not lead to any selection bias.

Next, definitions of the variables used in Equation [3.4] are presented. All monetary variables are expressed at constant values at 2009 base prices (nominal values have been deflated using the GDP deflator).

[23] PITEC includes this information from 2009.

[24] The authors modify the OP framework by introducing the decision to engage in international trade.

[25] Results without this filter remain almost identical.

3.4.1 Dependent variable

Firm output is approximated by the total sales that firm *i* has declared at time *t*.

3.4.2 Independent variables

Inputs

As explanatory variables in Equation [3.4], we include the traditional inputs in the production function, namely, the physical capital stock, computed using the perpetual inventory method (see below) and labour, defined as the number of employees. In addition, human capital, measured as the percentage of employees with higher education, and innovation, defined as internal and external R&D stock[26], are also incorporated in the analysis.

As is widely accepted in the literature[27], a firm's output is assumed to be affected by accumulated stocks of physical capital and R&D expenditure, rather than by current flows. We use the well-known perpetual inventory method:

$$K_t = K_{t-1} \cdot \left(1 - \delta_h^k\right) + C_t$$
$$K_0 = \frac{C_0}{g_s^k + \delta_h^k} \qquad [3.8]$$

and

[26] As acknowledged in Chapter 2, the concept of innovation is very wide including not only R&D expenditure, but also the acquisition of machinery, equipment and hardware/software, training staff directly involved in developing the innovation, introduction of innovation in the market, design, etc. However, it has been seen that most firms that engage in innovation activities also do so in R&D. In addition, R&D is the main component of innovation activities, accumulating three quarters of total spending. Finally, the literature usually approximates innovation by using R&D expenditures. For all of these reasons, here innovation is proxied by R&D stock.

[27] See Hall and Mairesse (1995), Bönte (2003) and Ortega-Argilés *et al.* (2011) to name just a few.

$$RD_t = RD_{t-1} \cdot (1 - \delta_h^{rd}) + RDI_t$$
$$RD_0 = \frac{RDI_0}{g_s^{rd} + \delta_h^{rd}} \quad [3.9]$$

with $t = 2004, \ldots, 2009 \quad h = 1, 2, 3, 4 \quad s = 1, \ldots, 51.$

where C_t is the real investment in material goods and RDI_t is the real R&D expenditure. We apply different depreciation rates according to the technology level (h). 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 apply sectoral depreciation rates of 6 and 7% for physical capital (δ_h^k) and 15 and 18% for innovation (δ_h^{rd}) to low-tech and high-tech sectors respectively[28]. In the case of growth rates, if we use the initial periods for their computation, we lose a considerable amount of information given that our panel has a short time dimension (2004-2009). Thus, we opted to calculate g_s^c and g_s^{rd} as the average rate of change in real investment in material goods and real R&D expenditure in each sector(s) over the period 1995-2003[29]. We used the OECD's ANBERD database to calculate physical capital growth rates (g_s^c) and the OECD's STAN database for innovation growth rates(g_s^{rd}).

Externalities

As discussed in Chapter 1, due to the many different ways in which spillovers can occur (movements of workers between firms, scientific articles in journals, conferences, informal communication between

[28] The results are almost identical if a fix depreciation rate is used (6% for physical capital and 15% for innovation).

[29] 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…".

scientists, disclosure of patents, reverse-engineering, etc.), measuring them is a far from easy task. If we consult the literature, there is no generally accepted method for formalising these external knowledge flows. While R&D expenditures are typically used to approximate existing knowledge in the environment, different weights are employed to measure the influence of this external knowledge on the firm (geographical distance, technological proximity and/or input-output linkages).

The simplest measure to compute, and also one of the most frequently employed in the literature, is the unweighted sum of the R&D stock (Beneito, 2001; Los and Verspagen, 2001; Wakelin, 2001; Bloch, 2013; Medda and Piga, 2014). Thus intra-industry externality corresponding to firm i belonging to sector s is defined as:

$$S_{ist}^{intra} = \sum_{j \neq i} RD_{jst} \qquad [3.10]$$

where RD_{jst} is total R&D stock carried out in sector s at time t (except the firm's own R&D investment); in other words, the total R&D expenditure made by all the other firms in the same sector. As acknowledged in the literature, this definition is open to criticism since it attaches the same weight to all the firms in the same sector. Thus, it assumes that the propensity to benefit from the R&D expenditure in the sector is the same for all firms. However, by employing this definition, the technological effort of the sector in which the firm is located is captured and so it serves as an indicator of the magnitude of the technological effort currently available in the sector.

On the other hand, it can be supposed that firms which maintain commercial relationships benefit from the knowledge embodied in the products in which they trade. Thus, the more they buy and sell, the more they benefit from the knowledge originated in the other sector. This approach has been called into question by a number of authors on the grounds that it does not reflect pure knowledge spillovers. However, given the tacit and "non-codifiable" nature of knowledge, any interaction between firms is likely to create information flows that generate spillovers. In fact, the literature highlights the difficulty of drawing a distinction between rent and pure knowledge spillovers and, for this reason, spillovers here are defined in this broad sense. Additionally, it is believed that using products originated in another sector reflects the knowledge associated with them, assuming that technology is embodied in the purchased goods. For instance, products bought from the IT industry are likely to have an impact on the performance of firms in other sectors. Several authors have used this approach to approximate spillovers (Medda and Piga, 2014). Here, therefore, the inter-industry externality corresponding to firm *i* belonging to sector *s* is defined in the following way:

$$S_{ist}^{inter} = \sum_{\substack{j \neq i \\ m \neq s}} w_{sm} \cdot RD_{jmt} \qquad [3.11]$$

where RD_{jmt} is R&D stock undertaken in all the other sectors and w_{sm} is defined as the quotient between the intermediate purchase by sector *s* of goods and services supplied by sector *m* and the total sum of intermediate purchases of sector *s*. Thus, the influence that the R&D expenditures of firms in sector *m* has 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 weights the symmetric input-output table for Spain for 2005 (the latest year available) has been used. An exercise of correspondence has had to be carried out between the branches of business activity according to which PITEC data are classified and the branches of business activity in the input-output table.

As seen in section 3.2, both positive and negative coefficients are possible. On the one hand, an external pool of knowledge is expected to have a positive impact on the production of other firms, since they can benefit from new knowledge and ideas. However, on the other hand, if rival firms increase their R&D investment a competitive effect might appear. This is what some authors refer to as the "market-stealing effect" (De Bondt, 1996; Bitzer and Geishecker, 2006; Kafouros and Buckley, 2008; Bloom et al., 2013). Therefore, both possibilities need to be taken into consideration.

As can be seen in expression [3.4], both externalities have been lagged two periods, since the assumption of a contemporary relationship between them and firm performance seems inappropriate, given that there is no immediate impact. On the contrary, it is likely that the diffusion of external knowledge takes some time before it can affect the firm[30].

Controls

The regression controls are represented by technology level and a trend to capture time changes[31].

3.5 Results

3.5.1 Descriptive analysis

Table 3.1 shows the descriptive statistics for the main variables in the model across the different technology levels.

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[30] Since the panel is short, externalities have been lagged two years; however, similar results are obtained when they are lagged three or four years.

[31] Although industry dummies would capture technological opportunities as well as specificities of the sector, they cannot be included since this would give rise to perfect multicollinearity with the inter-industry externalities.

First, it can be seen that sales in manufacturing firms vary slightly with the level of technology. However, in the case of the service sector, firms that operate in non-knowledge-intensive services present higher sales than those reported by their counterparts operating in knowledge-intensive services. In the case of physical capital, low-tech firms (LTMI and NKIS) show a somewhat higher ratio than that recorded by high-tech firms (HTMI and KIS). As expected, firms belonging to service sectors are larger (higher number of employees) than manufacturing firms. As far as human capital is concerned, the average percentage of qualified employees is much higher in more advanced firms. Specifically, in knowledge-intensive services approximately 42% of workers have completed higher education, a number that is almost twice that of the average (22.8%).

Innovation is also greater in technologically advanced firms (in both the industrial and service sectors). In particular, firms belonging to non-knowledge-intensive services are the ones that invest least in R&D, with a value (4.97) far below the average (9.95). On the other hand, in both sectors, firms present higher capital stock than R&D stock. This differential is most marked in low tech-firms (13.9 vs 10.3 in the industrial sector and 13.7 vs 5 in the service sector). Thus, low-tech firms would appear to be much more capital intensive than their high-tech counterparts. Finally, the intra-industry externality presents much greater values in high-tech firms (HTMI and KIS) – values that are notably above the average, while the inter-industry externality shows a more uniform distribution.

Table 3.1 Descriptive statistics by technology level

		Total sample		LTMI		HTMI		NKIS		KIS	
		Mean	Sd.	Mean	Sd.	Mean	Sd.	Mean	Sd.	Mean	Sd.
Sales	overall	16.22	1.79	16.24	1.63	16.22	1.60	17.14	1.83	15.78	1.98
	between		1.77		1.60		1.58		1.82		1.94
	within		0.35		0.32		0.32		0.29		0.42
Physical capital	overall	13.50	4.76	13.87	4.88	13.59	4.23	13.73	5.32	12.81	4.74
	between		4.36		4.52		3.87		4.77		4.30
	within		2.09		2.05		1.89		2.46		2.11
Labour	overall	4.44	1.41	4.26	1.20	4.18	1.22	5.10	1.60	4.59	1.60
	between		1.40		1.18		1.21		1.60		1.59
	within		0.19		0.18		0.17		0.18		0.23
Human capital	overall	22.79	25.66	12.16	13.61	20.88	18.64	13.93	20.03	42.25	33.26
	between		23.58		11.63		16.63		17.55		29.95
	within		10.44		7.13		8.77		9.79		14.78
Innovation	overall	9.95	5.99	10.35	5.43	12.69	4.10	4.97	6.15	9.22	6.44
	between		5.78		5.23		3.92		5.96		6.20
	within		1.45		1.49		1.26		1.57		1.52
Intra-industry externality	overall	698.9	699.05	386.43	276.54	1205.35	671.75	425.35	475.17	755.31	879.20
	between		674.74		267.28		655.30		406.28		839.13
	within		190.49		70.05		130.33		251.15		286.08
Inter-industry externality	overall	489.5	180.90	525.75	163.62	556.25	142.74	426.85	250.83	410.46	153.60
	between		147.92		124.95		89.01		237.09		113.94
	within		103.94		106.42		112.56		74.42		104.37
Obs		50,349		17,470		12,764		6,483		13,632	
(%)				(34.7)		(25.3)		(12.9)		(27.1)	
Firms		9,115		3,160		2,291		1,152		2,512	
(%)				(34.7)		(25.1)		(12.6)		(27.6)	

Notes: LTMI (low and medium-low tech manufacturing industries), HTMI (medium-high and high tech manufacturing industries), NKIS (non-knowledge-intensive services), KIS (knowledge-intensive services). Between variation means variation across individuals and within variation means variation over time around individual mean. Source: PITEC; own calculations.

In order to test whether there are differences in sales according to technology level, we conducted a Kruskal-Wallis test. The result clearly rejects the null hypothesis (p-value=0.0001) of equal population medians[32].

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[32] The nonparametric Kruskal-Wallis test is a safer alternative than parametric tests in which there are concerns about the normality assumptions or suspicions of outlier problems.

In addition, from Table 3.1 it can be seen that between variation, i.e. variation across individuals, is much higher than within variation, i.e. variation over time for each individual (around the individual mean).

3.5.2 Empirical results

In this section we present the results of the estimates of Equation [3.4]. For this we use the OP estimator using the “opreg” command from Stata (Yasar, et al. 2008) to account for the existence of simultaneity and selection bias. To derive the OP estimator, we define physical capital stock and R&D stock as “state variables” (since they are quasi-fixed inputs), we consider labour, human capital and externalities as “free” inputs, the investment in both physical capital and R&D is our “proxy variable” (or in other words, the variable that controls for unobserved productivity) and, finally, the remaining variables are controls.

Table 3.4 shows the results of the estimation for the sample as a whole and for the sub-samples according to the technology level of the sector in which the firm operates. Our aim is to determine whether there are differences in the returns firms obtain from their own R&D expenditures and those obtained from externalities.

First, it can be seen that, in general, capital stock has a positive impact on firm performance. Second, the results presented in Table 3.4 show a positive elasticity regarding the number of employees and, in consonance with previous research, our findings highlight the role played by human capital in firm performance.

In line with the literature, R&D stock has a positive impact on the sample as a whole. However, once the level of technology is taken into account, only firms belonging to the knowledge-intensive service sector present a positive influence. Surprisingly, in the rest of the sectors the level of a firm's output is not related to R&D stock. Although this finding is not common in the literature, it is not as counterintuitive as it might seem at first glance. First of all, this result could be related to the motive to invest in R&D. If firms undertake R&D investment in order to reduce the taxes they have to pay, their expenditure does not necessarily increase their production. Second, as pointed out by Griliches (1979), R&D investments might take several years to have an impact on a firm's performance. Finally, this result is in line with the new approach introduced by Crépon, Duguet and Mairesse (1998). In their seminal paper the authors argue that R&D expenditures do not have a direct effect on firm productivity, or as the authors say "we explicitly account for the fact that it is not innovation input (R&D) but innovation output that increases productivity" (page 116). To sum up[33]: it is the firm's capacity to generate innovations and its ability to translate innovations into economic performance, rather than R&D investment itself, that might have an impact on firm's production. It is our belief that this line of thinking is quite logical and, moreover, it helps shed light on the results obtained here. Bearing this in mind, the differences reported here in relation to the level of technology may suggest, first, that firms in the knowledge-intensive service sector have a greater capacity to manage their R&D expenditures efficiently. KIS sectors are characterised by high technology industries (such as telecommunications, research and development and computer activities) that could be more adept at transferring their research effort into innovations, which in turn have a positive impact on production. Second, manufacturing firms may need more time to generate innovation outcomes from their R&D investments. For instance, from some interviews conducted

[33] It should be borne in mind that the aim here is not to compare the two approaches, but rather to provide a plausible explanation for the results obtained.

with Spanish firms it emerged that R&D may take from four to ten years in the automotive, pharmaceutical or chemistry industry to materialize into new products. Whereas in the KIS sector new software or a new mobile phone application, for example, may need less time to be implemented and to be profitable.

Table 3.2 OP estimates. Estimation results of Equation [3.4] 2004-2009. Dependent variable: ln(sales).

	Total (1)	LTMI (2)	HTMI (3)	NKIS (4)	KIS (5)
Physical capital	0.0367*** (0.0068)	0.0260*** (0.0081)	0.0284*** (0.0097)	0.0218 (0.0170)	0.0567*** (0.0164)
Labour	0.8793*** (0.0101)	0.9464*** (0.0181)	0.9817*** (0.0221)	0.8786*** (0.0267)	0.8000*** (0.0177)
Human capital	0.0030*** (0.0004)	0.0058*** (0.0009)	0.0026*** (0.0008)	0.0082*** (0.0018)	0.0019** (0.0007)
R&D stock	0.0122** (0.0053)	0.0108 (0.0069)	-0.0059 (0.0110)	0.0012 (0.0131)	0.0314*** (0.0112)
Intra-industry externality	-0.0000* (0.0000)	0.0004*** (0.0001)	0.0000* (0.0000)	0.0010*** (0.0001)	-0.0003*** (0.0000)
Inter-industry externality	-0.0002** (0.0001)	-0.0001 (0.0001)	0.0004* (0.0002)	0.0007*** (0.0001)	-0.0012*** (0.0001)
Trend	-0.0131* (0.0069)	-0.0394*** (0.0098)	-0.0855*** (0.0186)	-0.1925*** (0.0168)	0.1240*** (0.0133)
HTMI	0.0835*** (0.0217)				
NKIS	0.1359*** (0.0377)				
KIS	-0.7224*** (0.0275)				
Obs	50,349	17,470	12,764	6,483	13,632

Note: Low and medium-low tech manufacturing industries (LTMI), medium-high and high tech manufacturing industries (HTMI), non-knowledge-intensive services (NKIS), and knowledge-intensive services (KIS). Externalities are lagged two periods. Reference group: LTMI. Bootstrapped errors in parenthesis (100 replications).*** Significant at 1%, ** significant at 5%, * significant at 10%.

As for the intra-industry externalities, although very small, they present a negative coefficient in the sample as a whole. Thus, if the rest of the firms in the same sector increase their R&D expenditure, the production of the firm falls. Although, if other firms invest in R&D, the pool of knowledge available in the sector will rise, a competition effect may also appear as firms might be rivals. This could compensate for, or even come to dominate (as in this case), the benefits derived from the R&D investment of others, suggesting the existence of a "market-stealing effect".

The breakdown by technology level illustrates that, in general, intra-industry externalities have a positive effect on firm output, except in the case of firms operating in knowledge-intensive services that show negative return from intra-industry externalities. Although a negative coefficient is not an "attractive" result, it is completely plausible since firms in this sector are characterised by a higher degree of technology and this might give rise to a higher degree of competition. In contrast, the impact is positive on the rest of the sub-samples. This may seem to contradict the fact that firms do not increase their production with their own R&D expenditures; however, the lack of ability to turn investments into innovation does not mean they cannot benefit indirectly from external knowledge. A possible explanation might be that firms use the existing external knowledge in the sector to imitate or "copy" what other firms do, thus acting as "free-riders". By doing so, they benefit from the R&D expenditures of others and increase their sales. Additionally, it might reflect the fact that firms might observe the results of their competitors' investment (their successes and failures) and learn from them, using this external pool of knowledge to be more efficient in their own production.

In contrast to Beneito's (2001) findings, here it can be seen that firms operating in advanced high-tech sectors (HTMI and KIS) benefit less from the R&D expenditure made by all other firms in their sector than is the case of firms in less technologically advanced sectors (LTMI and NKIS). There would appear to be, therefore, a "technology threshold" beyond which firms benefit less from the R&D expenditure made by all other firms in the sector.

This might reflect the fact that in high-tech sectors (especially in KIS) there is a competition effect which compensates for (or even dominates) the benefits stemming from external R&D, unlike the situation that prevails in low-tech sectors.

As for inter-industry externalities, our estimates present a high degree of heterogeneity. First, in the sample as a whole they affect firm's sales negatively. Second, when the sample is broken down according to technology level, these externalities are not significant for firms operating in low-tech manufacturing industries. This suggests that firm performance is not influenced by the innovation carried out by the rest of the sectors that serve as its suppliers. On the contrary, their effect is positive and significant in the case of high-tech manufacturing industries. This result is consistent with the "absorption capacity" hypothesis forwarded by Cohen and Levinthal (1989), which suggests that the degree to which a firm benefits from external innovation is strongly dependent on its own innovation expenditure. Thus, firms with greater technological capital are the ones that obtain the most benefits from externalities. Advanced firms have better infrastructure and are probably more capable of understanding and integrating external knowledge in their products and processes. In the case of the service sector, once again knowledge-intensive services present a negative coefficient. This finding could be related to a price increase, given that suppliers may charge more after investing in R&D and, so, the firm also raises its prices. Thus, in a competitive environment, as in knowledge-intensive sectors, this might result in a reduction in sales. On the other hand, inter-industry externalities show a positive and significant coefficient for non-knowledge-intensive services, i.e. firms belonging to these sectors increase their performance thanks to the R&D expenditure of firms operating in other sectors. This result could reflect the complementarity of the technology effort between the supplier sectors and non-knowledge-intensive services. It should be remembered that non-knowledge-intensive services present the lowest R&D stock (see Table 3.1), which would explain why they benefit most from the investments made by all the other firms (both in their own sector and in other sectors).

3.6 Further explorations

This section seeks to shed some light on the non-significant impact of R&D stock on firms' production (see Table 3.2.). In line with Crépon, Duguet and Mairesse (1998), there would appear to be a process that leads from R&D investments to innovation outputs and from there to productivity. Thus, here, as an initial attempt at adopting this new approach, innovation is defined from an output perspective. Specifically, innovation is proxied with a dummy variable that takes a value of 1 if the firm declares that it has obtained a product or process innovation during the period *[t-2, t]*. It is expected that firm's sales in time *t* increase if the firm has obtained an innovation output in the preceding three years.

As can be seen in Table 3.3, when adopting this new definition, innovation is clearly positive and significant in the sample as a whole and in all sub-samples. Although, as discussed above, the aim of this chapter is not to undertake a structural analysis, the results of this section are highly informative as they suggest that Spanish firms are able to generate a profit and increase their sales from their innovation outcomes. As such what needs to be explored in greater depth is the ability to turn R&D investment into innovation outputs. In line with the literature, advanced firms (HTMI and KIS) present a greater impact than less advanced companies.

Finally, with regard to externalities, it can be seen that the results in Table 3.3 are very similar to those obtained earlier. Low-tech firms benefit from intra-industry externalities, while knowledge-intensive services show a negative coefficient. In the case of inter-industry externalities, the same heterogeneous impact can be observed.

Table 3.3 OP estimates. Estimation results of Equation [3.4] 2004-2009. Dependent variable: ln(sales).

	Total (1)	LTMI (2)	HTMI (3)	NKIS (4)	KIS (5)
Physical capital	0.0381*** (0.0071)	0.0316*** (0.0088)	0.0290*** (0.0101)	0.0159 (0.0189)	0.0713*** (0.0216)
Labour	0.8833*** (0.0099)	0.9675*** (0.0170)	1.0117*** (0.0205)	0.8916*** (0.0251)	0.7914*** (0.0156)
Human capital	0.0045*** (0.0004)	0.0073*** (0.0010)	0.0042*** (0.0008)	0.0090*** (0.0015)	0.0033*** (0.0006)
Innovation (output)	0.1771*** (0.0194)	0.0581** (0.0255)	0.0904*** (0.0342)	0.1550*** (0.0576)	0.2650*** (0.0484)
Intra-industry externality	0.0000 (0.0000)	0.0004*** (0.0001)	0.0000 (0.0000)	0.0010*** (0.0001)	-0.0002*** (0.0000)
Inter-industry externality	-0.0001* (0.0001)	-0.0000 (0.0001)	0.0004** (0.0002)	0.0007*** (0.0002)	-0.0011*** (0.0002)
Trend	-0.0175** (0.0072)	-0.0449*** (0.0112)	-0.0866*** (0.0178)	-0.1967*** (0.0202)	0.1109*** (0.0147)
HTMI	0.0914*** (0.0261)				
NKIS	0.1172*** (0.0318)				
KIS	-0.7289*** (0.0286)				
Obs	50,349	17,470	12,764	6,483	13,632

Note: Low and medium-low tech manufacturing industries (LTMI), medium-high and high tech manufacturing industries (HTMI), non-knowledge-intensive services (NKIS), and knowledge-intensive services (KIS). Externalities are lagged two periods. Reference group: LTMI. Bootstrapped errors in parenthesis (100 replications).*** Significant at 1%, ** significant at 5%, * significant at 10%.

3.7 Concluding remarks

This chapter has studied the extent to which the level of technology of a firm affects the returns that firms in Spain can obtain from their own investment in R&D activities and from the R&D carried out by all other firms (both in the same sector and in other sectors). In particular, the research questions posed at the beginning of this chapter were: (i) Does the impact of innovation on firm performance differ according to a firm's level of technology? (ii) Are Spanish firms able to benefit from externalities? (iii) And if so, do these benefits vary according to a firm's technology level?

A Cobb-Douglas production function has been employed, including not only firm own R&D investments but also intra-industry and inter-industry externalities. The empirical analysis is applied to a panel data of Spanish firms from 2004 to 2009 using the Olley and Pakes estimator to account for simultaneity and selection bias. By doing so, it is possible to obtain robust and consistent estimates allowing for firm heterogeneity, simultaneity and selection biases.

The following conclusions can be drawn. In the first place, when the whole sample is taken into consideration, the expected positive impact of R&D investment is found. In the second place, and contrary to expectations, the results according to the level of technology suggest that, in general (with the exception of KIS), R&D expenditures do not have a direct impact on firm sales. Although this result is unexpected, it is in line with the Crépon, Duguet and Mairesse (1998) approach, which holds that there is a sequential process leading from R&D to innovation outputs and from there to productivity. Therefore, the result obtained here, although somewhat surprising, provides us with valuable information in this regard. Specifically, when innovation is proxied by innovation output (as opposed to innovation input, i.e., R&D), the results clearly present positive coefficients. Therefore, with respect to the first research question, it can be concluded that the impact of innovation output differs according to the level of technology, being notably greater for those firms that operate in high-tech sectors (HTMI and KIS).

Interestingly, the "inability" of firms to benefit from their own R&D efforts does not prevent them from benefiting from external knowledge. In particular, it has been seen that, although the impact is negative for the sample as a whole, in most technology levels Spanish firms increase their sales when the rest of the firms in their sector increase their R&D expenditure. Specifically, low-tech sectors manage to benefit to a greater extent from the R&D expenditure carried out by all the other firms in the same sector. This result could indicate that firms of this type seek to compensate for their smaller investment effort by taking advantage of innovation originating in firms in the same sector. It might also reflect the fact that high-tech sectors face higher competition, probably due to the higher degree of technology, which compensates or dominate the benefits stemming from external R&D.

Inter-industry externalities have been shown to play an ambiguous role and there would appear to be no specific pattern of behaviour associated with different levels of technology. However, the results suggest the presence of a certain complementarity for the technological efforts with supplier sectors in the case of firms belonging to high-tech manufacturing industries and non-knowledge-intensive services.

In short, and in answer to the second research question, it has been shown that Spanish firms are able to benefit from spillovers. Moreover, these benefits depend to some extent on the technology level – which results in an affirmative answer to the last question. More specifically, technology level appears to have an influence on intra-industry externalities, i.e., the more advanced the firm, the less benefits it derives from intra-industry externalities, while its effect is much more ambiguous in the case of inter-industry externalities.

Chapter 4: The importance of spillovers using the CDM model

4.1 Introduction[34]

Since the publication of Crépon, Duguet and Mairesse's seminal paper in 1998, the way of examining the relationship between innovation and productivity has changed. Whereas the traditional literature relied on R&D expenditure as a proxy for innovation – including it as an additional input in the production function, these authors proposed fitting a structural model (also known as CDM model). This new approach allows us to distinguish between two processes: (i) the generation of innovations from R&D expenditures and (ii) the impact of these innovations on firm performance. Thus, the topic that for so many decades has generated so much interest among researchers is now being addressed from a different perspective.

It might be thought that the more a firm invests in R&D, the more its productivity rises. However, unfortunately, this is not true. Why? Because the firm first has to be able to turn its investment into innovations and then translate these innovations into economic performance[35]. As one can imagine, not all R&D expenditures result in successful innovations and not all innovations have an immediate impact on productivity. Hence, if a firm seeks to increase its productivity, it not only needs to invest in R&D activities, it must also have the necessary mechanisms to transform this investment into innovations that can raise its productivity.

The results obtained in the previous chapter suggest that R&D does not have the expected strong, positive effect when it is used as a proxy for innovation. On the contrary, when innovation is defined from an output

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[34] I am very grateful to Elena Huergo and Joaquín Artés who kindly read this chapter. Their comments and suggestions have been very useful.

[35] At the end of the day, innovations are designed to improve firm performance and competitiveness (Peters, 2008).

perspective, a clear positive impact emerges. This chapter, therefore, aims at enhancing the ideas developed in the previous chapter by analysing the relationship between innovation and productivity from the perspective provided by the CDM model. Specifically, the main goal of this chapter is to assess the extent to which the innovations carried out by others might impact on a firm's behaviour and on a firm's performance. As explained in earlier sections, the benefits from research efforts are not fully appropriable by their producers. On the contrary, knowledge generated inside a firm may spill over and become available for other firms that can use it for "free" (assimilation costs aside – see Chapter 1). To the best of our knowledge, no previous paper has examined spillover effects by applying the CDM model.

It is also worth mentioning that most papers employing a structural model use cross-sectional data [36] and control for neither unobserved firm heterogeneity nor the time lag between the different stages of the model. In this regard, this study seeks to shed further light on the research question by analysing the case of Spain drawing on the PITEC database for the period 2004 to 2010. An additional improvement on other studies is that here both manufacturing and service firms are considered, together with their different levels of technology.

Overall, our purpose is to determine the extent to which external knowledge can have an impact across the structural model. For this reason not only do we consider the effect of external knowledge on a firm's productivity (last stage of the model), but we also take into consideration whether a firm's decision to engage in R&D activities or not might be influenced by the actions taken by other firms (first stage). Specifically, this chapter seeks to address the following questions: (i) Is a firm's decision as to whether or not

[36] Exceptions include Chudonovsky et al. (2006) and Huergo and Moreno (2011).

to engage in R&D activities affected by what other firms in its sector do? (ii) Do Spanish firms benefit from the innovations carried out by the rest of the firms in its sector and in other sectors?

Chapter 3 concluded that the level of technology of the sector in which a firm operates leads to different results; however, it was not possible to establish a clear pattern. For this reason, this factor is again taken into consideration in order to see if a clearer pattern emerges.

The rest of the chapter presents the literature review in section 4.2, the empirical model in section 4.3, the variables in section 4.4, the main findings in section 4.5 and finally the conclusions are drawn in section 4.6.

4.2 What do we know so far?

As discussed in the previous chapter, since the seminal papers of Griliches (1979, 1986), many studies have been published analysing the impact of innovation on firm productivity. However since the publication of Crépon, Duguet and Mairesse (1998), the approach taken in this line of the literature has shifted, moving from an input definition of innovation[37] to an output perspective. These authors estimate a structural model involving three steps: (i) the firm's decision whether or not to engage in R&D activities, and the intensity of that investment, (ii) the realization of innovations from R&D expenditures and (iii) the relationship between innovation output and firms 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

[37] Typically this has been proxied as R&D expenditures and included in the production function as an additional input.

innovative effort, production of innovation outcomes and the impact of these "successful" innovations 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 firm productivity (see Hall and Mairesse, 2006 for a survey, as well as Janz et al., 2004 for Germany and Sweden; Lööf and Heshmati, 2006 for Sweden; Benavente, 2006 for Chile; Jefferson et al., 2006 for China; 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; Hall et al., 2009 and Antonietti and Cainelli, 2011 for Italy to name just a few). In the case of Spain no more than 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 ESEE dataset (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 discussed previously, most studies use cross-sectional data and only a few employ 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[38]. In line with these, the present 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 across the whole process (from the firm's decision to engage in R&D activities or not to its impact on productivity through innovation output).

It is worth mentioning that other authors also employ panel data; however, they focus on just 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 adopts a Heckman-type model to capture both the long-run decision (whether to conduct R&D activities or not) and the short-run decision (how much to invest in these projects). Lhuillery (2011) also focuses 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. In contrast, Huergo (2006), Du et al. (2007) and Raymond et al. (2010) consider the innovation equation (the second stage of the CDM model) to analyse the role played by R&D in the process of generating innovations using panel data (for Spain, Ireland and the Netherlands).

As some evidence points out, the impact of innovation on firm productivity may depend on the level of technology operated by that firm (as noted in Chapter 3). While many articles tackle this question from the production function perspective (see for instance, Verspagen, 1995; Tsai and Wang,

[38] In this case, the authors focus their attention on the persistence in firms' behaviour.

2004, and Ortega-Argilés, 2010; 2011), there is much less evidence in papers that apply the CDM model[39].

As introduced above, spillovers play an important role when the relationship between R&D, innovation and productivity comes under analysis. Numerous studies have examined the impact of spillovers on R&D expenditures and productivity (see section 3.2 for a review). However, and to the best of our knowledge, no paper has examined this issue in any country from the perspective provided by the CDM model. A number of articles have attempted to explain part of this external knowledge in the first stage of the model by introducing dummy variables to capture the importance of several sources of information – internal, competitors, suppliers, universities, etc. – for the firm's technological effort (Lööf and Heshmati, 2002; Griffith et al., 2006; Masso and Vather, 2008; and Segarra-Blasco, 2010, among others). However, this variable is an ordinal measure and is completely subjective. In addition, this information is only available for innovative firms; hence, it cannot be included when studying the firm's decision whether to engage in R&D activities or not. One exception to date 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 rivals' knowledge with regard to the probability of engaging 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 innovative effort. Apart from

[39] As Segarra-Blasco (2010) notes, 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.

these attempts to include spillovers in the first stage of model, no other evidence using the CDM approach is available, to the best of our knowledge.

Given this preliminary evidence, this chapter aims to contribute to the existing (and short) literature with regard to the use of panel data within a structural model framework. The main challenge is to determine whether external knowledge has an impact on the firm's decision to engage or not in R&D projects (first stage of the model) and/or on firm's productivity (last stage of the model) in Spain. Finally, given that Chapter 3 points to different outcomes depending on the level of technology, but do not allow the drawing of relevant conclusions, it would be interesting to assess the role played by technology in this process. In addition, given the small body of literature examining this question from the perspective provided by the CDM model, and the lack of consensus, it would be interesting to clarify this issue for the Spanish case.

4.3 Model and estimation strategy

The model adopted to estimate the relationship between innovation and productivity is a modified version of the CDM model (see Griffith et al., 2006). Moreover, we extend the original model by introducing measures of external knowledge in two equations as is shown below. The model, which consists of three stages, can be formalized in four sequential equations[40]. See section 4.4 for a full description of the variables.

[40] It is worth pointing out that it is a recursive model, hence feedback effects are not allowed (Griffith, et al., 2006).

4.3.1 First stage: The research equations

This first stage of the model is concerned with the firm's research activities, modelling the process that leads the firm to decide whether or not to undertake a research project, and how much to invest in it. 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:

$$RD_{it} = \begin{cases} 1 \;\; if \;\; RD_{it}^{*} = x_{it}^{(1)}\beta^{(1)} + \delta S_{t-1}^{j} + \alpha_{i}^{(1)} + \varepsilon_{it}^{(1)} > \overline{c} \\ 0 \;\; if \;\; RD_{it}^{*} = x_{it}^{(1)}\beta^{(1)} + \delta S_{t-1}^{j} + \alpha_{i}^{(1)} + \varepsilon_{it}^{(1)} \leq \overline{c} \end{cases} \qquad [4.1]$$

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 a value of 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 $\bar{c}$, $x_{it}^{(1)}$ is a set of explanatory variables and S_{t-1}^{j} is our measure of external knowledge lagged one year. Finally, $\alpha_{i}^{(1)}$ captures the unobserved firm heterogeneity and $\varepsilon_{it}^{(1)}$ is an error term.

In line with our main goal, the most relevant variable here is the spillover measure that seeks to assess how a firm's decision to engage in R&D activities might be affected by what other firms have done in the previous period (see next section for a detailed definition).

We estimate Equation [4.1] 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 a major limitation since it relies on the assumption that the errors are not correlated with the regressors. In the case of this assumption not holding, the estimates would be inconsistent. To deal with this problem it is possible to parameterise the effect. To do so we augment the model with the Mundlak specification[41]; in other words, we include a vector of the means of the time-variant regressors as 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:

$$RDI_{it} = \begin{cases} RDI_{it}^{*} = x_{it}^{(2)}\beta^{(2)} + \alpha_i^{(2)} + \varepsilon_{it}^{(2)} & if \quad RD_{it} = 1 \\ 0 & if \quad RD_{it} = 0 \end{cases} \qquad [4.2]$$

where $\mathrm{RDI}_{\mathrm{it}}^{*}$ 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 is much more dependent on internal factors (such as, availability of funding) than on what other firms do[42].

This equation is estimated using the consistent estimator proposed by Wooldridge (1995)[43]. This method consists of two steps. In the first, a selection equation for each year is estimated using a probit model. By doing so, T inverse Mills ratios are obtained (one for each year). The second step is to estimate a pooled OLS including the T inverse Mills ratios interacted with time dummies for the selected sample ($RD_{it} = 1$). This procedure

[41] Thus, we allow the individual effects to be correlated with the within-individual means of the regressors.

[42] Besides, as discussed in the previous section, Lhuillery (2011) finds that knowledge spillovers originating from competitors are a factor to take into account in the first but not in the second equation.

[43] Given that Heckman type selection model (1979) is not available for panel data; Wooldridge (1995) is followed to address the selection problem.

allows us to account for the selection bias through the inclusion of the correction terms, the inverse Mills ratios, in the second step. In addition, as Wooldridge (2002) points out, an exclusion restriction is needed in order to avoid multicollinearity problems, since inverse Mills ratios have been incorporated in the second equation.

4.3.2 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:

$$I_{i(t-2,t)} = \gamma \widehat{RDI}_{it-2} + x_{it}^{(3)}\beta^{(3)} + \alpha_i^{(3)} + \varepsilon_{it}^{(3)} \qquad [4.3]$$

where $I_{i(t-2,t)}$ is an innovation output indicator that takes a value of 1 if the firm develops an innovation during the preceding three years (*t-2, t-1* or *t*), and $\widehat{RDI}_{it-2}$ is the innovation effort predicted from Equation [4.2] and lagged two periods[44]. $x_{it}^{(3)}$ is a vector of other determinants of knowledge production, $\alpha_i^{(3)}$ captures the unobserved firm heterogeneity and $\varepsilon_{it}^{(3)}$ is an error term.

The innovation production function is estimated using a random effect probit model (see Huergo, 2006) and includes a vector of the means of the time-variant regressors as control variables. This allows individual effects

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[44] Two lags ($R\&D_{t-2}$) are chosen because this is the minimum lag for explaining innovation ($I_{i(t-2,t)}$). $R\&D_{t-1}$ would not explain innovation obtained in the period [*t-2,t*], since innovations in *t-2* cannot be due to investments in *t-1*. Certainly, more lags may be needed since it is generally accepted that investments in R&D take some time to materialise in something new or because completing an R&D project might take more than one year. However, as PITEC is a short panel and the information available at this stage of the model will be reduced to four years, it is decided to work with two lags. In addition, by including lags a possible simultaneity problem may be mitigated.

to be correlated with the within-individual means of the regressors (Mundlak, 1978).

4.3.3 Third stage: The productivity equation (production function)

This last step is modelled using an augmented Cobb-Douglas production function. It is assumed that a firm's productivity is dependent both on its own investment and on external knowledge:

$$y_{it} = \delta \hat{I}_{i(t-2,t)} + x_{it}^{(4)} \beta^{(4)} + \rho S_{it-1}^{j,intra} + \pi S_{it-1}^{j,inter} + \alpha_i^{(4)} + \varepsilon_{it}^{(4)} \qquad [4.4]$$

where i indexes the firm, j indexes the firm's sector and t indexes the year. y_{it} is labour productivity; $\hat{I}_{i(t-2,t)}$ is the innovation output predicted from Equation [4.3]; $x_{it}^{(4)}$ is a set of explanatory variables (which include: labour, physical and human capital); $S_{it-1}^{j,intra}$ and $S_{it-1}^{j,inter}$ are the intra- and inter-industry externalities lagged one period respectively. Last, $\alpha_i^{(4)}$ captures the unobserved firm heterogeneity and $\varepsilon_{it}^{(4)}$ is the error term.

As can be seen in Equation [4.4], and as a key feature of this study, industry spillovers are incorporated in the Cobb-Douglas production function. Thus, assuming that an external effect exists because of the public nature of knowledge, two types of externality are considered: intra-industry externalities $(S_{it}^{j,intra})$ which capture the innovation effort made by all the other firms in the same sector, and inter-industry externalities $(S_{it}^{j,inter})$, understood as the innovation effort made by the rest of the firms in all other sectors (see next section for a detailed definition).

In line with previous equations, this final step is estimated by a random effects model. To sum up, our model comprises Equations [4.1], [4.2], [4.3] and [4.4] which are estimated sequentially. Following Griffith et al (2006), all firms are included in the analysis even if they do not report any R&D expenditures. As the authors explain, it is believed that all firms engage in some innovative effort, albeit that they do not report it. For instance, firms may invest in other innovation expenditures, not just in R&D. In addition, as the authors recognise, workers are likely to spend some of their time thinking about how to improve their performance and how they can be more efficient in their jobs. Finally, firms may well invest in physical capital, which incorporates new knowledge. Therefore, although it is perhaps most logical for an innovation to be developed once a firm invests in R&D, this does not rule out other possibilities.

To the best of our knowledge, none of the empirical articles analysing the relationship between innovation and productivity based on the CDM model considers externalities.

4.4 Data and variables

The data used in this chapter comprise an unbalanced panel of 9,042 firms (57,379 observations) for the period 2004-2010. According to the model adopted in this chapter, the sample is restricted to firms that are present in the three stages of the model. Therefore, we retain all those that remain at least three years in a row in the panel. This filter results in a sample that is more than 90% of the whole unbalanced panel (63,615 observations). Table A.3 in the Appendix shows that the properties of the sample are preserved after this change.

Below we present the variables used in estimating each stage of the model. A detailed definition of each variable can be found in Table 4.1.

Table 4.1 Definition of variables

Firms' characteristics	
Labour productivity	Sales per employee in *t* (in logs).
Firm size	Number of employees in *t* (in logs).
Physical capital	Physical capital per employee in *t*. Stock measure using the perpetual inventory method (in logs).
Advanced machinery	Investment in acquisition of advanced machinery, equipment (including computer hardware) or software to produce innovations per employee in *t-2*. Stock measure using the perpetual inventory method (in logs).
Human capital	Percentage of employees with higher education in *t*.
Group	Dummy variable that takes the value 1 if the firm belongs to a group in *t*; 0 otherwise.
International competition	Dummy variable that takes the value 1 if the firm traded in an international market during the period [*t-2, t*]; 0 otherwise.
Knowledge / Innovation	
R&D engagement	Dummy variable that takes the value 1 if the firm has a positive R&D expenditure (intramural and/or extramural) in *t*; 0 otherwise.
R&D intensity	Intramural and/or extramural R&D expenditure per employee in *t* (in logs).
Continuous R&D	Dummy variable equals 1 if the firm performs R&D continuously, and 0 if it is occasional or the firm does not perform any R&D.
Personnel in R&D	Personnel working on internal R&D in *t-2* (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 [*t-2, t*]; 0 otherwise.
Product innovation	Dummy variable which takes the value 1 if the firm reports having introduced a new or significantly improved product during the period [*t-2, t*]; 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*]; 0 otherwise.
Cooperation	Dummy variable which takes the value 1 if the firm cooperated with others to carry out innovation activities during the period [*t-2, t*]; 0 otherwise.
External knowledge	
Spillover (Eq [4.1])	Proportion of firms in the same sector undertaking R&D activities in *t-1*.
Intra-industry Spillover (process) (Eq [4.4])	Sum of the R&D stock incurred by the rest of the firms in the same sector in the previous two years provide that they achieve a successful process innovation in the next three years; 0 otherwise.
Intra-industry Spillover (product) (Eq [4.4])	Sum of the R&D stock incurred by the rest of the firms in the same sector in the previous two years provide that they achieve a successful product innovation in the next three years; 0 otherwise.

To be continued on the next page

Table 4.1 – *continued from the previous page*

External knowledge	
Inter-industry Spillover (process) (Eq [4.4])	Weighted sum of the R&D stock carried out by the rest of the firms in other sectors in the previous two years provide that they achieve a successful process innovation in the next three years; 0 otherwise. (Weights are defined using the input-output table).
Inter-industry Spillover (product) (Eq [4.4])	Weighted sum of the R&D stock carried out by the rest of the firms in other sectors in the previous two years provide that they achieve a successful product innovation in the next three years; 0 otherwise. (Weights are defined using the input-output table).
Public Funding	
Local	Dummy variable which takes the value 1 if the firm receives local or regional funding for innovation activities during the period [*t-2, t*]; 0 otherwise.
National	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*]; 0 otherwise.
European	Dummy variable which takes the value 1 if the firm receives EU funding for innovation activities during the period [*t-2, t*]; 0 otherwise.
Sources of information	
Internal	Dummy variable equals 1 if the firm declares that information coming from inside the company or group has been an important source of information to undertake or complete innovation projects during the period [*t-2, t*]; 0 otherwise.
Market	Dummy variable equals 1 if the firm declares that information coming from suppliers, clients, competitors or consultants has been an important source of information to undertake or complete innovation projects during the period [*t-2, t*]; 0 otherwise.
Institutional	Dummy variable equals 1 if the firm declares that information coming from governments or universities has been an important source of information to undertake or complete innovation projects during the period [*t-2, t*]; 0 otherwise.
Others	Dummy variable equals 1 if the firm declares that information coming from conferences, scientific journals, professional associations, etc. has been an important source of information to undertake or complete innovation projects during the period [*t-2, t*]; 0 otherwise.

Note: Monetary variables are expressed in real terms (base 2010, using the GDP deflator).

Apart from the variables described, we control for time and industry effects[45]. Industry dummies capture technological opportunities and specific industry characteristics. Note, however, that they are not included in either the first or the last equations given that we incorporate spillovers. We are aware, especially in the last equation, that spillovers might be capturing not only external knowledge but also specificities of the sector. Unfortunately, industry dummies cannot be incorporated since there would be perfect multicollinearity with the inter-industry spillover variable. This is mitigated to some extent by the fact that we estimate according to technology level (low-tech and high-tech manufacturing firms, and knowledge-intensive and non-knowledge-intensive services).

4.4.1 First stage

In Equation [4.1] our endogenous variable is proxied by a dummy variable that takes a value of 1 if the firm has positive R&D expenditures (intramural and/or extramural).

As determinants of a firm's engagement in R&D activities, we include firm size, measured as the logarithm of the number of workers – which reflects scale economies and access to finance; physical capital stock per employee, using the perpetual inventory method (see section 3.4.2); and human capital, measured as the percentage of workers with higher education. We also include a dummy variable that takes a value of 1 if the firm belongs to a group – which might not only reflect 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 an international

[45] Although it would be interesting to control also for firm age, PITEC did not provide this information until 2009. Therefore it is not available for all firms in the sample.

market in the preceding three years. As Ganotakis and Love (2011) explain strong competition in foreign markets encourages 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 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). It is believed that the appropriation of 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 over the preceding three years are also included – those firms that receive such subsidies are expected to have a greater propensity to carry out R&D activities.

Finally, the main variable of interest at this point is the spillover, which is introduced in the model in order to capture if a firm's decision to undertake R&D projects is affected by the decisions of other firms in its sector. It is defined as follows:

$$S_t^j = \frac{n_t^j}{N_t^j} \cdot 100 \qquad [4.5]$$

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*. Thus, assuming that firm *i* operates in sector *j*, we define the spillover as the proportion of firms in the same sector undertaking R&D activities[46]. This variable is lagged 1 year.

[46] We have also taken into consideration other definitions of spillover (for example, a definition based on intra-industry R&D expenditures), but they were found not to be relevant.

There are two different consequences of knowledge spillovers. On the one hand, a positive effect might be recorded, given that an external pool of knowledge could serve as an incentive and encourage firms to undertake R&D activities. This would be in line with the idea of absorptive capacity (Cohen and Levinthal, 1989), whereby firms are interested in investing in R&D so as to be able to benefit from external knowledge. Additionally, firms might decide to take part in R&D projects because they want to improve their competitiveness vis-à-vis their rivals. Therefore, the greater the proportion of firms undertaking R&D projects in a sector, the higher the probability a firm would have of engaging in such activities. On the other hand, a negative effect is also plausible. In particular, a disincentive effect might arise as firms may see external knowledge as a substitute for their own production of knowledge. Thus, they prefer to adopt a free-riding behaviour instead of making their own technological effort (in line with Lhuillery, 2011).

In equation [4.2] we define our endogenous variable, R&D intensity, as the logarithm of intramural and extramural R&D expenditures per employee. The explanatory variables in this case are the same as those in Equation [4.1] with the exception of firm size. Following the literature, this variable is selected as an exclusion restriction to provide more robust estimations. A dummy variable indicating whether a firm cooperated with others to carry out its R&D projects in the previous three years is also added. This variable captures the external knowledge shared between firms that decide to collaborate. It is worth stressing that this information is only available for innovative firms, which is why we have been unable to include it in Equation [4.1] [47].

4.4.2 Second stage

In Equation [4.3] two definitions of innovation output are considered: process innovation and product innovation. The former is defined as a dummy variable equal to 1 if the firm has introduced at least one process innovation over the last three years. Process innovation improves production techniques, reduces costs, etc. leading to higher productivity performance. On the other hand, product innovation is defined as a dummy variable equal to 1 if the firm has introduced at least one product innovation over the last three years. This kind of innovation is more closely associated with product differentiation and the creation of new markets, leading to an increase in a firm's sales[48].

As explanatory variables in Equation [4.3], we include the predicted value of R&D intensity obtained in Equation [4.2] lagged two years as a proxy for innovative effort. By so doing, R&D investments carried out in *t-2* may turn into an innovation in *t-2, t-1* and/or *t.* Firm size, investment in advanced machinery, equipment or software to produce innovations and personnel in R&D are included and lagged two periods. We also incorporate a set of dummy variables, including having used protection methods, operating in international markets, declaring information from outside the company as

[47] As discussed in Chapter 2, unfortunately not all firms are requested to answer all the survey questions, while the firms that engage in innovation activities have to complete a larger number of items. For this reason more information is available for Equation [4.2], while we only have limited information for Equation [4.1].

[48] Some articles analyse solely the impact of process innovation on productivity (see for instance Vivero, 2002; Huergo and Jaumandreu, 2004b; Rochina-Barrachina et al., 2010 and Mañez et al., 2013). However, here, both definitions are considered so as to obtain a broader picture of the situation.

an important source of information and performing R&D continuously (lagged two years). It is thought that by regularly investing in R&D a firm can increase its probability of obtaining an innovation, unlike a firm which only occasionally makes such investment[49].

4.4.3 Third stage

In the final step of the model, Equation [4.4], labour productivity is defined as the logarithm of sales per employee. As explanatory variables we include the traditional inputs of labour and physical capital defined previously. Human capital is also included in order to capture the fact that the higher the workers' qualifications, the more efficiently they carry out their tasks, and the more productive the firm tends to be. We also incorporate innovation output, proxied by the process or product innovations predicted in Equation [4.3] and which refers to period [*t-2, t*]. Finally, two measures of spillovers are included: intra-industry and inter-industry externalities.

These externalities are defined in line with Chapter 3 above, although they are modified in order to fit the CDM approach better. In other words, the CDM model explains productivity in terms of innovation output as opposed to innovation input. Thus, here, our definition of externalities also needs to be in line with this idea. The definition of spillovers presented below seeks to capture, therefore, not only the knowledge flow in the sector, but also the fact that firms achieve a successful innovation output thanks to this knowledge (see Beneito, 2001).

[49] Continuity is a factor to take into consideration, as pointed out by several authors (for instance, Huergo and Moreno, 2011) that study the persistence of innovation.

Hence, intra-industry spillovers corresponding to firm i belonging to sector j in year t are defined as follows:

$$S_{it}^{j,intra} = \sum_{k \neq i} \left(G_{kt-2}^{j} * I_{k(t-2,t)}^{j} \right) \qquad [4.6]$$

where G_{kt-2}^{j} is R&D stock incurred 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 equals to 1 if firms have achieved successful innovation output (process or product innovation) in the following 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 firms not reporting any effective innovation results are not included in the calculation of the spillover variable[50].

Likewise, inter-industry spillovers corresponding to firm i belonging to sector j at year t are defined as:

$$S_{it}^{j,inter} = \sum_{\substack{k \neq i \\ m \neq j}} w_{jm} \left(G_{kt-2}^{m} * I_{k(t-2,t)}^{m} \right) \qquad [4.7]$$

where G_{kt-2}^{m} is R&D stock 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 (process or product innovation) in the following three years, or 0 otherwise; and $\mathrm{w_{jm}}$ are the weighs indicating the relative importance that sector m has as a supplier to sector j. As in Chapter 3, they are defined as the quotient between the intermediate purchase by sector j of goods and

[50] As pointed out in Chapter 3, 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.

services supplied by sector *m* and the total sum of intermediate purchase of sector *j* using the symmetric input-output table for Spain for 2005.

As discussed above in section 3.4.2, assuming a contemporary relationship between spillovers and productivity seems inappropriate since the diffusion of external knowledge requires some time before it can have an impact on the firm. Even though the definition itself includes R&D lagged two periods (since the innovation indicator is for the period [*t-2, t*]), the externalities in expression [4.4] are lagged 1 year[51].

4.5 Results

4.5.1 Descriptive analysis

Table 4.2 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.

In the case of the knowledge variables, high-tech firms (HTMI and KIS) are more likely to engage in R&D activities, their intensity is usually greater, their investment in R&D more continuous and the number of personnel working on R&D activities is higher than it is in low-tech firms (LTMI and NKIS). Likewise, the proportion of firms reporting a process or product innovation is higher among high-tech firms. Moreover, the latter protect their innovations and cooperate more than is the case of their low-tech counterparts.

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[51] The same results are obtained when externalities are not lagged.

As for external knowledge, in the high-tech sector the proportion of firms that engage in R&D activities is substantially higher than it is in less advanced sectors. Likewise, intra-industry spillover (defined in terms of process or product innovations) presents a higher coefficient for high-tech firms (especially in HTMI), while inter-industry externality shows a more ambiguous pattern. Finally, the number of firms that employ some source of information or receive government financial support is also higher in high-tech sectors. Therefore, given the differences presented it is worth analysing each technology level separately.

Table 4.2 Descriptive statistics

		TOTAL		LTMI		HTMI		NKIS		KIS	
		mean	st dv	mean	st dv	mean	st dv	mean	st dv	mean	st dv
Firms' characteritics											
Labour	overall	11.788	1.018	11.985	0.839	12.037	0.736	12.041	1.102	11.184	1.156
productivity [a, d]	between		0.968		0.796		0.692		1.063		1.074
(cont.)	within		0.332		0.297		0.287		0.282		0.422
Firm size [a]	overall	4.433	1.410	4.253	1.196	4.169	1.215	5.095	1.602	4.593	1.602
(cont.)	between		1.400		1.182		1.203		1.599		1.593
	within		0.205		0.193		0.185		0.197		0.240
Physical	overall	9.563	3.314	10.087	3.445	9.778	2.936	9.304	3.474	8.820	3.250
capital [a, d]	between		3.065		3.230		2.708		3.137		2.985
(cont.)	within		1.421		1.442		1.344		1.577		1.385
Advanced	overall	3.598	4.088	4.012	4.298	4.012	4.056	2.347	3.556	3.280	3.929
machinery [a, d]	between		3.563		3.779		3.455		3.143		3.407
(cont.)	within		2.017		2.079		2.146		1.670		1.964
Human	overall	22.722	25.600	12.136	13.538	20.882	18.457	13.762	19.817	42.157	33.358
Capital [a]	between		23.770		11.603		16.577		17.438		30.191
(cont.)	within		10.407		7.139		8.659		9.835		14.761
Group [a]	overall	0.407	0.491	0.362	0.481	0.421	0.494	0.510	0.500	0.402	0.490
(0/1)	between		0.459		0.450		0.464		0.468		0.454
	within		0.172		0.163		0.168		0.177		0.183
International	overall	0.479	0.500	0.583	0.493	0.718	0.450	0.283	0.451	0.215	0.411
Competition [a]	between		0.434		0.418		0.378		0.375		0.349
(0/1)	within		0.247		0.264		0.252		0.252		0.214

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Table 4.2 – *continued from the previous page*

		TOTAL		LTMI		HTMI		NKIS		KIS	
		mean	**st dv**	**mean**	**st dv**	**mean**	**st dv**	**mean**	**st dv**	**mean**	**st dv**
Knowledge / Innovation											
R&D	overall	0.576	0.494	0.578	0.494	0.782	0.413	0.256	0.437	0.535	0.499
engagement [a]	between		0.412		0.391		0.329		0.367		0.425
(0/1)	within		0.273		0.303		0.255		0.242		0.260
R&D	overall	9.458	1.555	9.023	1.329	9.835	1.216	8.386	1.855	9.784	1.882
intensity [b]	between		1.692		1.401		1.270		1.995		2.039
(cont.)	within		0.446		0.454		0.342		0.661		0.498
Continuous	overall	0.787	0.409	0.735	0.441	0.825	0.380	0.710	0.454	0.819	0.385
R&D [b]	between		0.376		0.395		0.337		0.431		0.354
(0/1)	within		0.261		0.283		0.248		0.260		0.248
Personnel in	overall	1.128	1.275	0.954	1.076	1.598	1.258	0.416	0.919	1.248	1.459
R&D [a]	between		1.141		0.913		1.140		0.806		1.312
(cont.)	within		0.540		0.549		0.518		0.429		0.593
Process	overall	0.568	0.495	0.633	0.482	0.634	0.482	0.381	0.486	0.513	0.500
innovator [a]	between		0.398		0.383		0.385		0.390		0.398
(0/1)	within		0.297		0.295		0.295		0.291		0.304
Product	overall	0.544	0.498	0.546	0.498	0.730	0.444	0.269	0.443	0.500	0.500
Innovator [a]	between		0.418		0.408		0.367		0.375		0.417
(0/1)	within		0.270		0.286		0.256		0.240		0.276
Protection [a]	overall	0.271	0.445	0.273	0.446	0.337	0.473	0.183	0.386	0.249	0.432
(0/1)	between		0.342		0.339		0.368		0.292		0.331
	within		0.285		0.287		0.297		0.256		0.282
Cooperation [c]	overall	0.373	0.483	0.326	0.469	0.373	0.484	0.312	0.463	0.459	0.498
(0/1)	between		0.386		0.365		0.382		0.370		0.408
	within		0.295		0.295		0.298		0.285		0.294
External knowledge											
% firms with	overall	57.63	22.20	57.77	10.50	78.15	7.87	25.65	15.40	53.48	24.66
R&D activities [a]	between		21.36		7.45		5.63		14.82		24.24
[0-100]	within		5.93		7.49		5.51		4.27		4.60
Intra-industry	overall	525.11	533.25	307.66	234.65	914.9	575.96	306.36	361.31	541.69	616.99
spillover (process)[a, d]	between		516.17		225.49		558.70		299.29		600.47
(cont.)	within		135.38		58.435		117.67		207.47		172.49
Intra-industry	overall	563.51	598.13	291.64	223.73	1047.09	631.33	334.66	398.29	566.15	685.06
spillover (product)[a, d]	between		579.42		215.64		611.44		346.06		663.21
(cont.)	within		148.17		52.95		126.00		201.94		207.79
Inter-industry	overall	362.58	142.57	386.89	128.59	406.01	108.10	330.26	217.54	307.14	119.62
spillover (process) [a, d]	between		114.88		92.523		68.233		206.95		85.726
(cont.)	within		86.036		91.66		87.55		64.12		86.30
Inter-industry	overall	373.60	154.74	403.42	139.60	417.82	120.44	327.33	238.20	317.04	125.25
spillover (product) [a, d]	between		128.01		106.44		82.41		226.87		92.12
(cont.)	within		87.80		92.07		91.00		67.95		87.57

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Table 4.2 – *continued from the previous page*

		TOTAL		LTMI		HTMI		NKIS		KIS	
		mean	st dv	mean	st dv	mean	st dv	mean	st dv	mean	st dv
Public funding [a]											
Local	overall	0.217	0.412	0.216	0.411	0.262	0.440	0.080	0.272	0.240	0.427
(0/1)	between		0.316		0.293		0.325		0.200		0.360
	within		0.265		0.289		0.295		0.189		0.233
National	overall	0.200	0.400	0.170	0.376	0.256	0.436	0.065	0.247	0.250	0.433
(0/1)	between		0.309		0.272		0.325		0.179		0.356
	within		0.255		0.259		0.291		0.172		0.247
European	overall	0.050	0.218	0.029	0.169	0.041	0.199	0.020	0.140	0.100	0.299
(0/1)	between		0.168		0.109		0.137		0.100		0.251
	within		0.138		0.129		0.144		0.099		0.159
Sources of information [c]											
Internal	overall	0.598	0.490	0.551	0.497	0.642	0.479	0.536	0.499	0.633	0.482
(0/1)	between		0.376		0.384		0.363		0.387		0.366
	within		0.330		0.331		0.325		0.331		0.333
Market	overall	0.483	0.500	0.456	0.498	0.514	0.500	0.485	0.500	0.486	0.500
(0/1)	between		0.379		0.375		0.381		0.383		0.378
	within		0.337		0.338		0.331		0.338		0.341
Institutional	overall	0.150	0.357	0.139	0.346	0.142	0.349	0.095	0.293	0.192	0.394
(0/1)	between		0.274		0.266		0.266		0.215		0.303
	within		0.225		0.221		0.222		0.189		0.244
Others	overall	0.175	0.380	0.152	0.359	0.179	0.384	0.137	0.344	0.213	0.409
(0/1)	between		0.288		0.266		0.291		0.273		0.315
	within		0.245		0.243		0.246		0.215		0.257
Firms		9,042		3,126		2,272		1,140		2,504	
(%)				(34.6)		(25.1)		(12.6)		(27.7)	
Observations		57,379		19,838		14,547		7,400		15,594	
(%)				(34.6)		(25.3)		(12.9)		(27.2)	

Notes: LTMI (low and medium-low tech manufacturing industries), HTMI (medium-high and high tech manufacturing industries), NKIS (non-knowledge-intensive services), KIS (knowledge-intensive services). In brackets type of variables (continue, dycothomic, or percentage) [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. Source: PITEC; own calculations.

4.5.2 Estimation results

First stage: Research Equations

Table 4.3 presents the results for Equations [4.1] and [4.2]. 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 the table (columns 5 - 8) 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 spillover); thus, the coefficients show the effect of changing the dummy variable from 0 to 1.

First of all, the results of this first stage of the model suggest that the determinants of R&D intensity differ between industry and the services sector.

Specifically, in the case of manufacturing firms: the larger the firm (according to Chudnovsky, 2006; Artés, 2009 and Lhuillery, 2011) and the greater the physical and human capital, the more likely a firm is to engage in R&D activities and the greater its investment is likely to be. In addition, those firms that operate in international markets (in line with Artés, 2009, and Huergo and Moreno, 2011, who use exports to capture the importance of the external market), protect their innovations (in consonance with Lhuillery, 2011, who shows that protection has a strong impact on the decision to engage in R&D activities) and receive public funding – both national and local, are more likely to carry out R&D projects and to invest more money in them. However, group membership seems to have a weak influence on the decision to engage in R&D activities and then only in low-tech firms, while its impact is negative on a firm's investment intensity (columns 5 and 6). This might be because firms benefit from innovation carried out by other firms within their group, so they need to invest less money in R&D activities.

Table 4.3 Research Equations (2004-2010)

(Dep var)	Engage in R&D activities (RE Probit)				R&D intensity (Consistent estimator, Wooldridge1995)			
	LTMI (1)	**HTMI** (2)	**NKIS** (3)	**KIS** (4)	**LTMI** (5)	**HTMI** (6)	**NKIS** (7)	**KIS** (8)
Firm size	0.116***	0.0128***	-0.00549*	-0.0016	--	--	--	--
	(0.0151)	(0.00304)	(0.00307)	(0.0117)				
Physical capital	0.0217***	0.0022***	0.0070***	0.018***	0.0410***	0.0477***	0.00520	0.057***
	(0.00419)	(0.000785)	(0.00195)	(0.00604)	(0.00602)	(0.00523)	(0.0209)	(0.00972)
Human capital	0.005***	0.001***	0.0009***	0.0023***	0.0083***	0.0049***	-0.0005	-0.0010
	(0.000887)	(0.000177)	(0.000237)	(0.00044)	(0.0017)	(0.0012)	(0.003)	(0.0012)
Group	0.0603*	0.00159	0.0185*	0.0293	-0.110***	-0.062***	-0.099	-0.10***
	(0.0331)	(0.0042)	(0.0096)	(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***	0.015***	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)
Public Funding								
Local	0.254***	0.022***	0.087***	0.306***	0.519***	0.202***	0.0673	-0.0204
	(0.0207)	(0.0047)	(0.0336)	(0.0247)	(0.0510)	(0.0404)	(0.158)	(0.0702)
National	0.280***	0.021***	0.191***	0.304***	0.635***	0.247***	-0.0514	-0.107
	(0.0202)	(0.0050)	(0.0584)	(0.0280)	(0.0531)	(0.0345)	(0.146)	(0.0683)
European	0.156***	-0.0025	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	0.010***	0.002***	0.0021***	0.012***	--	--	--	--
	(0.00179)	(0.00042)	(0.00043)	(0.00096)				
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: LTMI (low and medium-low tech manufacturing industries), HTMI (medium-high and high tech manufacturing 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 [4.1] and adjusted R^2 in Equation [4.2]. *** Significant at 1%, ** significant at 5%, * significant at 10%.

On the other hand, the fact of having cooperated with other firms also increases innovative effort but only in low-tech firms. Finally, and regarding our main contribution at this stage of the model, the results presented in Table 4.3 show that a firm's decision as to whether or not to engage in R&D activities is positively influenced by the fact that the rest of the firms in its sector performed R&D in the previous period. This might reflect an incentive effect[52], since the greater the number of firms undertaking R&D activities in the same sector, the more likely a firm is to engage in R&D projects. One implication of this is the possible existence of a "virtuous cycle", given that if firms in one sector innovate this is likely to stimulate the others to do likewise, and so on and so forth.

Last of all, and regarding the level of technology operated by the firm, it seems that the impact of all the variables is greater for low-tech than it is for high-tech manufacturing firms.

In the case of the service sector, physical and human capital have a positive impact on the propensity of firms to engage in R&D activities, while firm size is not relevant. As in the case of the manufacturing sector, having operated in international markets, using protection methods and receiving public funding increase the likelihood of carrying out R&D projects. If we now turn to our variable of interest, we can see that spillover is also important in the case of service firms. Particularly, knowledge-intensive services (column 4) increase their probability of engaging in R&D activities 1.20 percentage points if the proportion of firms in the same sector that perform R&D increased by 1 percentage point in the previous year.

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[52] As explained in Section 4.4.1, this incentive effect could be due to two factors: i) investment in R&D generates a pool of knowledge in the sector and allows firms to benefit from this information and expertise (through their 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 to lose market share.

Finally, there is no clear pattern – not in the first or in the second equation – regarding the firm's level of technology in the service sector. Specifically, no variable is significant when explaining R&D intensity in the case of non-knowledge-intensive services, while only physical capital and belonging to a group are significant in the case of knowledge-intensive services.

Last of all, the inverse Mills ratios obtained from Equation [4.1] are clearly significant, showing the importance of taking the selection problem into consideration. In addition, the control variables are also statistically significant.

Second stage: Innovation equation

Table 4.4 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, firm size, personnel in R&D and investment in advanced machinery); thus, the coefficients show the effect of changing the dummy variable from 0 to 1.

As expected, the greater the R&D intensity (predicted by Equation [4.2]) carried out two years previously, the greater the probability of achieving both a process and product innovation. If we analyse the differences between technology levels, we observe that among manufacturing sectors, low-tech firms are more likely than high-tech firms to report a successful innovation given their R&D intensity. For instance, a unit increase in the logarithm of R&D intensity results in an increase of 20 (45) percentage points in the probability of achieving a process (product) innovation in low-tech firms vs. 5.25 (1.5) percentage points in high-tech firms. While it is true that low-tech manufacturing firms have lower overall R&D expenditures, Table 4.4 shows that their R&D effort leads to a higher propensity to obtain both process and product innovations.

Table 4.4 Innovation Equation (2007-2010)

(Dep var)	**Process Innovation** (RE probit)				**Product Innovation** (RE probit)			
	LTMI (1)	HTMI (2)	NKIS (3)	KIS (4)	LTMI (5)	HTMI (6)	NKIS (7)	KIS (8)
Predicted R&D intensity	0.197***	0.0525**	0.150***	0.209***	0.446***	0.0149***	0.0252*	0.415***
	(0.0304)	(0.0212)	(0.0448)	(0.0425)	(0.0704)	(0.00562)	(0.0149)	(0.0478)
Firm size	0.0504***	0.0782***	0.0493***	0.0723***	0.0537**	0.00129	-0.00037	-0.0216
	(0.0101)	(0.0175)	(0.0181)	(0.0210)	(0.0252)	(0.00132)	(0.00189)	(0.0172)
Protection	0.0508**	0.0395**	-0.0422	0.0428	0.106***	0.00382	0.00279	0.176**
	(0.0233)	(0.0179)	(0.0692)	(0.0435)	(0.0389)	(0.00249)	(0.00651)	(0.0742)
Advanced machinery	0.0263***	0.0173***	0.0359***	0.0429***	0.0247***	0.000686**	0.00308*	0.0259***
	(0.00363)	(0.00427)	(0.0103)	(0.00695)	(0.00691)	(0.000345)	(0.00173)	(0.00992)
Continuous R&D	0.0274	0.00658	-0.0410	0.132***	0.196***	0.00762*	0.0440	0.184***
	(0.0235)	(0.0255)	(0.0740)	(0.0410)	(0.0446)	(0.00399)	(0.0380)	(0.0498)
Personnel in R&D	0.0520***	0.0139	0.0831*	0.0287	0.148***	0.00681**	0.00836	0.113***
	(0.0121)	(0.0105)	(0.0450)	(0.0176)	(0.0313)	(0.00333)	(0.00527)	(0.0258)
International competition	0.0346	0.00834	0.0742	-0.0145	0.150***	0.00282	0.0111	0.0634
	(0.0256)	(0.0266)	(0.0667)	(0.0612)	(0.0405)	(0.00208)	(0.00727)	(0.0667)
Sources of information								
Internal	0.169***	0.0695***	0.558***	0.388***	0.221***	0.0106*	0.0714**	0.370***
	(0.0214)	(0.0226)	(0.0823)	(0.0440)	(0.0434)	(0.00565)	(0.0337)	(0.0436)
Market	0.149***	0.0618***	0.571***	0.317***	0.169***	0.00930**	0.0170*	0.362***
	(0.0194)	(0.0213)	(0.0772)	(0.0382)	(0.0372)	(0.00466)	(0.00870)	(0.0474)
Institutional	-0.0122	0.0120	0.0103	0.0175	0.000999	3.71e-05	-0.00084	-0.0515
	(0.0318)	(0.0156)	(0.115)	(0.0514)	(0.0339)	(0.00236)	(0.00974)	(0.0736)
Others	0.0544***	0.0608***	-0.102*	0.0647	0.203***	0.00209	0.00284	0.158***
	(0.0205)	(0.0172)	(0.0616)	(0.0589)	(0.0313)	(0.00243)	(0.0106)	(0.0601)
Means [(1)]	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***
Time dummies	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***
Industry dummies	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***
Observations	10,460	7,731	3,980	8,082	10,460	7,731	3,980	8,082
Number of groups	3,003	2,167	1,109	2,340	3,003	2,167	1,109	2,340
Rho[(2)]	0.857	0.908	0.848	0.836	0.906	0.897	0.897	0.888
Corrected predictions	77,77%	71,88%	78,89%	75,20%	73,50%	81,37%	82,31%	77,83%
Adjusted R^2 [(3)]	0,1570	0,1028	0,2530	0,1604	0,1487	0,1694	0,2697	0,2456

Notes: LTMI (low and medium-low tech manufacturing industries), HTMI (medium-high and high tech manufacturing industries), NKIS (non-knowledge-intensive services), KIS (knowledge-intensive services). Reported marginal effects (at the sample means) are for the probability of obtaining an 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). [(3)] Adjusted McFadden's pseudo R^2. *** Significant at 1%, ** significant at 5%, * significant at 10%.

This finding is in line with Hall et al. (2009), who point out that this might be because innovating in less advanced sectors requires less R&D effort, given that innovation output is linked to changes in the organizational process that are unlikely to be so strongly linked to the firm's technology. This result might also indicate that high-tech manufacturing firms need a longer period of time to obtain an innovation. In contrast, in the case of the services sector the probability of achieving a process or product innovation is clearly higher for knowledge-intensive services than non-knowledge intensive services.

Additionally, the probability of obtaining a process innovation increases with firm size, while the propensity to introduce a product innovation rises with the fact that R&D investment is made on a regular basis. Finally, personnel in R&D, investment in advanced machinery and information from inside the company and from the market all seem to increase the likelihood of obtaining process and product innovations. However, operating in an international market (Harris et al., 2003, and Woerter and Roper, 2010) does not seem have an influence on the development of an innovation in most cases. Finally, no clear pattern can be established according to a firm's level of technology.

Third stage: Productivity Equation

Table 4.5 shows the estimates of the production function equation. To account for the high correlation between process and product innovation[53] and to avoid multicollineartity problems, two separate estimations are performed (see other authors who have encountered the same problem, for example, Raffo et al., 2008). The first four columns show the results when

[53] The correlation between the predicted process innovation and the predicted product innovation is 0.65 on average.

the predicted values for process innovation are included, while the last four columns show the results for product innovation. The main interest at this stage of the model is to analyse the impact of innovation and spillovers on firm labour productivity.

As in the first stage of the model, the respective results from this last step for industry and the services sector clearly differ.

First of all, manufacturing firms increase their productivity with firm size, physical and human capital. In line with the literature, the results confirm the positive effect of process and product innovations. Thus, generating an innovation in the preceding three years (value predicted in Equation [4.3]) has a positive effect on the productivity of a manufacturing firm.

Turning now to our variables of interest, it can be seen that both intra- and inter-industry externalities have a positive impact on the productivity of manufacturing firms. Even though the coefficients are low, they are clearly significant. Thus, R&D expenditures carried out by firms in the same sector or in other sectors[54] – provided they achieve an innovation – increase their productivity. In particular, low-tech manufacturing firms present a similar coefficient regardless of the type of externality (intra or inter) or innovation (process or product). Therefore, if the rest of the firms increase their R&D expenditures by 1 million euros and obtain an innovation (process or product), then the productivity of low-tech industries would rise by around 0.06 %. In the case of high-tech manufacturing firms there is a difference in this magnitude. As can be seen in Table 4.5, companies benefit more from innovation carried out by firms in other sectors (0.12% for process and 0.15%

[54] 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 4.4.3).

for product) than that conducted by firms in the same sector (0.02% for process and product). A possible explanation for this might be that the rivalry between these firms is greater, which reduces the positive impact of the external R&D of firms in their same sector[55].

Table 4.5 Productivity Equation (2007-2010)

(Dep var)	Labour Productivity (RE)							
	LTMI (1)	**HTMI** (2)	**NKIS** (3)	**KIS** (4)	**LTMI** (5)	**HTMI** (6)	**NKIS** (7)	**KIS** (8)
Predicted process innovation	0.038**	0.041**	0.020	0.073***	--	--	--	--
	(0.0149)	(0.0184)	(0.0191)	(0.0197)				
Predicted product innovation	--	--	--	--	0.059***	0.039**	0.063**	0.048
					(0.0103)	(0.0197)	(0.0252)	(0.0322)
Firm size	0.0326	0.0872***	-0.180***	-0.052**	0.029	0.089***	-0.179***	-0.051**
	(0.0221)	(0.0146)	(0.0298)	(0.0220)	(0.0255)	(0.0159)	(0.0281)	(0.0204)
Physical capital	0.057***	0.048***	0.036***	0.101***	0.056***	0.048***	0.036***	0.102***
	(0.0054)	(0.0073)	(0.0102)	(0.0144)	(0.0051)	(0.0061)	(0.0100)	(0.0121)
Human capital	0.002***	0.002***	0.001	0.000	0.002***	0.002***	0.001	0.000
	(0.0007)	(0.0004)	(0.0005)	(0.0004)	(0.0006)	(0.0004)	(0.0005)	(0.0004)
Intra-industry spillover *t-1*	0.0006***	0.0002***	0.0000	-0.0001***	0.0007***	0.0002***	0.0000	-0.0001***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Inter-industry spillover *t-1*	0.0006***	0.0012***	0.0001	-0.0003	0.0005***	0.0015***	-0.0001	-0.0003
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Constant	10.995***	10.761***	12.597***	10.575***	10.994***	10.605***	12.635***	10.588***
	(0.1074)	(0.0935)	(0.2021)	(0.1659)	(0.0989)	(0.1021)	(0.1893)	(0.1528)
Time dummies	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***
Ind dummies	No	No	No	No	No	No	No	No
Observations	10,460	7,731	3,980	8,082	10,460	7,731	3,980	8,082
Number of groups	3,003	2,167	1,109	2,340	3,003	2,167	1,109	2,340
R^2 within	0.0995	0.0834	0.0960	0.0305	0.106	0.0881	0.0964	0.0301
R^2 between	0.139	0.180	0.0383	0.108	0.135	0.175	0.0417	0.106
R^2 overall	0.147	0.176	0.0472	0.110	0.144	0.173	0.0503	0.108

Notes: LTMI (low and medium-low tech manufacturing industries), HTMI (medium-high and high tech manufacturing 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%.

In the case of the service sector, physical capital increases firm productivity whereas firm size has a negative impact. Moreover, process innovation has a positive impact on the productivity of knowledge-intensive services, while the opposite is the case of product innovation. More interestingly, the rest of the variables, even spillovers, are not, in general, relevant, one

[55] This result is consistent with findings in Chapter 3.

exception being the case of knowledge-intensive services that present a negative coefficient. In keeping with Chapter 3, this finding might reflect the competitive effect discussed earlier; in other words, a firm might reduce its productivity if its competitors increase their R&D expenditure and obtain an innovation. This apart, the results in Table 4.5 suggest that firms in the service sector are not influenced by what other firms do.

Finally, although the coefficients vary across technology levels, they do not follow any specific pattern.

4.6 Concluding remarks

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

In seeking to answer these questions, information has been drawn from the PITEC database for the period 2004-2010. Generally speaking, this study tries to shed some light to the scarce literature that analyses this topic, given that most papers tend to use cross-sectional data. Working with panel data enables us to control for both unobserved firm heterogeneity and the time lag in the whole process. To the best of our knowledge, no previous paper has examined the spillover effect in any country by adopting the CDM perspective.

Returning to the hypothesis posed at the beginning of this chapter, the structural model shows that not only is R&D important to increase a firm's productivity, but so is the firm's ability to turn this investment into innovations (what some authors refer to as "innovativity"). In fact, this study shows that innovation input (R&D intensity) affects innovation output and that in turn this output has a positive impact on a firm's productivity.

The following conclusions can be drawn from this chapter. First of all, manufacturing and service firms cannot be treated equally, since their behaviour differs in the course of the process. Specifically, the findings indicate that some variables that are relevant for manufacturing firms are not significant for the service sector. Thus, the results presented here need to be interpreted with caution as far as the service sector is concerned. Secondly, although the coefficients vary with technology level across the model, they do not adhere to any specific pattern. One exception, however, is the higher returns of low-tech manufacturing firms in relation to the determinants of the R&D decision. Thirdly, and in answer to the first research question, it has been found that the firm's decision to engage in R&D activities or not is influenced in some degree by what other firms opt to do. The results show that the higher the number of firms undertaking R&D activities in a given sector, the more likely a firm in that sector is to engage in R&D projects. This means that an external pool of knowledge encourages firms to carry out R&D activities (both in the industrial and service sectors). Finally, and in answer to the second research question, the results suggest that there is an element of complementarity between manufacturing firms (but not those in the service sector), both between firms in the same sector and firms operating in different sectors. Thus, the R&D expenditures incurred by firms in the same sector (intra-industry externalities) or in other sectors (inter-industry externalities) – provided an innovation is produced as a result of the investment – have a positive impact on a firm's productivity. Furthermore, it has been shown that high-tech manufacturing firms increase their productivity more when adopting R&D from other sectors (inter-industry externality) than when employing the R&D from their own sector.

Chapter 5: How important are internal knowledge flows for firm's innovative performance?

5.1 Introduction

Knowledge within a firm is one of its most valuable resources. Like fuel for a car, knowledge is the information that nourishes new ideas, generating improvements and innovations that can boost a firm's performance. It is not surprising, therefore, that firms seek to maximize this input. One means available to a firm to achieve just that is to transfer knowledge within the firm. The transmission of information inside the company broadens firm knowledge and can contribute positively to its innovativeness and performance. As Argote et al. (2000) argue "organizations that are able to transfer knowledge effectively from one unit to another are more productive and more likely to survive than those that are less adept at knowledge transfer".

Many papers in the field of organizational learning have analysed knowledge transfers within (as well as between) organizations[56]. However, in the innovation literature most of the articles focus their attention on the impact of external knowledge flows on innovation performance, while there is little discussion about the relevance of internal knowledge transfers. Thus, cooperation with different partners (Belderbos et al., 2004) and the information sources used to carry out innovation projects (Escribano et al., 2009) have been considered throughout the literature as the means for capturing external knowledge. One question that needs to be addressed, however, is whether internal knowledge flows are also relevant. Although a number of papers include among their explanatory variables an indicator as to whether a firm has obtained information from an internal source or not, it

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[56] See for instance, Argote et al. (2002), van Wijk et al. (2008) and Maurer et al. (2011). Many studies examine organizational knowledge transfer from a management perspective. However, our goal here is somewhat different so that social network analysis and knowledge management lie beyond the scope of this study.

tends merely to be a control since the interest of the authors typically lies elsewhere (R&D, collaborative agreements with several partners, etc.). To the best of our knowledge, no further research into the importance of internal knowledge on a firm's innovative performance has been carried out.

Given that sharing knowledge within a firm can, for example, allow one department to benefit from the experience of another or help its workers perform a task more efficiently, it is interesting to analyse the extent to which internal knowledge flows affect innovation performance. Despite the interest in external knowledge flows, it is not unreasonable to think that it is easier for a firm to benefit from knowledge generated from within the firm (or within the group) than from that originating from outside the firm (or group). For instance, there is a shared network, internal compilation of information (research reports, technical documents, databases etc.), exchange of information between workers (via email, company meetings, workshops and so on), training programs, social interaction between colleagues (in other words, daily situations which can lead to informal knowledge sharing), job rotation (between departments or firms that belongs to the same group), etc.

Therefore, even though internal information transfers have faded into the background since the literature has preferred to focus its attention on external knowledge, internal knowledge flows are believed to play a role in a firm's performance. For this reason, the aim of this chapter is to analyse the impact of internal knowledge flows on firm innovative sales. In order to do so, a distinction is drawn between voluntary and involuntary knowledge flows; the former arise as a result of (intended) formal collaborations, while the latter emerge unintentionally. Both voluntary and involuntary knowledge flows can be seen as instruments for disseminating information and sharing experience within a firm, thus improving its technological performance and boosting its innovative sales. An additional question that needs to be taken into consideration is whether a firm's absorptive capacity (Cohen and Levinthal, 1989) increases the impact that internal knowledge transfers have on innovation performance. Given that there is evidence that internal R&D improves a firm's learning capacity, it is clearly of interest to assess whether this ability enhances the efficiency of internal knowledge transfers making firms more innovative.

The data used for this study cover the period 2004-2011 (see Chapter 2 for a full description of the dataset). Although in previous chapters the level of technology of the sector in which the firm operates is taken into account, the results do not suggest any specific pattern or point to any clear behaviour. As a consequence, here the analysis is undertaken for the whole sample and no differentiation is made according to technology level.

To sum up, after controlling for a firm's own R&D investment and external knowledge flows, the role played by internal knowledge spillovers is examined. In particular, this chapter seeks to address the following questions: (i) Are internal knowledge flows (voluntary and involuntary) important for the performance of innovative firms? (ii) Does this impact differ depending on a firm's absorptive capacity?

The remainder of the chapter is organised as follows. The next section presents an overview of the previous literature regarding the different sources of knowledge. Section 5.3 forwards the empirical model, while data and variable definitions are explained in section 5.4. The main results are shown in section 5.5 whilst section 5.6 presents some further explorations. Finally, the main conclusions are discussed in the last section.

5.2 What do we know so far?

In recent years, there has been a growing interest in the literature to examine the impact of external knowledge flows on firm's innovative performance. Many studies have analysed intentional knowledge transfers between companies embodied in formal collaboration agreements, while others have recognised the importance of (unintended) knowledge spillovers. Both voluntary and involuntary knowledge flows can be considered as mechanisms for spreading information and experience within companies, thus helping them to perform better technologically. Despite this evidence, internal knowledge transfers within a firm or group have rarely been examined in depth.

In this section previous research on the relationship between knowledge flows and innovation performance is examined differentiating between voluntary and involuntary knowledge transfers.

5.2.1 Voluntary knowledge flows

Cooperation between firms when undertaking their innovation activities is identified as a channel for increasing innovation performance. Given that firms cannot always have access to everything they need, collaboration with others allows them to engage in innovation activities. For this reason, several authors include a variable indicating whether a firm collaborates with others or not. Some report a positive impact of cooperation on innovation performance (Klomp and van Leeuwen, 2001 and Mohnen et al. 2006), but others fail to identify this effect (Frenz and Ietto-Gillies, 2009, and Raymond et al. 2010).

A number of empirical studies have assessed whether this impact depends on the type of partner and they obtain a range of different results. Belderbos et al. (2004), in a study including 2,056 firms in the Netherlands, find that competitor and university cooperation increase innovative sales of products new to the market. Nieto and Santamaria (2007), with a sample of 1,300 Spanish manufacturing firms, show that collaborative agreements with other partners have a positive impact on product innovation as well as on the degree of product novelty. Aschhoff and Schmidt (2008) analyse 699 German firms and find that competitors and research institutions have a positive impact on innovation performance, whilst suppliers and customers do not have any influence. Tsai and Wang (2009) study 753 Taiwanese firms and show that in no instance does a cooperation partner increase innovation performance. Finally, Zeng et al. (2010), in a study of 137 Chinese manufacturing firms, report that collaboration agreements have a positive impact on firm performance, especially vertical cooperation. Other papers turn their attention to a specific kind of innovation. For instance, Lööf and Brostrom (2008) and Monjon and Waelbroeck (2003) investigate collaborations with universities and Robin and Schubert (2013) analyse the impact of cooperation with public research bodies.

Nevertheless, all of these studies focus only on cooperation agreements with external partners and do not deal with the possibility of internal collaborations. Since cooperation partners of different types may not have the same impact on firm performance, it is interesting to enquire as to the impact of internal collaboration. As pointed out in the literature, belonging to a group of companies benefits firms not only in terms of economies of scale and access to finance, but also in terms of intra-group knowledge spillovers (Mohnen et al., 2006 and Frenz and Ietto-Gillies, 2009). In order to capture these effects, previous studies incorporate a dummy variable to indicate whether a firm belongs to a group of companies or not. So far, however, no attention has been paid to the possible collaboration between these firms. Sharing a common internal network can increase the transmission of knowledge and experience, while collaboration between these companies could stimulate even more information flows and technological expertise, or improve distribution and the organizational process. Thus, cooperation between firms that form part of the same group (internal cooperation) can generate positive synergies leading to a higher innovation performance, while appropriability is not an overriding concern since the benefits will remain in the same group of companies.

5.2.2 Involuntary knowledge flows

As explained in previous chapters, unintended knowledge transfers need to be taken into account when innovation performance is analysed. Such knowledge transfers occur when information from one firm flows beyond its boundaries, enabling others to use this information even if they have not paid for it. Recently, the increasing availability of innovation surveys has led to information sources being used as a proxy for involuntary knowledge flows [57]. Firms are asked to identify which sources have provided information for their undertaking of innovation projects or for finishing an existing project. Numerous studies have adopted such measures in their analyses. In particular, information coming from different types of partners is often included as a control variable (Lööf and Heshmati, 2002; Janz et al., 2004; Griffith et al., 2006; Masso and Vather, 2008; Raffo et al., 2008). Nevertheless, sometimes only information coming from research institutions or universities is taken into consideration. Mohnen et al. (2006) and Raymond et al. (2010) are two examples of such studies, since the

[57] Various articles have relied on other proxies for these incoming spillovers, such as, the pool of external knowledge. Bearing in mind that any measure has its advantages and disadvantages, here it is decided to use a direct measure that enables researchers to determine which information has been important (and to what extent) in undertaking or completing an innovation project.

authors only include a dummy variable to capture proximity to basic research. Elsewhere, involuntary knowledge sources are used to build an indicator of external knowledge (see Escribano et al., 2009) or openness (Robin and Schubert 2013). Interestingly, Belderbos et al. (2004) go a step further and estimate an auxiliary regression in order to separate the effect of incoming spillovers from cooperation. Their findings suggest that customer and university spillovers (which are not due to formal collaborations) increase innovative sales.

Likewise in the case of voluntary knowledge flows, far too little attention has been paid to knowledge flows originating from within the firm or the group of companies. Even though some articles control for internal information transfers in their equations (Lööf and Heshmati, 2002; Masso and Vather, 2008 and Raffo et al., 2008), their research is focused on the impact of R&D on innovation output rather than on the effect of internal knowledge flows. However, their results indicate that internal knowledge is an important source of information.

5.2.3 The role of absorptive capacity

Cohen and Levinthal (1989) claim that firms with the greatest technological capital are the ones that benefit most from external knowledge. In their seminal article, the authors develop the notion of "absorptive capacity" which has become a key factor in recent years. Firms need to be able to recognize external information in order to absorb it and use it for their own benefit. Being exposed to external knowledge is not enough to acquire it. Therefore, firms that perform better technologically and own a high level of knowledge not only increase their innovation performance per se but also are more able to identify and exploit information outside their boundaries (also known as "the dual role of R&D").

Some recent studies have investigated this hypothesis. Escribano et al. (2009), using a sample of 2,265 Spanish firms, show that firms with higher levels of absorptive capacity can handle external information more effectively. The authors apply principal component analysis to create an indicator to capture absorptive capacity, which they interact with involuntary knowledge flows. Their results suggest that absorptive capacity positively affects the impact of these transfers on innovation performance. A similar result is reported by Tsai and Wang (2009), who argue that internal R&D investment (used as a proxy for absorptive capacity) increases both innovation performance and the efficiency of collaboration with different partners. However, Frenz and Ietto-Gillies (2009), who take into account the possible complementarity between internal and external sources, reach different conclusions. Although the authors expected firms with in-house R&D to benefit more from external knowledge and to generate higher innovative sales, the results do not support their hypothesis.

In line with Frenz and Ietto-Gillies (2009), the second goal of this chapter is to determine if absorptive capacity affects the relationship between internal knowledge flows and innovation performance. Given that there is evidence that internal R&D improves a firm's learning capacity, it would be interesting to assess if this ability enhances the efficiency of internal knowledge transfers resulting in more innovative firms.

To the best of our knowledge, no previous research has considered information originating from inside the firm or group itself as the main focus of its analysis and no evidence regarding the effect of absorptive capacity on such internal knowledge flows has been taken into consideration to date.

5.3 Model and estimation strategy

The goal of this study is to analyse how internal knowledge flows affect the innovation performance of firms. However, the way in which PITEC, as well as other innovation surveys, is organised leads to selection problems, since only innovative firms are required to answer an additional set of questions regarding innovation activities (see Chapter 2 for further details). This means that measures of innovation performance are only observed for innovative firms. It is important to bear this point in mind given the selection bias the estimates are likely to suffer. In order to deal with this problem, a Heckman type selection model is used[58]. This comprises two equations: i) a selection equation indicating whether the firm innovates or not and ii) an intensity equation accounting for the firm's innovative performance. The second equation includes a correction term, the inverse Mills ratio, computed in the first equation, to cope with the fact that innovation performance can only be estimated for those firms that innovate. Both equations can be specified as follows (Wooldridge, 1995, 2002):

$$y1_{it} = \begin{cases} 1 & if\ x_{it}^{(1)}\beta^{(1)} + \alpha_i^{(1)} + \varepsilon_{it}^{(1)} > 0 \\ 0 & otherwise \end{cases} \qquad [5.1]$$

$$y2_{it} = \begin{cases} x_{it}^{(2)}\beta^{(2)} + \alpha_i^{(2)} + \hat{\lambda}_{it} + \varepsilon_{it}^{(2)} & if \quad y1_{it} = 1 \\ 0 & if \quad y1_{it} = 0 \end{cases} \qquad [5.2]$$

where *i* and *t* index firm and year respectively. $y1_{it}$ takes a value of 1 if the firm is an innovator. Here, an innovator is defined as a firm that has introduced at least one product or process innovation during the last three

[58] This kind of model has been widely used in the literature to handle selection bias problems (see Mohnen et al., 2006; Griffith et al., 2006; Artes 2009; Frenz and Ietto-Gillies, 2009; Raymond et al., 2010; Antonietti and Cainelli, 2011; Lhuillery, 2011 and Robin and Shubert, 2013, among others).

years [*t-2, t*]. $y2_{it}$ is equal to the firm's innovation intensity, define as the share of innovative sales in *t*, and it is observed only if the firm is innovative ($y1_{it} = 1$). $\mathrm{x}_{\mathrm{it}}^{(1)}$ and $\mathrm{x}_{\mathrm{it}}^{(2)}$ are a set of explanatory variables and $\beta^{(1)}$ and $\beta^{(2)}$ are the parameters to be estimated. $\alpha_{\mathrm{i}}^{(1)}$ and $\alpha_{\mathrm{i}}^{(2)}$ capture the unobserved firm heterogeneity, $\hat{\lambda}_{it}$ is the inverse Mills ratio computed in the first equation, and finally $\varepsilon_{\mathrm{it}}^{(1)}$ and $\varepsilon_{\mathrm{it}}^{(2)}$ are the error terms. Following Wooldridge (2002) an exclusion restriction is needed. In other words, $\mathrm{x}_{\mathrm{it}}^{(1)}$ should contain an additional variable (not included in $\mathrm{x}_{\mathrm{it}}^{(2)}$) to avoid multicollinearity problems, since the inverse Mills ratios are incorporated in the second equation[59].

Since our interest in this chapter is focused on innovation performance and not on the determinants of the qualitative decision to innovate, the analysis is concerned primarily with the second equation[60]. In particular, in order to analyse the impact of internal knowledge flows on firm innovative performance, Equation [5.2] can be specified as follows:

$$y2_{it} = \beta_0 + \beta_1 VKF_{i(t-2,t)} + \beta_2 IKF_{i(t-2,t)} + X2\,\Upsilon + \alpha_i^{(2)} + \hat{\lambda}_{it} + \varepsilon_{it}^{(2)} \quad if \quad y1_{it} = 1 \qquad [5.3]$$

where *VKF* refers to voluntary knowledge flows and *IKF* to involuntary knowledge flows for the period [*t-2, t*] that might have an impact on innovative performance in *t*. *X2* refers to a group of control variables.

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[59] In this case, human capital is used as exclusion restriction since it is likely that the percentage of workers with higher education affects the probability of achieving an innovation but not the amount of innovative sales. On the other hand, it is worth remembering that not all firms are requested to answer all the questions on the questionnaire. Only innovative firms are asked about various aspects of their innovation activities. For this reason, there is plenty of information available for Equation [5.2], but information is more limited for Equation [5.1].

[60] See Chapter 4 for a structural model that includes an analysis of the determinants to achieve an output innovation.

As for the second goal, this chapter seeks to assess if firms with higher levels of absorptive capacity can handle internal knowledge flows more effectively, and thus increase their innovative performance. To do so, the coefficients of internal knowledge flows are expected to depend on the absorptive capacity (AC) of each firm (lagged two years[61]):

$$\beta_k = \delta_k + \gamma_k \cdot AC_{it-2} \qquad where \;\; k = 1,2 \qquad [5.4]$$

By combining Equations [5.3] and [5.4]:

$$y2_{it} = \beta_0 + \delta_1 VKF_{i(t-2,t)} + \gamma_1 VKF_{i(t-2,t)} \cdot AC_{it-2} + \delta_2 IKF_{i(t-2,t)} + \gamma_2 IKF_{i(t-2,t)} \cdot AC_{it-2} + \\ + X2\,\Upsilon + \alpha_i^{(2)} + \hat{\lambda}_{it} + \varepsilon_{it}^{(2)} \quad if \;\; y1_{it} = 1 \qquad [5.5]$$

See next section for a detailed definition of the variables.

As in Chapter 4, the consistent estimator proposed by Wooldridge (1995) is used to account for selection bias. Equation [5.5] is therefore estimated using a pooled OLS including T inverse Mills ratios interacted with time dummies (obtained from estimating the selection equation for each year separately using a probit model).

5.4 Data and variables

The data used in this chapter consist of an unbalanced panel containing 8,932 firms (63,644 observations), of which 7,665 are innovative firms (45,036 observations), for the period 2004-2011. In consonance with the previous chapters, firms that remain at least three years in the panel are considered since some variables are lagged two periods[62]. This filter provides a sample that is more than 91% of the whole sample of innovative

[61] Absorptive capacity is lagged two periods since it is supposed to affect internal knowledge flows which are produced from *t-2* to *t*.

[62] Results without this filter remain almost identical.

firms (49,436 observations). Table A.4 in the Appendix shows that the sample preserves the properties after applying this filter and that it does not lead to any bias.

The definition of the variables used in the econometric analysis can be found below. See Table 5.1 for a detailed definition.

5.4.1 Dependent variable: Innovation performance

A firm's innovation performance is defined as the share of innovative sales due to new or significantly improved products in *t*. This measure includes both innovative sales new only to the firm but not to the market (which could be considered as imitations) and innovative sales new to the market (true innovations). The main analysis is conducted without drawing any distinction between the two since we are interested in the impact of internal knowledge flows on a firm's innovative performance as a whole. However, section 5.6.4 analyses the differences specifically with regard to the novelty of the innovation. To handle the fact that the endogenous variable is a proportion, a logit transformation is performed[63].

5.4.2 Independent variables

Voluntary and involuntary knowledge flows

As discussed at the beginning of this chapter, two kinds of internal knowledge flows can be distinguished. The first appear as a result of (intentional) formal collaboration and are viewed as "voluntary" spillovers, while the second do not arise out of cooperation agreements and are viewed

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[63] Since the endogenous variable is a proportion, its values are bounded by 0 and 1. Applying the logit transformation, $\ln(y2/1\text{-}y2)$, real values are obtained (from $-\infty$ to $+\infty$). To do so, 0 values (value for process innovators only) are replaced by 0.01 and 1 by 0.99 (see Mohnen et al., 2006, and Raymond et al., 2010).

as unintentional. In other words, the firm does not engage in any particular action or make any commitment in order to benefit from internal information; thus, they are considered to be "involuntary". They include, for example, information garnered from interactions between employees, at company meetings, or as a result of worker mobility between different offices and so on.

Voluntary knowledge flows are proxied by internal cooperation, which is defined as a dummy variable that takes a value of 1 if the firm belongs to a group and has cooperated in innovation activities with other firms within that group. It is expected that internal cooperation agreements entered into in the period [*t-2, t*] will have an impact on the innovation performance in *t*.

Involuntary knowledge flows are calculated by using a direct measure of the importance of internal information sources. According to PITEC, firms can identify different information sources (internal, clients, suppliers, competitors, universities, etc.) in their innovation activities as well as their degree of importance. In other words, firms declare whether or not they have used a source and at what level of intensity (low, medium or high on a four-point Likert scale). Thus, a dummy variable, which takes a value of 1 if the firm declares that internal information (within the company or group) has been used at a high level of intensity to undertake or finish innovation projects during the period [*t-2, t*], is employed to measure involuntary knowledge flows.

As Belderbos et al. (2004) point out, the effect of the knowledge flows that arise from formal cooperation has to be separated from the effect arising from involuntary knowledge transfers. To do so, involuntary spillovers are defined only for those firms that do not engage in internal cooperation. PITEC shows that 99% of firms that collaborate in innovation activities with other firms in their group declare that internal information is, to some extent (low, medium or high), a relevant source. Hence, in order to separate both effects, collaborative firms are excluded from the definition of the involuntary spillover variable. This means that a value of 0 is assigned to those firms that declare that internal information is not an important source of information, and also to those firms that declare that it is an important source of information but that they engage in cooperation activities with other firms within their group. In contrast, a value of 1 is given to those firms for which internal information is important and which do not enter into internal collaboration agreements.

Finally, *innovation intensity* is also included as an explanatory variable in order to account for accumulated knowledge and experience. This variable is used in the literature as a proxy for research effort and has a positive impact on innovation output. Here, it is defined as the ratio of innovation expenditures over sales (in logarithm) and it is lagged two years[64].

Control variables

In line with the previous literature, firm size, measured as the logarithm of the number of employees, is included to capture economies of scale and access to finance. Its quadratic form is also incorporated to account for possible non-linearities. In addition, a dummy variable indicating whether the firm has operated in an international market in the preceding three years

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[64] This is a plausible assumption since innovation efforts do not have an immediate impact on innovative performance, rather time is needed. In addition, it helps to mitigate possible simultaneity problems. Certainly, a longer lag phase may be required since it is generally accepted that investments in innovation take some time to materialise in something new or because completing an R&D project might take more than one year. However, this variable is also included in Equation [5.1] where it is lagged two periods since the innovation indicator refers to the period [*t-2, t*]. In addition, as PITEC is a short panel it is decided to work with a two-year lag.

is introduced. Firms that face high levels of competition are encouraged to invest in innovation and improve their innovation performance in order to be competitive. A dummy variable indicating if a firm does not belong to a group of companies is also incorporated. This variable seeks to compensate for the fact that internal cooperation (voluntary knowledge flows) is only defined for those firms that belong to a group[65]. Additionally, a dummy variable that takes a value of 1 for non-innovation performer firms (lagged two years) is included.

Two dummy variables to control for external knowledge flows and to compare with the impact of internal knowledge transfers are also incorporated[66]. The first of these is a dummy variable referring to external cooperation, which takes a value of 1 if the firm has cooperated in innovation activities with other firms (outside its group) over the last three years (including suppliers, competitors, clients, universities, etc.). Likewise, a dummy variable for external information sources (originating from suppliers, competitors, clients, competitors, etc.) is introduced in the model. Following the definition of internal information, only those firms that do not engage in cooperation activities with other firms (outside their group) are considered at this point (see Table 5.1 for a detailed definition).

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[65] In practice, this variable can be considered to have three categories: i) firms not belonging to a group, ii) firms belonging to a group but not undertaking internal cooperation (reference group), iii) firms belonging to a group and involved in internal cooperation. By doing so, it is possible to see not only the effect on firms of not forming part of a group, but also the effect of voluntary knowledge flows compared to firms that can cooperate (because they belong to a group of companies) but decide not to do so.

[66] Both variables are defined as general measures of external cooperation and external information since the interest here does not lay in analysing differences between types of partners (see Belderbos et al., 2004; Amara and Landry, 2005; or Tsai and Wang, 2009 for such kind of analysis). The concern at this point is to compare the effect of external and internal knowledge flows on innovation performance.

Table 5.1 Definition of variables

Dependent variable	
Innovation performance	Ratio of innovative sales due to new or significantly improved products over total sales in *t*.
Independent variables	
Internal Cooperation (*voluntary knowledge flows*)	Dummy variable equals 1 if the firm belongs to a group of companies and has cooperated in innovation activities with other firms of its group over the last three years; 0 otherwise.
Internal information (*involuntary knowledge flows*)	Dummy variable equals 1 if the firm declares that information coming from the firm or group has been an important source to undertake or finish innovation projects during the last three years as long as it has not cooperated with other firms of its group during that period; 0 otherwise.
Innovation intensity [(1)]	Ratio of the innovation expenditures over total sales in *t-2* (in logs). This measure includes intramural R&D investment, external R&D, acquisition of machinery, equipment and software, acquisition of external knowledge (not included in R&D), training for innovative activities, market introduction of innovation, design and others. It is computed as a stock measure using the perpetual inventory method (depreciate rate of 15%).
Absorptive capacity	Ratio of intramural R&D stock over total sales in *t-2* (in logs) using the perpetual inventory method.
Controls	
Size [(1)]	Number of employees in *t-2* (in logs).
International market	Dummy variable equals1 if the firm trades in an international market in the previous three years; 0 otherwise.
No group [(1)]	Dummy variable equals 1 if the firm does not belong to a group of companies in *t-2*; 0 otherwise.
Non-innovation performer[(1)]	Dummy variable equals 1 if the firm does not engage in any innovation activity in *t-2*; 0 otherwise.
External cooperation	Dummy variable equals 1 if the firm has cooperated in innovation activities with other firms (including suppliers, clients, competitors, universities, etc.) over the last three years; 0 otherwise.
External information	Dummy variable equals 1 if the firm declares that information coming from suppliers, clients, competitors, universities, etc. has been an important source of information to undertake or finish innovation projects during the last three years as long as it has not cooperated with other firms at the same time; 0 otherwise.

Note: Monetary variables are expressed in real terms (base 2011, using the GDP deflator). [(1)] These variables are lagged two periods since they are included in Equation [5.1], where they explain the probability of obtaining a product or a process innovation for the period [*t-2, t*].

Finally, industry dummies, time dummies and the inverse Mills ratio are included to capture specific industry characteristics and technological opportunities, time trends and selection bias respectively.

Absorptive capacity

Even though there are different measures to proxy absorptive capacity, here it is employed one of the most commonly used in the literature: R&D intensity (Cohen and Levinthal, 1989). However, in order to capture the accumulation of knowledge absorptive capacity is defined as the ratio of internal R&D stock over sales (in logarithm).

5.5 Results

5.5.1 Descriptive analysis

Table 5.2 presents the descriptive statistics for the dependent, independent and control variables used in the econometric analysis.

As can be seen, 52% of the innovative firms recognise that internal information is an important source of information for undertaking new innovation projects or finishing existing ones. Additionally, 26% of the firms that belong to a group (42.2%) opted to engage in cooperation agreements with other firms in the same group.

As shown in columns 7 and 8, the share of innovative sales differs statistically between groups. In particular, firms that consider internal information to be highly important have a greater share of innovative sales (0.32) than firms that do not (0.28). A similar result is found for those firms that cooperate internally (0.32 vs. 0.27). Significant differences can also be found in relation to the control variables. The share of innovative sales is higher for those firms that operate in an international market, those that do not belong to a group[67], those that undertake innovation expenditures and those firms that cooperate with external partners.

Table 5.2 Descriptive statistics for innovative firms

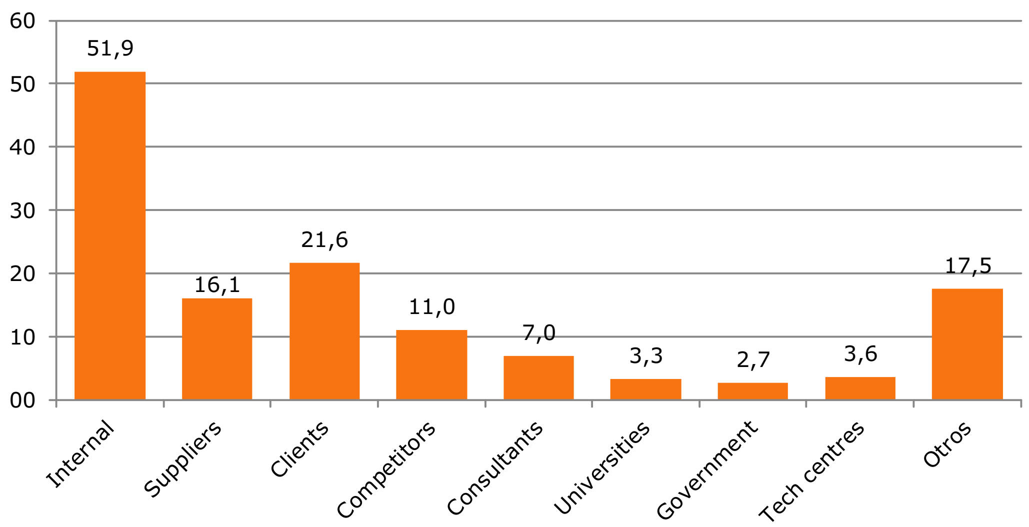
	Type	Mean	Standard deviations			Share of innovative sales per group			
			overall	between	within	0	1	Test 1[1]	Test 2[2]
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable									
Share innovative sales	[0-1]	0.30	0.37	0.28	0.25				
New to the firm only	[0-1]	0.177	0.29	0.22	0.21				
New to the market	[0-1]	0.123	0.25	0.18	0.17				
Independent variables									
Innovation intensity	cont.	0.233	0.39	0.37	0.14				
Internal information (involuntary)	(0/1)	0.519	0.50	0.37	0.34	0.28	0.32	-9.3***	-15.2***
Internal cooperation (voluntary)	(0/1)	0.259	0.44	0.34	0.27	0.27	0.32	-9.3***	-18.0***
Absorptive Capacity	cont.	0.171	0.35	0.33	0.12				
Control variables									
Size	cont.	4.389	1.34	1.34	0.19				
International market	(0/1)	0.560	0.50	0.44	0.25	0.28	0.31	-7.4***	-19.8***
No group	(0/1)	0.578	0.49	0.46	0.17	0.28	0.31	-9.1***	-7.5***
Non-innovation performer	(0/1)	0.167	0.37	0.27	0.28	0.32	0.23	18.7***	36.8***
External information	(0/1)	0.313	0.46	0.33	0.33	0.30	0.30	0.27	-0.26
External cooperation	(0/1)	0.355	0.48	0.37	0.30	0.29	0.33	-10.7***	-21.8***
Number of observations		45,036							

Note: It is tested whether there are significant differences in the share of innovative sales within two groups. Column 5 indicates the mean of innovative sales for the first group (i.e. Xi=0) and column 6 for the second group (i.e. Xi=1). In order to do so, two tests are used: parametric test (column 7) and non-parametric test (column 8). (1) Test 1 is a parametric test to check whether the share of innovative sales has the same mean within two groups. (2) Test 2 is the non-parametric Wilcoxon rank-sum test, also known as Mann–Whitney two-sample statistic, which tests the hypothesis that two independent samples are from populations with the same distribution. Source: PITEC; own calculations.

[67] Even though firms that belong to a group present greater innovation sales than those who do not belong to any group, their sales are much higher, leading to a lower ratio (innovative sales/sales).

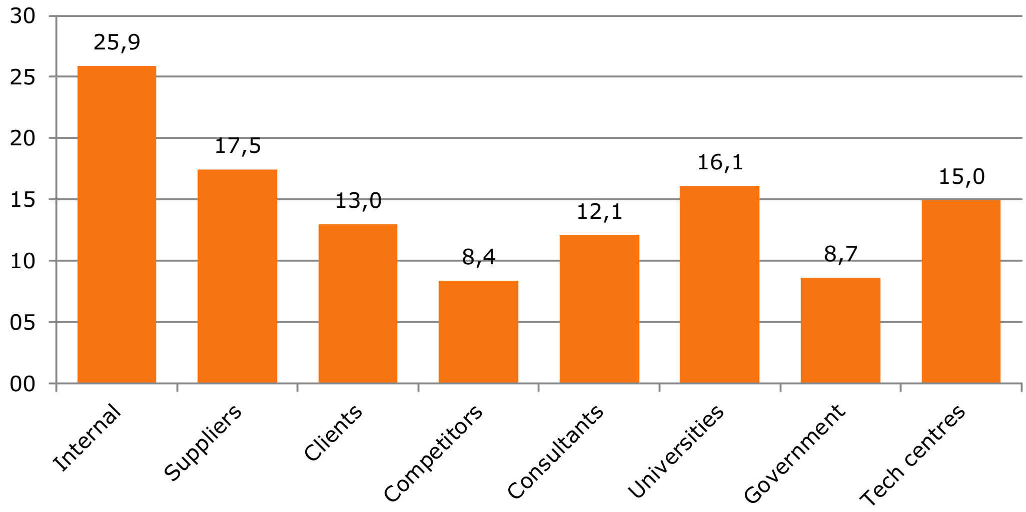
A comparison of internal and external knowledge flows shows that the proportion of firms declaring internal information as important is higher (52%) than that recognising the importance of external information (31%), while the opposite is the case with cooperation (26% vs. 35%). As discussed above, a global measure for external knowledge transfer has been used. If instead all types of information flow are taken into account, it can be seen that internal knowledge flows are the most relevant for both voluntary and involuntary spillovers. Figure 5.1 presents the distribution of the different sources of information that have been considered in terms of as a highly important. As shown, information originating from within the firm or the group is clearly the most important. Likewise, Figure 5.2 illustrates that internal cooperation is the most frequent kind of cooperation adopted when undertaking innovation activities.

Figure 5.1 High important sources of information (% of innovative firms)



Source: PITEC; own calculations.

Figure 5.2 Cooperation in innovation activities with different types of partners (% of innovative firms)



Source: PITEC; own calculations.

5.5.2 Estimation results

Table 5.3 presents the results for Equation [5.5], which is estimated by using the consistent estimator proposed by Wooldridge (1995) to account for the selection bias arising from the fact that only innovative firms are included in the regression. Results of the Equation [5.1], estimated for each year, are provided in Table A.5 in the Appendix. Column (1) in Table 5.3 shows the general results in which the importance of voluntary and involuntary internal knowledge flows are analysed (our first research question). The rest of the table includes the interaction terms described in section 5.3 in order to verify whether absorptive capacity affects the impact of internal knowledge transfers on innovation performance (our second research question). As can be seen, these interactions are incorporated separately (columns 2 and 3) and then jointly (column 4).

Following Escribano et al. (2009), these interaction terms are orthogonalized to reduce multicollinearity problems. The variance inflation factors (VIF) have been computed to detect such problems and the values for all the interaction terms are below 3, indicating that there are no multicollinerarity problems. On the other hand, the inverse Mills ratio is significant. Although some of the interactions with the time dummies are not significant, the Wald test (performed to check for joint significance) clearly identifies a selection bias problem and a correction is necessary to ensure consistent results. Finally, the errors are bootstrapped in order to account for the generated regressor problem, which is likely to appear given that the inverse Mills ratio (predicted in Equation [5.1]) is included as an explanatory variable.

Turning now to the variables of interest, it can be seen that both internal knowledge flows (voluntary and involuntary) have a positive and significant impact on innovation performance. In particular, those firms that cooperate with firms from their own group present a ratio of innovative sales greater than those firms that do not engage in cooperation of this kind. Likewise, those firms that identify internal information as an important source for undertaking or completing innovation projects record a higher share of innovation sales than those firms that do not. In addition, the results obtained show firms benefit more from voluntary (originating from collaborative agreements within the group) than involuntary spillovers. This result is not surprising since the information obtained from cooperative agreements is expected to be more desirable or to provide a better fit than information gathered unintentionally.

Interestingly enough, internal knowledge flows, both voluntary and involuntary, present higher coefficients than those presented by external knowledge transfers. In other words, information exchange within the company, or with other companies in the same group, is more relevant for explaining innovation performance than information received from outside the firm (or group). Bearing in mind that knowledge transfer involves people, a possible explanation for this result might be that people within firms are more similar to one another than are people working in different firms (Argote and Ingram, 2000). Thus, the absorption of knowledge originating from within the company may be faster or easier, resulting in greater innovative sales. By contrast, acquiring knowledge from a different firm might require more time for its implementation while workers may require training in order to use it. In addition, information gathered from within the company is probably more straightforward to exploit than information originating from other companies. Finally, another possible explanation might be that everyone within the company strives to move in the same direction to achieve the firm's goals (from the individual level to that of management policies), whereas knowledge acquired from firms outside the group may have different purposes and may need to be adapted to the new context. To sum up, this result highlights the relevance of internal information, which has tended to be ignored with the literature opting to focus its attention on external knowledge.

As for the second goal of this chapter, it can be seen that absorptive capacity (proxied by internal R&D stock) affects the relationship between internal knowledge flows and innovation performance in different ways. Columns 2 and 4 show that, while firms that collaborate with other firms in their group present greater innovation performance, this result is not influenced by their own R&D stock. Yet, in the case of involuntary knowledge flows, the results suggest that the more absorptive capacity the firm has, the greater the performance of involuntary knowledge transfers (columns 3 and 4). Thus, if two firms that declare internal information to be an important source are compared, innovation performance tends to be higher for that firm with greater investment in R&D. This points to the dual role of R&D, since own-generation of knowledge not only increases innovation performance per se, but it also provides the firm with the ability to exploit involuntary spillovers more efficiently.

Table 5.3 Estimates of Equation [5.5] using Wooldridge (1995) consistent estimator for panel data with sample selection. PITEC 2004-2011.

Dependent variable	Share of innovative sales (logit transformation)			
	(1)	(2)	(3)	(4)
Innovation intensity	1.053***	1.052***	1.055***	1.056***
	(0.0712)	(0.0698)	(0.0707)	(0.0722)
Internal cooperation	0.406***	0.405***	0.415***	0.416***
(voluntary)	(0.0705)	(0.0627)	(0.0601)	(0.0649)
Internal information	0.253***	0.252***	0.256***	0.257***
(involuntary)	(0.0415)	(0.0353)	(0.0391)	(0.0403)
Abs Cap * Internal cooperation		-0.00938		0.0102
		(0.0178)		(0.0203)
Abs Cap * Internal information			0.0366*	0.0416*
			(0.0198)	(0.0231)
Control Variables				
Size	4.480***	4.439***	4.463***	4.506***
	(1.631)	(1.427)	(1.439)	(1.591)
$Size^2$	-2.270***	-2.250***	-2.262***	-2.283***
	(0.806)	(0.703)	(0.711)	(0.784)
International market	0.171***	0.170***	0.169***	0.169***
	(0.0470)	(0.0447)	(0.0509)	(0.0417)
No group	0.0491	0.0473	0.0437	0.0450
	(0.0496)	(0.0442)	(0.0390)	(0.0404)
Non-innovation performer	-0.282	-0.282	-0.280	-0.279
	(0.210)	(0.185)	(0.220)	(0.198)
External cooperation	0.230***	0.230***	0.229***	0.229***
	(0.0478)	(0.0431)	(0.0475)	(0.0432)
External information	0.187***	0.187***	0.188***	0.189***
	(0.0475)	(0.0434)	(0.0420)	(0.0447)
$\hat{\lambda}_{it}$	-0.527**	-0.526**	-0.533**	-0.534**
	(0.247)	(0.247)	(0.263)	(0.234)
$\hat{\lambda}_{it}$ * 2007	-0.424***	-0.424***	-0.424***	-0.424**
	(0.139)	(0.144)	(0.112)	(0.166)
$\hat{\lambda}_{it}$ * 2008	0.0261	0.0259	0.0258	0.0259
	(0.123)	(0.150)	(0.135)	(0.152)

To be continued on the next page

Table 5.3 - *continued from the previous page*

	(1)	(2)	(3)	(4)
$\hat{\lambda}_{it}$ * 2009	0.0553	0.0551	0.0541	0.0542
	(0.165)	(0.138)	(0.155)	(0.147)
$\hat{\lambda}_{it}$ * 2010	0.0220	0.0219	0.0193	0.0190
	(0.177)	(0.163)	(0.152)	(0.147)
$\hat{\lambda}_{it}$ * 2011	-0.252*	-0.253*	-0.251**	-0.251*
	(0.130)	(0.137)	(0.128)	(0.130)
Constant	-2.239***	-2.231***	-2.228***	-2.235***
	(0.201)	(0.200)	(0.199)	(0.236)
Industry dummies	Yes	Yes	Yes	Yes
Wald Test:				
Industry dummies	1245.13***	1182.52***	974.53***	1112.35***
$\hat{\lambda}_{it}$ * T	44.57***	45.98***	54.75***	60.83***
Observations	32,481	32,481	32,481	32,481
Adjusted R^2	0.07	0.07	0.07	0.07

Notes: Bootstrapped standard errors are in brackets. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Finally, the control variables have the expected sign. Clearly, innovation investment shows a positive and significant coefficient, increasing a firm's innovative performance. Firm size presents an inverted U-shaped relationship. Operating in an international market increases innovation performance. Last of all, firms benefit from external knowledge flows (both voluntary and involuntary), albeit to a lesser extent than they benefit from internal knowledge transfers as has been shown above.

5.6 Further Explorations

5.6.1 Alternative measure of involuntary knowledge flows

As discussed in section 5.4.2, it is important to distinguish between the effects of voluntary and involuntary spillovers, since they are prone to overlap (the more a firm cooperates, the greater the importance attached to information flows). In order to avoid this, information flows originating from cooperative firms are deducted from the previously used definition of involuntary knowledge flows.

Here, an alternative measure of involuntary knowledge transfer is adopted. Following Belderbos et al. (2004), who conduct an auxiliary regression in which involuntary spillovers are explained by voluntary spillovers, industry dummies and time dummies is estimated[68]. The former is a dummy equal to 1 if the firm declares that information originating from the firm or group has been an important source for undertaking or finishing innovation projects in the last three years. The residuals are then used to approximate involuntary knowledge flows, since the effect of internal cooperation has been removed from them. The same strategy is applied to external knowledge flows.

As can be seen, the results are largely unaltered. Internal knowledge flows are clearly significant in explaining a firm's innovation sales. Nonetheless, now the magnitude of the impact is very similar with both voluntary and involuntary spillovers presenting similar coefficients. Additionally, and in line with the main results, internal knowledge flows are more relevant than external information transfers, stressing the importance of information exchange inside the company. As far as absorptive capacity is concerned, it can be observed that it does not affect the relationship between involuntary knowledge flows and innovation performance when this new definition is applied.

Tables 5.3 and 5.4 appear to indicate that the effectiveness of internal knowledge flows is not particularly related to the firm's stock in R&D. It is possible that organizational abilities and management policies have a greater impact on the efficiency of internal information transfers. For instance, improving workplace organization or undertaking a good

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[68] A random effect probit model is employed given the panel structure of the data and the binary character of the dependent variable.

knowledge management program could stimulate knowledge sharing and make internal information flows more profitable.

Table 5.4 Estimates of Equation [5.5] using Wooldridge (1995) consistent estimator for panel data with sample selection. PITEC 2004-2011. Alternative definition for involuntary spillovers.

Dependent variable	Share of innovative sales (logit transformation)			
	(1)	(2)	(3)	(4)
Innovation intensity	1.053***	1.052***	1.054***	1.053***
	(0.0721)	(0.0727)	(0.0638)	(0.0753)
Internal cooperation	0.222***	0.222***	0.222***	0.223***
(voluntary)	(0.0646)	(0.0539)	(0.0581)	(0.0561)
Internal information ([1])	0.218***	0.218***	0.218***	0.217***
(involuntary)	(0.0344)	(0.0365)	(0.0311)	(0.0336)
Abs Cap * Internal cooperation		-0.0126		-0.0132
		(0.0177)		(0.0159)
Abs Cap * Internal information			0.0177	0.0182
			(0.0239)	(0.0233)
Control Variables				
Size	4.489***	4.434***	4.513***	4.457***
	(1.610)	(1.616)	(1.619)	(1.589)
$Size^2$	-2.274***	-2.248***	-2.286***	-2.259***
	(0.795)	(0.799)	(0.799)	(0.785)
International market	0.178***	0.177***	0.177***	0.177***
	(0.0451)	(0.0419)	(0.0489)	(0.0427)
No group	0.0466	0.0442	0.0461	0.0435
	(0.0481)	(0.0444)	(0.0488)	(0.0414)
Non-innovation performer	-0.328	-0.328*	-0.328*	-0.328*
	(0.200)	(0.181)	(0.185)	(0.199)
External cooperation	0.169***	0.168***	0.168***	0.167***
	(0.0421)	(0.0407)	(0.0363)	(0.0394)
External information ([1])	0.109***	0.109***	0.109***	0.109***
	(0.0307)	(0.0346)	(0.0311)	(0.0357)
$\hat{\lambda}_{it}$	-0.431*	-0.430*	-0.434*	-0.433*
	(0.258)	(0.220)	(0.233)	(0.235)
$\hat{\lambda}_{it}$ * 2007	-0.442***	-0.443***	-0.441***	-0.442***
	(0.146)	(0.138)	(0.124)	(0.135)
$\hat{\lambda}_{it}$ * 2008	-0.0279	-0.0281	-0.0259	-0.0260
	(0.147)	(0.151)	(0.123)	(0.135)

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Table 5.4 – *continued from the previous page*

	(1)	(2)	(3)	(4)
$\hat{\lambda}_{it}$ * 2009	-0.0181	-0.0183	-0.0162	-0.0163
	(0.140)	(0.158)	(0.132)	(0.135)
$\hat{\lambda}_{it}$ * 2010	-0.107	-0.107	-0.104	-0.104
	(0.164)	(0.157)	(0.143)	(0.161)
$\hat{\lambda}_{it}$ * 2011	-0.295**	-0.297**	-0.294**	-0.295**
	(0.133)	(0.139)	(0.122)	(0.133)
Constant	-2.004***	-1.994***	-2.006***	-1.995***
	(0.181)	(0.171)	(0.204)	(0.207)
Industry dummies	Yes	Yes	Yes	Yes
Wald Test:				
Industry dummies	1298.04***	1068.37***	1184.88***	1310.11***
$\hat{\lambda}_{it}$ * T	50.86***	42.73***	47.07***	50.91***
Observations	32,481	32,481	32,481	32,481
Adjusted R^2	0.07	0.07	0.07	0.07

Notes: Bootstrapped standard errors are in brackets. ([1]) New definition for involuntary spillovers: internal and external information are proxied by the residuals obtained from an auxiliary regression where information is regress against cooperation, industry dummies and time dummies using a RE probit model. *** Significant at 1%, ** significant at 5%, * significant at 10%.

5.6.2 Absorptive capacity as a discrete measure

In this section, the role of absorptive capacity is addressed from a discrete perspective. Since absorptive capacity – defined as intramural R&D stock over sales – is a variable that can vary greatly, it is decided to introduce it in the model in a discrete form. In this regard, three levels are considered: low, medium and high. The interactions between these dummies and internal knowledge flows are included in Equation [5.3], as opposed to internal knowledge flows on their own. By doing so, it is possible to observe if the impact of internal knowledge flows differs according to the level of absorptive capacity (low, medium or high) and whether that impact is different to that experienced by firms that do not benefit from internal knowledge flows whatsoever.

The results in Table 5.5 suggest that absorptive capacity plays a clear role. First of all, it can be seen that a firm that cooperates with other firms in its same group and which has a low absorptive capacity presents a higher ratio of innovative sales than those presented by firms that do not engage in such kind of activity (reference group). Second, firms that cooperate internally and which have medium absorptive capacity present a higher value, while those with high absorptive capacity benefit the most from internal cooperation. Yet, when internal information is analysed it can be seen that there is no difference between firms that do not identify internal information as an important source and those which do so but whose absorptive capacity is low. By contrast, companies with medium or high absorptive capacity increase their innovative sales with internal information. All in all, the performance attributable to internal knowledge transfers is clearly influenced by a firm's level of absorptive capacity.

Table 5.5 Estimates of Equation [5.5] using Wooldridge (1995) consistent estimator for panel data with sample selection. PITEC 2004-2011. Dummy variables to proxy absorptive capacity.

Dependent variable	Share of innovative sales (logit transformation)			
	(1)	(2)	(3)	(4)
Innovation intensity	1.053*** (0.0712)	1.029*** (0.0716)	1.010*** (0.0883)	0.971*** (0.0726)
Internal cooperation *(voluntary)*	0.406*** (0.0705)		0.403*** (0.0683)	
Internal information *(involuntary)*	0.253*** (0.0415)	0.255*** (0.0399)		
AbsCap low * Internal Coop		0.280*** (0.0926)		0.221** (0.107)
AbsCap med * Internal Coop		0.339*** (0.0914)		0.339*** (0.0876)
AbsCap high * Internal Coop		0.594*** (0.0950)		0.644*** (0.0789)
AbsCap low * Internal Info			-0.0171 (0.0596)	-0.0302 (0.0629)
AbsCap med * Internal Info			0.378*** (0.0515)	0.377*** (0.0575)
AbsCap high * Internal Info			0.370*** (0.0480)	0.393*** (0.0491)
Size	4.480*** (1.631)	4.734*** (1.453)	4.736*** (1.648)	5.068*** (1.507)

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Table 5.5 – *continued from the previous page*

	(1)	(2)	(3)	(4)
$Size^2$	-2.270***	-2.393***	-2.389***	-2.550***
	(0.806)	(0.718)	(0.815)	(0.743)
International market	0.171***	0.172***	0.163***	0.164***
	(0.0470)	(0.0503)	(0.0425)	(0.0445)
No group	0.0491	0.0568	0.0343	0.0433
	(0.0496)	(0.0479)	(0.0509)	(0.0439)
Non-innovation performer	-0.282	-0.284	-0.234	-0.235
	(0.210)	(0.190)	(0.205)	(0.174)
External cooperation	0.230***	0.230***	0.219***	0.217***
	(0.0478)	(0.0477)	(0.0481)	(0.0472)
External information	0.187***	0.187***	0.186***	0.186***
	(0.0475)	(0.0426)	(0.0484)	(0.0455)
$\hat{\lambda}_{it}$	-0.527**	-0.522**	-0.476*	-0.464**
	(0.247)	(0.258)	(0.251)	(0.230)
$\hat{\lambda}_{it}$ * 2007	-0.424***	-0.426***	-0.452***	-0.457***
	(0.139)	(0.134)	(0.145)	(0.137)
$\hat{\lambda}_{it}$ * 2008	0.0261	0.0241	-0.0204	-0.0258
	(0.123)	(0.123)	(0.147)	(0.145)
$\hat{\lambda}_{it}$ * 2009	0.0553	0.0534	0.00257	-0.00312
	(0.165)	(0.127)	(0.138)	(0.138)
$\hat{\lambda}_{it}$ * 2010	0.0220	0.0192	-0.0431	-0.0506
	(0.177)	(0.135)	(0.157)	(0.152)
$\hat{\lambda}_{it}$ * 2011	-0.252*	-0.255**	-0.308**	-0.316**
	(0.130)	(0.127)	(0.135)	(0.146)
Constant	-2.239***	-2.283***	-2.276***	-2.336***
	(0.201)	(0.216)	(0.207)	(0.214)
Industry dummies	Yes	Yes	Yes	Yes
Wald Test:				
Industry dummies	1245.13***	1535.04***	1161.89***	721.44***
$\hat{\lambda}_{it}$ * T	44.57***	49.80***	36.77***	51.83***
Observations	32,481	32,481	32,481	32,481
Adjusted R^2	0.07	0.068	0.069	0.070

Notes: Bootstrapped standard errors are in brackets. *** Significant at 1%, ** significant at 5%, * significant at 10%.

5.6.3 Alternative measure for Absorptive Capacity: Personnel in R&D

As discussed, absorptive capacity can be proxied by different variables. Although R&D is one of the most frequently used in the literature, other variables have also been employed (e.g., operating an R&D department, human capital, etc.). In consonance with the concept of absorptive capacity, external knowledge needs to be recognized, assimilated and exploited. A firm's ability to do this depends to a great extent on its workforce. For this reason, absorptive capacity is defined here as the number of employees engaged in R&D activities.

Table 5.6 shows that the main results are almost identical; however, when using this new definition of absorptive capacity both interactions present a positive coefficient. This means that the impact of internal knowledge flows on innovation performance increases with absorptive capacity. Thus, those firms with more personnel engaged in R&D activities will manage internal information flows more efficiently. A possible explanation for this could be that this definition refers to those working in R&D activities that can both share knowledge accurately as well as increase the firm's ability to assimilate and exploit knowledge acquired (internally).

Table 5.6 Estimates of Equation [5.5] using Wooldridge (1995) consistent estimator for panel data with sample selection. PITEC 2004-2011. Alternative definition of absorptive capacity.

Dependent variable	Share of innovative sales (logit transformation)			
	(1)	(2)	(3)	(4)
Innovation intensity	1.053***	1.037***	0.977***	0.950***
	(0.0712)	(0.0700)	(0.0720)	(0.0787)
Internal cooperation	0.406***	0.118	0.472***	0.120
(voluntary)	(0.0705)	(0.103)	(0.0648)	(0.109)
Internal information	0.253***	0.258***	0.0387	0.0259
(involuntary)	(0.0415)	(0.0405)	(0.0566)	(0.0459)
Abs Cap(1) * Internal cooperation		0.129***		0.161***
		(0.0307)		(0.0341)
Abs Cap(1) * Internal information			0.147***	0.160***
			(0.0264)	(0.0195)
Control Variables				
Size	4.480***	4.002**	4.911***	4.353***
	(1.631)	(1.816)	(1.558)	(1.289)
Size^2	-2.270***	-2.038**	-2.492***	-2.224***
	(0.806)	(0.897)	(0.769)	(0.636)

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Table 5.6 – *continued from the previous page*

	(1)	(2)	(3)	(4)
International market	0.171***	0.167***	0.153***	0.146***
	(0.0470)	(0.0434)	(0.0436)	(0.0426)
No group	0.0491	0.0439	0.0518	0.0455
	(0.0496)	(0.0422)	(0.0412)	(0.0484)
Non-innovation performer	-0.282	-0.269	-0.191	-0.166
	(0.210)	(0.182)	(0.180)	(0.200)
External cooperation	0.230***	0.227***	0.209***	0.202***
	(0.0478)	(0.0514)	(0.0455)	(0.0462)
External information	0.187***	0.187***	0.188***	0.188***
	(0.0475)	(0.0475)	(0.0458)	(0.0421)
$\hat{\lambda}_{it}$	-0.527**	-0.521**	-0.526**	-0.519**
	(0.247)	(0.230)	(0.213)	(0.257)
$\hat{\lambda}_{it}$ * 2007	-0.424***	-0.429***	-0.427***	-0.433***
	(0.139)	(0.119)	(0.130)	(0.151)
$\hat{\lambda}_{it}$ * 2008	0.0261	0.0187	0.0275	0.0184
	(0.123)	(0.134)	(0.129)	(0.139)
$\hat{\lambda}_{it}$ * 2009	0.0553	0.0466	0.0450	0.0334
	(0.165)	(0.150)	(0.129)	(0.134)
$\hat{\lambda}_{it}$ * 2010	0.0220	0.0108	0.00834	-0.00681
	(0.177)	(0.155)	(0.132)	(0.142)
$\hat{\lambda}_{it}$ * 2011	-0.252*	-0.256*	-0.243*	-0.246*
	(0.130)	(0.135)	(0.135)	(0.139)
Constant	-2.239***	-2.149***	-2.151***	-2.030***
	(0.201)	(0.196)	(0.224)	(0.214)
Industry dummies	Yes	Yes	Yes	Yes
Wald Test:				
Industry dummies	1245.13***	1070.56***	1255.13***	980.12***
$\hat{\lambda}_{it}$ * T	44.57***	48.98***	36.77***	50.16***
Observations	32,481	32,481	32,481	32,481
Adjusted R^2	0.07	0.07	0.07	0.07

Notes: Bootstrapped standard errors are in brackets. ([1]) Absorptive capacity is defined as the number of employees working on R&D activities (in logs). *** Significant at 1%, ** significant at 5%, * significant at 10%.

5.6.4 Is the degree of novelty in the innovation important?

Finally, PITEC offers information about the novelty of the innovation distinguishing between innovations new only to the firm (but already available on the market) and innovations that are new to the market. According to the literature, the former can be considered to be "imitations", while the second types are known as "true innovations".

This raises the question as to whether the impact of internal knowledge flows differs depending on the type of innovation (imitation vs. true). Table 5.7 seems to suggest it is, though it should be stressed that the first four columns of the model are poorly adjusted, indicating that these findings should be interpreted with caution. However, generally speaking, both internal and external knowledge flows appear to have a greater impact on the share of innovative sales that are new to the market.

In the case of internal knowledge flows, while it is true that internal cooperation is relevant for both innovative sales new to the firm and to the market, internal information only has a positive impact on the development of “true innovations” (and no significance can be found for innovative sales of products that are only new to the firm). This might be because internal information transfers are not relevant in the case of imitations, since the firm is basically reproducing something completed outside its boundaries. However, sharing information and experience within the company helps firms not only to be more efficient and to perform better technologically but also to create something new, a “true innovation”. On the other hand, external cooperation is only relevant for raising innovative sales of products new to the market. This result may be explained by the fact that innovation projects of this nature are usually risky and costly being cooperation with other firms a good means for coping with these obstacles. Finally, Table 5.7 shows that the impact of absorptive capacity on involuntary spillovers is relevant solely in the case of innovations new to the market.

Table 5.7 Estimates of Equation [5.5] using Wooldridge (1995) consistent estimator for panel data with sample selection. PITEC 2004-2011. Estimations according to the degree of novelty

Dependent variable	Share of innovative sales (logit transformation)							
	New to the firm (only)				New to the market			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Innov inten.	0.305***	0.305***	0.305***	0.307***	0.883***	0.882***	0.885***	0.886***
	(0.0640)	(0.0597)	(0.0625)	(0.0653)	(0.0700)	(0.0667)	(0.0636)	(0.0579)
Int coop	0.282***	0.283***	0.284***	0.286***	0.285***	0.285***	0.295***	0.296***
(voluntary)	(0.0532)	(0.0513)	(0.0656)	(0.0531)	(0.0460)	(0.0524)	(0.0516)	(0.0553)
Int infor	0.0123	0.0128	0.0129	0.0145	0.328***	0.326***	0.331***	0.331***
(involuntary)	(0.0315)	(0.0279)	(0.0345)	(0.0362)	(0.0294)	(0.0249)	(0.0304)	(0.0285)
Abs Cap *		0.00700		0.0136		-0.0162		0.00433
Int coop		(0.0160)		(0.0138)		(0.0153)		(0.0194)
Abs Cap *			0.00733	0.0140			0.0415**	0.0436**
Int infor			(0.0154)	(0.0166)			(0.0168)	(0.0212)
Controls								
Size	-1.939*	-1.909	-1.943*	-1.886	7.33***	7.26***	7.31***	7.33***
	(1.148)	(1.374)	(1.116)	(1.297)	(1.144)	(1.149)	(1.158)	(1.214)
$Size^2$	0.917	0.902	0.919*	0.891	-3.640***	-3.60***	-3.63***	-3.64***
	(0.567)	(0.680)	(0.551)	(0.640)	(0.565)	(0.568)	(0.572)	(0.600)
Inter market	0.0938**	0.0940***	0.0934**	0.0934**	0.143***	0.143***	0.141***	0.141***
	(0.0368)	(0.0364)	(0.0369)	(0.0370)	(0.0325)	(0.0287)	(0.0293)	(0.0283)
No group	0.0404	0.0418	0.0394	0.0410	0.0227	0.0196	0.0166	0.0171
	(0.0367)	(0.0385)	(0.0418)	(0.0391)	(0.0297)	(0.0301)	(0.0291)	(0.0305)
Non-innov	-0.402**	-0.402**	-0.401**	-0.400**	0.105	0.104	0.108	0.108
performer	(0.163)	(0.190)	(0.176)	(0.175)	(0.135)	(0.127)	(0.114)	(0.128)
Ext coop	0.0134	0.0140	0.0130	0.0140	0.341***	0.339***	0.339***	0.339***
	(0.0380)	(0.0414)	(0.0384)	(0.0422)	(0.0329)	(0.0346)	(0.0344)	(0.0306)
Ext infor	0.0975**	0.0975***	0.0978***	0.0981***	0.165***	0.165***	0.167***	0.167***
	(0.0390)	(0.0367)	(0.0375)	(0.0351)	(0.0299)	(0.0315)	(0.0274)	(0.0292)
$\hat{\lambda}_{it}$	0.034	0.033	0.033	0.030	-0.69***	-0.69***	-0.69***	-0.70***
	(0.212)	(0.228)	(0.224)	(0.218)	(0.171)	(0.152)	(0.134)	(0.152)
$\hat{\lambda}_{it}$ * 2007	-0.40***	-0.40***	-040***	-0.40***	-0.0043	-0.0046	-0.0040	-0.0039
	(0.127)	(0.112)	(0.119)	(0.125)	(0.0793)	(0.0713)	(0.0734)	(0.0808)
$\hat{\lambda}_{it}$ * 2008	-0.0321	-0.0319	-0.0321	-0.0319	0.113	0.113	0.112	0.113
	(0.127)	(0.131)	(0.138)	(0.115)	(0.0806)	(0.0800)	(0.0782)	(0.0770)
$\hat{\lambda}_{it}$ * 2009	0.00586	0.00599	0.00564	0.00568	0.0954	0.0951	0.0941	0.0941
	(0.130)	(0.139)	(0.122)	(0.121)	(0.0814)	(0.0847)	(0.0734)	(0.0814)
$\hat{\lambda}_{it}$ * 2010	0.0406	0.0406	0.0401	0.0397	-0.0270	-0.0271	-0.0300	-0.0301
	(0.128)	(0.144)	(0.134)	(0.136)	(0.0859)	(0.103)	(0.0811)	(0.0843)

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Table 5.7 - *continued from the previous page*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{\lambda}_{it}$ * 2011	-0.254*	-0.253**	-0.254**	-0.253**	-0.0051	-0.0064	-0.0044	-0.0040
	(0.133)	(0.110)	(0.112)	(0.118)	(0.0872)	(0.0817)	(0.0715)	(0.0736)
Constant	-2.43***	-2.44***	-2.43***	-2.44***	-4.43***	-4.42***	-4.42***	-4.42***
	(0.175)	(0.186)	(0.166)	(0.174)	(0.137)	(0.122)	(0.139)	(0.142)
Ind dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald Test:								
Ind dummy	608.2***	958.7***	631.6***	660.68***	1400.6***	1333.5***	1233.4***	1651.8***
$\hat{\lambda}_{it}$ * T	21.16***	29.35***	41.25***	26.53***	39.93***	48.11***	40.45***	34.18***
Observations	32,481	32,481	32,481	32,481	32,481	32,481	32,481	32,481
Adjusted R^2	0.023	0.023	0.023	0.023	0.084	0.084	0.084	0.084

Notes: Bootstrapped standard errors are in brackets. *** Significant at 1%, ** significant at 5%, * significant at 10%.

5.7 Concluding remarks

The purpose of this study has been to analyse the extent to which internal knowledge flows affect firm performance. Since most of the innovation literature to date has focused its attention on external knowledge transfers, internal flows have gone largely ignored. However, the transmission of information and experience within a company can help firms to perform better technologically and to be more efficient, making a positive contribution to their innovativeness and performance. For this reason, the goal of this chapter has been to assess the impact of internal knowledge flows – distinguishing between voluntary and involuntary flows – on innovative sales. Drawing on a sample of Spanish innovators for the period 2004-2011, the following research questions have been posed: (i) Are internal knowledge flows (voluntary and involuntary) important for the performance of innovative firms? (ii) Does this impact differ depending on a firm's absorptive capacity?

In seeking a response to these questions, a Heckman-type selection model has been applied so as to correct for selectivity bias. In the case of the first research question, the results show that internal knowledge transfers increase innovation performance, an impact that is greater for voluntary than it is for involuntary knowledge flows. Interestingly, the results also indicate that even though external knowledge transfers have a positive impact on innovation performance, this is not as great as the effect of internal flows. Thus, external cooperation or information originating from outside the firm does not affect innovative sales as much as that knowledge which stems from inside the company. Additionally, this study indicates that knowledge transfers are more relevant for innovative sales attributable to products new to the market than products new only to the firm.

In relation to the second research question, the findings of this study show, in general, an ambiguous effect of absorptive capacity on the relationship between internal knowledge flows and innovative sales. According to the literature, absorptive capacity can be expected to enhance a firm's ability to recognize and absorb *external* knowledge. However, the results of this study suggest that this is not the case for *internal* knowledge transfers. More specifically, the absorptive capacity only affects the impact that involuntary knowledge transfers have on innovative performance. Thus, firm own-generation of knowledge not only increases innovation performance but also makes the firm more efficient at exploiting involuntary (though not voluntary) knowledge flows. Interestingly, when absorptive capacity is categorised (low, medium and high), its role becomes readily apparent. Thus, firms with a medium or high absorptive capacity enjoy a better performance from internal knowledge flows (both voluntary and involuntary). By contrast, when an alternative definition of involuntary knowledge transfer is used, the positive effect of absorptive capacity disappears. On the other hand, when the number of personnel in R&D is used as definition of absorptive capacity, a positive effect is observed. The more personnel that the firm employs in R&D, the more efficiently it manages both voluntary and involuntary internal flows.

To conclude, the results of this research highlight the importance of internal knowledge flows and their positive effect on innovation performance. However, no clear conclusions can be drawn about the role played by absorptive capacity, its role varying with the definition adopted.

Chapter 6: General conclusions

6.1 Summary and policy implications

This dissertation has investigated the relationship between innovation and productivity, taking into account the impact of spillovers. In particular, the third and fourth chapters have analysed the importance of external knowledge flows on firm's innovative behaviour and productivity, while the fifth chapter focused its attention on internal knowledge transfers and their impact on firm's innovative performance. On balance, the purpose of this thesis is to provide a better understanding of the impact of involuntary knowledge flows on innovation and productivity.

This last section brings together the main findings of each chapter. It also includes some policy implications, as well as limitations and futures lines of research.

Chapter 3 analyses the impact that R&D expenditures and intra- and inter-industry externalities have on Spanish firms' performance. Despite the extensive literature studying the link innovation - productivity, there are only few articles examining the importance of sectoral externalities, especially focused on Spain. In particular, the goal of this chapter is twofold. First, it seeks to analyse the extent to which the level of technology of the sector in which the firm operates affects the returns that firms obtain from their investment in innovation. Second, it assesses if firms benefit from external knowledge flows coming from other firms' R&D investment (both in the same sector and in other sectors). The results, obtained from a traditional Cobb Douglass production function, suggest that, unlike previous studies, there is no direct impact of R&D investment on firm performance. However, once the innovation is measured from the output side, a positive effect is found. This finding is in line with Crépon, Duguet and Mairesse (1998) approach which hold that there is a sequential process which drives from R&D to innovation outputs and from these outputs to productivity. In addition, firm's technology level affects this relationship being the impact of innovation greater for those firms in high-tech sectors (manufacturing and service sectors). As for spillovers, the results point out that Spanish firms are able to benefit from external innovation. In most technology levels, firms increase their sales if the rest of the firms in their sector increase their R&D expenditure, especially low-tech sectors, while in knowledge-intensive services a competitive effect would dominate. Inter-industry externalities, however, present a more ambiguous effect and there appears to be no specific behaviour pattern as for technology level.

Chapter 4 aims at improving and extending the previous chapter by analysing the impact of innovation activities and externalities on firms' productivity using a structural model. The main goal is to determine the extent to which external knowledge may affect both firm behaviour and firm performance. In fact, the results show that 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. Therefore, an external pool of knowledge would encourage firms to carry out R&D activities suggesting the existence of "an incentive effect". In addition, R&D expenditures incurred by others firms (provided that an innovation is achieved with their investment) have a positive impact on a firm's productivity. However, this is only true for manufacturing firms. Finally, regarding the technology level, no clear pattern has been found.

All in all, it seems that external knowledge flows play a role along the process of engaging innovation activities and their translation into economic performance. Internal knowledge flows, on the other hand, have faded into the background as most the innovation literature focused its attention on external knowledge transfers. Nevertheless, transmission of information and experience within the company can improve its technological performance impacting positively on their innovativeness and leading to higher innovative sales. For that reason, Chapter 5 examines the importance of such kind of flows, which are born, grown and shared within a company.

The objective of the final empirical analysis undertaken in this dissertation is, therefore, to study the impact of internal knowledge flows on firm's innovative performance. A distinction between voluntary and involuntary knowledge transfers is made. In addition, the role of absorptive capacity is analysed to assess if it enhances the efficiency of internal knowledge flows to some extent. The main findings point out that internal knowledge flows have a clearly positive impact on innovation performance. In particular, firms increase more innovative sales with voluntary knowledge transfers than with involuntary. More interestingly, the effect of internal knowledge flows is greater than the impact of external knowledge transfers. In other words, information exchange within the company (or group) is more relevant for innovation performance than information received from outside the firm, thereby highlighting the importance of internal knowledge flows. Last of all, the effect of absorptive capacity depends on how it is proxied. Positive results can be found when personnel in R&D are used or when it is defined as internal R&D expenditures and introduced in the model as a discrete variable.

In view of the findings of this study, it would be interesting to design certain policies to foster innovation in order to increase firms' performance and competitiveness, which is essential in today's globalized world.

First of all, the results in Chapter 4 show that the more a firm invests in R&D and the fact that it is done on a continuous basis, the more likely it is to achieve an innovation. Therefore, it would be interesting to design some policies to promote R&D investment given that, in general, Spanish firms face a number of difficulties to engage in such kind of activity. In particular, Spanish business owners take various factors into account, including the high risks associated with such uncertain ventures and the difficulty in retaining exclusive control over all of the benefits that such investment might generate. To break this first barrier and encourage firms to start R&D projects, the government could offer tax breaks and savings in social security payments when hiring qualified personnel, supporting high-risk undertakings and reducing bureaucratic procedures, etc. Likewise, it should be noted that the Spanish business sector is made up of mainly small and medium-sized firms, which might find raising the funds needed to carry out such projects beyond their capabilities. In fact, results obtained in Chapter 4 point out 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. Nevertheless, the access to loans has decreased since 2007, reaching one of the lowest values in Europe in 2011. Therefore, even though the current economic situation, the government should find a way to increase its financial support for innovation projects. As reported by the findings in this thesis, cutting back public subsidies will determine Spanish firms' behaviour. Moreover, innovate is a learning process being the probability of achieving an innovation greater when it is done regularly, as evidenced by the results. For this reason, financial support would be more profitable if it was addressed to promote R&D activities in a continuous way instead of isolated projects.

Although innovation policies need to be aimed at providing incentives to help with investments, they should not be applied on a one-size-fits-all basis, but rather, they need to be designed according to different profile types. For instance, it has been seen that firm size favour both firm decision whether to engage in R&D activities or not and the probability of achieving a process innovation. However, Spanish economy consists of small and medium-sized firms. Consequently, policies might take this factor into consideration, prioritising somehow their necessities, seeking cooperation between firms in order to palliate their small size and promoting enlargement or fusion of firms. As recommended by the European Commission (2013) "Spain should review spending priorities and reallocate funds to support SMEs".

Finally, the positive effect of spillovers should be taken under consideration when policies are designed. Even though the business owner might perceive this phenomenon as a negative consequence since part of their investment spills over to other companies, it is a positive side-effect for the economy as a whole. As it has been seen in this dissertation, an incentive effect can appear since the more firms undertaking R&D projects, the better, given that this increases the probability of starting R&D activities. On the other hand, the higher the R&D expenditures in a sector or in other sectors, the more a firm is going to increase its performance. Thereby, government support to help one particular firm would overtake the boundaries of this company, having a positive effect on other firms' behaviour as well as performance.

Having said that, and more as a reflection than an implication from the findings of this thesis, the government efforts might not have the desired results if the motive driving firms R&D investment is other than increasing their ability and knowledge. For instance, if firms engage in R&D in order to obtain tax shelters, it is likely that their investment does not lead to a higher production. Strategies to control and avoid that kind of situation should be applied to ensure a good use of the available funds.

Needless to say, investment in innovation activities is a considerable challenge in the current economic situation. According to the *Europe 2020 strategy* and the national target adopted by the Spanish government, Spain should invest 2% of its GDP in R&D activities by 2020. Last information available shows that Spain is far from reaching this goal as R&D intensity was 1.3% in 2012, far from the European standards. Therefore, despite the economic situation Spain should make an effort to promote innovation. As reported by the European Commission, "the main challenges for Spain remain, therefore, to invest in knowledge and to better ensure the effectiveness of this investment in creating a more knowledge-intensive economy." It should not be forgotten though that R&D does not increase firm performance per se. As discussed earlier, innovation policies should not be applied to one-size-fits-all basis as R&D do not always raise productivity. This will depend on the type of firm including R&D intensity, technology level, innovative behaviour, etc. (see Del Monte and Papagni, 2003 and Demirel and Mazzucato, 2012).

Lastly, the results from Chapter 5 highlight the importance of internal knowledge flows and their positive effect on innovation performance. Therefore, authorities could encourage companies to make an effort to optimize knowledge already existing inside their boundaries. Fostering the flow of ideas, rewarding employees, promoting teamwork and job rotation, and especially stimulating internal collaborations could be, among others, good practices to make the most of knowledge already existing in the firm.

Policies should aim at improving firms' innovation management capacity. By doing so, organizations could manage information and knowledge more efficiently, thereby increasing the probability of translating new ideas into real innovations which would boost their economic performance.

6.2 Limitations and future research

A number of caveats need to be considered regarding the present study. The first limitation lies in the definition of spillovers. Although it is believed that any interaction between firms might generate information flows, the approximation of spillovers using commercial relationships can be considered a shortcoming. Other definitions using firms' characteristics or geographical proximity may broaden the knowledge of external flows, as well as allow for comparison between different channels through which knowledge can spill over. Unfortunately, PITEC does not provide information to undertake such kind of analysis. However, an alternative measure could be pursued through the use of patents (information available with PITEC). While it is true that several articles have employed this variable, other papers have recognised that it is a restrictive measure, since only a small number of firms patent (Peters, 2009 and Bloch, 2013). As Griliches (1998, page 296) points out "not all inventions are patentable, not all inventions are patented". Chapter 4 goes a step further and includes an innovation indicator in the spillover definition. By doing so, it follows the same approach than the CDM model and also improves slightly the definition of spillover since not only commercial interactions are considered but only R&D coming from suppliers who are innovators is taken under consideration. All in all, there is room for improvement in defining spillovers, using PITEC or other databases.

The current dissertation is also limited by the fact that R&D expenditures are used as a proxy for innovative effort in Chapters 3 and 4. This decision was undertaken following the literature, however it is acknowledged that investing in R&D is not the only way to increase innovation input. In particular, as it was seen in Chapter 2, Spanish firms spend a significant amount of money on acquisition of advanced machinery, equipment and software designated to innovation. Therefore, using R&D measure might underestimate the results for innovation activities. In Chapter 5, this limitation is overcome and the entire innovation investments are incorporated.

An issue that is not addressed in this thesis is persistence. However, it is possible that the probability to invest in R&D in one period increases if the firm has already invested in the previous period, or the probability of obtaining an innovation is higher if the company has achieved one during the previous years. In fact, several studies have revealed the importance of this factor from an input and output perspective. For instance, Peters (2009) provides evidence of true state of dependence on innovation investment decision for German firms. On the other hand, Raymond et al. (2010) analyse the persistence in innovation output of Dutch manufacturing firms. The authors find that there is persistence on both the probability of innovation, as well as the intensity of the innovation output but only in high-tech firms. Another recent study is the one carried out by Huergo and Moreno in 2011, which accounts for persistence on both the input and output side. Thereby, using a sample of Spanish manufacturing firms, the authors show the existence of true state of dependence in the decision of R&D investment and in the probability of obtaining an innovation. Therefore, it would be very interesting to investigate the persistence of innovation and allow for a dynamic framework, at the same time where spillovers are considered.

Another weakness of this dissertation is the poor quality of the service sector estimates. As mentioned at the beginning of this thesis, this is only a first attempt to study the service sector and, according to Chapter 4, the results presented here need to be interpreted with caution. Manufacturing and service firms should not be treated equally. Consequently, more research regarding this issue would be of a great help in order to have a better understanding of the situation in the service sector.

In addition, more work needs to be done in evaluating the impact of absorptive capacity when internal knowledge flows are analysed. After observing the importance of internal knowledge flows on firm's innovative performance in Chapter 5, it would be interesting to assess more accurately the effect of absorptive capacity. It is probable that, not only R&D or personnel in R&D, but also other factors play a role in managing internal information transfers.

Finally, a future study analysing the effect of firm size could be very interesting. External and internal knowledge flows are likely to be different according to the number of employees. On the one hand, it is possible that large firms benefit to a greater extent from information flows since they have better equipment, specialised workers, technological expertise, etc. On the other hand, given the better financial situation of large firms, they may not pay that much attention to external information and they rely on their own capacity to generate knowledge. By contrast, it seems plausible that knowledge shared within firms is more likely to happen when the workforce is low, whereas large firms might suffer from "departmentalism", power struggles and turf wars. Consequently, instead of being a mere control variable firm size may play an important role on the transmission of knowledge.

Appendices

Table A. 1 Outliers by technological level

	LTI	HTI	NKIS	KIS	*Total*
Chapter 3					
Physical capital	51	18	39	158	*266*
R&D expenditure	17	18	9	322	*366*
Observations	*17,470*	*12,764*	*6,483*	*13,632*	*50,349*
Chapter 4					
Physical capital	56	19	46	184	*305*
R&D expenditure	22	22	10	365	*419*
Observations	*19,838*	*14,547*	*7,400*	*15,594*	*57,379*
Chapter 5					
Physical capital	64	21	50	201	*336*
R&D expenditure	24	24	10	404	*462*
Observations	*21,977*	*16,172*	*8,222*	*17,273*	*63,644*

Source: PITEC; own calculations.

Table A. 2 Descriptive statistics Chapter 3 before filters

		Total		LTMI		HTMI		NKIS		KIS	
		Mean	Sd.	Mean	Sd.	Mean	Sd.	Mean	Sd.	Mean	Sd.
Sales	overall	16.21	1.83	16.24	1.65	16.22	1.64	17.11	1.83	15.77	2.01
	betw		1.83		1.64		1.65		1.84		2.00
	within		0.36		0.33		0.32		0.30		0.43
Physical capital	overall	13.36	4.90	13.77	5.01	13.54	4.30	13.59	5.45	12.63	4.92
	betw		4.76		4.92		4.13		5.16		4.79
	within		2.09		2.05		1.90		2.48		2.11
Labour	overall	4.46	1.45	4.26	1.21	4.18	1.24	5.11	1.61	4.63	1.66
	betw		1.46		1.21		1.25		1.62		1.68
	within		0.21		0.19		0.18		0.20		0.26
Human capital	overall	22.83	25.92	12.11	13.66	21.03	18.87	13.95	20.16	41.07	33.60
	betw		24.11		11.76		17.10		18.04		30.50
	within		10.59		7.20		8.86		9.87		14.79
Innovation	overall	9.74	6.09	10.25	5.50	12.63	4.21	4.89	6.13	8.89	6.52
	betw		5.94		5.37		4.16		5.91		6.30
	within		1.48		1.49		1.27		1.61		1.55
Intra-industry externality	overall	748.58	756.17	403.76	287.57	1346.72	745.63	432.16	478.45	785.76	908.28
	betw		734.31		278.60		724.05		407.06		875.16
	within		194.03		68.52		158.07		255.05		273.76
Inter-industry externality	overall	484.17	181.10	523.30	163.75	553.68	143.58	422.50	245.00	406.26	155.08
	betw		151.44		127.77		97.10		229.40		121.82
	within		103.37		106.06		111.82		74.95		103.85
Obs		55,303		18,652		13,617		7,267		15,767	
(%)				(37.1)		(27.1)		(14.5)		(31.3)	
Firms		10,834		3,573		2,603		1,399		3,259	
(%)				(33.0)		(24.0)		(12.9)		(30.1)	

Notes: LTMI (low and medium-low tech manufacturing industries), HTMI (medium-high and high tech manufacturing industries), NKIS (non-knowledge-intensive services), KIS (knowledge-intensive services). Between variation means variation across individuals and within variation means variation over time around individual mean. Source: PITEC; own calculations.

Table A. 3 Descriptive statistics Chapter 4 before filters

		TOTAL		LTI		HTI		NKIS		KIS	
		mean	st dv	mean	st dv	mean	st dv	mean	st dv	mean	st dv
Firm's characteristics											
Labour	over	11.756	1.048	11.978	0.851	12.038	0.756	11.999	1.112	11.140	1.181
productivity [a, d]	betw		1.015		0.812		0.731		1.080		1.118
(cont.)	with		0.344		0.312		0.291		0.305		0.430
Firm size [a]	over	4.456	1.452	4.253	1.213	4.179	1.243	5.107	1.614	4.634	1.663
(cont.)	betw		1.463		1.212		1.245		1.626		1.680
	with		0.230		0.212		0.200		0.220		0.275
Physical	over	9.418	3.450	10.000	3.547	9.732	2.991	9.129	3.626	8.596	3.446
capital [a, d]	betw		3.406		3.542		2.907		3.496		3.412
(cont.)	with		1.434		1.450		1.352		1.593		1.406
Advanced	over	3.456	4.063	3.911	4.290	3.935	4.055	2.251	3.518	3.063	3.871
machinery [a, d]	betw		3.550		3.782		3.487		3.091		3.359
(cont.)	with		1.993		2.069		2.145		1.630		1.916
Human	over	22.948	25.873	12.380	13.741	21.381	19.105	14.166	20.272	40.967	33.587
Capital [a]	betw		24.329		12.196		17.592		18.569		31.022
(cont.)	with		9.733		6.646		8.234		8.902		13.610
Group [a]	over	0.412	0.492	0.366	0.482	0.427	0.495	0.506	0.500	0.409	0.492
(0/1)	betw		0.461		0.451		0.466		0.468		0.458
	with		0.172		0.162		0.169		0.181		0.181
International	over	0.465	0.499	0.575	0.494	0.714	0.452	0.284	0.451	0.205	0.404
Competition [a]	betw		0.436		0.423		0.386		0.380		0.341
(0/1)	with		0.245		0.264		0.252		0.250		0.212
Knowledge / Innovation											
R&D	over	0.564	0.496	0.570	0.495	0.777	0.416	0.254	0.435	0.516	0.500
engagement [a]	betw		0.418		0.395		0.336		0.370		0.432
(0/1)	with		0.272		0.304		0.255		0.240		0.259
R&D	over	9.436	1.579	9.011	1.341	9.837	1.224	8.316	1.866	9.723	1.910
intensity [b]	betw		1.717		1.415		1.284		1.973		2.055
(cont.)	with		0.449		0.452		0.348		0.661		0.500
Continuous	over	0.785	0.411	0.732	0.443	0.825	0.380	0.699	0.459	0.816	0.387
R&D [b]	betw		0.381		0.399		0.344		0.435		0.363
(0/1)	with		0.259		0.282		0.246		0.262		0.246
Personnel in	over	1.103	1.274	0.942	1.078	1.598	1.273	0.412	0.913	1.186	1.437
R&D [a]	betw		1.136		0.913		1.155		0.788		1.277
(cont.)	with		0.543		0.555		0.525		0.435		0.585

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Table A.3 – *Continued from the previous page*

		TOTAL		LTI		HTI		NKIS		KIS	
		mean	**st dv**	**mean**	**st dv**	**mean**	**st dv**	**mean**	**st dv**	**mean**	**st dv**
Process	over	0.555	0.497	0.624	0.484	0.630	0.483	0.369	0.483	0.496	0.500
innovator [a]	betw		0.407		0.393		0.392		0.395		0.408
(0/1)	with		0.295		0.295		0.294		0.285		0.301
Product	over	0.532	0.499	0.538	0.499	0.725	0.447	0.262	0.440	0.482	0.500
Innovator [a]	betw		0.424		0.413		0.375		0.376		0.424
(0/1)	with		0.270		0.285		0.258		0.237		0.274
Protection [a]	over	0.267	0.442	0.271	0.445	0.337	0.473	0.181	0.385	0.242	0.428
(0/1)	betw		0.345		0.343		0.373		0.292		0.335
	with		0.283		0.286		0.296		0.256		0.279
Cooperation [c]	over	0.373	0.483	0.325	0.469	0.376	0.484	0.312	0.464	0.452	0.498
(0/1)	betw		0.392		0.371		0.388		0.379		0.415
	with		0.292		0.293		0.296		0.281		0.292
External knowledge											
% firms with	over	56.40	22.54	57.04	10.68	77.72	7.84	25.39	14.84	51.63	25.10
R&D activities [a]	betw		21.93		8.00		5.83		14.34		24.68
[0-100]	with		5.85		7.46		5.38		4.22		4.58
Intra-industry spillover	over	414.42	438.49	239.58	182.24	752.15	468.07	227.01	306.25	415.60	502.95
(process)[a, d]	betw		412.99		176.39		434.83		218.16		477.44
(cont.)	with		145.41		43.89		162.59		216.96		165.43
Intra-industry spillover	over	467.35	504.02	229.59	174.20	865.07	530.13	350.60	435.87	457.79	562.10
(product)[a, d]	betw		481.29		168.34		500.22		372.56		541.56
(cont.)	with		143.62		43.15		158.62		231.29		153.86
Inter-industry spillover	over	360.95	142.14	387.01	128.74	405.75	108.32	329.25	212.33	306.89	119.88
(process) [a, d]	betw		115.41		93.58		70.00		200.79		88.41
(cont.)	with		85.64		91.46		87.16		64.47		85.83
Inter-industry spillover	over	371.77	154.07	403.53	139.66	417.57	120.71	325.90	232.01	316.67	125.44
(product) [a, d]	betw		128.11		107.27		84.024		219.40		94.67
(cont.)	with		87.37		91.89		90.615		67.846		87.07
Public Funding											
Local	over	0.212	0.409	0.213	0.409	0.260	0.439	0.080	0.271	0.230	0.421
(0/1)	betw		0.320		0.296		0.331		0.202		0.360
	with		0.261		0.287		0.292		0.189		0.228
National	over	0.197	0.398	0.170	0.375	0.258	0.438	0.066	0.248	0.238	0.426
(0/1)	betw		0.312		0.276		0.331		0.186		0.355
	with		0.252		0.257		0.290		0.170		0.241

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Table A.3 – *Continued from the previous page*

		TOTAL		LTI		HTI		NKIS		KIS	
		mean	**st dv**	**mean**	**st dv**	**mean**	**st dv**	**mean**	**st dv**	**mean**	**st dv**
European	over	0.050	0.218	0.030	0.170	0.043	0.202	0.020	0.140	0.095	0.293
(0/1)	betw		0.172		0.114		0.147		0.105		0.244
	with		0.138		0.130		0.144		0.096		0.156
Sources of information											
Internal	over	0.596	0.491	0.547	0.498	0.644	0.479	0.530	0.499	0.630	0.483
(0/1)	betw		0.384		0.389		0.369		0.394		0.378
	with		0.328		0.330		0.323		0.330		0.330
Market	over	0.481	0.500	0.454	0.498	0.512	0.500	0.483	0.500	0.480	0.500
(0/1)	betw		0.386		0.380		0.388		0.388		0.389
	with		0.334		0.336		0.329		0.336		0.338
Institutional	over	0.147	0.355	0.137	0.344	0.142	0.349	0.094	0.292	0.185	0.388
(0/1)	betw		0.277		0.267		0.268		0.224		0.309
	with		0.222		0.218		0.222		0.187		0.238
Others	over	0.173	0.379	0.152	0.360	0.177	0.382	0.139	0.346	0.208	0.406
(0/1)	betw		0.294		0.270		0.291		0.282		0.325
	with		0.243		0.242		0.244		0.213		0.251
Firms		10870		3581		2610		1404		3275	
(%)				(32.9)		(24.0)		(12.9)		(30.1)	
Observations		63615		21,385		15643		8389		18198	
(%)				(33.6)		(24.6)		(13.2)		(28.6)	

Notes: LTMI (low and medium-low tech manufacturing industries), HTMI (medium-high and high tech manufacturing 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.

Table A. 4 Descriptive statistics Chapter 5

	Type	Mean	Standard deviations			Share of innovative sales per group			
			over	betw	with	0	1	Test 1[1]	Test 2[2]
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable									
Share innovative sales	[0-1]	0.30	0.37	0.29	0.25				
New to the firm only	[0-1]	0.18	0.29	0.23	0.21				
New to the market	[0-1]	0.12	0.25	0.19	0.17				
Independent variables									
Innovation intensity	cont.	0.23	0.39	0.37	0.14				
Internal information (involuntary)	(0/1)	0.51	0.50	0.38	0.34	0.28	0.31	-9.89***	-15.8***
Internal cooperation (voluntary)	(0/1)	0.26	0.44	0.34	0.27	0.26	0.32	-10.5***	-19.8***
Absorptive Capacity	cont.	0.18	0.36	0.35	0.13				
Control variables									
Size	cont.	4.40	1.38	1.40	0.21				
International market	(0/1)	0.55	0.50	0.44	0.25	0.29	0.31	-7.58***	-20.8***
No group	(0/1)	0.57	0.49	0.47	0.17	0.28	0.31	-10.3***	-8.63***
Non-innovation performer	(0/1)	0.17	0.38	0.28	0.28	0.31	0.22	20.94***	39.59***
External information	(0/1)	0.31	0.46	0.34	0.33	0.30	0.30	-0.11	-0.52
External cooperation	(0/1)	0.35	0.48	0.38	0.30	0.29	0.33	-11.3***	-22.9***
Number of observations		49,436							

Note: We test whether there are significant differences in the share of innovative sales within two groups. Column 5 indicates the mean of innovative sales for the first group (i.e. *Xi*=0) and column 6 for the second group (i.e. *Xi*=1). In order to do so, two tests are used: parametric test (column 7) and non-parametric test (column 8). [(1)] Test 1 is a parametric test to check whether the share of innovative sales has the same mean within two groups. [(2)] Test 2 is the non-parametric Wilcoxon rank-sum test, also known as Mann–Whitney two-sample statistic, which tests the hypothesis that two independent samples are from populations with the same distribution.

Table A. 5 Estimates of the Equation [5.1]. Probit models. 2006- 2011

Dependent variable	Probability of achieving an innovation (product and/or process) in [*t-2, t*]					
	T=2006	T=2007	T=2008	T=2009	T=2010	T=2011
Innovation int_{t-2}	0.152	0.228***	0.237**	0.263**	0.401***	0.0664
	(0.107)	(0.0803)	(0.114)	(0.117)	(0.110)	(0.0710)
$Size_{t-2}$	-2.137	-0.417	-2.173	-2.057	-2.872*	-0.985
	(1.697)	(1.500)	(1.565)	(1.614)	(1.696)	(1.572)
$Size^2_{t-2}$	1.058	0.230	1.075	1.029	1.427*	0.507
	(0.836)	(0.739)	(0.772)	(0.797)	(0.837)	(0.776)
No $group_{t-2}$	-0.0272	0.00235	-0.0451	-0.0213	0.0295	-0.0549
	(0.0448)	(0.0403)	(0.0427)	(0.0438)	(0.0446)	(0.0421)
International	0.294***	0.246***	0.172***	0.144***	0.174***	0.172***
market $_{(t-2,\ t)}$	(0.0440)	(0.0388)	(0.0412)	(0.0436)	(0.0459)	(0.0428)
Human	0.132***	0.101***	0.0982***	0.0628***	0.0337**	0.0499***
$capital_{t-2}$	(0.0145)	(0.0135)	(0.0138)	(0.0140)	(0.0133)	(0.0130)
Non-innov	-1.468***	-1.512***	-1.651***	-1.641***	-1.633***	-1.757***
performer $_{t-2}$	(0.0450)	(0.0400)	(0.0416)	(0.0431)	(0.0434)	(0.0415)
Constant	0.775***	0.334*	0.962***	0.960***	1.187***	0.709***
	(0.202)	(0.184)	(0.186)	(0.188)	(0.196)	(0.185)
Ind. dummies	Yes	Yes	Yes	Yes	Yes	Yes
Wald test	148.79***	171.63***	171.84***	180.37***	235.14***	90.05***
Observations	7,047	8,403	8,126	7,765	7,415	7,000
McFadden's pseudo R^2	0.4690	0.3368	0.3766	0.3754	0.3770	0.3670

Notes: Robust standard errors are in brackets. *** Significant at 1%, ** significant at 5%, * significant at 10%.

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