UNIVERSITAT DE BARCELONA

R&D offshoring and firm's innovativeness: The role of firms', regional, and sectoral characteristics

Damián Tojeiro Rivero

PhD in Economics

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To my parents, to my lovely wife, the most wonderful woman ever created,

and to my little boys

If you give fish to a hungry man, you feed him for a day.
If you teach him to fish, you will nourish him all his life.

— Lao-Tzu

Acknowledgments

This should be one of the easiest parts of a dissertation, yet, you just understand its difficulty when you realize of the importance many people have had in your learning process. As we—economists of innovation—recognize in our research field, knowledge is cumulative, takes advantage of past as well as other's knowledge, and evolve through learning processes. I think there is not a better way of synthetizing what a PhD mean than the latter sentence.

Graphically, a PhD is like a $sen\,(x)$, it is a challenging and demanding progression of small steps facing sad moments (i.e. your models do not work at all, you a have a good idea but data does not go at hand, you do not receive any comment in a congress, etc.) and moments of deep pride when you see your work accepted for publication. In my modest opinion, this is mainly due to my own effort, and to the invaluable supervision of my thesis' director Rosina Moreno.

In my case, I feel that having Rosina as my supervisor was the right choice. I first meet her as my teacher in my last year of the undergraduates in Economics, thereafter having her again as my teacher in the master course of spatial econometrics. If anyone ask me to tell about what like me the most about Rosina, I would say that is not fair to ask just for a single attribute. As a teacher, she has the ability to convert something very complicated into a simple problem, thus, you might better change career if you cannot follow her classes, because then you would not follow any class. As a person she is even better—if possible. I can go to her office without arrange any meeting and always has attended me, never complaining about the informality of most of our meetings. As a researcher I think her curriculum say everything. All this is just to say I have no words to thank my supervisor for her support, for encouraging me to have a critical point of view, because as she says, econometrics is just a tool, the value of the research is in the idea behind it; for showing interest not just in my research but also when facing personal difficulties. For all this, thanks a lot for everything Rosina!

I also would like to thank to my research group AQR-IREA and other professors in the department of Econometrics, Statistics and Applied Economics. Let me start by showing my deepest gratitude to Antonio Di Paolo, who has always found the time for helping me. My three research papers have benefited tremendously when having informal conversations with him, especially regarding the technical issues. I am also thankful to Quique, who helped me to see several issues behind my ideas as well as some other issues regarding the data. Furthermore, I thank Ernest Miguelez for his recommendation about my third chapter of the thesis, which I am sure it improve its quality. In addition, I thank to Esther Vayá for giving me a mini-course about input-output tables that I plan to implement in a future study, as well as to Vicente Royuela for his enthusiastic advices about panel data and instrumental variables issues, he really enjoy teaching. However, I feel that choosing this department for my four years journey was worth not just because of the professors working in my research area, but because to all other professors as well as the rest of the personnel. Therefore, I would also like to thank to Jordi Suriñach, Alessia Matano, Raul Ramos, and Josep-Lluis Carrión. Additionally, many thanks to Bibiana, Coloma, and Isabel for all their support with the administrative stuff and for always receiving me with a smile. I do really think that you all make me feel this is my second home.

Since knowledge is cumulative, and thus, comes from many different sources, I would also thank my Master and PhD colleagues for all the support, the time, and conversations that allow me to be unplugged from the PhD and not to become crazy. Especially to my office colleague Nicola Rubino, with whom I have started the most philosophical, anecdotal, and critical conversations trying to fix our uncertain future.

It is important to me to mention other people that have contributed to my development. Thanks to Professor Montse Vilalta for her support during my undergraduate and Master studies, to Jordi Roca and UB Economics for his support with administrative stuff, and to the University of Barcelona for the economic funding through the APIF scholarship that make me feel as a helpful member for the society. Of course, I also would like to thank to Jordi Catalán, Josep Sabaté,... as well as other professors that because of space restriction I cannot mention. Aditionally, I would like to thank to Anastasia Semykina and Valentina Tartari for their very useful comments for the second chapter; as well as to Fernando Bruna, Malcom Fairbrother and Carla Rampichini for their useful comments on earlier versions of the third chapter.

Now I want to thank my parents, who have always gave me everything they could in every step of my life. Starting by my dad, who decided to escape from the socialism with 58 years old and came to a city in which he was completely alone just to offer me the opportunity to have a plenty life. Also, to my mom,

who has always sacrifice herself with regard to me. Yep, I remember every effort made by you. This thesis is in part because of them.

Finally, to my wife, who has changed my life in all the aspects for better since the very first moment we meet, 17 years ago. There is no person in my life as important and necessary as you, Kary. Thank you for believing in me, for encouraging me to pursue my dream, for supporting me in every aspect in this long and tough journey, for being here in my deepest moments, and thank God, the providence or whatever it is, for giving me the best woman ever created.

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CHAPTER 1

Introduction

1.1. What is an innovation and why is it so relevant?

The study of technological change has evolved through the time. As signaled by Vonortas et al. (2012, chapter 1), starting by those who avoided it in their mathematical analyses (i.e. Walras, Wicksteed and Barone), nowadays, it is recognized as the main engine of economic growth (Grossman and Helpman, 1991; Lucas, 1988; Romer, 1986, 1990). These scholars recognized economic growth being conditioned by increases in productivity, which in turn, is also affected by technological changes/innovations. The study of the causes and consequences of technological changes can be first assigned to Schumpeter (1939). For him, economic growth is determined by disruptive innovations displacing older paradigms through a dynamic process that he called creative destruction. Therefore, for him, innovation is the main contributor of capitalism, which takes shape due to long waves creating business cycles due specifically to the appearance of new and disruptive innovations.

Broadly speaking, an innovation is a new creation of economic significance; therefore, the innovative activity is completed when it reaches a commercial stage. However, the concept of innovation can be defined in a narrow way as for instance, technological innovations: processes by which firms master and generates products designs and manufacturing processes that are new to them. Or in a more Schumpeterian sense, including aspects like the organizational, or others like the institutional, or commercial types of innovations (Edquist, 1998), acknowledging the importance of not just the inclusion of new factors, but the combinations of such factors inducing innovations. In the present thesis, and without denying the importance of other types of innovations, I focus exclusively on technological innovations (i.e. product innovations) since building on previous evidences, external R&D processes are recognized to affect more product innovation than process innovation (Nieto and Rodríguez, 2011).

Successful innovations come from the accumulation, re-combination, and re-interpretation of previously unconnected ideas. As signed by Krugman and Wells

(2009), the idea that internal R&D efforts made by the firm offers the opportunity to improve its innovative performance comes long ago from the XIX century. Back in a day, Thomas Edison in Menlo Park (New Jersey) created the first R&D laboratory hiring twenty-five men at full time with the aim of creating new products and processes. Of course, before Edison, there were inventors with the aim of creating an invention and taking profit from it; however, he was the first with the aim of creating new ideas year after year.

One of the first economists pointing out the importance of knowledge external to the firm was Alfred Marshall, who highlighted the necessity for firms to clustering in order to benefit from the ideas in the air (Marshall, 1890). The latter is a remarkable breakpoint, since, it gives importance not just to internal processes of knowledge creation, but also, to external sources.

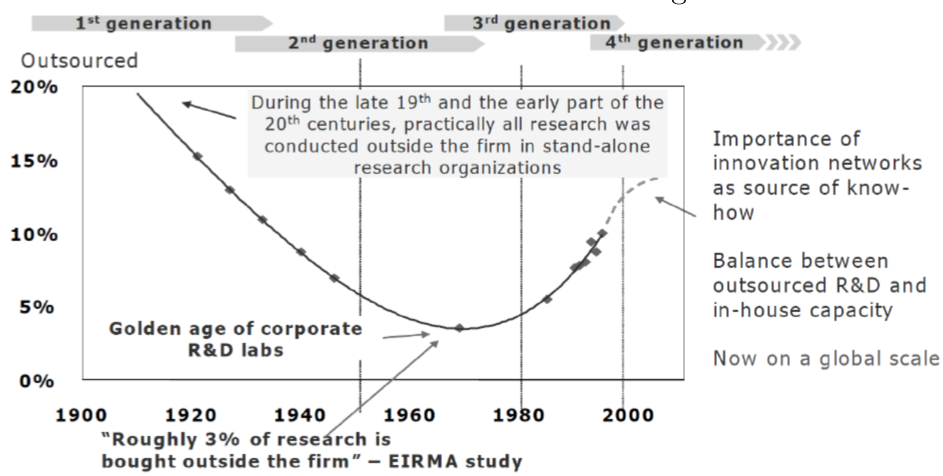
1.2. The importance of accessing to others' knowledge: networking matters

After Marshall, many authors have stressed the relevance of the acquisition of knowledge outside the boundaries of the enterprise itself to improve its products and processes of production and even to generate new knowledge to develop breakthrough innovations. The Open Innovation literature has posit into consideration its relevance for firms in order to survive, grow, and to approximate to leadership (Chesbrough, 2003). In the 1960s and 1970s it was seen as a small contributor to enterprises' innovative processes since it was developed by just 5 percent of companies (OECD, 2008). Nowadays, enterprises have notice the significance of accessing to external knowledge as an essential step for increasing their innovative activity as it is highlighted by Murphy and Siedschlag (2015).

Recently, several studies have emphasized the relevance not just of knowledge external to the firm, but also of that of foreign sources. The internationalization strategy tries not only to get access to markets abroad, but more importantly, to knowledge that is specific of the host location. Among other advantages, enterprises get profit from resources owned by foreign enterprises or foreign institutions, as well as from the international talent (Youngdahl and Ramaswamy, 2008). The reasoning rests on the idea that R&D researchers cannot be substituted by low cost workers as suggested by Grimpe and Kaiser (2010). Reason why Bunyaratavej et al. (2007) stresses that services offshoring is done with enterprises in countries in which the mean salary is increasing. Therefore, we should take notice of other determinants beyond cost reduction being more relevant when deciding to access to foreign knowledge, as for instance knowledge specificities.

Additionally, it is said that geographic distance could increase the communication cost and reduce cultural and institutional proximities, leading to a difficult implementation of foreign knowledge. However, the globalization, the new information and communication technologies, and the changes into an open market with new intellectual property laws can smooth or counteract those effects. As the OECD (2008) reports, nine out of ten of the companies that spend the most on R&D, do so around 15 percent with other organizations (see Figure 1.1), evidencing an increasing trend, and how complements are external and internal sources of knowledge creation.

FIGURE 1.1. Global Outsourcing



Source: European Commission (2005b).

1.3. Is the whole more than the sum of its parts? The relevance of the context

If knowledge creation, and thus, innovation, is only due to firm's characteristics, then, we should observe that two given firms with similar characteristics should behave the same in terms of knowledge creation if located in different places. Instead, this is not what we can see, there are other relevant players in the process of innovations, like for instance, institutions, being the latter understood in a broad sense (Edquist, 1998).[1]

Economic geography remarks the importance of knowledge externalities, as it is a fact that knowledge and therefore innovations are spatially bounded (Balland

[1]Universities, research centers, R&D laboratories, patent systems, labor market organizations, government agencies, but also, norms, habits, practices, routines, etc.

and Rigby, 2017; European Commission, 2014). Knowledge diffusion in the form of knowledge spillovers is crucial in this literature as a cause of the geographic agglomeration of firms (Audretsch and Feldman, 1996; Jaffe et al., 1993). As previously remarked, at the end of the nineteenth century, Marshall (1890) already described how firms could benefit from spatial concentration: taking advantage of input-output relationships within industries, thanks to labor market pooling, as well as benefiting from positive knowledge externalities arising from other firms. In this sense, geographical proximity is important because of the transmission of tacit knowledge and the creation of relationships based on trust, reducing transaction costs and avoiding opportunistic behaviors.

It is a fact that the new information and communication technologies have connected quite well knowledge hot spots around the world. For instance, much of the work within companies like Apple or Google could be due at home without the necessity of going every day to the work place. Why then, are these companies building their huge knowledge centers trying to agglomerate all their work force in the same place? The answer is knowledge spillovers, the possibility of sharing different ways of doing and thinking, reduced costs when sharing new knowledge. Consequently, proximity becomes a condition to knowledge dissemination.

Other scholars, however, and without denying the geographical proximity importance for knowledge diffusion, point to the necessity of incorporating another level, like the industrial context. Aspects like learning patterns, organizational processes, knowledge base, or technological regimes, among others, are recognized as sectoral specificities (Malerba, 2002; Malerba and Adams, 2014). The result of this is that within a given sector, firms will show similar learning patterns, as well as will present similar behaviors in terms of product generation, while being bounded by similar organizational forms. All this, linked to a standard and easy to codify type of knowledge, as in the case of R&D offshoring, will make geographical proximity less relevant—as in the opposite case of technological collaboration with the need of sharing more tacit knowledge (Teirlinck and Spithoven, 2013). Therefore, other types of proximities, like cognitive and/or organizational may be more at work (Boschma, 2005).

As a consequence, it is sensible to think that the environment in which firms are located (geographical context), or within which firms are connected to other agents (sectoral characteristics), are key for knowledge diffusion, and thus, for innovation.

R&D offshoring is the central area of work around which this dissertation gravitates. However, as previously said, I am also interested in understanding how the environment in which firms operate may affect the processes of firms' innovation through the acquisition of external knowledge. Throughout this thesis, R&D offshoring is understood as the market based transaction through licensing and/or contractual agreements of a client enterprise acquiring external R&D from another institution located abroad (Cusmano et al., 2009), also known as offshoring outsourcing (Nieto and Rodríguez, 2011) or international outsourcing (Phene et al., 2006), with the objective of performing innovation activities.

Specifically, this thesis provides new evidence on three broad issues: first, how foreign acquisition of knowledge affects the economic return of radical innovations as in the contrary case of incremental innovations at the firm level, with a differentiation between different moments of the economic cycle (the recent economic crisis). Second, how the geographical environment in which firms locate may influences the relationship between networking strategies used to access external knowledge and firms' generation of innovations. Third, how sectoral externalities coming from foreign acquisition of knowledge may have a pervasive relation with firms' innovative performance.

1.4. Outline of the dissertation

After this first introductory chapter, this dissertation consists of three essays with a marked empirical orientation, which are intended to be a contribution to the Economics of Innovation and Economic Geography literatures. Each of the chapters constitutes a separate piece of research in itself and are developed according to their own structure and methodological framework. A final chapter summarizes the main findings and sketches the policy implications and directions for future research.

In chapter two, I analyze the relation between firms' economic return to innovations and their acquisition of foreign knowledge. As highlighted by the OECD (2008), the global tendency in the 1960s and 1970s was for firms to develop around 95 percent of their research projects in their own R&D laboratories. However, in the 1980s, there was an increasing trend towards the international acquisition of knowledge. Nowadays, around 70 percent of European enterprises have increased their R&D offshoring strategy during the last decade. This just manifests the fact that R&D offshoring is a relatively recent topic in the innovation literature, which is partly due to the recent process of purchasing innovations from abroad. While previous studies have focused their attention on the role of R&D offshoring in the generation of product and/or process innovations; I am interested in the innovative performance that a firm obtains with regard to the intensity of radical innovations. This second chapter contribute to the literature of Open innovation in the study of the heterogeneity in the influence of R&D offshoring according to the nature of the agents, as well as to the phase of the economic cycle. The evidence for Spanish firms between 2004 and 2013 shows that R&D offshoring influences significantly the intensity of radical but not of incremental innovations. This influence is apparently smaller when external knowledge comes from universities or research institutions rather than from the business sector. With regard to the economic cycle, the recent financial crisis also exerted a detrimental effect on this influence, as compared with the previous period of economic growth. This chapter has been published as: Tojeiro-Rivero, D., Moreno, R. & Badillo, E.R. Rev Ind Organ (2018). https://doi.org/10.1007/s11151-018-9659-3

In chapter three, I combine two research areas, which are Open Innovation and Geography of Innovation. Usually, the former has been more directed to knowledge acquisition as a way to achieve better innovative outcomes at the firm level; while the latter, has focused on the study of the role of the territory on the innovative processes. However, as stressed by Crescenzi and Gagliardi (2018) in a recent paper, the geography of innovation has often adopted a more aggregate perspective neglecting firms' heterogeneity. On the other hand, differences in technological performance cannot be explained by firms in isolation but at the regional level (Uyarra, 2009). This way, I investigate whether the regional innovative environment affects the innovative performance of enterprises through networking activities (technological collaboration and R&D outsourcing); and on the other hand, if the knowledge structure of regional stakeholders affects such a process. To answer this question, I focus on the Spanish economy making use of a multilevel framework. The results suggest that firms obtain a higher return of technological cooperation if they are located in regions with higher knowledge capacity. On the contrary, firms obtain a higher return from R&D outsourcing if they are located in regions with low knowledge endowment. When studying the type of stakeholder's knowledge of the region, I observe that the returns to technological cooperation are higher if the firm is located in regions with higher research expenditures developed by private agents, while the benefits obtained from cooperation are lower if they are located in regions with a rich knowledge stock in the government and university sectors. On the contrary, I observe that firms located in regions with higher research expenditures by private agents obtain lower returns from their R&D outsourcing strategy; whereas those located in regions with higher amount of research developed by public institutions obtain higher returns from outsourcing. This chapter has been published as: Tojeiro-Rivero, D., Moreno, R. Research Policy (2019). https://doi.org/10.1016/j.respol.2019.04.006

In chapter four, I extend the discussion of the relevance of the context by particularly focusing on the role of the sectoral environment studying its influence on the firm's innovative processes. The Open Innovation literature has realized of the benefits of obtaining knowledge external to the firm, especially if coming from different national contexts and type of partners (see my second chapter description). However, none of the previous literature has been devoted to investigate how sectoral externalities coming from foreign acquisition of knowledge—R&D offshoring—may have an influence on firms' innovative performance. Most studies tend to analyze R&D offshoring at firm level. Yet, the downside is that the context also affects firms' performance (van Oort et al., 2012), and focusing on just one level may generate an incomplete analysis (Backman, 2014). I argue that a relative increase in sectoral R&D offshoring has a positive influence in firms' innovativeness, but only until an intermediate threshold; thereafter, higher levels of offshoring may end in pervasive forces inducing negative returns.

The evidence provided for Spanish firms from 2005-15 indicates that R&D offshoring is key for enrolling in product innovation, while also indicates that the propensity to innovate is positively affected by the industrial level of offshoring. Hence, confirming the relevance that the pool of knowledge coming from a different NIS has for firms' innovative processes.

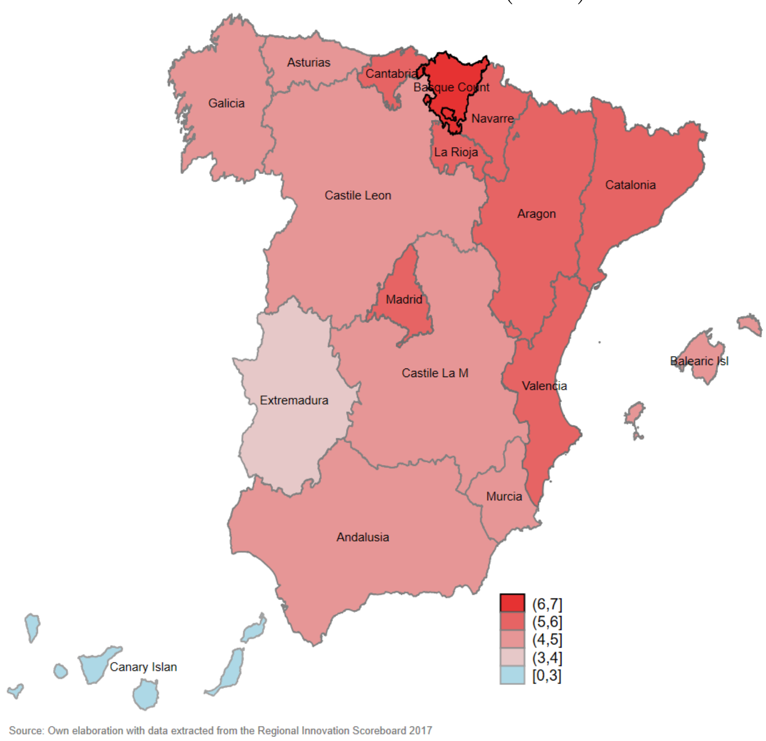
Yet, too much of this industry externality generates negative returns. Therefore, as suggested by Chesbrough (2003), it seems that too much offshoring at the industry level may posit a damage into its firms' innovativeness which is supported by these results.

The chapter also finds empirical support for the heterogeneity present among firms pertaining to the same industry. Therefore, smaller firms, as well as those enterprises presenting higher levels of collaboration and offshoring experience with other organizations are the ones less harmed when the sectoral R&D offshoring is high. Besides, those enterprises increasing their internal capacity through a more skilled workforce are the ones benefiting the most from their industrial context presenting positive returns coming from sectors with the highest sectoral spillovers.

1.5. Presentation of the study case: An overview of Spain

The three empirical chapters of this thesis are applied to Spanish firms. Spain is an open economy that is well integrated in a trade and monetary union with some of the world's technology leaders (García-santana et al., 2016). Being part of the European Union (EU) implies solid laws of intellectual property rights, which leads to a substantial benefit from offshoring strategies, since as suggested by Tübke and Bavel (2007) most of the R&D offshoring of European firms is conducted between firms within the European Union. The Spanish case is interesting since it is at the middle of the EU technological ranking, below the average R&D expenditure in the EU according to the INE.[2] Most of the productive sector is based on SMEs; and the public sector is the main source of knowledge, with the largest share of R&D workers, around 56 percent in 2014: 19 percent for research centers, and 37 percent for universities. In addition, Spain suffered one of the biggest and most negative impacts of the financial and economic crisis at the end of 2008.

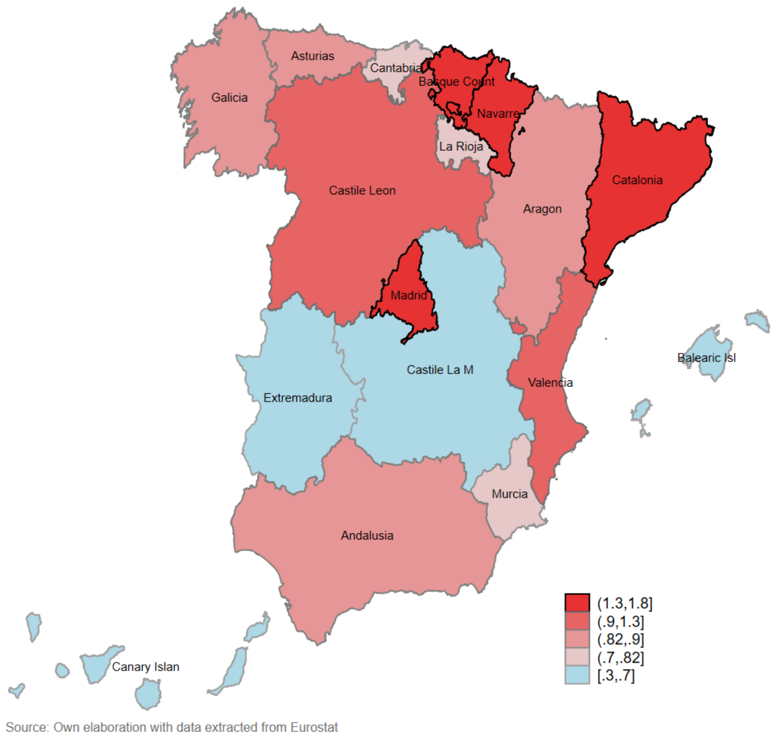
FIGURE 1.2. RII index (2017)



Third chapter considers the information of the region where the firm is located. Spain is an interesting study case since it is one of the four European countries presenting the widest regional heterogeneity in innovation (European Commission, 2014). For instance, according to Figure 1.2, which uses the Regional Innovation

[2]1.22 percent of GDP for Spain in 2014 and 2.08 percent of GDP for the UE15.

FIGURE 1.3. GERD (as percentage of GDP)



Index (RII)[3]—a composite indicator distinguishing between Enablers, Firm activities, and Outputs—Spain presents five different regional classifications, going from low innovative regions such as Canary Islands and Extremadura to higher innovators as in the case of the Basque Country, Catalonia, and Madrid. However, as Figure 1.3 shows, there is also huge heterogeneity in knowledge inputs as for the case of R&D expenditures; not having a perfect correspondence since regions as Cantabria and La Rioja present lower amounts of R&D expenditures even though performing quite well in terms of innovations if compared to regions as Catalonia and Madrid as shown in Figure 1.2. Spanish regions have also legal competencies and financial autonomy in terms of innovation policies and present important socio-cultural differences that could lead to different learning processes as stressed by Cooke et al. (1997). Finally, regarding the socio-cultural aspect, which is an important source of the learning process according to the Regional Innovation System literature, Spain has four different languages apart from Spanish, which are officially talked in six regions—Catalonia, Valencia, Basque Country,

[3]This index classify European region into twelve categories going from Modest Innovators to Innovation Leaders.

Galicia, Balearic Island, and Navarre—highlighting a social and cultural diversity higher than in other European countries.

The data used in this dissertation combines two surveys on firm's innovative activities, as well as a dataset extracted from Eurostat for contextual characteristics. For instance, in the second and four chapters, firms innovativeness are accessed through the Technological Innovation Panel (PITEC) which is an unbalanced panel tracing the innovation activity of Spanish enterprises from 2003 until 2015.[4] It uses two surveys: The first—Survey on Technological Innovation of Firms—is the Spanish counterpart to the Community Innovation Survey (CIS) from the Eurostat, following the guidelines of the Oslo Manual; the second is the Statistics on R&D Activities. The PITEC is representative of small and medium-size as well as large firms; enterprises with internal R&D expenditures, as well as those with external R&D expenditures without having internal R&D; and finally those small and medium-size firms without any expenditures on innovation. The stratification of the sample is for all business sectors that are included in the National Classification of Economic Activities (NACE two digit level); and the representativeness of the panel is assured thanks to the annual inclusion of firms with similar characteristics to those that disappear from the sample. The response rate is very high since it is mandatory for firms, and the territorial covering is the whole Spanish economy.

The second survey source at the firm level which is used in my third chapter, is the Spanish Survey on Business Strategies—ESEE—that consists on an unbalanced panel of manufacturing enterprises starting from 1990 until 2014 with around 1,800 firms surveyed yearly by the SEPI Foundation with an agreement with the Ministry of Industry. Firms are classified into twenty industries using the two-digit European classification (NACE). The ESEE's population of reference is composed of firms with 10 or more employees within the manufacturing industry. Moreover, the geographical scope of reference is the Spanish economy as a whole even though information of the location of the main plant is targeted in the survey. The initial selection was carried out combining exhaustiveness for firms with more than 200 employees and random sampling for firms employing 10 to 200 workers. These firms were selected through a stratified, proportional and systematic sampling with a random seed.

[4] Notice that because of data availability, the time period covered is not the same throughout the three chapters of the dissertation. For instance, the second chapter uses the period 2004-2013, while the fourth chapter extends to 2005-2015.

Despite the fact that both, PITEC and ESEE, are surveys in which values are self-reported, in this kind of surveys, where anonymity is a legal concern, it is not expected a systematic propensity for over- or under-reporting the innovation that is carried out by the enterprise.

As for the regional dataset used in the third chapter, I use the Eurostat at the NUTS 2 level. In the Spanish case these territorial units represent administrative and policy authorities.

CHAPTER 2

Radical innovations: The role of knowledge acquisition from abroad

2.1. Introduction

When buying technology from others, the purchasing firms can choose from among firms and institutions that belong to the same country or ones beyond its boundaries. As highlighted by the OECD (2008), the global tendency in the 1960s and 1970s was for firms to develop around 95 percent of their research projects in their own R&D laboratories. In the 1980s, there was an increasing trend towards the international acquisition of knowledge. Nowadays, around 70 percent of European enterprises have increased their R&D offshoring strategy during the last decade, and approximately 87 percent see the external acquisition of knowledge as an important step in increasing their innovation capacity.

In this chapter, we focus on R&D offshoring and provide evidence with regard to its influence on the intensity of radical innovations. As these innovations incorporate a high level of innovativeness, they may depend more on external and diversified sources, which may imply knowledge that differs significantly from that already present in the firm (Laursen and Salter, 2006). We hypothesize that the impact of outsourcing knowledge from foreign countries is greater for radical innovations than in the case of incremental innovations, which are more connected with an imitation strategy that does not require different knowledge from that available internally.

While previous studies have focused their attention on the role of R&D offshoring in the generation of product and/or process innovations (Bertrand and Mol, 2013; Nieto and Rodríguez, 2011), we are interested in the innovative performance that a firm obtains in terms of the share of sales due to product innovations. The innovative activity is completed when it reaches a commercial stage; and, even in such a case, not all innovations lead to the same amount of profitability in terms of sales. That is, the relevant step is not only the decision to innovate; in this chapter, we focus on the success of commercializing the firm's inventions once a firm has decided to innovate.

Our further contribution concerns the study of the heterogeneity in the influence of R&D offshoring according to the nature of the agents, as well as to the phase of the economic cycle. With respect to the former, the reasoning lies in the idea that the type of knowledge that can be acquired from foreign universities and research centers—more basic know-how—is different from that provided by the business sector, which is more focused on market profitability. Second, we contribute to the literature that studies the influence of the last economic recession on the role of R&D offshoring, which has also not been explored in previous studies. The differentiation between small and large firms is also considered.

The outline of the chapter is as follows: The second section provides a literature review, while the third exposes the main hypotheses of the chapter. Section 2.4 sketches the empirical model, before section 2.5 presents the data. The main results are provided in section 2.6; and finally we discuss the results and conclude.

2.2. Literature review

Among the main reasons for the importance of the acquisition of foreign knowledge is the reduction of costs that it implies, as well as the access to a well-prepared labor force (Lewin et al., 2009; Youngdahl and Ramaswamy, 2008). People—scientists, researchers, or engineers—are not perfectly mobile, and talent is an intangible good that is embedded in individuals, not easy to imitate, and part of the knowledge base of an enterprise (Lewin et al., 2009).

Another relevant advantage of outsourcing is the widening of the scope of a firm's internationalization. It allows access to new markets and new knowledge, increases the efficiency of the firm's internal capabilities, and leads to an improvement in its competitiveness and a positive impact on its innovation capacity (Grimpe and Kaiser, 2010; Cassiman and Veugelers, 2006; Love et al., 2014; OECD, 2008, pp. 20, 91). These theoretical advantages of knowledge offshoring are expected to be translated into a positive impact on innovation performance.

The European Union Survey (Tübke and Bavel, 2007) reported that the most important reason for offshoring R&D is the access to specialized R&D knowledge; cost reduction is the least important. Most of the papers that provide empirical evidence have reached the conclusion that external knowledge-sourcing strategies have a positive and significant impact on innovation performance (Laursen and Salter, 2006; Mihalache et al., 2012; Nieto and Rodríguez, 2011); as pointed out by (Dachs et al., 2012, p. 10), studies that find a negative impact are scarce.

The acquisition of external knowledge connects the firm with an array of know-how and new knowledge, which are necessary to develop new processes and products. This leads the enterprise to avoid being locked in and to gain access to new ideas. When the external knowledge comes from a different country, the firm comes into contact with a different national innovation system—with diverse technological paths or trajectories—and provides it with an opportunity set that, combined with the internal R&D process, leads to new knowledge.

Enterprises find that more novel innovations often require the exploration of entirely new types of business models and technologies (Ahuja and Lampert, 2001). Moreover, this different knowledge might encourage a different perspective not only from implementing it but also from modifying the external technology into a new and different product.

As enterprises move abroad geographically to acquire new technologies, it is feasible to take advantage of different national innovation systems, which can be associated with differences in culture, market regulations, industry specialization, educational level, and welfare state laws or preferences (Filippetti and Archibugi, 2011; Phene et al., 2006). This could lead not only to an improvement in the adaption of existing products but also to the creation of new ones—especially ones of a more novel nature. As signaled by Castaldi et al. (2015), radical innovation often stems from the connection of previously unrelated technologies.

With respect to how the external acquisition of knowledge affects the innovation performance of firms, it seems that the result may differ according to the type of innovation pursued: process or product innovation. Previous studies have seemed to support the idea that external knowledge exerts a greater effect on product than on process innovations. The reasoning lies in the fact that the kind of knowledge that is needed to achieve product innovations tends to be more explicit and easier to codify, so it is more transferable across borders (D'Agostino et al., 2013). If the knowledge can be codified into a new product, there is no problem in acquiring it from others.

However, when the new knowledge requires coordination between the two parties at the organizational and knowledge levels—which is more often the case in process innovations—the host firm will need skills that are close to those of the foreign firm; and, given the differences in culture, customers' demands, labor laws, and other characteristics, it can be more difficult to implement (Phene et al., 2006).

In line with the latter, Nieto and Rodríguez (2011) found evidence that, in the Spanish case, the R&D offshoring strategy has a larger impact on product than on process innovations; this is a similar result to that for France, as shown by Bertrand and Mol (2013). With these previous results in mind, we focus our empirical research on the influence of R&D offshoring on product innovation.

2.3. Hypotheses

Our main concern is to identify the degree to which the acquisition of geographically external knowledge can affect the degree of novelty of the innovations that are achieved by a firm. Indeed, the new products that are obtained by a firm thanks to its innovation strategy can be associated with existing products/services that have been improved—incremental innovations—as well as products that are completely new to the market—radical innovations.[1]

A radical product innovation can be understood as a novel and unique technological advance in a product category that significantly alters the consumption patterns in a market (Zhou and Li, 2012). This completely new product can generate a new platform or business domain that could imply new benefits and expansion into new markets (O'Connor et al., 2008).

To connect R&D offshoring and radical innovations, we rely on the tension theory (Ahuja and Lampert, 2001; Weisberg, 1998), which emphasizes the importance of a wide search or combinations of different sources to implement and recombine dissimilar and distant knowledge to achieve a revolutionary innovation. A search in a small segment of innovative sources has a negative influence on enterprises' performance and promotes only incremental improvements.

Indeed, Laursen and Salter (2006) emphasized that the search for knowledge from different sources can stimulate radical innovations, as the access to specialized labor communities in specific types of knowledge (Lewin et al., 2009) plays a fundamental role in enterprises' productivity (Belderbos et al., 2013).

There is evidence that international outsourcing—when technological proximity exists—generates breakthrough innovations (Phene et al., 2006). This is

[1]By radical innovations we mean those that embed a more novel component than in the case of incremental innovations. As explained in the data section, we use information on new or significantly improved products for the market as a proxy for radical innovation (as compared with new or significantly improved products only for the firm). As signaled by a referee, it is obvious that not everything that is new to the market is a radical or breakthrough innovation. However, this is the only proxy that we can obtain for radical innovations with the information contained in a CIS-type survey, and it has been used by prior studies for measuring breakthrough or radical innovations (Coad et al., 2016; Laursen and Salter, 2006; Tether and Tajar, 2008; Van Beers and Zand, 2014). Thus, we decided to keep the term radical innovations, despite being aware that it could overstate the variables. We thank an anonymous referee for highlighting this point.

related to the idea that firms are more efficient when implementing and recombining knowledge from sources that are close to their knowledge base or close to their research fields (Cohen and Levinthal, 1990). In addition, despite the technological proximity, international differences in national innovation systems and in managerial capabilities—human capital, social capital, and cognition[2] —help induce the novel recombination of such distant knowledge, which could result in a radical innovation (Phene et al., 2006).

Taking the above evidence into account, we believe that knowledge that is acquired from foreign enterprises that belong to different national innovation systems may have a stronger degree of novelty, so the likelihood that it will result in the development of a product that is completely new and/or of greater economic value can be higher (Kaplan and Vakili, 2015; Phene et al., 2006). Therefore, we pose the following hypothesis:

H1. The acquisition of knowledge from abroad is expected to have a greater influence on innovations that incorporate a higher degree of novelty.

Nevertheless, the influence of the external acquisition of knowledge on innovations that incorporate a high degree of novelty may differ according to the nature of the agent from which the external knowledge is acquired: either an industrial firm or an institutional/scientific agent. Certainly, "the interaction between industry and science is one of the most prominent institutional interfaces for knowledge diffusion" (Robin and Schubert, 2013). Universities play an important role in innovation: They provide scientific research, produce knowledge with industrial applications, and provide human capital (Schartinger et al., 2002).

This is an important issue, since, as suggested by Cohen and Levinthal (1990), the type of knowledge that comes from scientific/technological agents is completely different from the type that can be understood and implemented according to the internal capabilities of enterprises. Previous evidence on R&D cooperation has shown that enterprises collaborate more with top foreign universities than with less highly regarded local universities (Laursen et al., 2011). In fact, universities like to partner with highly innovative enterprises, which means that links with universities are not restricted to national boundaries (Monjon and Waelbroeck, 2003).

Also, D'Este et al. (2013) found that the key point in taking advantage of the link with research institutions is the location of the enterprise in a cluster of firms—not the location of the university. This implies gives less importance to

[2]Beliefs and ways of solving problems that allow decision making in certain directions (see Phene et al., 2006).

the spatial proximity between the two players. Furthermore, from the perspective of product innovations, geographical distance has been losing its relevance for firm-university collaboration (Maietta, 2015).

In addition, evidence exists of an increased probability of outsourcing certain activities focused on knowledge specificities when the enterprise uses more complex knowledge and has a strong connection with universities (Spithoven and Teirlinck, 2015). This kind of relation between firms and public institutions allows enterprises to access a wider pool of knowledge, which strengthens their knowledge base (Aschhoff and Schmidt, 2008). At the same time, this increased knowledge base could enable access to a higher degree of understanding and implementing of foreign technologies that come from different partners, which increases the likelihood of generating radically new products.

However, it is widely accepted that the type of knowledge that is developed by universities and institutional research centers is, in most cases, not focused on market profitability. Indeed, they develop more basic know-how with or without industrial application, which can incorporate novel knowledge that could lead to more radical innovation, although this is not necessarily the case, since the knowledge could be far from what the market needs.

Although more related to the topic of cooperation in innovation, Vega-Jurado et al. (2009) considered that agreements with scientific agents in the case of Spanish firms might be more motivated to obtain funds from the Government when developing research projects in government-sponsored programs than to improve their innovative capacities—thanks to the integration of complementary knowledge from external sources. Furthermore, Spanish firms' perception is that knowledge acquired from research organizations offers a smaller chance of having real applicability (Nieto and Santamaría, 2007).

These reasons lead us to think that knowledge that is incorporated from the business sector can generally be more market-oriented and, as a consequence, can have a more direct influence on the share of sales that is due to products that are new to the market. Taking into account all the above arguments, competing hypotheses arise:

H2a. The influence of the acquisition of external knowledge from an international industrial-based agent is expected to be greater than that of knowledge acquired from an international research-based one; or

H2b. The influence of the acquisition of external knowledge from an international research-based agent is expected to be greater than that of knowledge acquired from an international industrial-based one.

Unexplored in previous studies is the way in which the economic crisis in 2008 affected the influence of R&D offshoring on radical innovations. In Spain, this is particularly relevant due to the strong impact of the crisis and the difficulties that firms faced in obtaining funding for innovation. On the one hand, the countercyclical approach states that innovation increases during recessions, as, with low demand, the opportunity costs of conducting innovation are lower than in periods of growth (Barlevy, 2004); this reasoning comes from the idea of the ease of reallocating internal capabilities from production to R&D (Aghion and Saint-Paul, 1998; Schumpeter, 1939).

Alternatively, the procyclical approach points out that financial constraints might prohibit firms from maintaining or increasing their R&D budget (Stiglitz, 1993) and that firms postpone innovation to periods of expansion to maximize the returns (Barlevy, 2004). Previous evidence has shown that the procyclical argument tends to prevail over the countercyclical one relative to innovation (Paunov, 2012), even though there are countries (such as Sweden) in which the response to the recent economic crisis was countercyclical (Makkonen, 2013).

For the case of Spain, Makkonen (2013) found that, "according to government science and technology budgets, Spain was one of the European countries most affected by the crisis" (see also OECD, 2012, p. 48). Regarding the accessibility of funds for Spanish enterprises and according to the INE (Spanish National Institute of Statistics), the rate of success of enterprises in obtaining funding for their innovation projects was 80 percent in 2007 and 50 percent in 2010. Meanwhile, with respect to the perception of the evolution of the relative access to funding between 2007 and 2010, only 1.1 percent answered that it was better and for 33.6 percent it was worse.

Innovative firms have a propensity to adopt risky business models, which are difficult for banks to value, so public subsidies—following the countercyclical argument—generally imply a relevant source of recovery from the crisis "by stimulating business innovation giving rise to market novelties" (Beck et al., 2016). Accordingly, Paunov (2012) found that firms with public financing are less likely to discontinue their projects, as they are useful in alleviating capital market imperfections.

We want to provide evidence on whether the acquisition of foreign R&D had a lesser or greater influence on the intensity of radical product innovations during this period of financial constraints. We do not have a clear hypothesis a priori, since there are arguments for both results:

On the one hand, with lower access to R&D funding in crisis periods, if internal and external R&D expenses are reduced and the two are complementary (Añón-Higón et al., 2014; Cassiman and Veugelers, 2006), we would expect the return of each euro that is devoted to the external acquisition of knowledge to decrease. This is because, according to the complementary relationship, the marginal increase of adding one activity—offshoring—when already performing the other—internal innovation—is larger than the marginal increase from performing only one activity—offshoring. Therefore, when the internal innovation is reduced, the marginal effect of offshoring is expected to decrease.

However, one would expect that, in a crisis period with lower funding levels, firms would be more cautious about the resources that they spend on new innovation projects and would try to choose those with higher chances of success. In such a case, the return that is obtained from the offshoring strategy would be higher. Given the ambiguity of the different effects of offshoring before and during the crisis, we aim to provide evidence that shows which kinds of arguments have been more determinant in the Spanish case.

We therefore present the following two competing hypotheses:

H3a: The economic crisis led to an increase in R&D offshoring's return on radical innovation; or

H3b: The economic crisis led to a decrease in R&D offshoring's return on radical innovation.

Finally, it is sensible to think that the effect of R&D offshoring can differ with respect to the firms' size.[3] In this sense, large enterprises have more internal resources, like researchers, and can benefit more from implementing and recombining knowledge from abroad. In addition, large companies are more likely to belong to a company group, so that part of the external knowledge may come from enterprises in the group—with less risk of appropriation, information asymmetry, and opportunism—with a consequently higher impact on the innovative performance of the enterprise (Nieto and Rodríguez, 2011).

Indeed, previous evidence on R&D offshoring has mainly focused on multinational firms and, to a lesser extent, on small and medium-sized enterprises (SMEs). However, on the other hand, SMEs may offshore R&D to increase their partial innovation capabilities. Therefore, we will investigate this concern empirically for the Spanish case.

[3]We thank the editor of the Review of Industrial Organization for highlighting this point.

2.4. Methodology

We regress firms' innovative performance as a function of the acquisition of foreign technology, while controlling for firms' characteristics. This kind of analysis can lead to a sample selection problem. Indeed, we are testing our hypotheses only for innovative firms—those that have positive expenditures on innovation; this is a possible source of sample selection that was posited by Heckman (1976) that can lead not only to bias but also inconsistent parameters (Wooldridge, 2010a, p. 805). We therefore use a methodology that allows us to detect and correct for sample selection problems with the use of the panel structure of the data, following two steps (Wooldridge, 1995):

(i) We perform a yearly probit model of the probability of being an innovative firm as a function of firms' characteristics plus some exclusion restrictions[4]and compute the yearly inverse Mill´s ratios. In order to detect the sample selection bias, we perform a Wald test on the joint significance of the inverse Mill´s ratios included in the main equation in the second step.

(ii) We regress our measure for the firm's innovative performance with respect to the offshoring of innovation activities plus a set of control variables, our main equation, which is estimated by pooled OLS with bootstrap errors.[5] Following Wooldridge (1995, 2010a), this approach allows us to obtain consistent estimations of the parameters as in the case of the fixed-effect estimation in presence of a panel structure of the data.

As we are using time invariant regressors (sectoral dummy variables), we cannot use the fixed-effects model. Besides, the random effects model assumes no correlation among the observed characteristics of the firms and the unobserved heterogeneity, which seems not to be plausible in our case.[6] Having that in mind, the way in which we can correct for the unobserved heterogeneity of firms depends on the observable characteristics (Mundlak, 1978).

Therefore, we follow Wooldridge (1995; 2010a) and take the mean values of the exogenous time varying variables and include them into the analysis, jointly with

[4]The excluded variables are presented in section 2.5.2. These exclusion restrictions guarantee the identification of the system and avoid problems of collinearity in the last step.

[5]We decided to estimate bootstrap errors because of the use of the generated variables (Mill´s ratios) in this second stage. As explained by Heckman (1979), the non-inclusion of those ratios can be seen as an omitted variable problem due to the fact that the expected value of the dependent variable depends on the selection term—the probability of being an innovative firm—leading to an inconsistency of the parameters of interest in the second stage (Wooldridge, 2010a, p. 805).

[6]The exogenous variable could be correlated with managerial abilities, which are unobserved.

the annual varying variables. We are, thus, correcting for the possible endogeneity among the observable characteristics and the unobserved heterogeneity.

The selection equation for the first step is specified as follows:

$$s_{it} = 1\left(Z_{it}\delta_t + \upsilon_{it} > 0\right) \qquad \upsilon_{it}|Z_{it} \sim Normal\left(0,1\right) \tag{2.1}$$

Where: s_{it} is our selection variable: the probability of being an innovative firm; Z_{it} is a vector of explanatory variables with valid exclusion restrictions; δ_t is the vector of their parameters; and the error term υ_{it} is assumed to be normally distributed.

Conditioning on $s_{it} = 1$ our equation of interest will be:

$$E\left(y_{it}|X_{it}, \overline{X}_i, \hat{\lambda}_{it}, s_{it} = 1\right) = X_{it}\beta + \overline{X}_i\eta + \gamma_t\hat{\lambda}_{it} \tag{2.2}$$

Where: y_{it} is our variable that proxies for innovation performance; and $X_{it}\beta$ will include our key measures of the external acquisition of knowledge and the vector of control variables —without the exclusion restrictions[7]—with their corresponding parameters. The mean values and their vector of parameters are represented by $\overline{X}_i\eta$, which are the correction for the correlation between the explanatory variables and the unobserved heterogeneity. Finally, $\gamma_t\hat{\lambda}_{it}$ is a vector of the inverse Mill´s ratios and their coefficients.[8] All of the RHS variables are lagged one period in order to lessen simultaneity problems and to allow for the necessary time from the start of a R&D investment until the generation of profits.

2.5. Data set, variables and descriptive analysis

2.5.1. Data set. The data set that we use is an unbalanced panel that is taken from the PITEC (Technological Innovation Panel): a yearly survey with around 450 variables on the innovation activity that is carried out by Spanish enterprises. It uses two surveys: The first—Survey on Technological Innovation of Firms—is the Spanish counterpart to the Community Innovation Survey (CIS) from the Eurostat, following the guidelines of the Oslo Manual; the second is the Statistics on R&D Activities. The data set offers direct measures of the innovation output as product and process innovations—instead of relying only on measures of semi-output, such as patents, or on inputs, such as R&D expenditures.

[7]In this case, X_{it} and Z_{it} can have possibly common elements.

[8]We interact the inverse Mill's ratios with time dummy variables in order to allow γ to be different across t.

The PITEC is representative of: small and medium-size as well as large firms; enterprises with internal R&D expenditures, as well as those with external R&D expenditures without having internal R&D; and finally those small and medium-size firms without any expenditures on innovation. It covers all of the business sectors that are included in the National Classification of Economic Activities (NACE); the representativeness of the panel is assured thanks to the annual inclusion of firms with similar characteristics to those that disappear from the sample. The response rate is very high due to the fact that it is mandatory for firms.

Our sample covers the period 2004 to 2013, with around 86,000 observations for 12,000 enterprises. However, after deleting missing values, taking into account only companies with more than 10 workers, dropping those observations for firms that declare that they do not have any innovative expenditure while having data for the share of sales due to new products, as well as those outliers with more than 20 percent of market share in a given sector,[9] we arrive at around 7,700 enterprises and around 41,000 observations.

Being part of the EU implies solid laws of intellectual property rights, which leads to a substantial benefit from offshoring strategies.[10] The Spanish case is interesting since it is at the middle of the EU technological ranking, below the mean of R&D/GDP in the EU: 1.22 percent for Spain in 2014 and 2.08 percent for the UE15, according to the INE. Most of the productive sector is based on SMEs; and the public sector is the main source of knowledge, with the largest share of R&D workers, around 56 percent in 2014: 19 percent for research centers, and 37 percent for universities. In addition, Spain suffered one of the biggest and most negative impacts of the financial and economic crisis at the end of 2008.

Given that PITEC is a survey in which values are self-reported, one could think of the problem of measurement bias and measurement errors. However, in this kind of survey, where anonymity is a legal concern, there is not a systematic propensity for over- or under-reporting the innovation that is carried out by the

[9]Firms with more than 20 percent of the market share in a given sector represent around 0.19 percent of total observations and 0.07 percent of the enterprises in the sample. The threshold of 20 percent of the market share was chosen following previous evidence that is also based on the PITEC survey, such as López-García and Montero (2010). Additionally, in the case of those observations for which internal R&D expenditures are more than two times the volume of sales, we have replaced such values with a maximum value of 2—representing around 0.6 percent of total observations. Although the selection of a value of 2 is arbitrary, other smaller values did not imply any change in the results. These additional estimates are available upon request.

[10]Most R&D offshoring of European firms is conducted between firms within the European Union (Tübke and Bavel, 2007).

enterprise (Aarstad et al., 2016). In addition, Lucena (2016) shows that the PITEC database does not suffer from common-method bias.

2.5.2. Variables.

Dependent variables. We focus our empirical research on the influence of R&D offshoring on product innovation and how this has an effect on firms' sales. Obtaining a new product does not imply that the sales are consequently increased; at least, not all new products imply an equivalent increase in the sales. In the PITEC survey, firms are asked whether they have developed product innovations in the current year or in the previous two years: either products that are new only to the firm or products that are new to the market. Firms are also asked about the economic impact of these innovations in the current year with respect to their sales. Using this information, we developed two endogenous variables:

Incremental innovation reflects the share of sales that are due to product innovations that are new only to the firm; *Radical innovation* considers the share of sales that are due to product innovations that are new to the market (Arvanitis et al., 2015; Barge-Gil, 2013; Grimpe and Kaiser, 2010).[11] Moreover, *Innovative enterprise*, which is our selection variable, captures whether the firm is innovative (1) or not (0). Table 2.1 provides a detailed description of our variables (dependent, independent, control variables, and exclusion restrictions), while Table 2.2 shows the correlation matrix among the variables used in the regression analysis.

Independent variables. For hypothesis 1, we use the variable *Offshoring*, which measures the expenditures on purchased R&D from abroad over total sales.[12] Several studies have found a positive relationship between the purchase of external knowledge and innovation performance—both as dummy variables. However, we analyze the influence of the amount of expenditure devoted to the foreign acquisition of knowledge (a continuous variable) on the intensity of radical product innovations. To test our second hypothesis, we split the offshoring measure into two: the external purchases from foreign research institutes (*Offshoring public*),

[11]Following previous studies that use CIS-type survey data, we develop the ratio between the percentage of sales over one minus the percentage of sales, and take the logs of the ratio. As the log of the bounds (zero and one) are not defined, we apply a winsorizing process for the extreme values, assigning 0.9999 to 1 and 0.0001 to 0 (see Klomp and Van Leeuwen, 2001; Mohnen et al., 2006; Raymond et al., 2010; Robin and Schubert, 2013). We decided to use this transformation because it is closer to a normal distribution and lies in the set of real numbers that vary from $-\infty$ to $+\infty$. As the variable is very skewed, this is a necessary transformation in order to get close to a normal distribution.

[12]The offshoring variable, as in the PITEC database, refers to the acquisition of knowledge through licensing and does not include joint ventures.

Table 2.1. Definition of the variables included in the empirical analysis

Variables	Definitions
Dependent Variables	
Innovative enterprise	1 if the firm declare to have expenditures (internal or external) in R&D, acquisition of machinery and software, expenditures on the acquisition of external knowledge, expenditures on production/distribution, expenditure on training, and other preparations, 0 otherwise
Incremental innovation	Sales share of new or significantly improved products for the firm
Radical innovation	Sales share of new or significantly improved products for the market
Main Variables	
Offshoring	Expenditure on purchased R&D/Total Sales
Offshoring public	Expenditure on purchased R&D from public institutions/Total Sales
Offshoring private	Expenditure on purchased R&D from private firms/Total Sales
Offshoring Pre crisis	[Expenditure on purchased R&D/Total Sales]*[Dummy variable equal to 1 if time<=2008 and 0 otherwise]
Offshoring Crisis	[Expenditure on purchased R&D/Total Sales]*[Dummy variable equal to 1 if time>2008 and 0 otherwise]
Controls	
Cooperation	1 if the firm reported engagement in collaborative agreements with partners; 0 otherwise
Internal R&D	Ratio between intramural R&D expenditure and turnover
Size	Number of employees
Permanent	1 if the firm reported that it performed internal R&D continuously; 0 otherwise
Openness	Number of information sources for innovations that a firm reported it has used (from within the firm or group, suppliers, clients, competitors, private R&D institutions, conferences, scientific reviews or professional associations) going from 0 (any) to 8 (the firm uses all types of information).
Demand pull	1 if at least one of the following demand-enhancing objectives for the firm's innovations is given the highest score [number between 1 (not important) and 4 (very important)]; 0 otherwise: extend product range; increase market or market share; improve quality in goods and services
Exclusion Restrictions	
Group	1 if the firm belongs to a group of enterprises; 0 otherwise
Market share	Ratio of the sales of a firm over the total sales of the two-digit industry it belongs to
Risk obstacles	Sum of score of importance that the firm attributed [number between 1 (high) and 4 (not used)] to the uncertain demand for innovative goods or services and to the market dominated by established enterprises as factors that hampered its innovation activities. Rescaled from 0 (unimportant) to 1 (crucial)
Cost obstacles	Sum of the scores of importance that the firm attributed [number between 1 (high) and 4 (not used)] to the following factors that hampered its innovation activities: lack of funds within the enterprise or enterprise group; lack of finance from sources outside the enterprise; innovation costs too high. Rescaled from 0 (unimportant) to 1 (crucial)
Knowledge obstacles	Sum of the scores of importance that the firm attributed [number between 1 (not important) and 4 (very important)] to the following factors that hampered its innovation activities: lack of qualified personnel; lack of information on technology; lack of information on markets; difficulty in finding cooperation partners for innovation. Rescaled from 0 (unimportant) to 1 (crucial)
Other obstacles	Sum of the scores of importance that the firm attributed [number between 1 (not important) and 4 (very important)] to the following factors that hampered its innovation activities: not necessary due to previous innovations; not necessary due to the absence of demand. Rescaled from 0 (unimportant) to 1 (crucial)

and purchases from foreign private companies (*Offshoring private*), both over total sales.

Controls. To control for relevant firm characteristics, *Cooperation* has been observed to have an important role on product innovation (Robin and Schubert, 2013); it captures whether the firm acquires external knowledge through other channels. *Internal R&D* captures the effect of the internal capabilities of the

TABLE 2.2. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Offshoring	1												
(2) Cooperation	0.14	1											
(3) Internal R&D	0.09	0.15	1										
(4) Size	0.01	0.06	-0.05	1									
(5) Permanent	0.13	0.23	0.22	-0.01	1								
(6) Openness	0.11	0.28	0.13	0.02	0.34	1							
(7) Demand pull	0.06	0.19	0.07	-0.01	0.28	0.34	1						
(8) Group	0.14	0.14	-0.08	0.15	0.04	0.06	0.02	1					
(9) Market share	0.08	0.09	-0.05	0.38	0.04	0.05	0.02	0.22	1				
(10) Risk obstacles	0.01	0.07	0.03	-0.07	0.12	0.22	0.13	-0.08	-0.06	1			
(11) Cost obstacles	-0.02	0.06	0.08	-0.08	0.10	0.19	0.14	-0.15	-0.08	0.44	1		
(12) Knowledge obstacles	-0.01	0.10	0.04	-0.05	0.09	0.23	0.10	-0.10	-0.06	0.55	0.50	1	
(13) Other obstacles	-0.07	-0.12	-0.08	0.00	-0.23	-0.11	-0.15	-0.02	-0.01	0.14	0.02	0.14	1

enterprise, which have been recognized as an important complement for R&D offshoring (Cassiman and Veugelers, 2006; Spithoven and Teirlinck, 2015).

We also account for the *Size* of the firm: measured by the number of employees. In addition, *Permanent* measures whether the company develops internal R&D efforts continuously, whereas the *Openness* variable counts the number of sources of information that the company has: internal sources, market sources and institutional sources (Laursen and Salter, 2006; Robin and Schubert, 2013). Finally, *Demand Pull* is a variable that proxies for the objectives of product innovations: accessing new markets; gaining market share; or having greater quality of products.

Exclusion restrictions. In our first stage for controlling for sample selection, the variable *Group* tries to capture the effect of belonging to a group of enterprises (Raymond et al., 2010; Vega-Jurado et al., 2009). Belonging to a group could affect the likelihood of being an innovator through more internal contact with the rest of the company, accompanied by a lower risk of appropriation and an increased amount of internal sources of innovation.

In line with previous scholars, we also used *Market share*, which may be an important factor in encouraging innovation; the effect of a more favorable position in the industry due to market concentration (Raymond et al., 2010). Finally, we used obstacles to innovation—*Risk obstacles, Cost obstacles, Knowledge obstacles, and Other obstacles*—to account for the perception of the firm about the barriers to innovation (Archibugi et al., 2013; Belderbos et al., 2013). As in the previous literature, these exclusion restrictions are assumed to affect the likelihood to innovate while not affecting innovation performance.

2.5.3. Descriptive analysis. Table 2.3 provides summary statistics for the variables in the analysis. Around 63 percent of firms are innovators—have expenditures on innovation—while the average share of sales that a firm declares to occur as a result of its product innovations is around 11.7 percent for the case of products new to the firm, and 7.6 percent for those new to the market. Also, 5 percent of innovative firms offshore R&D. Firms tend to perform more offshoring with private organizations (4.16 percent) instead of research institutions or universities (0.6 percent). On average, around 41 percent of the innovative firms conduct internal R&D continuously, while internal R&D expenditures representing around 6 percent of total sales.

TABLE 2.3. Descriptive statistics of the variables in the analysis

	Whole Sample				No R&D Offshoring				R&D Offshoring			
VARIABLES	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Dependent Variables												
Innovative enterprise	0.63	0.48	0	1	0.61	0.49	0	1				
Incremental innovation	11.69	25.54	0	100	11.45	25.48	0	100	16.67	26.20	0	100
Radical innovation	7.58	20.04	0	100	7.27	19.78	0	100	14.05	24.02	0	100
Main Variables												
Offshoring	0.05	0.21	0	1								
Offshoring public	0.01	0.08	0	1					0.13	0.34	0	1
Offshoring private	0.04	0.20	0	1					0.93	0.25	0	1
Offshoring pre crisis	0.02	0.15	0	1					0.31	0.46	0	1
Offshoring crisis	0.02	0.15	0	1					0.35	0.48	0	1
Controls												
Cooperation	0.37	0.48	0	1	0.36	0.48	0	1	0.64	0.48	0	1
Internal R&D	0.06	0.22	0	2	0.05	0.21	0	2	0.16	0.41	0	2
Size	347	1,552	10	41,509	344	1,570	10	41,509	409	1,099	10	21,905
Permanent	0.41	0.49	0	1	0.39	0.49	0	1	0.80	0.40	0	1
Openness	3.81	3.26	0	8	3.69	3.25	0	8	6.32	2.25	0	8
Demand pull	0.65	0.48	0	1	0.64	0.48	0	1	0.76	0.42	0	1
Exclusion Restrictions												
Group	0.43	0.49	0	1	0.41	0.49	0	1	0.70	0.46	0	1
Market share	0.01	0.02	0	0.20	0.00	0.02	0	0.20	0.01	0.03	0	0.20
Risk obstacles	0.46	0.33	0	1	0.46	0.33	0	1	0.52	0.29	0	1
Cost obstacles	0.54	0.34	0	1	0.54	0.34	0	1	0.58	0.29	0	1
Knowledge obstacles	0.37	0.27	0	1	0.36	0.27	0	1	0.39	0.23	0	1
Other obstacles	0.27	0.27	0	1	0.27	0.28	0	1	0.15	0.22	0	1

Interesting differences can be extracted when we compare firms that carry out R&D offshoring with those that do not. Offshoring enterprises double the amount of sales that are due to radical innovations and have a larger share of their sales due to incremental innovations. Furthermore, they spend three times more on internal R&D resources as a percentage of their total sales, and cooperate and perform internal R&D continuously more than do non-offshored enterprises; also, offshoring enterprises tend to be larger.

2.6. Regression results

Table 2.4 shows the results of the first stage of our regressions. The results of the second stage, that is, the estimation of our main equation of interest, are presented in Table 2.5.[13] With regard to the latter: Time and sectoral dummy variables are included and are jointly significant in most of the specifications. With respect to Heckman's correction, we find strong evidence of the sample selection problem in all the specifications, as concluded from the Wald test on the joint significance of the inverse Mill's ratios (Wooldridge, 1995), which indicate the necessity of such correction.

Finally, with regard to the Mundlak approach to control for the possible correlation among the exogenous variables and the unobserved heterogeneity, its joint significance points to the need to control for such unobserved heterogeneity.

Columns (1) to (4) in Table 2.5 display the results of our first hypothesis. The coefficient for the offshoring variable is positive and highly significant for radical innovation, while it is not significant for incremental innovation; this gives full statistical support to our first hypothesis: There is a clearer influence of the foreign acquisition of knowledge on the intensity of radical product innovations than on that obtained from incremental ones. This is especially true for LEs. It appears that R&D offshoring activities—instead of deterring the offshoring firms from innovating—allow them to increase their innovative performance, especially for those innovations that incorporate more novelty.

Consistent with previous studies, knowledge that is acquired from a different national innovation system brings a higher degree of novelty, which, combined with the internal knowledge, may lead to greater benefit.[14]

The results in columns (5) and (6) show that the influence of knowledge that comes from the foreign business sector is positive and highly significant in the case

[13] As stressed in the hypotheses section, in order to consider whether there is a different role of offshoring in large and small enterprises, we split the sample into large enterprises (LEs), those firms with more than 200 workers, and small and medium-sized enterprises (SMEs), with 200 workers and fewer, following the classification in the PITEC survey. The results of the Chow tests at the bottom of columns 2, 4, and 6 in Table 2.5 stress the significant differences between SMEs and LEs. Thus, we test our first two hypotheses taking into account this difference. In the case of our third hypothesis—different impact of offshoring before and during the crisis—we decided to use two dummy variables: one for the pre-crisis period, and another one for the crisis, and interact them with the offshoring variable (columns 7 and 8 of Table 2.5). This procedure allows a fair comparison between the parameters while avoiding an important reduction in the number of observations in each subsample. The sectoral dummy variables are at the two-digit level (NACE 1.1).

[14] We acknowledge the possibility of reverse causality, as detailed in section 2.6.1.

Table 2.4. Marginal effects of the first stage (Sample selection)

VARIABLES	(2005) Innovative enterprise	(2006) Innovative enterprise	(2007) Innovative enterprise	(2008) Innovative enterprise	(2009) Innovative enterprise	(2010) Innovative enterprise	(2011) Innovative enterprise	(2012) Innovative enterprise	(2013) Innovative enterprise
Group	0.059***	0.045***	0.062***	0.074***	0.065***	0.067***	0.063***	0.056***	0.077***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)	(0.015)
Market share	1.010***	1.027***	1.183***	2.444***	2.060***	3.995***	3.262***	2.088***	1.824***
	(0.333)	(0.345)	(0.408)	(0.422)	(0.467)	(0.632)	(0.569)	(0.482)	(0.517)
Risk obstacles	0.198***	0.123***	0.104***	0.154***	0.129***	0.136***	0.166***	0.161***	0.201***
	(0.025)	(0.021)	(0.023)	(0.024)	(0.024)	(0.025)	(0.026)	(0.026)	(0.028)
Cost obstacles	0.117***	0.141***	0.178***	0.187***	0.174***	0.112***	0.087***	0.088***	0.104***
	(0.024)	(0.020)	(0.023)	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)
Knowledge obstacles	0.085***	0.143***	0.149***	0.161***	0.141***	0.208***	0.203***	0.208***	0.188***
	(0.032)	(0.027)	(0.030)	(0.031)	(0.031)	(0.032)	(0.033)	(0.034)	(0.036)
Other obstacles	-0.440***	-0.441***	-0.469***	-0.482***	-0.491***	-0.539***	-0.505***	-0.567***	-0.554***
	(0.022)	(0.019)	(0.021)	(0.022)	(0.022)	(0.023)	(0.024)	(0.025)	(0.026)
Size (in logs)	-0.001	0.003	0.010**	0.023***	0.031***	0.029***	0.046***	0.054***	0.056***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	7,720	9,112	8,629	8,307	8,167	7,727	7,517	7,207	6,868

Standard errors in parentheses. Sectoral dummy variables included. *** p<0.01, ** p<0.05, * p<0.1

of LE, whereas the knowledge that comes from research centers or universities from abroad is not; this gives support to hypothesis 2.a.[15] Again, SMEs do not present any significant impact. This result is in line with that obtained in the study of the impact of cooperation agreements in Spanish firms by Vega-Jurado et al. (2009), who found that the impact of cooperation with science-based agents is smaller than with private enterprises.[16]

Finally, but no less important, we examine how the current economic crisis is affecting the return that is obtained from the R&D offshoring undertaken by Spanish firms. A descriptive analysis through time shows that Spanish firms have exerted slightly less effort in offshoring strategies during the crisis than before it. Indeed, the share of firms that offshored innovation in 2004 was 5 percent, whereas in 2009 it was 4.48 percent and in 2013 it was 4.04 percent. Since our sample decreases over time because some firms may report a major issue,[17] we

[15]We should also be aware that the share of firms that purchase technology from foreign research centers or universities is very small as compared with the share that purchase from the business sector (see also Gutiérrez Gracia et al., 2007).

[16]We also run the regressions for a balanced panel for hypotheses 1–2, thereby trying to take into account a possible attrition problem; and the results barely change (the results are available from the authors on request). This seems to show that there is no problem of attrition as we would expect since the rate of dropout from the panel is very small. We thank the editor for pointing this out.

[17]The major issues reported include: a firm belonging to a sector with high employment turnover; an acquired firm; a change in the unit of reference; a change in or abandonment

Table 2.5. Influence of R&D offshoring on incremental and radical product innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
							Balanced Panel	
VARIABLES	LEs Incremental innovation	SMEs Incremental innovation	LEs Radical innovation	SMEs Radical innovation	LEs Radical innovation	SMEs Radical innovation	LEs Radical innovation	SMEs Radical innovation
Offshoring $_{t-1}$ (in logs)	0.035	-0.008	0.059**	0.015				
	(0.026)	(0.020)	(0.024)	(0.019)				
Offshoring public $_{t-1}$ (in logs)					0.093	0.037		
					(0.163)	(0.098)		
Offshoring private $_{t-1}$ (in logs)					0.071**	0.030		
					(0.036)	(0.030)		
Offshoring Pre crisis $_{t-1}$ (in logs)							0.067***	0.047
							(0.025)	(0.034)
Offshoring Crisis $_{t-1}$ (in logs)							0.014	-0.002
							(0.039)	(0.033)
Cooperation $_{t-1}$	0.358***	0.108	0.108	0.250***	0.111	0.250***	0.065	0.205*
	(0.137)	(0.094)	(0.120)	(0.078)	(0.118)	(0.078)	(0.118)	(0.105)
Internal R&D $_{t-1}$	-0.828	0.003	2.303**	1.284***	2.299**	1.277***	1.731	1.363***
	(0.669)	(0.186)	(1.078)	(0.189)	(1.114)	(0.188)	(1.264)	(0.348)
Size $_{t-1}$ (in logs)	0.157	0.495***	0.338*	-0.024	0.336*	-0.024	-0.048	0.029
	(0.207)	(0.150)	(0.199)	(0.127)	(0.182)	(0.127)	(0.314)	(0.184)
Permanent $_{t-1}$	0.417**	0.132	0.392**	0.396***	0.394**	0.396***	0.471***	0.209*
	(0.185)	(0.092)	(0.157)	(0.084)	(0.157)	(0.084)	(0.170)	(0.119)
Openness $_{t-1}$	0.014	0.035**	0.031	0.059***	0.032	0.059***	0.042	0.045**
	(0.031)	(0.018)	(0.025)	(0.015)	(0.028)	(0.015)	(0.043)	(0.019)
Demand pull $_{t-1}$	0.512***	0.217**	0.282**	0.333***	0.283**	0.333***	0.267**	0.350***
	(0.156)	(0.098)	(0.128)	(0.076)	(0.131)	(0.076)	(0.134)	(0.100)
Constant	-5.031***	-7.242***	-11.895***	-7.199***	-11.081***	-6.764***	-13.050***	-7.593***
	(1.156)	(0.656)	(1.009)	(0.553)	(1.708)	(1.094)	(1.520)	(0.754)
Observations	10,537	30,417	10,537	30,417	10,537	30,417	7,018	15,577
R-squared	0.071	0.036	0.125	0.101	0.125	0.101	0.169	0.134
Test F lambda	69.03***	102.4***	36.95***	122***	42.43***	122.2***	62.77***	59.36***
Wald Test Mean values (Mundlak)	79.77***	162.8***	201.9***	548.4***	195.9***	547***	268.2***	521***
Wald Test Sectoral dummy variables	394.6***	228.8***	264.8***	683***	406.3***	679.3***	55.95***	598.4***
Wald Test Time dummy variables	13.69*	13.97*	3.047	74.57***	3.535	74.64***	29.23***	22.48***
Chow Test		2.529***		3.030***		2.983***		

Bootstrap errors in parentheses. Means fixed effect, time and sectoral dummy variables included. Dependent variables correspond to the log-transform: log[y/(1-y)]. *** p<0.01, ** p<0.05, * p<0.1. Large enterprises (LEs) are those firms with more than 200 workers, while small and medium-sized enterprises (SMEs) are those firms with less or equal to 200 workers as determined in the PITEC.

test our predictions on a balanced panel of firms that are present throughout the whole period from 2004 to 2013.

The results in columns (7) and (8)—for the whole period, dividing the effect of R&D offshoring using an interaction term with a time dummy variable—show that the parameter for the offshoring variable for the period during the crisis is not significant, while it is significant before the crisis for the case of LEs. Indeed, the result of the Chow test on the whole sample with respect to the subsamples before and in the crisis—without separating LEs and SMEs—shows that a structural

of activity; a firm remaining from an acquisition process (not part of the acquisition); a firm in liquidation; a merged firm; a firm that has employees ceded by other firms; a consequence of the crisis; and a firm that cedes employees to other firms. The time frame for the pre-crisis period is 2004-2008, while the crisis period is 2009-2013. The reasoning comes from the fact that the crisis started to show its impact in 2009 (Hud and Hussinger, 2015).

change occurred in 2009. These results support to our hypothesis 3.b: The crisis implied a lower return from seeking new knowledge abroad.

With respect to the control variables, Table 2.5 also shows interesting results: With regard to cooperation with other organizations and internal R&D, the coefficients show a positive impact on the firms' innovative performance. The latter supports the internal capabilities theory: A firm needs internal resources—personal, equipment, and instruments—with a high degree of knowledge to access, understand, and implement new knowledge (Cohen and Levinthal, 1990).

We also find evidence of a positive relationship with firms' size, so larger firms achieve better innovative performance (as in Bertrand and Mol, 2013)—probably because they are less constrained by the scarcity of financial, infrastructural, and technological resources.

Developing internal R&D activity continuously (permanent), and having a wide variety of information sources for the external acquisition of knowledge (openness) show the expected positive sign, whereas demand pull (having the objective of accessing new markets, gaining market share, or having greater quality of products when innovating) will affect the innovativeness performance of the enterprise positively.

2.6.1. Robustness checks. We acknowledge the possibility of reverse causality between offshoring and radical innovation performance, since those firms with better innovation performance would probably tend to acquire more knowledge from abroad. Due to the anonymity laws in Spain, it is impossible to match our data set with external data sets to find truly exogenous instruments for the firm.

In an attempt to control for this, we match our data with sectoral data from the Spanish National Institute of Statistics; we thereby can develop an instrument at the sectoral level instead of at the firm level. This instrument is the percentage of purchases of intermediate material from the Internet for each sector (Amiti and Wei, 2005; Görg and Hanley, 2011). We also try to use the growth rate of R&D offshoring at the firm level (Görg and Hanley, 2011). Unfortunately, the results are not satisfactory in the sense of those instruments having very poor predictive power.

Therefore, since the impossibility of obtaining data for good instruments does not allow us to correct for the endogeneity problem, we decide at least to lessen it by using two lags for the case of the offshoring variables used in Table 2.5. We find that the results (the first robustness part of Table 2.6) hold and are essentially the same as the main results that are reported in Table 2.5; they change only marginally for the case of the offshoring variables. Despite not solving the problem, this points to a likely low impact of the potential reverse causality.

To check the external validity of our results—the extent to which the results can be extrapolated to other economies—we now investigate if our results are sensitive to different definitions of the dependent variable and the offshoring variables, as previously used in other papers:

First, we measure radical innovation as the share of sales that are due to products that are new to the market, without taking logs or performing any winsorizing processes. As shown in the second part of Table 2.6, most of the main results that are related to the offshoring of R&D hold; this presents a positive and significant impact of offshoring on radical innovation, as in the German case that is reported by Grimpe and Kaiser (2010).

Second, we use a dummy variable as a proxy for R&D offshoring (yes/no R&D offshoring), as is mostly done in previous studies. From the results in the third part of Table 2.6, we observe that there is no qualitative difference in the influence of offshoring on innovation performance when the dichotomous offshoring variable is used. This is in line with the evidence obtained in the case of Arvanitis et al. (2015) for the Netherlands, Bertrand and Mol (2013) for France, and Cusmano et al. (2009) for Lombardy, although in all of these cases the authors did not distinguish between radical and incremental innovation.

Finally, we perform two further sensitivity analyses: First, we test whether our second hypothesis is robust to the business cycle: whether the difference in the influence of the acquisition of external knowledge from an international industrial-based agent versus a research-based one changed as a result of the crisis. Accordingly, we divide the offshoring effect according to two time periods using an interaction term with a time dummy variable: before and during the crisis period for LEs and for SMEs (Table 2.7, columns 1 and 2). The results hold for LEs in the sense that the knowledge that is acquired from business organizations is more relevant to radical innovations than that from research institutions before the crisis; this is in line with our main results.

Second, we investigate whether the sectoral dimension plays any role when considering the impact of R&D offshoring.[18] Specifically, given that a Chow test rejects only marginally the null hypothesis that manufacturing and services behave similarly, we include a dummy variable for those companies that belong to the service sector and cross it with the offshoring variables (Table 2.7 columns 3 to

[18]We thank the editor for highlighting this point (results upon request from the authors).

Table 2.6. Robustness checks

Robustness check 1. Two lags of the offshoring variables

VARIABLES	(1) LEs Incremental innovation	(2) SMEs Incremental innovation	(3) LEs Radical innovation	(4) SMEs Radical innovation	(5) LEs Radical innovation	(6) SMEs Radical innovation	(7) Balanced Panel LEs Radical innovation	(8) Balanced Panel SMEs Radical innovation
Offshoring $_{t-2}$ (in logs)	0.022	-0.019	0.063**	0.036*				
	(0.027)	(0.023)	(0.027)	(0.021)				
Offshoring public $_{t-2}$ (in logs)					-0.120	0.059		
					(0.160)	(0.102)		
Offshoring private $_{t-2}$ (in logs)					0.089**	0.047		
					(0.040)	(0.031)		
Offshoring Pre crisis $_{t-2}$ (in logs)							0.045**	0.029
							(0.020)	(0.033)
Offshoring Crisis $_{t-2}$ (in logs)							0.000	0.011
							(0.046)	(0.037)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mill Ratios	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Means fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Sectoral dummy variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,968	24,869	8,968	24,869	8,968	24,869	6,296	13,671

Robustness check 2. Changing the dependent variable (no winsorizing transformation)

Offshoring $_{t-1}$ (in logs)	0.085	0.006	0.200*	0.161				
	(0.146)	(0.114)	(0.121)	(0.115)				
Offshoring public $_{t-1}$ (in logs)					-0.012	0.499		
					(0.636)	(0.544)		
Offshoring private $_{t-1}$ (in logs)					0.295	0.283		
					(0.192)	(0.179)		
Offshoring Pre crisis $_{t-1}$ (in logs)							0.461**	0.346
							(0.228)	(0.214)
Offshoring Crisis $_{t-1}$ (in logs)							0.116	0.155
							(0.199)	(0.186)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mill Ratios	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Means fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Sectoral dummy variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,537	30,417	10,537	30,417	10,537	30,417	7,018	15,577

Robustness check 3. Offshoring as a dummy variable

Offshoring $_{t-1}$	0.097	-0.048	0.322**	0.029				
	(0.139)	(0.120)	(0.133)	(0.117)				
Offshoring public $_{t-1}$					-0.168	-0.018		
					(0.273)	(0.391)		
Offshoring private $_{t-1}$					0.321**	0.053		
					(0.142)	(0.092)		
Offshoring Pre crisis $_{t-1}$							0.416*	0.108
							(0.231)	(0.194)
Offshoring Crisis $_{t-1}$							0.147	-0.052
							(0.203)	(0.194)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mill Ratios	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Means fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Sectoral dummy variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,537	30,417	10,537	30,417	10,537	30,417	7,018	15,577

Bootstrap errors in parentheses. Control variables, means fixed effects, time and sectoral dummy variables included. Dependent variables in parts 1 and 3 of the table correspond to the log-transform: log[y/(1-y)]; in part 2 correspond to the sales share of new or significantly improved products (for the firm and for the market) without logs or winsorizing process (from 0 to 100). *** p<0.01, ** p<0.05, * p<0.1. Large enterprises (LEs) are those firms with more than 200 workers, while small and medium-sized enterprises (SMEs) are those firms with less or equal to 200 workers as determined in the PITEC.

TABLE 2.7. Further Analyses

	(1)	(2)	(3)	(4)	(5)	(6)
	LEs	SMEs				Balanced Panel
VARIABLES	Radical Innovation	Radical Innovation	Radical Innovation	Radical Innovation	Radical Innovation	Radical Innovation
Offshoring public Pre crisis t-1 (in logs)	0.314	0.162				
	(0.192)	(0.119)				
Offshoring public Crisis t-1 (in logs)	-0.423	-0.166				
	(0.329)	(0.127)				
Offshoring private Pre crisis t-1 (in logs)	0.091*	0.034				
	(0.046)	(0.032)				
Offshoring private Crisis t-1 (in logs)	0.052	0.032				
	(0.060)	(0.046)				
Offshoring t-1 (in logs)			0.019	0.004		
			(0.019)	(0.016)		
Offshoring public t-1 (in logs)					-0.021	
					(0.090)	
Offshoring private t-1 (in logs)					0.005	
					(0.024)	
Offshoring Pre crisis t-1 (in logs)						0.047
						(0.029)
Offshoring Crisis t-1 (in logs)						-0.007
						(0.025)
Services (dummy variable)			-1.293***	1.112***	3.692**	0.480
			(0.443)	(0.398)	(1.700)	(0.663)
Offshoring t-1 (in logs)*Services (dummy variable)			-0.029	0.131***		
			(0.038)	(0.033)		
Offshoring public t-1 (in logs)*Services (dummy variable)					0.264	
					(0.178)	
Offshoring private t-1 (in logs)*Services (dummy variable)					0.180***	
					(0.049)	
Offshoring Pre crisis t-1 (in logs)*Services (dummy variable)						0.109*
						(0.057)
Offshoring Crisis t-1 (in logs)*Services (dummy variable)						0.131**
						(0.057)
Cooperation t-1	0.140	0.256***	0.189***	0.213***	0.214***	0.165**
	(0.127)	(0.080)	(0.073)	(0.073)	(0.073)	(0.083)
Internal R&D t-1	2.240**	1.291***	-0.004	1.418***	1.415***	1.568***
	(1.007)	(0.198)	(0.162)	(0.188)	(0.188)	(0.320)
Size t-1 (in logs)	0.323*	-0.010	0.345***	0.180*	0.180*	0.171
	(0.191)	(0.130)	(0.105)	(0.103)	(0.103)	(0.167)
Permanent t-1	0.476***	0.484***	0.192**	0.403***	0.404***	0.275***
	(0.160)	(0.080)	(0.083)	(0.070)	(0.070)	(0.099)
Openness t-1	0.044*	0.069***	0.034**	0.051***	0.051***	0.041***
	(0.023)	(0.016)	(0.016)	(0.013)	(0.013)	(0.015)
Demand pull t-1	0.304**	0.375***	0.295***	0.318***	0.318***	0.332***
	(0.118)	(0.084)	(0.085)	(0.067)	(0.067)	(0.082)
Constant	-8.934***	-5.688***	-5.960***	-8.887***	-9.080***	-9.527***
	(2.040)	(1.285)	(0.450)	(0.424)	(0.944)	(0.579)
Observations	10,411	30,052	40,954	40,954	40,954	22,595
R-squared	0.133	0.106	0.040	0.102	0.102	0.137
Test F lambda	44.62***	78.28***	145.9***	89.75***	89.67***	81.66***
Wald Test Mean values (Mundlak)	208.2***	661.5***	211***	790***	789.9***	665.3***
Wald Test Sectoral dummy variables	203.5***	1064***	373.5***	584.1***	585.2***	628.6***
Wald Test Time dummy variables	7.210	67.29***	19.86**	56.43***	56.57***	21.64***

Bootstrap errors in parentheses. Means fixed effects, time and sectoral dummy variables included. Dependent variables correspond to the log-transform: log[y/(1-y)]. *** p<0.01, ** p<0.05, * p<0.1. Large enterprises (LEs) are those firms with more than 200 workers, while small and medium-sized enterprises (SMEs) are those firms with less or equal to 200 workers as determined in the PITEC.

6). The results point to a higher impact of R&D offshoring in the service sector than for manufacturing enterprises.

Among other reasons, we could think that developed economies are making a fast transition to deindustrialization and giving more weight to service firms. There are also some studies that point to the fact that service firms are more prone than manufacturing ones to take advantage of innovation processes (Mina et al., 2014). However, further analysis is needed in this case since there is a lack of empirical evidence in the related literature to build a conceptual framework for this latter analysis.

2.7. Discussion and conclusions

While being an innovative firm could make the difference between being a leader and being a follower in an industry, it is also important to access wider and different types of knowledge (Ahuja and Lampert, 2001), such as knowledge in foreign countries, to increase the market power of a firm and to obtain a lower-cost and highly prepared labor force (Lewin et al., 2009). R&D offshoring is a relatively recent topic in the innovation literature, which is partly due to the recent process of purchasing innovations from abroad. Our research contributes to the literature on innovation offshoring in three different ways:

First, it provides empirical evidence on the influence of knowledge that comes from a foreign country on the innovations that incorporate more novelty in the market (known as radical innovations). Second, we consider the success that follows from such innovations (share of sales due to new products) instead of the more common proxy that just considers whether the firm has achieved product innovations or not. Third, we study the heterogeneity in the returns to R&D offshoring depending on the technological differences of the agent from which the knowledge is obtained: either a business organization (market oriented) or a research institution (knowledge-based oriented).

The evidence provided for Spanish firms from 2004 to 2013 indicates that R&D offshoring has a significant and positive influence on radical product innovations (measured by sales share) but not on incremental ones. We also find that knowledge from a foreign business organization has a greater influence than that from foreign research-based institutions, which is probably related to the perception by Spanish firms that knowledge acquired from research organizations offers a smaller chance of having real applicability (Nieto and Santamaría, 2007).

Following the heterogeneity of the influence of the R&D offshoring strategy before and within the crisis periods, our findings suggest a greater influence in a no-crisis period. This is interesting, since we observe that the amount of Spanish enterprises that engage in R&D offshoring has decreased over the entire period—a conclusion that also holds for the balanced panel—while the return that they obtain has also decreased.[19] This could be due to the complementary relationship

[19]Not only the number of enterprises but also the amount of money that is allocated to this strategy has been reduced among those enterprises that conducted R&D offshoring throughout the entire period.

between internal and external expenditures on innovation in the Spanish case, as pointed out by Añón-Higón et al. (2014).

Finally, we empirically study the differences between LEs and SMEs with respect to the impact of R&D offshoring on the innovative performance of the firm. Our results indicate that LEs obtain the most benefit from seeking knowledge from abroad. Following the arguments of Di Gregorio et al. (2008) and Nieto and Rodríguez (2011), LEs have greater financial, technological, and internal resources, so they are more able to implement and recombine the knowledge from abroad, while they face less risk of appropriation, information asymmetry, and opportunism, and therefore profit more from such knowledge.

CHAPTER 3

Technological cooperation, R&D outsourcing, and innovation performance at the firm level: The role of the regional context[1]

3.1. Introduction

Literature on innovation economics has extensively analyzed how the combination and recombination of previously unconnected ideas lead to new knowledge production and subsequent technological innovations (Aghion et al., 1998). Knowledge diffusion in the form of knowledge spillovers is crucial in this literature as a cause of the geographic agglomeration of firms (Audretsch and Feldman, 1996; Jaffe et al., 1993). At the end of the nineteenth century, Marshall (1890) already described how firms could benefit from spatial concentration: taking advantage of input-output relationships within industries, thanks to labor market pooling, as well as benefiting from positive knowledge externalities arising from other firms. Almost one century later, endogenous growth models (Lucas, 1988; Romer, 1986, 1990; Grossman and Helpman, 1991) restored the emphasis on knowledge spillovers with the consideration that firms create new knowledge profiting from the body of knowledge of the whole society.

As a consequence of the existence of shared agglomeration externalities, and more specifically for our case, the existence of knowledge spillovers, most geography of innovation scholars have confirmed the role of physical proximity in fostering knowledge diffusion. It is widely believed that firms sharing the same environmental conditions are more similar in their innovation performance than firms that do not share the same environment, emphasizing the impact of the context in which the firm is located on the innovation ability of the firm (Cooke and Morgan, 1998; Storper, 1997). However, we believe that the mechanism by which the regional context shapes the innovative performance of firms is still poorly understood. The present chapter tries to give a step forward in this direction

[1]This chapter has been awarded the "Premi-Innova" to the young researcher presenting the best paper on R&D and Innovation in the 6th PhD-Student Workshop on Industrial and Public Economics (WIPE).

with the main objective of providing evidence on the hypothesis that the regional context not only exerts a direct effect on firms' innovation performance but also mediates with firms' internal characteristics/activities. Specifically, we hypothesize that the returns that the firms obtain from their networking activities may vary across regions depending on regional determinants.

Indeed, the networking activities carried by the firms have been considered in previous literature to be one of the main determinants of firms' innovation performance (Laursen and Salter, 2006; Nieto and Rodríguez, 2011). This is so as networking is a relevant tool to acquire knowledge external to the firm (Breschi and Lissoni, 2001), both at the local level but also through building pipelines to benefit from knowledge hotspots around the world (Bathelt et al., 2004). Among other strategies, we can think of technological collaboration agreements or R&D outsourcing, which act as channels through which knowledge is transferred throughout the space allowing for new recombination of ideas (Fratesi and Senn, 2009). Although the positive impact of such strategies on firms' innovation performance is well documented in the literature, an important novel insight in this third chapter is that these benefits may not be the same across different regional contexts. Explicitly, we hypothesize that the transformation of firms' networking activities into innovation may vary depending on the regional environment in which the firm is located.

All in all, this chapter aligns to the literature trying to analyze the role of the regional determinants of innovation using firm-level data. From a methodological perspective, we take into account the fact that characteristics at the regional level are not automatically reproduced at the firm level because information on the variance between firms is lost when data at an aggregated regional level are used (van Oort et al., 2012)—what is known as the ecological fallacy. Using multilevel modeling allows the micro and macro levels to be modeled simultaneously (Hox, 2002) and can be understood as a natural way to assess the relevance of the regional context. We use a panel of manufacturing enterprises in Spain starting from 2000 until 2012 and take into account some characteristics related to the knowledge generation capacity of the region where the firm is located.

Among the main results, we obtain that the regional context seems to exert a positive direct influence on firms' innovative performance but not as much as firm characteristics themselves. Among such internal characteristics, technological cooperation and R&D outsourcing present a significant influence. However, the regional context implies a more subtle and indirect effect shaping the return that firms obtain from such networking activities. As such, firms located in knowledge-intensive regions obtain higher returns of cooperation agreements in terms of innovative performance. On the contrary, firms in regions with low knowledge levels tend to present higher returns to R&D outsourcing.

The chapter is outlined as follows. Next, we offer the literature review upon which this chapter is based, followed by the dataset section with the description of the variables, while the methodology is subsequently presented. Then, we offer the main results of the study, and finally, we present the main conclusions of the chapter.

3.2. Literature review

3.2.1. Firm's networking activities. A firm that wants to survive and grow needs to be innovative and adapt to more dynamic and global markets. Having the knowledge to do this is of the upmost importance, and it can be found within the firm but also beyond its boundaries. Indeed, the current tendency to acquire external knowledge through mechanisms such as cooperation agreements or through outsourcing (OECD, 2008) is gaining weight as an strategy to become more innovative.

Many papers provide empirical evidence that external knowledge-sourcing strategies have a positive and significant impact on innovation performance (Laursen and Salter, 2006; Nieto and Rodríguez, 2011; Mihalache et al., 2012), whereas as noted by Dachs et al. (2012, 10) studies that find a negative impact are very scarce. In this sense, the open innovation literature (Chesbrough, 2003) has stressed the necessity for firms to access such knowledge external to the firm in order not to be locked in the internal structure/way of thinking of the enterprise.

On the one hand, collaborative research with a broad range of partners may enable innovating firms to acquire the required information from a variety of sources which could lead to more synergies and intake of complementary knowledge, thus promoting innovation performance (Belderbos et al., 2006; Laursen and Salter, 2006). In this sense, collaboration with other organizations is due to the necessity of solving new kinds of problems for which the market does not have a proper solution, leading to the need for more interactions among organizations. This kind of strategy requires face-to-face contacts reducing the likelihood of appropriation of some specific ideas/projects due to the fact that both enterprises have knowledge of each other's projects while building a relationship of trust. At the same time, collaboration may give access to a more intangible and tacit knowledge and know-how not easy to spill over (Teirlinck and Spithoven, 2013). Indeed, previous literature has recognized that cooperation embeds a complex/technical knowledge structure which fits with the idea previously stressed related to the appearance of new types of problems-solving requirements (Teirlinck and Spithoven, 2013; Dhont-Peltrault and Pfister, 2011).

On the other hand, outsourcing part of the innovation process allows an enterprise to gain access to a new source of well-prepared labor (Lewin et al., 2009), to capture external knowledge cheaply, as well as to widen the scope of internationalization of the firm, gaining access to new markets and new knowledge, increasing the efficiency of its internal capabilities (Cassiman and Veugelers, 2006; OECD, 2008, 20, 91). At the same time, outsourcing may allow the enterprise to gain in productivity and efficiency through an improved restructuring of its internal resources, like managerial attention and a focus on core competences in what the firm does best while taking advantage of what the contracted firm is specialized in. However, R&D outsourcing may have a higher risk of appropriation of internal knowledge (Nieto and Rodríguez, 2011) by the contracted firm, so that this could be a reason why firms tend to outsource non-core activities, which imply a less technical and more standardized and codified knowledge (Teirlinck and Spithoven, 2013).

On the basis of the arguments above and the empirical evidence obtained in previous literature, we posit our first hypothesis:

H1: Firms that cooperate in innovation activities and firms that do R&D outsourcing are expected to present a better innovative performance.

3.2.2. The firm's environment: Why does the region matter? The regional development literature (Storper, 1997; Cooke and Morgan, 1998) stresses that the environment where the firm is located can be essential to recombine and exploit previous existing pieces of knowledge. Regions concentrating research and development expenditures, highly skilled workers, institutions enabling innovation, the presence of research centers and universities, among others, are in a better position to generate new knowledge and innovation. In addition, a main advantage of a firm located in such an environment is due to the fact that the knowledge produced by a firm is only partially appropriated by the producer, whereas part of such knowledge spills over to other firms and institutions (Feldman and Audretsch, 1999; Jaffe et al., 1993). Thanks to the presence of such knowledge spillovers, firms can get external economies of scale if they co-locate close to other firms, pointing to the relevance of the regional context for firms' innovative performance. The notions of industrial districts (Scott and Storper, 2003), innovation milieu (Keeble and Wilkinson, 1999) and clusters (Porter, 1990) are some of the labels used to refer to such context.

In addition, the regional innovation system (RIS) literature (Cooke et al., 1997) considers that subnational units have the economic power and the capacity to use central funds in an autonomous way, or to finance and design their own innovation policies, so that differences in technological performance cannot be explained by firms in isolation but at the regional level (Uyarra, 2009). Besides, competitiveness and innovation are determined at regional levels basically because innovation is not homogenously distributed across space. Despite the spread of information and communication technologies (ICT), innovation is remarkably concentrated in the territory probably as a consequence of the relevance of geographical proximity for the generation of new ideas and knowledge (Boschma, 2005; European Commission, 2014). Thus, face-to-face contacts, the application of the same interpretative schemes of new knowledges, a similar experience with a particular set of problem-solving techniques, and shared cultural traditions, make interaction less costly in a shorter distance such as the one within a region (Malmberg and Maskell, 2006, 9).

As a consequence of the existence of regional knowledge spillovers and the relevance of the RIS, there is broad agreement that firms benefit from being located in regions with a rich knowledge base (Audretsch and Dohse, 2007). Previous evidence suggests that R&D spillovers are more abundant in regions with a high concentration of knowledge activities (Love and Roper, 2001). Therefore, the presence of a higher knowledge endowment/base in a region is expected to impact positively the innovation performance of its firms. That is, the regional context is assumed to have a positive direct impact of the innovative performance of the firms located in it.

As a consequence of the arguments above, we posit the next hypothesis:

H2: Firms located in regions with a large knowledge base will obtain a higher innovation output.

3.2.3. The interplay of networking activities and the regional context. As stated in López-Bazo and Motellón (2018), a drawback in most of the previous studies analyzing the impact of the regional context on the firms' innovative performance is the lack of consideration of the interactions between firm characteristics and regional variables. In our case, we believe that the regional innovative endowment not only presents a direct impact on the firms' innovative performance but can also have an indirect one by shaping the effect of firms' networking activities. Closely related to our objective, Love and Roper (2001) reported that the region affects the efficiency with which R&D, technology transfer and networking are translated into innovation outputs in Germany, Ireland and the UK. Indeed, knowledge acquisition through networking, such as technological cooperation and R&D outsourcing, can be assumed to link to the regional context, so that both become reciprocally supporting.

On the one hand, the more advanced the networking mechanisms that bring information about new technologies into a local environment, the more dynamic the milieu from which local actors profit. On the other hand, a more technologically advanced regional context presents stronger knowledge spillovers that may allow for better selection of external knowledge/partners (European Commission, 2014) as well as better translation and integration processes of such knowledge into the firm. Firms that work in more knowledge intensive environments will therefore have advantages in accessing new knowledge through networking activities in comparison to firms located in less innovative regions. This way, the regional context and firms' networking activities could complement each other (Malmberg and Maskell, 2006). This complementarity would imply a self-reinforcing mechanism between knowledge intensive firms and regions.

However, there are contrasting arguments pointing to negative effects coming from regions that present a lot of knowledge externalities. For instance, firms located in regions with a high knowledge pool may face a fierce degree of competition, which would lead to the necessity of firms incorporating a higher degree of novelty embedded in new technologies acquired through networking activities. Also, for enterprises with leading in-house knowledge, they would not benefit so much from the spillover of poorer knowledge, whereas they would lose if their richer knowledge spills over to competitors (Phene and Tallman, 2014). Another negative effect from locating in high knowledge regions in situations of intense rivalry is labor poaching, that is, the loss of qualified human capital to competitors, which in some cases can outweigh the benefits of labor market pooling (Grillitsch and Nilsson, 2017). As a consequence, in regions with a higher level of knowledge externalities, and possibly with a higher level of competition, the negative effects of knowledge spillovers could overcome the positive ones.

Derived from the contradicting arguments above, it is not straightforward whether networking activities (technological cooperation and R&D outsourcing, among the main ones) should benefit equally from the regional context. Given that the knowledge acquired through technological cooperation agreements tend to present different characteristics than the one acquired through R&D outsourcing, we argue that the role of the regional environment could be different in both strategies. The important point here is the explicit differentiation between tacit and codified/explicit knowledge (Polanyi, 1966). Codified knowledge may travel frictionless across the territory and across agents through, among other things, ICT and can be purchased in markets for technology with little interaction with other agents (e.g., R&D outsourcing). On the contrary, tacit knowledge, highly contextual, and hard to articulate in articles, patents, or books, is difficult to transfer and is better transmitted in the form of face-to-face interactions. This implies the necessity of interactive learning (Maskell and Malmberg, 1999) that would give place to cooperation agreements.

As a consequence of this differentiation, the endowment of knowledge available in the region where the firm is located conditions the returns of these two strategies, albeit in different ways. Indeed, in the case of firms carrying out technological cooperation agreements as a way to introduce external knowledge with a more tacit component, the gains from local knowledge spillovers can be stronger given that they will allow the firm to further elaborate the external knowledge acquired through cooperation. Thus, there would exist a reinforcement link between a firm pursuing cooperation in innovation activities and being located in a region with a high knowledge pool. This leads to our third hypothesis:

H3: Firms located in regions with high knowledge endowment will obtain higher returns to technological cooperation in terms of innovative output.

In contrast, when outsourcing codified knowledge, firms located in low-knowledge regions may prosper because they are less dependent on local knowledge spillovers (the knowledge acquired through outsourcing is standard and easy to codify) and are less likely to experience negative knowledge spillovers coming from closely located competitors given the low amount of innovation taking place in them. This way, the benefits associated with knowledge agglomerations may not be so necessary for firms that outsource part of their knowledge, at least the most codified knowledge. That is, firms that outsource part of their R&D activity are in a better position to get the knowledge produced elsewhere and to lessen the weaknesses of the region where they are located while not incurring in fierce competition. Thus, our fourth hypothesis stands as follows:

H4: Firms located in regions with low knowledge endowment will obtain higher returns to R&D outsourcing in terms of innovative output.

Since the research in a region can be made both by private and/or public institutions and given the different characteristics they present (Cohen and Levinthal, 1990), one may think that the knowledge spillovers generated from both agents would be different. In such a case, how the regional knowledge base influences the efficiency of firms' networking activities can be different depending on the prevalence of a public over a private knowledge base, or the other way around, at the regional level.

First, the research developed by the private sector presents a more applied component and is focused mainly on market profitability, cost effectiveness, reliability of new solutions and time to market, whereas the type of research developed by public research centers has a more science-based component and is not focused on market profitability, being far away from the necessities of private firms in several respects. Second, previous literature stresses the relevance of short term innovations in the case of private organizations in contrast to public research institutions that spend a much longer time frame for developing an innovation—around seven years as stressed by Feldman and Florida (1994). Finally, another important difference lies on the moment of the life-cycle of R&D, public institutions being more focused in the early stages and private organizations in the latter stages.

As argued in the hypotheses above, a firm that cooperates in innovation activities gets higher benefits from regional knowledge spillovers given that they will allow the firm to further elaborate the external knowledge acquired through cooperation which tends to be of a more tacit component. If the regional knowledge base is mainly the result of research developed by the private sector (i.e. with an applied component, market-oriented and focused in the latter stages of the life-cycle of R&D), the knowledge spillovers arising from such a region can make cooperation more effective in terms of generating higher returns to the firm's innovative performance. On the contrary, if the regional knowledge base is mainly the result of research developed by the public sector (i.e. being science-oriented and not market-oriented, devoting much longer time frame for developing an innovation, and focused in the early stages of the R&D), the knowledge spillovers arising from such a region will not be profitable for the firms' purpose and will make cooperation less effective since the firm may incur in a higher cost for implementing such a knowledge. As a consequence of the arguments above, our fifth hypotheses stand as follows:

H5a: The returns to cooperation activities will be higher if the firm is located in regions with higher research expenditures developed by private agents.

H5b: The returns to cooperation activities will be lower if the firm is located in regions with higher research expenditures developed by public agents.

For a firm that outsources part of its R&D, we have given arguments above that the kind of knowledge that can be purchased is of a codified/stardard nature, so that firms are less dependent on local knowledge spillovers (because the knowledge acquired through outsourcing is easy to codify). Thus, being in a region with a low knowledge base does not present a main disadvantage while benefiting from the fact of being less likely to experience fierce competition due to the low innovation activity in them. The same happens if the firm is located in a region where the knowledge base is mainly the result of research developed by the public sector, which does not imply competition in innovation terms and which, despite being not market-oriented, does not involve any disadvantage for the firm making outsourcing since the knowledge spillovers coming from regional context are less important in them. Quite the reverse would happen if the outsourcing firm is located in a region where the knowledge base is mainly the result of research developed by the private sector. In such a case, the competition for getting innovations is fierce (given that a lot of private innovation activity with a market-oriented profile is taking place) whereas the benefits from the knowledge spillovers stemming from the private sector are minimal in the case of the outsourcing strategy. Then, our last hypotheses arise:

H6a: The returns to R&D outsourcing activities will be higher if the firm is located in regions with higher research expenditures developed by public agents.

H6b: The returns to R&D outsourcing activities will be lower if the firm is located in regions with higher research expenditures developed by private agents.

3.3. Dataset and variables

3.3.1. Dataset. The dataset we use at the firm level is the Spanish Survey on Business Strategies—ESEE from now on—that consists on an unbalanced panel of manufacturing enterprises starting from 1990 until 2014 with around 1,800 firms surveyed yearly by the SEPI Foundation with an agreement with the Ministry of Industry. Firms are classified into twenty industries using the two-digit European classification NACE (see Table A.1 in the online Appendix).[2] The ESEE's population of reference is composed of firms with 10 or more employees within the manufacturing industry. Moreover, the geographical scope of reference is the Spanish economy as a whole even though information of the location of the main plant is targeted in the survey. The initial selection was carried out combining exhaustiveness for firms with more than 200 employees and random sampling for

[2]More details on the sample, the quality and validation of the information can be obtained from: https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp

firms employing 10 to 200 workers. These firms were selected through a stratified, proportional and systematic sampling with a random seed.

As for the regional dataset, we use Eurostat at the NUTS 2 level. In the Spanish case these territorial units represent administrative and policy authorities, and even though all of them belong to the same national context, they present an important heterogeneity. First, Spain is one of the four European countries presenting the widest regional heterogeneity in innovation (European Commission, 2014). Second, Spanish regions have legal competencies and financial autonomy in terms of innovation policies and present important socio-cultural differences that could lead to different learning process as stressed by Cooke et al. (1997). Third, the territorial coverage as well as the implementation of the operational programs of the European Structural funds—an instrument of the European Union cohesion policy that aim to reduce the regional disparities in R&D and innovation—in Spain is at NUTS 2 regional level (European Commission, 2014). Finally, regarding the socio-cultural aspect which is an important source of the learning process according to the RIS literature, Spain has four different languages apart from Spanish, which are officially talked in six regions—Catalonia, Valencia, Basque Country, Galicia, Balearic Island, and Navarre—highlighting a social and cultural diversity higher than in other European countries. All these reasons endorse the regional heterogeneity expected in our empirical exercise. The period under consideration ranges between 2000 and 2012, since some of the variables taken from Eurostat are not provided for more recent years.

Given that the ESEE is a survey in which values are self-reported, one could think of the problem of measurement errors and/or self-reported values. However, in this kind of survey, where anonymity is a legal concern, we do not expect a systematic propensity for over or under-reporting the innovation carried out by the enterprise (Aarstad et al., 2016).

3.3.2. Firm level variables. Our dependent variable is the number of product innovations (*NIP*), as a proxy for the innovative output, which has been used in previous studies at the firm level (Blundell et al., 1995; Chatterji and Fabrizio, 2014; Hagedoorn and Cloodt, 2003; Katila and Ahuja, 2002; Segarra-Ciprés et al., 2012). In our opinion, this measure is more accurate than just the decision to engage on product innovations (as in Naz et al., 2015; Srholec, 2010) since it takes into account the number of innovations made. Following the explanation given by Katila and Ahuja (2002), a firm developing a higher number of product innovations may see an improve in its markets share, its market value, as well as in its survivability. Moreover, we have reasons to focus on product instead of process innovations. Building on previous evidence, networking activities aiming at the acquisition of knowledge external to the firm has a higher impact on product rather than on process innovations (Bertrand and Mol, 2013; Nieto and Rodríguez, 2011). This is due to the type of knowledge required in each case, which for product innovations tends to be more explicit, while for process innovations organizational closeness among the enterprises is also required, which is more difficult.[3]

We consider two different networking strategies. *Cooperation* is a dummy equal to 1 if the enterprise cooperates in innovation activities in a given year with at least one partner and zero otherwise; whereas *Outsourcing* equals to 1 if the enterprise declares to have external R&D expenditures in a given year and zero otherwise.[4]

To control for other firm characteristics relevant to explain innovative performance, we use the log of internal R&D expenditures per employee (*Internal R&D*)[5] to capture the firm's absorptive capacity (Cohen and Levinthal, 1990). To measure the size of the firm (*Size*), we employ the total number of employees and its squared term to account for a non-linear relationship. Another relevant variable is whether the firm belongs to a multinational corporate group, since this may imply more resources, such as better financial resources and a better innovative environment (Belderbos et al., 2013). We proxy it with a dummy variable (*Foreign*) being one in the case that the firm has more than 50 percent of its capital from abroad (Srholec, 2010). Finally, we include a dummy variable which equals 1 in the case the firm received public funding from a government—regional, central, or others—for developing R&D above the total average and zero otherwise (*R&D government*).

[3]We restrict the range of the variable to be in between 0 and 30, which accounts for 99 percent of the observations and discard just 0.1 percent of enterprises in the sample. In our opinion, this is a necessary process for three reasons: i) outliers can bias the estimations when dealing with non-linear multilevel models; ii) this seems to be a more appropriate range for the variable; and iii) we find convergence problems in the estimation when dealing with the entire range of the variable.

[4]We are proxying the networking strategies used by the firm without any distinction between the knowledge coming from within the region or beyond its boundaries, information not available in our dataset. Moreover, the information from our dataset refers to technological cooperation instead of R&D cooperation, so that an enterprise can collaborate with other organization while having zero internal R&D expenditure (see Table 3.2). We thank an anonymous referee for pointing out this issue.

[5]This variable has been deflated using the Consumer Price Index.

3.3.3. Regional level variables. We are interested in measuring the knowledge endowment of a region. As highlighted in previous studies, it can be approximated by regional R&D expenditures (Tödtling and Trippl, 2005) which are considered to be an important driver of economic growth accounting for the innovativeness of the region (European Commission, 2014). The concentration of R&D activities in a region provides knowledge, new scientific discoveries, and develops new opportunities for the firms located in the region (Feldman and Florida, 1994). Therefore, on the input side, we account for the regional effort on R&D (*GERD* referring to R&D expenditures) as a regional driver of firms' innovative performance (Sternberg and Arndt, 2001). This variable can be disaggregated into the regional R&D expenditure of private enterprises (*GERD business*), government (*GERD government*), and higher education sector (*GERD HES*).

In order to account for the accumulative process characterizing innovation, we employ a measure of the stock of such knowledge instead of the flows of expenditure. This has several advantages. First, it takes into account the fact that knowledge is path-dependence as well as cumulative. And second, the stock is less affected by punctual shocks (exogenous or endogenous to the region like certain policies) than the flows. Thus, we use the perpetual inventory method (Peri, 2005) with a geometric mean of the growth rates of R&D spending and a depreciation rate of five percent, all measured in purchased power parity at constant prices of 2005.

On the output side of the innovation process, we propose to use information on the number of patents in each region (*Regional patents*) through the computation of its stock using the perpetual inventory method. This measure has been considered a proxy of the regional differences regarding the regional innovation performance in previous studies (European Commission, 2014).[6]

Finally, in order to control for the wealth as well as the educational level of the region, we employ *GDP per capita* and the percentage of people aged 25-64 years with tertiary education (*Tertiary education*), respectively. In addition, we introduce technological sectoral dummies and time dummies. All variables in the model are lagged one period in order to lessen simultaneity problems.

[6]Although there exist other indicators for measuring the regional knowledge base from the output side such as the number of product and process innovations, statistical information on them are not available at the regional level for Spain. We thank a referee for pointing this.

3.4. Methodology

The importance of accounting for regional differences through hierarchical models relies on several theoretical reasons. First, the use of standard estimations—OLS—does not take into account the dependence of those firm observations within the same region ending in a smaller standard error, which would lead to artificially higher significance of the parameters (Hox, 2002). They are usually assumed to be independent under this method of estimation, whereas firms within the same region are more likely to be more similar among them than those in different regions (van Oort et al., 2012). Second, the use of the multilevel approach allows us to model variances instead of means as in the case of standard OLS regressions. This allows dividing the total effect into firm-level effects and regional effects through random intercepts accounting for the unobserved heterogeneity (van Oort et al., 2012). Third, the ecological fallacy stresses that the study of individual relationships—firms in our case—cannot be analyzed using aggregated data, so that the mixed of firm and regional level variables is an interesting type of analysis.

Since our number of regions is not too high—17 groups—we are aware of a possible bias in our estimates, specifically, in the case of the regional variance component (Maas and Hox, 2005). Previous research on the topic making use of multilevel modeling with such amount of regions can be found in López-Bazo and Motellón (2018), also with 17 groups, and Srholec (2015) with 15 groups. Following Stegmueller (2013), the random intercept model is the best case scenario when the amount of the highest level group is in between 15 and 20. In such a case, the bias of the macro effects as well as the confidence interval are virtually inexistent, justifying the use of the random intercept model instead of the random slope one. Moreover, in order to determine how regional characteristics affect the innovation performance of firms, we plan to use cross interactions between some of our firm and regional variables. In this sense, we follow Snijders and Bosker (2012) who stressed the latter as an appropriated strategy when having theoretical/empirical reasons for them.

One of the assumptions of the multilevel model is the absence of correlation among the explanatory variables and the random effects, otherwise leading to inconsistent estimations (Rabe-Hesketh and Skrondal, 2012). We correct this possible endogeneity relying on Mundlak (1978) and divide the time varying explanatory variables at the firm level into between and within effects using the mean of those variables (Snijders and Bosker, 2012). This way, we guarantee the absence of endogeneity due to the correlation among the firm level variables and the firm's random effects.

In our case, the Hausman test adds no information in order to choose between the fixed and the random effects estimation since we are accessing to the same within effect as in the fixed effect estimation.[7] On the one hand, due to the poor within variabilities of our set of variables (see Tables A.2 and A.3 in the online Appendix) we think it is more appropriate to use random effects on top of fixed effects, since the latter only exploit within variabilities. On the other hand, with the fixed effect estimation it is not possible to model the effect of the regional context on the firm level performance, which can be done in the multilevel model. That is, with the fixed effect estimation it is not possible to do inferences about time invariant variables as well as for higher-level variances (Bell and Jones, 2015).

Another important issue is that given that the dependent variable is a count variable with non-negative values, a normal distribution is not satisfactory due to the skewness of the variable and, consequently, a Poisson model is preferred. However, as the Poisson distribution is very restrictive in the sense that it assumes that the mean equals the variance, we decided to use the Negative Binomial model that allows for overdispersion, being more robust (Snijders and Bosker, 2012, chapter 17). Moreover, Bell et al. (2016) stressed that when estimating the Negative Binomial, the multilevel random effects augmented with the between-within effects is the best choice to produce within effects with the lower bias due to omitted higher-level variables.[8]

3.4.1. Model specification. The structure of our specification is hierarchical since firms are nested in regions. However, as we are dealing with a panel dataset, time is in fact our first level of analysis (Rabe-Hesketh and Skrondal, 2012). Therefore, the hierarchy is the following: individual observations (time-firms) are nested on firms, and firms are nested on regions.[9]

[7]Running a Wald test to the means of the firm level variables is asymptotically equivalent to a Hausman test (Rabe-Hesketh and Skrondal, 2012). Moreover, other researchers stressed the misconception of many studies when choosing between the fixed and the random effects estimation based on the Hausman test (Bell and Jones, 2015).

[8]This is extremely important in our case since the low amount of highest-level units in the sample forces us to use only a small set of highest-level controls.

[9]As we aim to studying regional differences in the innovative performance of firms, it is important to highlight that in the multilevel framework, the variables of the higher levels do not have to vary at the lower levels. That is, all firms pertaining to a region will share the same value for a given regional variable. This is done by means of time averaging regional variables, which is also useful for removing fluctuations.

In order to account for this scheme, our reduced form specification is as follows, where subscript i refers to the firm, j refers to the region and t refers to time:

$$\begin{aligned} log\left[E\left(Y_{ijt}\right)\right] = \gamma_{00} + \sum_{m=1}^{s} \gamma_{010m} X_{ijtm} + \sum_{m=s+1}^{M} \gamma_{001m} X_{ijtm} + \sum_{k=1}^{K} \gamma_{01k} X_{ijk} + \\ \sum_{n=1}^{N} \gamma_{10n} Z_{jn} + \sum_{m=1}^{s} \sum_{n=1}^{h} \gamma_{11mn} X_{ijtm} Z_{jn} + \mu_{0j} + \mu_{0ij} \end{aligned} \tag{3.1}$$

where Y_{ijt} refers to our dependent variable and X_{ijtm} refers to the M time varying firm-level characteristics, so that s is the number of time varying firm-level characteristics that are our key firm-level variables (technological cooperation and R&D outsourcing), the rest being control firm-level variables. X_{ijk} are the K time invariant firm-level characteristics (sectoral dummies plus between/Mundlak effects in our case), and Z_{jn} will proxy for N regional-level variables (being h the number of these regional-level characteristics that are our key region-level variables, that is, the ones proxying for the endowment of knowledge available in the region). Moreover, $\mu_{0j} \sim Normal\left(0,\, \sigma^2_{\mu 0}\right)$ and $\mu_{0ij} \sim Normal\left(0,\, \sigma^2_{\mu 0}\right)$ are the random parts of the model accounting for the error term of the region and the firm, respectively, which are assumed to be independent of each other, of the covariates, across regions, and μ_{0ij} is assumed to be independent across firms as well. Therefore, we are estimating a multilevel negative binomial random effect model with two random intercepts, one for the firm and another for the region.

3.5. Results

3.5.1. Descriptive analysis. Table 3.1 provides summary statistics of the regional variables in our first and last year of analysis. It is worth noting the huge diversity found among regions, since in the year 2000 the region with the highest value of R&D per capita (Madrid) is eight times higher than that of the region with the lowest amount (Baleares). More impressive is the difference in the case of patents, since Catalunya has 40 times more patents per million inhabitants than Cantabria. This difference is much higher than the variability found in the case of GDP per capita and the share of tertiary education, which is only double.

These figures show important regional differences in the innovative levels across Spanish regions, pointing to the necessity of controlling for them when studying firms' innovative performance. Another remarkable fact is that for some regions public R&D expenditures (government and universities) may compensate for the scarcity of private expenditure.

TABLE 3.1. Descriptive statistics of the variables proxying for the regional knowledge base (regional level)

	Year 2000							Year 2012						
Regions	GERD	GERD business	GERD government	GERD HES	Regional patents	GDP per capita	Tertiary education	GERD	GERD business	GERD government	GERD HES	Regional patents	GDP per capita	Tertiary education
Andalusia	99.2	32.5	18.9	47.6	5.16	16,570	18.8	175.3	63.3	37.5	74.2	10.02	16,817	26.5
Aragon	149.1	84.1	23.5	40.6	31.35	23,450	23.8	230.9	121.4	53.8	55.4	54.01	24,470	35.1
Asturias	143	70.3	19.2	50.3	7.84	18,816	21.7	180.9	93.8	26.4	60.5	9.18	20,140	35.9
Balearic Isl.	56.8	7	12.3	37.4	12.89	28,084	17.6	81	13.2	30	37.7	9.16	23,564	24.8
Canary Isl.	96	20.6	22.4	53	6.85	21,905	18.4	100.6	20.7	29.3	50.4	5.05	19,234	26
Cantabria	89.9	22.5	19.8	40.2	1.32	20,923	23.4	211.3	75.9	40.2	107	16.88	20,643	36.1
Castile Leon	120.2	49.8	10.2	59.8	8.77	20,220	23.4	241.4	149.1	21.1	71	12.28	21,348	34
Castile La Mancha	90.7	58.5	8.2	24	3.99	17,412	15.5	108.6	68.3	17.3	27.1	8.11	18,025	25.3
Catalonia	267.8	180.4	20	64.6	53.01	27,241	23.5	394.8	220.8	81.1	91.7	57.04	26,282	32.8
Valencia	139.9	59.1	11.9	66.6	20.69	21,344	20.1	199.6	80.5	25.5	93.4	21.4	19,435	30.1
Extremadura	71.1	18.8	16.7	35.6	2.65	14,182	16.2	115.4	23.1	31.4	66	1.36	15,407	23.7
Galicia	103.3	33.2	17.8	51.9	2.30	17,412	18.7	174.6	80.3	30.3	69.1	10.84	19,636	31.3
Madrid	438.3	238.8	119.5	75.3	25.26	29,909	31.4	530.1	291.3	140.2	97.7	38.29	30,915	44.5
Murcia	118.9	51.5	19.3	48.1	9.22	18,676	20.8	154.6	59.7	25.8	68.9	20.1	18,327	26.3
Navarre	230.1	150.3	5	74.5	41.21	28,505	29.9	537.4	367.8	44.2	126.1	60.81	27,592	40.2
Basque Country	294	229.9	8.4	54.2	36.77	27,382	32	649.8	493	44.2	111.8	64.38	29,404	46
La Rioja	133.3	81.6	10	41.7	3.73	24,995	22.9	214.2	111.8	51.8	49.9	12.99	24,067	34.3
National average	155.4	81.7	21.4	50.9	16.1	22,178	22.2	252.9	137.3	42.9	73.9	24.2	22,076.8	32.5

Note: : GERD (total, business, government and HES, in purchased power standard at constant prices) and Regional patents are measured in units per million inhabitants. Tertiary education is the percentage of people with an undergraduate, master or PhD. GDP per capita is measured in euros.

TABLE 3.2. Descriptive statistics for enterprises cooperating and not cooperating (firm level)

VARIABLES	Full Sample mean	sd	N	min	max	Non Cooperative Firms mean	sd	N	min	max	Cooperative Firms mean	sd	N	min	max
Innovative Performance															
NIP	0.863	2.935	26,506	0	30	0.382	1.981	18,241	0	30	1.924	4.163	8,265	0	30
Networking activities															
Cooperation (dummy)	0.312	0.463	26,506	0	1										
Outsourcing (dummy)	0.228	0.420	26,506	0	1	0.0576	0.233	18,241	0	1	0.605	0.489	8,265	0	1
Controls															
Internal R&D	960.3	3,215	26,506	0	110,769	173.2	1,278	18,241	0	54,383	2,698	5,016	8,265	0	110,769
Size	223.0	692.1	26,506	1	15,003	108.5	350.4	18,241	1	10,100	475.9	1,083	8,265	5	15,003
R&D government (dummy)	0.067	0.250	26,506	0	1	0.005	0.069	18,241	0	1	0.204	0.403	8,265	0	1
Foreign (dummy)	0.162	0.368	26,506	0	1	0.103	0.305	18,241	0	1	0.290	0.454	8,265	0	1

TABLE 3.3. Descriptive statistics for enterprises doing outsourcing and not doing outsourcing (firm level)

VARIABLES	No R&D Outsourcing mean	sd	N	min	max	R&D Outsourcing mean	sd	N	min	max
Innovative Performance										
NIP	0.547	2.404	20,457	0	30	1.931	4.089	6,049	0	30
Networking activities										
Cooperation (dummy)	0.160	0.366	20,457	0	1	0.826	0.379	6,049	0	1
Controls										
Internal R&D (dummy)	402.8	2,013	20,457	0	110,769	2,846	5,194	6,049	0	73,057
Size	132.3	393.7	20,457	1	12,939	530.0	1,205	6,049	3	15,003
R&D government (dummy)	0.014	0.118	20,457	0	1	0.245	0.430	6,049	0	1
Foreign (dummy)	0.127	0.332	20,457	0	1	0.281	0.449	6,049	0	1

This could be the case of the Balearic and Canary Islands where public expenditures per capita are 7 and almost 4 times higher than private ones, respectively, or Extremadura with 2.7 times higher in 2000 and 4.2 in 2012. In addition, these differences in the proxies for knowledge endowments in the Spanish regions have not been decreasing in time, but the contrary.

Interesting observations can be extracted when comparing those firms that develop one of the two networking strategies (technological cooperation and R&D outsourcing) and those that do not. As shown in Table 3.2, the average internal expenditure on R&D per worker is around ten times higher for those that cooperate and they develop more product innovations. A similar conclusion can be made when looking at those enterprises engaging in R&D outsourcing if compared with those not engaged (see Table 3.3). In summary, firms engaged in technological cooperation and/or outsourcing use more innovation resources and have a better innovative performance than those enterprises that do not cooperate or outsource R&D.

Table 3.4 contains seven different estimations in order to analyze how firm and regional characteristics affect firms' innovative performance. We present the incidence rate ratios so that the coefficients can be interpreted as ratios of expected counts, the influence being either positive (if the ratio is higher than one) or negative (if lower than one) (Rabe-Hesketh and Skrondal, 2012). In our first specification (column 1), we only include firm characteristics—level-1 as well as level-2, that is, time varying and time invariant firm characteristics—to explain the variability of our dependent variable. As observed by the results of the Likelihood Ratio tests, it is worth pointing out several conclusions. First, the variance of the firm as well as the variance of the region is highly significant, pointing to the necessity of using the multilevel methodology. This way, our method of estimation takes into account the existence of a certain correlation among the observations for a given firm as well as the correlation among all firms pertaining to a given region. Second, although the regional variance is significant, it is lower than the firm level one. This is in accordance with recent literature, concluding that regional characteristics are relevant for the innovativeness of firms but not as much as firm characteristics themselves. Another interesting result is the existence of overdispersion in our dependent variable, which can be evaluated with the ln(alpha) parameter, so that the Negative Binomial is the most reasonable method of estimation in our case.

This first specification illustrates that all the variables at the firm level present the expected sign. Internal R&D expenditures have a positive and significant impact on the number of product innovations, validating the idea that more internal capabilities allow to develop new ideas that can be transformed into new products (Cohen and Levinthal, 1990). Regarding the size of the firm, we found evidence of a negative non-linear relationship, pointing to a more advanced position of larger enterprises until a certain threshold. The impacts of receiving public funding and of belonging to an international group do not seem to be different from zero. Our two key variables, Cooperation and Outsourcing, present a positive and highly significant effect on the number of product innovations, supporting our first hypothesis.

TABLE 3.4. Role of regional knowledge endowment on the benefits obtained from the acquisition of external knowledge

VARIABLES	(1) *NIP*	(2) *NIP*	(3) *NIP*	(4) *NIP*	(5) *NIP*	(6) *NIP*	(7) *NIP*
$Cooperation_{t-1}(dummy)$	1.308***	1.242***	1.242***	1.302***	1.303***	1.373***	1.375***
	(0.062)	(0.081)	(0.081)	(0.098)	(0.098)	(0.116)	(0.115)
$Outsourcing_{t-1}(dummy)$	1.158**	1.284***	1.284***	1.244**	1.245**	1.191	1.192
	(0.083)	(0.110)	(0.110)	(0.128)	(0.128)	(0.169)	(0.169)
$InternalR\&D_{t-1}$ (in log)	1.051***	1.050***	1.050***	1.050***	1.050***	1.050***	1.050***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$Size_{t-1}$ (in log)	2.041***	2.045***	2.045***	2.042***	2.042***	2.023***	2.025***
	(0.255)	(0.254)	(0.254)	(0.252)	(0.252)	(0.254)	(0.254)
$Size^2_{t-1}$ (in log)	0.962***	0.962***	0.962***	0.963***	0.963***	0.963***	0.963***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$R\&D\ government_{t-1}(dummy)$	1.067	1.067	1.067	1.068	1.068	1.068	1.068
	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)
$Foreign_{t-1}(dummy)$	1.289	1.292	1.292	1.289	1.289	1.289	1.289
	(0.214)	(0.215)	(0.215)	(0.214)	(0.213)	(0.214)	(0.214)
Technological dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
$Regional\ stock\ of\ patents_{t-1}$		1.171***	1.145***				
		(0.067)	(0.057)				
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		1.029*	1.029*				
		(0.015)	(0.015)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.947**	0.947**				
		(0.020)	(0.020)				
$Stock\ GERD_{t-1}$				1.021***	1.019***		
				(0.006)	(0.005)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				1.000	1.000		
				(0.003)	(0.003)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.996	0.996		
				(0.004)	(0.004)		
$Stock\ GERD\ business_{t-1}$						0.958	0.971
						(0.027)	(0.020)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.022***	1.022***
						(0.006)	(0.006)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.973***	0.973***
						(0.007)	(0.007)
$Stock\ GERD\ government_{t-1}$						0.989	0.986
						(0.013)	(0.019)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.976***	0.976***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.025***	1.025***
						(0.005)	(0.005)
$Stock\ GERD\ HES_{t-1}$						1.221***	1.197***
						(0.088)	(0.081)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.958**	0.957**
						(0.020)	(0.020)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.040	1.039
						(0.033)	(0.033)
GDP per capita		0.984		0.976		1.020	
		(0.016)		(0.015)		(0.023)	
Tertiari education			0.991		0.982		1.005
			(0.013)		(0.013)		(0.015)
Constant	0.013***	0.005***	0.004***	0.005***	0.005***	0.002***	0.002***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
Random Part of the Model							
$ln(alpha)$	0.568***	0.567***	0.567***	0.568***	0.568***	0.567***	0.567***
	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)
$Variance\ (Region)$	0.103	0.078	0.079	0.073	0.068	0.023	0.028
$Variance\ (Firm - Region)$	4.138	4.132	4.133	4.133	4.134	4.134	4.133
Observations	24,174	24,174	24,174	24,174	24,174	24,174	24,174
Number of groups	17	17	17	17	17	17	17
Likelihood ratio test Firm random intercept	4943***	4925***	4925***	4880***	4888***	4759***	4767***
Likelihood ratio test Region random intercept	21.13***	15.89***	15.89***	14.06***	11.80***	1.520	2.508*
Wald Test Mean values (Mundlak)	949.3***	859.3***	865.9***	794.6***	794.6***	817.6***	817.9***
Wald Test Time dummies	798.1***	791.9***	813.8***	780.9***	807.8***	818.1***	809.1***

Robust SE in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

Lastly, the Wald test for the technological, time, and firms' mean values concludes that all of them are jointly significant. Therefore, it is guaranteed that our firm level coefficients are not driven by being correlated with the firm random effects. Another important result when looking at all our different specifications in Table 4 is that the sign as well as the magnitude of the control variables' parameters at the firm level barely change. Finally, the regional variance is reduced in columns 2 to 7, in comparison with the baseline specification in column one, reflecting that our model accounts for a great part of the regional variability.

To start analyzing the rest of the hypotheses of the chapter, specifications 2 to 7 take into account different measures to proxy for the knowledge base of a region. In particular, specifications in columns 2 and 3 consider the regional stock of patents.[10] Again, we note the relevance of the networking strategies. Also, the variable measuring the regional stock of patents is highly significant, pointing to the fact that being located in a knowledge-dense region is important, even for those firms not cooperating or not engaged in outsourcing. This is in accordance with our second hypothesis and with the wide agreement that firms benefit from being located in knowledge-intensive regions (Audretsch and Dohse, 2007).

When we look at the cross effect between the regional innovation context and the firm's networking activities on firms' performance, an interesting result appears. Firms obtain a higher return of technological cooperation if they are located in regions with higher knowledge capacity (measured through patents) given the significant and higher than one value of the interaction term. On the contrary, the significant and lower than one parameter between outsourcing and regional patents indicates that firms obtain a higher return from R&D outsourcing if they are located in regions with low knowledge endowment. As argued in the literature review section, the explanation for this result may come from the type of knowledge embedded in each strategy. In the case of cooperating in technological activities, the knowledge is more technical and tacit, so that the gains from the regional context and, more specifically, from regional knowledge spillovers, can be important since they will allow the firm to further elaborate the external knowledge acquired through cooperation. While for outsourcing, the knowledge embedded tends to be less complex and more standard and it is not necessary to construct a very different knowledge from the one purchased, so that the knowledge spilling from other firms within the region is not so essential; and being located in low innovative performance regions would imply not being

[10]Due to a high correlation between GDP per capita and Tertiary education, we decided not to include both controls at the time (see Table A.4 in the online Appendix).

affected by fierce competition. These results give empirical support to our third and fourth hypotheses.

We now use the stock of R&D expenditures to proxy for the knowledge base of the region, controlling again by GDP per capita (column 4) and Tertiary education (column 5) as well as firm-level variables as in previous specifications. Again, we obtain that the regional stock of R&D exerts a positive and significant direct influence on the firm's innovative performance. However, when crossing the regional stock with our key variables (technological cooperation and R&D outsourcing), none of the parameters are significant.

In order to study the reason behind this non-significance of the cross-effect, as well as to provide empirical evidence for our hypotheses 5 and 6, we separate the regional stock of R&D into its different components, which could reflect a different type of research, more basic in the case of universities, research centers, and government, and more applied in the case of businesses. The results are shown in columns 6 and 7. When crossing the different types of stock of R&D with technological cooperation, we observe that the returns to technological cooperation are higher if the firm is located in regions with higher research expenditures developed by private agents. In contrast, the benefits that firms obtain from cooperation are lower if they are located in regions with a rich knowledge stock in the government and university sectors. These results support hypotheses 5. Moreover, it seems that the non-significance of such cross product in column 5 could be due to the different directions when splitting R&D expenditures into the public/business sectors canceling the significance of the effect. All in all, firms obtain higher returns from technological cooperation if they are located in regions with higher amount of private R&D expenditures or if they are located in regions with lower amount of public ones, given the nature of the knowledge embedded in both cases, more market-oriented in the first case and science-based in the second.

On the contrary, we observe that firms located in regions with higher research expenditures by private agents obtain lower returns from their R&D outsourcing strategy; whereas those located in regions with higher amount of research developed by public institutions obtain higher returns from outsourcing. These figures go in line with hypotheses 6 in the case of R&D outsourcing. The result seems to indicate that firms in regions where the public research base is higher might benefit from a lower degree of competition (because the private research base would be lower), while not being penalized by the little knowledge spillovers with a market-oriented profile (which they do not need since the knowledge acquired through outsourcing is easily absorbed due to its standard nature).

3.5.2. Robustness section. Several robustness analyses are considered.[11] In the analysis so far, we are using an unbalanced panel possibly leading to attrition problems. To correct for this, we use information present in the survey recording the reasons for an enterprise leaving the survey, so that once corrected by this, we may follow the assumption that missing values are random (Snijders and Bosker, 2012).[12] Estimations show that the results do not change for our key variables (see Table A.5 in the Appendix).

We acknowledge that some enterprises may move from one region to another during the period of analysis, possibly biasing our results due to the misrecognition of the characteristics of the region where the enterprise was previously located, as well as its contribution to the number of product innovations. According to Chung and Beretvas (2012), the bias due to the lack of control for this in a multilevel framework would be higher, the higher the percentage of firms changing locations, as well as the higher the number of regions they move to. We do not expect a high bias in our estimations since the number of firms changing locations in our sample is very low (3.8 percent) in comparison to theirs (10 percent). In any case, we re-estimated our model discarding these moving firms and the results show that, qualitatively speaking, our main conclusions are virtually the same (see Table A.6 in the Appendix).

Also, as suggested by Narula (2004), large enterprises (LEs) and small-medium sized enterprises (SME) differ in the intensity of use of the two networking strategies studied in this chapter. In the case of a small sample of European firms, Narula obtains that SMEs focus more on outsourcing rather than alliances because of the higher risks and costs of managing different partners while LEs prefer collaborative projects due to their larger portfolio of projects to offer to their partners. Although our interest lies on the impact of networking and not the intensity in their use, we wonder whether our results would maintain if the sample was divided between SMEs and LEs. Even though most of our main results are maintained, it is worth stressing that the regional context does not affect LEs as much as in the case of SMEs (see Tables A.7 and A.8 in the Appendix).

When using a multilevel model, some enterprises might have an impact on regional performance. Yet, this is probably not the case here since the territorial units we consider are large and represent administrative authorities where a single

[11]Because of space restrictions, all the results in this section are given in the appendix. We thank the three anonymous referees for highlighting some of the robustness checks in this section.

[12]We include a categorical variable with the following categories: the firm has split; it has acquired other firms; it is born after a split process; it is a result of a merger process; it has changed the trademarks and legal form; without change.

firm is not sufficiently important to affect regional performance. However, in order to test it, we skip very large enterprises—those with more than one thousand workers—and most of our results behave the same (see Table A.9 in the Appendix). The shortcoming of analyzing large regions—as in the case of NUTS2 level in Spain—is that it is assumed that all firms take a similar advantage of the regional capability; we acknowledge that a firm in Girona possibly should not take the same profit from its environment as another firm located in Barcelona (both being part of Catalonia). Unfortunately, we do not have further regional disaggregation to check for this.

In addition, we check the robustness of our results to the use of other proxies for some of our explanatory variables. First, in relation to the regional variables and specifically the use of the patents as a proxy for the knowledge base of the region, we acknowledge that patents are not always an equivalent measure of the innovative output across different sectors since some of them present a lower propensity to patent. Therefore, an alternative measure of the regional innovation base could be the employment in high and medium-high technological manufacturing industries, as stressed in Feldman and Florida (1994) and in European Commission (2014). Our results hold and behave in the same way, that is, those firms cooperating take more advantage of such cooperation if they are located in a region with a higher share of high and medium-high tech manufacturing employment. While for those firms doing outsourcing, the return is higher if they are located in regions with lower share of employment in high and medium-high tech manufactures (see Table A.10 in the Appendix).

Second, among the firm level explanatory variables, even though we measure the internal knowledge capacity of firms with the amount of R&D expenditures per employee as in most previous studies, we analyzed the sensitivity of our results to the use of other proxies such as the total employment in R&D, the employment in R&D with tertiary education (both measured as the number of people), and hiring of engineers/graduates with governmental/corporate experience in R&D (a dummy variable). In all the cases, the conclusions are maintained (see Tables A.11-A.13 in the Appendix).

Third, in order to account for the differential effect of sectors in the generation of new products innovations—instead of the technological classification—we include sector fixed effects. Moreover, to control for the cohort of firms as well as its possible different impact on our networking strategies, we include the age of the firm. In both cases the main conclusions are maintained (see Tables A.14 and A.15 of the Appendix, respectively). We also consider the sensitivity of our results to several depreciation rates in the computation of the measure of the stock of knowledge. If we use a 10 percent depreciation rate as in Peri (2005), instead of 5 percent, the results follow the same pattern (see Table A.16 in the Appendix).[13]

Finally, we have taken Wooldridge (2010b, chapter 3) advice, and despite the collinearity between our two main regional variables—GERD and Patents—we included them jointly in the model in order not to confound their relation with our dependent variable. Our results show that in fact this seems not to be an important issue since the pattern of our main results behaves the same qualitatively and barely changes quantitatively (see Table A.17 in the Appendix).

3.6. Conclusion

This chapter aligns in the literature that assesses the role of the regional context to fims' innovative performance. In addition to the direct effect of the regional characteristics where the firm is located, we hypothesize that it also shapes the returns to firms' networking activities. Specifically, we analyze how the knowledge endowment of the region can influence the efficiency of the networking activities carried out by the firm, explicitly technological cooperation agreements and R&D outsourcing. We estimate a multilevel framework that combines information at the firm level as well as the regional level for the case of Spanish manufactures in the 2000-2012 period, allowing to take explicit account of the multilevel structure of the data as well as its panel structure.[14]

Among the main results, first we find that although firms' characteristics are obtained to be more relevant than regional ones, something already stressed in recent studies (Backman, 2014; López-Bazo and Motellón, 2018; Naz et al., 2015; van Oort et al., 2012), the regional context explains an important part of the variability of firms' innovative performance measured through the number of product innovations introduced by the firm. We then give a step forward and try to analyze the mechanisms through which the regional environment exerts influence on firms' performance. Our analysis considers that regional innovation environments condition the returns of firms' networking activities. As a consequence, the efficiency of the technological cooperation and the R&D outsourcing carried out by the firm differs depending on the characteristics of the region in which it is located. Explicitly, we find evidence of a reinforcement effect between being in

[13] We also use 15 percent as in Rahko (2016) and results behave the same (results upon request from the authors).

[14] To our knowledge, this has been done only in one paper on topics related to innovation (Naz et al., 2015).

a highly knowledge endowed region and the returns obtained from cooperating technologically with other organizations. In contrast, enterprises that acquire external knowledge through an outsourcing strategy have a higher return when they are located in a region with a lower knowledge endowment.

In addition, we analyze if the results are maintained when we consider separately the regional research effort made by the private sector as compared to the public one. It seems that the benefits obtained from technological cooperative agreements are higher in regions with a high endowment of knowledge made by the private sector. On the other hand, the R&D outsourcing strategy is more beneficial in regions where the knowledge pool available is mainly due to public institutions. All in all, we can conclude that a firm's ability to exploit external knowledge acquired through networking activities depends crucially on the endowments of the region in which it operates.

Appendix

TABLE A.1. Technological classification of the manufacturing sectors

Sector	Denomination	NACE Rev.1	NACE Rev.2
	Low-Tech		
1	Meat products	151	101
2	Food and tobacco	152 to 158 + 160	102 to 109, 120
3	Beverage	159	110
4	Textiles and clothing	171 to 177 and 181 to 183	131 to 133, 139, 141 to 143
5	Leather, fur and footwear	191 to 193	151 + 152
6	Timber	201 to 205	161 + 162
7	Paper	211 + 212	171 + 172
8	Printing (before Printing and Edition)	221 to 223	181 + 182
19	Furniture	361	310
20	Other manufacturing	362 to 366, 371 to 372	321 to 325, 329
	Medium Low-tech		
10	Plastic and rubber products	251 to 252	221 + 222
11	Nonmetal mineral products	261 to 268	231 to 237, 239
12	Basic metal products	271 to 275	241 to 245
13	Fabricated metal products	281 to 287	251 to 257, 259
	Medium High-tech		
14	Machinery and equipment	291 to 297	281 to 284, 289
16	Electric materials and accessories	311 to 316 y 321 a 323	271 to 275, 279
17	Vehicles and accessories	341 to 343	291 to 293
18	Other transport equipment	351 to 355	301 to 304, 309
	High-tech		
9	Chemicals and pharmaceuticals (before Chemical products)	241 to 247	201 to 206, 211 + 212
15	Computer products, electronics and optical	300 + (331 to 335)	261 to 268

Source: ESEE and Eurostat. http://www.fundacionsepi.es/investigacion/esee/en/svariables/disponibles.asp

TABLE A.2. Descriptive statistics of the regional variables in the empirical analysis

VARIABLES		mean	sd	min	max	Observations	
Stock GERD	Overall	6,967	10,019	306.8	47,263	N	221
	Between		10,013	518.6	37,731	n	17
	Within		2,364	-1,768	16,524	T	13
Stock GERD business	Overall	3,662	5,923	37.28	25,866	N	221
	Between		5,925	92.93	20,245	n	17
	Within		1,374	-1,768	9,282	T	13
Stock GERD government	Overall	1,186	2,447	18.64	12,757	N	221
	Between		2,465	64.31	10,389	n	17
	Within		493.4	-796.8	3,553	T	13
Stock GERD HES	Overall	2,125	2,197	94.60	8,447	N	221
	Between		2,183	133.6	6,803	n	17
	Within		568.3	253.1	4,231	T	13
Stock Regional patents	Overall	633.5	1,120	6.42	5,880	N	221
	Between		1,108	40.07	4,469	n	17
	Within		303.9	-888.7	2,045	T	13
GDP per capita	Overall	24,272	4,861	14,182	35,607	N	221
	Between		4,749	16,446	32,846	n	17
	Within		1,518	20,478	27,429	T	13
Tertiary education	Overall	27.87	6.57	15.50	46	N	221
	Between		5.81	20.72	39.70	n	17
	Within		3.37	20.17	35.28	T	13

Table A.3. Descriptive statistics of the firm level variables in the empirical analysis

VARIABLES		mean	sd	min	max	Observations	
Cooperation (dummy)	Overall	0.312	0.463	0	1	N	26,506
	Between		0.402	0	1	n	4,010
	Within		0.251	-0.622	1.245	T-bar	6.61
Outsourcing (dummy)	Overall	0.228	0.420	0	1	N	26,506
	Between		0.357	0	1	n	4,010
	Within		0.236	-0.705	1.162	T-bar	6.61
log (Internal R&D)	Overall	2.174	3.402	0	11.62	N	26,506
	Between		3.075	0	10.71	n	4,010
	Within		1.603	-6.660	10.72	T-bar	6.61
log (Size)	Overall	4.211	1.439	0.693	9.616	N	26,506
	Between		1.357	0.693	9.406	n	4,010
	Within		0.257	-0.822	6.562	T-bar	6.61
R&D Government (dummy)	Overall	0.067	0.250	0	1	N	26,506
	Between		0.190	0	1	n	4,010
	Within		0.165	-0.866	1	T-bar	6.61
Foreign (dummy)	Overall	0.162	0.368	0	1	N	26,506
	Between		0.338	0	1	n	4,010
	Within		0.123	-0.772	1.095	T-bar	6.61

Table A.4. Correlation matrix of the variables in the empirical analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Cooperation (dummy)	1									
(2) Outsourcing (dummy)	0.604	1								
(3) log (Internal R&D)	0.709	0.575	1							
(4) log (Size)	0.497	0.439	0.482	1						
(5) R&D Government (dummy)	0.369	0.389	0.439	0.320	1					
(6) Foreign (dummy)	0.235	0.171	0.218	0.443	0.087	1				
(7) Stock of GERD	0.008	-0.003	0.057	0.005	-0.016	0.080	1			
(8) Stock of Regional patents	0.085	0.058	0.134	0.070	0.000	0.115	0.715	1		
(9) GDP per capita	0.071	0.064	0.126	0.076	0.061	0.132	0.750	0.582	1	
(10) Tertiary education	0.061	0.063	0.101	0.079	0.084	0.100	0.563	0.223	0.871	1

TABLE A.5. Assuming missing at random

VARIABLES	(1) NIP	(2) NIP	(3) NIP	(4) NIP	(5) NIP	(6) NIP
$Cooperation_{t-1}(dummy)$	1.309***	1.242***	1.242***	1.303***	1.304***	1.374***
	(0.062)	(0.080)	(0.080)	(0.098)	(0.098)	(0.115)
$Outsourcing_{t-1}(dummy)$	1.161**	1.288***	1.288***	1.249**	1.250**	1.198
	(0.083)	(0.109)	(0.109)	(0.127)	(0.127)	(0.168)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.171***	1.145***			
		(0.068)	(0.057)			
$Cooperation_{t-1}(dummy)$* $Regional\ stock\ of\ patents_{t-1}$		1.029**	1.029**			
		(0.015)	(0.015)			
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.947**	0.947**			
		(0.020)	(0.020)			
$Stock\ GERD_{t-1}$				1.021***	1.019***	
				(0.006)	(0.005)	
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				1.000	1.000	
				(0.003)	(0.003)	
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.996	0.996	
				(0.004)	(0.004)	
$Stock\ GERD\ business_{t-1}$						0.971
						(0.020)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.022***
						(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.973***
						(0.006)
$Stock\ GERD\ government_{t-1}$						0.986
						(0.019)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.976***
						(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.025***
						(0.005)
$Stock\ GERD\ HES_{t-1}$						1.198***
						(0.081)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.958**
						(0.019)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.038
						(0.033)
$GDP\ per\ capita$		0.984		0.976		
		(0.016)		(0.015)		
$Tertiari\ education$			0.991		0.982	1.005
			(0.013)		(0.013)	(0.015)
$Constant$	0.015***	0.006***	0.005***	0.006***	0.006***	
	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	
$Random\ Part\ of\ the\ Model$						
$ln(alpha)$	0.567***	0.567***	0.567***	0.567***	0.567***	0.566***
	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)
$Variance\ (Region)$	0.104	0.078	0.079	0.073	0.069	0.029
$Variance\ (Firm-Region)$	4.138	4.133	4.133	4.133	4.134	4.133
$Observations$	24,174	24,174	24,174	24,174	24,174	24,174
$Number\ of\ groups$	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	4945***	4928***	4928***	4883***	4891***	4770***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	21.25***	16***	16***	14.16***	11.89***	2.548*
$Wald\ Test\ Mean\ values\ (Mundlak)$	886.9***	805***	812.5***	744.3***	746.5***	767.1***
$Wald\ Test\ Time\ dummies$	863.7***	856.3***	881.4***	842.5***	873.3***	872***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89). We include a categorical variable (CAMBIO) with the following categories: it has splitted; it has acquired other firms; it has born after a split process; it is a result of a merger process;it has changed the trademarks and legal form; without change; being the first category the reference one. Specification (6) is missing due to convergence problems with the model.

Table A.6. Excluding enterprises moving among regions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	NIP	NIP	NIP	NIP	NIP	NIP	NIP
$Cooperation_{t-1}(dummy)$	1.323***	1.248***	1.248***	1.270***	1.271***	1.338***	1.341***
	(0.064)	(0.080)	(0.080)	(0.093)	(0.092)	(0.106)	(0.105)
$Outsourcing_{t-1}(dummy)$	1.155**	1.273***	1.273***	1.246**	1.247**	1.185	1.185
	(0.082)	(0.118)	(0.118)	(0.137)	(0.138)	(0.184)	(0.185)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.168***	1.152***				
		(0.066)	(0.058)				
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		1.032***	1.032***				
		(0.012)	(0.012)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.951**	0.951**				
		(0.023)	(0.023)				
$Stock\ GERD_{t-1}$				1.020***	1.018***		
				(0.006)	(0.005)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				1.002	1.002		
				(0.002)	(0.002)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.996	0.996		
				(0.004)	(0.004)		
$Stock\ GERD\ business_{t-1}$						0.948*	0.970
						(0.028)	(0.021)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.019***	1.019***
						(0.004)	(0.004)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.975***	0.975***
						(0.007)	(0.007)
$Stock\ GERD\ government_{t-1}$						0.983	0.979
						(0.014)	(0.021)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.986***	0.986***
						(0.003)	(0.003)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.020***	1.019***
						(0.005)	(0.005)
$Stock\ GERD\ HES_{t-1}$						1.249***	1.211***
						(0.097)	(0.088)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.966**	0.965**
						(0.015)	(0.014)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.039	1.039
						(0.035)	(0.035)
$GDP\ per\ capita$		0.990		0.983		1.033	
		(0.019)		(0.020)		(0.028)	
$Tertiari\ education$			0.994		0.986		1.009
			(0.016)		(0.016)		(0.018)
$Constant$	0.015***	0.004***	0.004***	0.005***	0.005***	0.001***	0.002***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)
$Random\ Part\ of\ the\ Model$							
$ln(alpha)$	0.580***	0.579***	0.579***	0.580***	0.580***	0.579***	0.579***
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
$Variance\ (Region)$	0.120	0.090	0.091	0.086	0.082	0.020	0.030
$Variance\ (Firm - Region)$	4.161	4.157	4.157	4.157	4.158	4.159	4.157
$Observations$	22,648	22,648	22,648	22,648	22,648	22,648	22,648
$Number\ of\ groups$	17	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	4595***	4577***	4578***	4540***	4545***	4412***	4426***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	20.72***	15.18 ***	15.18***	14.02***	11.42***	0.908	2.125*
$Wald\ Test\ Mean\ values\ (Mundlak)$	974.5***	912.8***	909.4***	830.3***	828.4***	878.1***	870.5***
$Wald\ Test\ Time\ dummies$	1364***	1427***	1418***	1439***	1434***	1397***	1397***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

Table A.7. Main results for Small and medium-sized enterprises (SMEs)

VARIABLES	(1) NIP	(2) NIP	(3) NIP	(4) NIP	(5) NIP	(6) NIP	(7) NIP
$Cooperation_{t-1}(dummy)$	1.214***	1.072	1.071	1.069	1.069	1.005	1.002
	(0.082)	(0.106)	(0.105)	(0.128)	(0.127)	(0.172)	(0.170)
$Outsourcing_{t-1}(dummy)$	1.215*	1.359**	1.359**	1.239	1.239	1.203	1.209
	(0.122)	(0.170)	(0.170)	(0.176)	(0.176)	(0.230)	(0.232)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.197**	1.175**				
		(0.093)	(0.076)				
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		1.068**	1.068**				
		(0.028)	(0.028)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.944	0.944				
		(0.033)	(0.033)				
$Stock\ GERD_{t-1}$				1.021**	1.019**		
				(0.010)	(0.008)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				1.007	1.007		
				(0.004)	(0.004)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.999	0.999		
				(0.006)	(0.006)		
$Stock\ GERD\ business_{t-1}$						0.920***	0.953**
						(0.023)	(0.021)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.007	1.008
						(0.007)	(0.007)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.970***	0.971***
						(0.010)	(0.010)
$Stock\ GERD\ government_{t-1}$						0.970**	0.956*
						(0.013)	(0.026)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.989*	0.989**
						(0.006)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.044***	1.044***
						(0.008)	(0.009)
$Stock\ GERD\ HES_{t-1}$						1.334***	1.285***
						(0.093)	(0.099)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.033	1.032
						(0.035)	(0.035)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.043	1.040
						(0.041)	(0.042)
$GDP\ per\ capita$		0.990		0.985		1.063**	
		(0.024)		(0.026)		(0.028)	
$Tertiari\ education$			1.001		0.992		1.027
			(0.020)		(0.022)		(0.021)
$Constant$	0.003***	0.001***	0.001***	0.001***	0.001***	0.000***	0.000***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
$Random\ Part\ of\ the\ Model$							
$ln(alpha)$	0.759***	0.758***	0.758***	0.758***	0.758***	0.756***	0.756***
	(0.041)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)
$Variance\ (Region)$	0.194	0.148	0.155	0.146	0.148	5.22e-30	0.019
$Variance\ (Firm - Region)$	4.972	4.967	4.966	4.968	4.968	4.995	4.987
$Observations$	17,852	17,852	17,852	17,852	17,852	17,852	17,852
$Number\ of\ groups$	17	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	2857***	2857***	2857***	2835***	2844***	2730.48***	2730.06***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	18.21***	14.07***	14.07***	13.91***	12.71***		0.55
$Wald\ Test\ Mean\ values\ (Mundlak)$	917.8***	1040***	1092***	983.8***	1025***	937.55***	978.16***
$Wald\ Test\ Time\ dummies$	20176***	20678***	20754***	18383***	18248***	12779***	12349***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

TABLE A.8. Main results for Large enterprises (LEs)

VARIABLES	(1) NIP	(2) NIP	(3) NIP	(4) NIP	(5) NIP	(6) NIP	(7) NIP
$Cooperation_{t-1}(dummy)$	1.491***	1.501***	1.500***	1.662***	1.660***	1.812***	1.812***
	(0.143)	(0.197)	(0.196)	(0.235)	(0.234)	(0.291)	(0.291)
$Outsourcing_{t-1}(dummy)$	1.101	1.220*	1.222*	1.211	1.216	1.139	1.145
	(0.089)	(0.128)	(0.128)	(0.154)	(0.154)	(0.196)	(0.196)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.115***	1.085***				
		(0.035)	(0.033)				
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.997	0.997				
		(0.033)	(0.033)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.946**	0.945**				
		(0.024)	(0.024)				
$Stock\ GERD_{t-1}$				1.021***	1.018***		
				(0.006)	(0.005)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.992	0.992		
				(0.006)	(0.006)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.994	0.994		
				(0.004)	(0.004)		
$Stock\ GERD\ business_{t-1}$						1.002	0.998
						(0.018)	(0.015)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.036***	1.036***
						(0.012)	(0.012)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.969***	0.969***
						(0.006)	(0.006)
$Stock\ GERD\ government_{t-1}$						1.018*	1.033***
						(0.010)	(0.011)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.941***	0.941***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.022***	1.022***
						(0.005)	(0.005)
$Stock\ GERD\ HES_{t-1}$						1.087	1.069
						(0.056)	(0.048)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.911*	0.910*
						(0.046)	(0.046)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.052	1.050
						(0.039)	(0.039)
$GDP\ per\ capita$		0.977*		0.969**		0.974	
		(0.012)		(0.014)		(0.017)	
$Tertiari\ education$			0.981***		0.973***		0.976***
			(0.007)		(0.005)		(0.009)
$Constant$	3.561	2.404	2.391	2.320	2.486	1.716	1.807
	(6.158)	(4.022)	(4.052)	(3.744)	(4.256)	(3.096)	(3.228)
$Random\ Part\ of\ the\ Model$							
$ln(alpha)$	0.279***	0.279***	0.279***	0.278***	0.278***	0.277***	0.277***
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
$Variance\ (Region)$	1.62e-32	1.62e-32	3.62e-35	7.32e-33	1.80e-35	5.06e-34	4.44e-35
$Variance\ (Firm - Region)$	2.842	2.842	2.839	2.842	2.833	2.834	2.830
$Observations$	6,322	6,322	6,322	6,322	6,322	6,322	6,322
$Number\ of\ groups$	17	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	1748***	1719***	1720***	1679***	1677***	1661***	1661***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	0.00374						
$Wald\ Test\ Mean\ values\ (Mundlak)$	314.2***	344.33***	365.37***	280.35***	357.75***	351.85***	400.65***
$Wald\ Test\ Time\ dummies$	1451***	1558***	1577***	1463***	1476***	1334***	1355***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

Table A.9. Excluding very large firms

VARIABLES	(1) NIP	(2) NIP	(3) NIP	(4) NIP	(5) NIP	(6) NIP	(7) NIP
$Cooperation_{t-1}(dummy)$	1.295***	1.216***	1.216***	1.263***	1.264***	1.267***	1.267***
	(0.050)	(0.061)	(0.061)	(0.080)	(0.079)	(0.096)	(0.094)
$Outsourcing_{t-1}(dummy)$	1.190***	1.310***	1.310***	1.290**	1.291**	1.237*	1.236
	(0.078)	(0.112)	(0.112)	(0.128)	(0.128)	(0.159)	(0.159)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.166**	1.148**				
		(0.071)	(0.062)				
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		1.036***	1.036***				
		(0.012)	(0.012)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.950**	0.950**				
		(0.021)	(0.021)				
$Stock\ GERD_{t-1}$				1.021***	1.020***		
				(0.006)	(0.005)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				1.001	1.001		
				(0.003)	(0.003)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.995	0.995		
				(0.003)	(0.003)		
$Stock\ GERD\ business_{t-1}$						0.946*	0.965
						(0.029)	(0.021)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.014***	1.015***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.976***	0.976***
						(0.007)	(0.007)
$Stock\ GERD\ government_{t-1}$						0.990	0.983
						(0.014)	(0.021)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.977***	0.977***
						(0.004)	(0.004)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.018***	1.018***
						(0.004)	(0.004)
$Stock\ GERD\ HES_{t-1}$						1.248***	1.218***
						(0.099)	(0.092)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.989	0.988
						(0.019)	(0.019)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.035	1.035
						(0.029)	(0.029)
$GDP\ per\ capita$		0.989		0.981		1.032	
		(0.020)		(0.019)		(0.027)	
$Tertiari\ education$			0.995		0.985		1.012
			(0.015)		(0.015)		(0.017)
$Constant$	0.009***	0.003***	0.002***	0.003***	0.003***	0.001***	0.001***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
$Random\ Part\ of\ the\ Model$							
$ln(alpha)$	0.620***	0.620***	0.620***	0.620***	0.620***	0.619***	0.619***
	(0.097)	(0.097)	(0.097)	(0.098)	(0.098)	(0.098)	(0.098)
$Variance\ (Region)$	0.128	0.101	0.103	0.093	0.091	0.026	0.035
$Variance\ (Firm-Region)$	4.213	4.208	4.208	4.208	4.209	4.211	4.209
$Observations$	23,372	23,372	23,372	23,372	23,372	23,372	23,372
$Number\ of\ groups$	17	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	4542***	4531***	4531***	4486***	4495***	4352***	4362***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	23.81***	19.33***	19.33***	16.84***	15.07***	1.52	2.95**
$Wald\ Test\ Mean\ values\ (Mundlak)$	948.6***	880.77***	882.79***	820.77***	818.55***	833.64***	826.3***
$Wald\ Test\ Time\ dummies$	3567***	3587***	3518***	3728***	3667***	3489***	3414***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

Table A.10. Employment in high and medium-high technological manufacturing industries

VARIABLES	(1) NIP	(2) NIP
$Cooperation_{t-1}(dummy)$	1.121	1.122
	(0.089)	(0.089)
$Outsourcing_{t-1}(dummy)$	1.440***	1.440***
	(0.183)	(0.183)
$Firm\ level\ controls$	Yes	Yes
$High\ med-high\ tech\ employment_{t-1}$	1.010	1.024
	(0.045)	(0.041)
$Cooperation_{t-1}(dummy) * High\ med-high\ tech\ employment_{t-1}$	1.028***	1.028***
	(0.011)	(0.011)
$Outsourcing_{t-1}(dummy) * High\ med-high\ tech\ employment_{t-1}$	0.963**	0.963**
	(0.018)	(0.018)
$GDP\ per\ capita$	1.002	
	(0.023)	
$Tertiari\ education$		0.993
		(0.020)
$Constant$	0.003***	0.004***
	(0.002)	(0.003)
$Random\ Part\ of\ the\ Model$		
$ln(alpha)$	0.568***	0.568***
	(0.029)	(0.029)
$Variance\ (Region)$	0.105	0.104
$Variance\ (Firm-Region)$	4.132	4.132
$Observations$	24,174	24,174
$Number\ of\ groups$	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	4935***	4942***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	20.55***	20.03***
$Wald\ Test\ Mean\ values\ (Mundlak)$	934.2***	936***
$Wald\ Test\ Time\ dummies$	802.9***	824.1***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

TABLE A.11. Controlling by Total employment in R&D

VARIABLES	(1) *NIP*	(2) *NIP*	(3) *NIP*	(4) *NIP*	(5) *NIP*	(6) *NIP*	(7) *NIP*
$Cooperation_{t-1}(dummy)$	1.305***	1.246***	1.246***	1.304***	1.306***	1.388***	1.390***
	(0.060)	(0.081)	(0.081)	(0.096)	(0.096)	(0.122)	(0.121)
$Outsourcing_{t-1}(dummy)$	1.163**	1.288***	1.288***	1.250**	1.251**	1.198	1.198
	(0.085)	(0.110)	(0.110)	(0.128)	(0.128)	(0.166)	(0.166)
$Total\ employment\ in\ R\&D_{t-1}$	0.999	0.999	0.999	0.999	0.999	0.999	0.999
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.173***	1.146***				
		(0.068)	(0.058)				
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		1.026*	1.026*				
		(0.016)	(0.016)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.948**	0.948**				
		(0.020)	(0.020)				
$Stock\ GERD_{t-1}$				1.022***	1.020***		
				(0.005)	(0.004)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				1.000	1.000		
				(0.003)	(0.003)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.996	0.996		
				(0.004)	(0.004)		
$Stock\ GERD\ business_{t-1}$						0.961	0.973
						(0.028)	(0.021)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.022***	1.022***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.973***	0.973***
						(0.007)	(0.007)
$Stock\ GERD\ government_{t-1}$						0.991	0.989
						(0.014)	(0.020)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.977***	0.977***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.025***	1.025***
						(0.005)	(0.005)
$Stock\ GERD\ HES_{t-1}$						1.213**	1.190**
						(0.092)	(0.083)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.953**	0.953**
						(0.020)	(0.019)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.039	1.039
						(0.032)	(0.033)
$GDP\ per\ capita$		0.982		0.975*		1.015	
		(0.017)		(0.015)		(0.024)	
$Tertiari\ education$			0.990		0.980		1.002
			(0.014)		(0.012)		(0.015)
$Constant$	0.015***	0.006***	0.005***	0.006***	0.006***	0.002***	0.003***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
$Random\ Part\ of\ the\ Model$							
$ln(alpha)$	0.571***	0.571***	0.571***	0.571***	0.571***	0.571***	0.571***
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
$Variance\ (Region)$	0.120	0.084	0 .084	0 .077	0 .072	0 .031	0 .035
$Variance\ (Firm - Region)$	4.144	4.140	4.140	4.140	4.141	4.139	4.139
$Observations$	23,900	23,900	23,900	23,900	23,900	23,900	23,900
$Number\ of\ groups$	17	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	4895***	4879***	4879***	4834***	4842***	4712***	4720***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	21.68***	16.62***	16.62***	14.21***	11.84***	2.324*	3.193**
$Wald\ Test\ Mean\ values\ (Mundlak)$	762.2***	704.9***	710.4***	651***	653.2***	670.2***	670.6***
$Wald\ Test\ Time\ dummies$	890.1***	878.7***	903.6***	873.5***	904.2***	914***	908.8***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

TABLE A.12. Controlling by Employment in R&D with tertiary education

VARIABLES	(1) NIP	(2) NIP	(3) NIP	(4) NIP	(5) NIP	(6) NIP	(7) NIP
$Cooperation_{t-1}(dummy)$	1.303***	1.236***	1.236***	1.292***	1.293***	1.366***	1.368***
	(0.059)	(0.079)	(0.079)	(0.096)	(0.095)	(0.117)	(0.116)
$Outsourcing_{t-1}(dummy)$	1.161**	1.285***	1.285***	1.242**	1.243**	1.181	1.181
	(0.085)	(0.110)	(0.110)	(0.129)	(0.129)	(0.164)	(0.164)
$Employment\ in\ R\&D\ with\ tertiary\ education_{t-1}$	0.996	0.996	0.996	0.996	0.996	0.996	0.996
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.173***	1.148***				
		(0.068)	(0.058)				
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		1.030**	1.030**				
		(0.015)	(0.015)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.948**	0.948**				
		(0.020)	(0.020)				
$Stock\ GERD_{t-1}$				1.022***	1.020***		
				(0.006)	(0.005)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				1.000	1.000		
				(0.003)	(0.003)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.996	0.996		
				(0.004)	(0.004)		
$Stock\ GERD\ business_{t-1}$						0.959	0.972
						(0.027)	(0.020)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.022***	1.022***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.972***	0.972***
						(0.007)	(0.007)
$Stock\ GERD\ government_{t-1}$						0.990	0.987
						(0.013)	(0.019)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.977***	0.977***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.026***	1.026***
						(0.005)	(0.005)
$Stock\ GERD\ HES_{t-1}$						1.219***	1.195***
						(0.088)	(0.081)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.957**	0.957**
						(0.020)	(0.019)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.045	1.045
						(0.033)	(0.033)
$GDP\ per\ capita$		0.984		0.976		1.020	
		(0.016)		(0.015)		(0.023)	
$Tertiari\ education$			0.992		0.982		1.005
			(0.013)		(0.013)		(0.015)
$Constant$	0.015***	0.005***	0.005***	0.006***	0.006***	0.002***	0.003***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)
$Random\ Part\ of\ the\ Model$							
$ln(alpha)$	0 .569***	0 .569***	0 .569***	0 .569***	0 .569***	0 .568***	0 .568***
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
$Variance\ (Region)$	0.106	0.079	0.080	0.072	0.068	0.023	0.028
$Variance\ (Firm - Region)$	4.108	4.103	4.103	4.104	4.105	4.105	4.104
$Observations$	24,110	24,110	24,110	24,110	24,110	24,110	24,110
$Number\ of\ groups$	17	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	4908***	4891***	4891***	4847***	4855***	4725***	4733***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	21.73***	16.38***	16.38***	13.98***	11.78***	1.523	2.511*
$Wald\ Test\ Mean\ values\ (Mundlak)$	1067***	954.8***	967.6***	867.7***	870.9***	890.4***	895.3***
$Wald\ Test\ Time\ dummies$	764.4***	759.1***	777.5***	750.7***	772.5***	783.8***	776.1***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

Table A.13. Controlling by engineers/graduates with governmental/corporate experience in R&D

VARIABLES	(1) NIP	(2) NIP	(3) NIP	(4) NIP	(5) NIP	(6) NIP	(7) NIP
$Cooperation_{t-1}(dummy)$	1.299***	1.229***	1.229***	1.293***	1.294***	1.356***	1.358***
	(0.062)	(0.080)	(0.079)	(0.099)	(0.099)	(0.115)	(0.114)
$Outsourcing_{t-1}(dummy)$	1.159**	1.287***	1.287***	1.246**	1.247**	1.190	1.190
	(0.083)	(0.111)	(0.111)	(0.129)	(0.129)	(0.170)	(0.171)
$Hiring\ Personnel\ in\ R\&D$	1.060	1.061	1.061	1.060	1.060	1.060	1.060
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.042)	(0.042)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.171***	1.146***				
		(0.067)	(0.057)				
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		1.031**	1.031**				
		(0.015)	(0.015)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.946**	0.946**				
		(0.021)	(0.021)				
$Stock\ GERD_{t-1}$				1.021***	1.019***		
				(0.006)	(0.005)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				1.000	1.000		
				(0.003)	(0.003)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.996	0.996		
				(0.004)	(0.004)		
$Stock\ GERD\ business_{t-1}$						0.957	0.972
						(0.027)	(0.020)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.022***	1.022***
						(0.006)	(0.006)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.972***	0.972***
						(0.007)	(0.007)
$Stock\ GERD\ government_{t-1}$						0.986	0.983
						(0.013)	(0.019)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.974***	0.974***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.025***	1.025***
						(0.005)	(0.005)
$Stock\ GERD\ HES_{t-1}$						1.225***	1.199***
						(0.088)	(0.081)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.960*	0.960*
						(0.021)	(0.020)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.042	1.041
						(0.034)	(0.034)
$GDP\ per\ capita$		0.984		0.978		1.022	
		(0.016)		(0.015)		(0.023)	
$Tertiari\ education$			0.991		0.982		1.005
			(0.013)		(0.013)		(0.015)
$Constant$	0.015***	0.005***	0.005***	0.006***	0.006***	0.002***	0.003***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)
$Random\ Part\ of\ the\ Model$							
$ln(alpha)$	0.568***	0.567***	0.567***	0.568***	0.568***	0.567***	0.567***
	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)
$Variance\ (Region)$	0.103	0.077	0.078	0.074	0.070	0.023	0.029
$Variance\ (Firm - Region)$	4.106	4.101	4.101	4.101	4.103	4.102	4.100
$Observations$	24,174	24,174	24,174	24,174	24,174	24,174	24,174
$Number\ of\ groups$	17	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	4921***	4903***	4903***	4858***	4865***	4730***	4740***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	21.81***	16.19***	16.19***	15.06***	12.48***	1.623	2.738**
$Wald\ Test\ Mean\ values\ (Mundlak)$	1697***	1693***	1717***	1585***	1575***	1691***	1668***
$Wald\ Test\ Time\ dummies$	743.7***	742***	761***	727.6***	751***	763***	754.5***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

Table A.14. Including sectoral fixed effects

VARIABLES	(1) *NIP*	(2) *NIP*	(3) *NIP*	(4) *NIP*	(5) *NIP*	(6) *NIP*	(7) *NIP*
$Cooperation_{t-1}(dummy)$	1.309***	1.245***	1.245***	1.307***	1.308***	1.381***	1.381***
	(0.063)	(0.081)	(0.080)	(0.098)	(0.098)	(0.115)	(0.113)
$Outsourcing_{t-1}(dummy)$	1.158**	1.282***	1.282***	1.242**	1.243**	1.183	1.183
	(0.082)	(0.114)	(0.114)	(0.132)	(0.132)	(0.173)	(0.173)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.181***	1.154***				
		(0.070)	(0.056)				
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		1.028*	1.028**				
		(0.015)	(0.014)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.948**	0.948**				
		(0.022)	(0.022)				
$Stock\ GERD_{t-1}$				1.022***	1.019***		
				(0.006)	(0.005)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				1.000	1.000		
				(0.003)	(0.003)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.996	0.996		
				(0.004)	(0.004)		
$Stock\ GERD\ business_{t-1}$						0.964	0.974
						(0.028)	(0.022)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.022***	1.022***
						(0.006)	(0.006)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.973***	0.973***
						(0.007)	(0.007)
$Stock\ GERD\ government_{t-1}$						0.982	0.977
						(0.015)	(0.022)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.975***	0.975***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.024***	1.024***
						(0.005)	(0.005)
$Stock\ GERD\ HES_{t-1}$						1.215***	1.201**
						(0.088)	(0.086)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.957**	0.957**
						(0.020)	(0.020)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.043	1.043
						(0.034)	(0.035)
$GDP\ per\ capita$		0.985		0.979		1.019	
		(0.017)		(0.016)		(0.022)	
$Tertiari\ education$			0.995		0.986		1.009
			(0.015)		(0.015)		(0.017)
$Constant$	0.011***	0.004***	0.003***	0.004***	0.004***	0.001***	0.002***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
$Random\ Part\ of\ the\ Model$							
$ln(alpha)$	0.567***	0.567***	0.567***	0.567***	0.567***	0.567***	0.567***
	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)
$Variance\ (Region)$	0.110	0.081	0.083	0.078	0.076	0.030	0 .035
$Variance\ (Firm - Region)$	3.950	3.945	3.945	3.945	3.946	3.944	3.943
$Observations$	24,174	24,174	24,174	24,174	24,174	24,174	24,174
$Number\ of\ groups$	17	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	4639***	4631***	4630***	4598***	4606***	4493***	4494***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	21.52***	15.75***	15.75***	14.67***	12.64***	2.398*	3.428**
$Wald\ Test\ Mean\ values\ (Mundlak)$	952***	854***	864.3***	804.2***	809.9***	847.2***	849.8***
$Wald\ Test\ Time\ dummies$	805.5***	794***	814***	782.8***	805***	816.3***	806.6***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

Table A.15. Controlling for Firm's Age

VARIABLES	(1) NIP	(2) NIP	(3) NIP	(4) NIP	(5) NIP	(6) NIP	(7) NIP
$Cooperation_{t-1}(dummy)$	1.305***	1.248***	1.248***	1.317***	1.318***	1.394***	1.396***
	(0.061)	(0.083)	(0.082)	(0.099)	(0.099)	(0.119)	(0.118)
$Outsourcing_{t-1}(dummy)$	1.158**	1.278***	1.279***	1.247**	1.248**	1.205	1.206
	(0.082)	(0.108)	(0.108)	(0.127)	(0.127)	(0.169)	(0.170)
$Firm\acute{}s\ Age$	0.999	0.999	0.999	0.999	0.999	0.999	0.999
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.177***	1.149***				
		(0.069)	(0.059)				
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		1.025	1.025				
		(0.016)	(0.016)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.949**	0.949**				
		(0.020)	(0.020)				
$Stock\ GERD_{t-1}$				1.022***	1.020***		
				(0.006)	(0.004)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.999	0.999		
				(0.003)	(0.003)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.996	0.996		
				(0.004)	(0.004)		
$Stock\ GERD\ business_{t-1}$						0.961	0.973
						(0.028)	(0.021)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.022***	1.022***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.976***	0.976***
						(0.007)	(0.007)
$Stock\ GERD\ government_{t-1}$						0.989	0.987
						(0.013)	(0.019)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.974***	0.974***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.021***	1.021***
						(0.006)	(0.006)
$Stock\ GERD\ HES_{t-1}$						1.218***	1.197***
						(0.091)	(0.083)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.954**	0.954**
						(0.020)	(0.019)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.032	1.031
						(0.032)	(0.032)
$GDP\ per\ capita$		0.982		0.975*		1.016	
		(0.016)		(0.015)		(0.023)	
$Tertiari\ education$			0.991		0.981		1.003
			(0.013)		(0.012)		(0.015)
$Constant$	0.013***	0.005***	0.004***	0.006***	0.005***	0.002***	0.002***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)
$Random\ Part\ of\ the\ Model$							
$ln(alpha)$	0.568***	0.568***	0.568***	0.568***	0.568***	0.567***	0.567***
	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)
$Variance\ (Region)$	0.108	0.080	0.081	0.076	0.071	0.029	0.033
$Variance\ (Firm - Region)$	4.136	4.131	4.132	4.130	4.131	4.129	4.128
$Observations$	23,907	23,907	23,907	23,907	23,907	23,907	23,907
$Number\ of\ groups$	17	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	4897***	4875***	4875***	4830***	4838***	4712***	4717***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	21.58***	15.89***	15.89***	14.40***	11.79***	2.104*	2.995**
$Wald\ Test\ Mean\ values\ (Mundlak)$	1030***	858.3***	871.5***	834.2***	838.7***	874.8***	881.2***
$Wald\ Test\ Time\ dummies$	1118***	1137***	1167***	1114***	1143***	1144***	1148***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

Table A.16. Using a depreciation rate of 10 percent for the computation of stocks

VARIABLES	(1) NIP	(2) NIP	(3) NIP	(4) NIP	(5) NIP	(6) NIP	(7) NIP
$Cooperation_{t-1}(dummy)$	1.308***	1.241***	1.241***	1.298***	1.300***	1.368***	1.369***
	(0.062)	(0.082)	(0.082)	(0.100)	(0.099)	(0.114)	(0.112)
$Outsourcing_{t-1}(dummy)$	1.158**	1.287***	1.287***	1.253**	1.254**	1.214	1.215
	(0.083)	(0.113)	(0.113)	(0.132)	(0.132)	(0.175)	(0.175)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.262***	1.220***				
		(0.108)	(0.090)				
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		1.042*	1.042*				
		(0.023)	(0.023)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.924**	0.924**				
		(0.029)	(0.029)				
$Stock\ GERD_{t-1}$				1.034***	1.030***		
				(0.009)	(0.007)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				1.001	1.001		
				(0.004)	(0.004)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.993	0.993		
				(0.006)	(0.006)		
$Stock\ GERD\ business_{t-1}$						0.936	0.956
						(0.039)	(0.030)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.034***	1.034***
						(0.009)	(0.009)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.962***	0.962***
						(0.009)	(0.009)
$Stock\ GERD\ government_{t-1}$						0.996	0.989
						(0.024)	(0.033)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.956***	0.956***
						(0.009)	(0.009)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.044***	1.044***
						(0.009)	(0.009)
$Stock\ GERD\ HES_{t-1}$						1.347***	1.310***
						(0.140)	(0.131)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.940**	0.939**
						(0.028)	(0.027)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.045	1.045
						(0.047)	(0.048)
$GDP\ per\ capita$		0.983		0.975		1.020	
		(0.016)		(0.015)		(0.023)	
$Tertiari\ education$			0.991		0.982		1.006
			(0.013)		(0.012)		(0.015)
$Constant$	0.013***	0.005***	0.004***	0.005***	0.005***	0.002***	0.002***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
$Random\ Part\ of\ the\ Model$							
$ln(alpha)$	0.568***	0.567***	0.567***	0.567***	0.567***	0.567***	0.567***
	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)
$Variance\ (Region)$	0.103	0.077	0.078	0.070	0.067	0.023	0.028
$Variance\ (Firm - Region)$	4.138	4.132	4.132	4.132	4.133	4.134	4.132
$Observations$	24,174	24,174	24,174	24,174	24,174	24,174	24,174
$Number\ of\ groups$	17	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	4943***	4924***	4924***	4877***	4886***	4769***	4774***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	21.13***	15.72***	15.72***	13.35***	11.60***	1.393	2.380*
$Wald\ Test\ Mean\ values\ (Mundlak)$	949.3***	857.4***	864***	792.8***	791.4***	807***	805.9***
$Wald\ Test\ Time\ dummies$	798.1***	790.9***	813.7***	780.9***	809***	819.4***	810.9***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

Table A.17. Including jointly both measures of regional knowledge endowment

VARIABLES	(1) *NIP*	(2) *NIP*	(3) *NIP*	(4) *NIP*	(5) *NIP*	(6) *NIP*	(7) *NIP*
$Cooperation_{t-1}(dummy)$	1.308***	1.242***	1.242***	1.303***	1.303***	1.375***	1.374***
	(0.062)	(0.081)	(0.081)	(0.098)	(0.098)	(0.115)	(0.114)
$Outsourcing_{t-1}(dummy)$	1.158**	1.284***	1.284***	1.245**	1.246**	1.194	1.194
	(0.083)	(0.110)	(0.110)	(0.128)	(0.128)	(0.169)	(0.169)
$Firm\ level\ controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Regional\ stock\ of\ patents_{t-1}$		1.084**	1.050	1.081**	1.046	1.141	1.209
		(0.044)	(0.046)	(0.041)	(0.043)	(0.178)	(0.191)
$Cooperation_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		1.029*	1.029*				
		(0.015)	(0.015)				
$Outsourcing_{t-1}(dummy)$ * $Regional\ stock\ of\ patents_{t-1}$		0.947**	0.947**				
		(0.020)	(0.020)				
$Stock\ GERD_{t-1}$		1.014***	1.014***	1.015***	1.015***		
		(0.005)	(0.005)	(0.005)	(0.005)		
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				1.000	1.000		
				(0.003)	(0.003)		
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD_{t-1}$				0.996	0.996		
				(0.004)	(0.004)		
$Stock\ GERD\ business_{t-1}$						0.924	0.921*
						(0.045)	(0.043)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						1.022***	1.022***
						(0.006)	(0.006)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ business_{t-1}$						0.973***	0.973***
						(0.007)	(0.007)
$Stock\ GERD\ government_{t-1}$						1.041	1.056
						(0.070)	(0.068)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						0.976***	0.976***
						(0.005)	(0.005)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ government_{t-1}$						1.025***	1.025***
						(0.005)	(0.005)
$Stock\ GERD\ HES_{t-1}$						1.198**	1.175**
						(0.095)	(0.082)
$Cooperation_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						0.957**	0.957**
						(0.020)	(0.019)
$Outsourcing_{t-1}(dummy)$ *$Stock\ GERD\ HES_{t-1}$						1.039	1.039
						(0.034)	(0.034)
$GDP\ per\ capita$		0.974*		0.974*		1.024	
		(0.015)		(0.015)		(0.023)	
$Tertiari\ education$			0.983		0.983		1.013
			(0.013)		(0.013)		(0.014)
$Constant$	0.013***	0.006***	0.005***	0.006***	0.005***	0.002***	0.002***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
$Random\ Part\ of\ the\ Model$							
$ln(alpha)$	0.568***	0.568***	0.568***	0.568***	0.567***	0.567***	0.567***
	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)
$Variance\ (Region)$	0.103	0.067	0 .068	0.068	0.068	0.018	0.022
$Variance\ (Firm - Region)$	4.138	4.133	4.134	4.133	4.134	4.136	4.134
$Observations$	24,174	24,174	24,174	24,174	24,174	24,174	24,174
$Number\ of\ groups$	17	17	17	17	17	17	17
$Likelihood\ ratio\ test\ Firm\ random\ intercept$	4943***	4895***	4900***	4881***	4887***	4759***	4758***
$Likelihood\ ratio\ test\ Region\ random\ intercept$	21.13***	12.59***	12.59***	12.60***	11.90***	0.852	1.561
$Wald\ Test\ Mean\ values\ (Mundlak)$	949.3***	809.9***	810.3***	795.6***	795.7***	803.9***	817***
$Wald\ Test\ Time\ dummies$	798.1***	791.6***	819.1***	780.6***	808***	832***	817.9***

Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Incidence rate ratios. Means and time fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a χ^2 distribution because it is not on the boundary of the parameter space. We corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89).

CHAPTER 4

What effect does the aggregate industrial R&D offshoring have on you? A multilevel study

4.1. Introduction

The Open Innovation literature has posit into consideration the relevance of the acquisition of knowledge external to the firm in order to survive, grow, and to approximate to leadership (Chesbrough, 2003). In the 1960s and 1970s it was seen as a small contributor to firms' innovative processes since it was developed by just 5 percent of companies (OECD, 2008). Nowadays, enterprises have noticed the importance of R&D offshoring as an essential step for increasing their innovative activity as highlighted by Murphy and Siedschlag (2015). In the present study, I refer to R&D offshoring as the market based transaction through licensing and/or contractual agreements of a client enterprise acquiring external R&D from another institution located abroad (Cusmano et al., 2009), also known as offshoring outsourcing (Nieto and Rodríguez, 2011) or international outsourcing (Phene et al., 2006).

A large number of studies have identified R&D offshoring as a mechanism by which firms could not just complement internal sources of knowledge (Añón-Higón et al., 2014; Cassiman and Veugelers, 2006), but also improve the likelihood as well as the intensity to innovation (Arvanitis et al., 2015; Bertrand and Mol, 2013; Nieto and Rodríguez, 2011). Nonetheless, scholars highlight the relevance of accessing to new and different ways of thinking and making, that is, to a different national innovation system (NIS). This is very important in the sense of not being trapped by the knowledge developed at home while being in contact with the newest ideas in the international markets (Phene et al., 2006).

However, too much R&D offshoring at the firm level may have negative consequences. Recent literature has paid less attention to the drawbacks of this, with just very few exceptions (Grimpe and Kaiser, 2010; Laursen and Salter, 2006; Mihalache et al., 2012). For instance, Kotabe (1989) studies the processes by which acquiring foreign knowledge may hamper the US multinational enterprises (MNEs) at home, since companies might lose their internal capacity and depend too much on foreign R&D, what is known as "hollowing-out". However, he suggests that even in the case of loss of jobs and know-how at home, it is good for the company to acquire foreign knowledge, since it takes advantage of a different technology developed abroad while increasing its overall R&D and international competitiveness. Yet, focusing on the search of external knowledge on a wider variety of sources can outweigh the benefits of acquiring external knowledge after a certain threshold (Laursen and Salter, 2006). Going abroad in search of new and different knowledge is not an easy task, it requires attention from the managers and is time consuming, possibly ending in higher organizational problems (Baier et al., 2015). Moreover, domestic companies may lack the ability to efficiently implement foreign knowledge at higher degrees of R&D offshoring as posit by Steinberg et al. (2017). Still, just a few studies try to investigate whether this process of too much offshoring has a negative effect in the firm's resource base possibly ending in a negative impact on their innovative performance as pointed out by Grimpe and Kaiser (2010).

Do the results in the studies surveyed above imply that higher degrees of R&D offshoring only affect firms acquiring such knowledge? Most studies tend to analyze R&D offshoring at firm level. However, the problem is that the context also affects firms' performance (van Oort et al., 2012), and focusing on just one level may generate an incomplete analysis (Backman, 2014). As suggested by Chesbrough (2003) there is a real possibility of underinvestment in basic research at the industry level diminishing the pool of knowledge to guarantee long-term industry growth when doing too much offshoring. Nevertheless, even though much of this research is focused mainly on MNEs in the manufacturing sector, much less is known about the importance of the sectoral context. In fact, we still do not know whether the aggregate industrial degree of offshoring externalities affects firms in a given industry, and up to what extent industries with higher shares of R&D offshoring may have a pervasive effect on its firms' innovative performance.

Having that in mind, the present chapter focus on the influence of sectoral R&D offshoring on the innovative performance of enterprises. Due to differences in learning processes, technological regimes, and knowledge base, the relevance of international spillovers may fluctuate across industries due to different channels of knowledge transmission like for instance R&D offshoring (Malerba et al., 2013). Therefore, the contributions of the study are the following: first, I study the influence of the aggregate acquisition of foreign knowledge in a given industry on firms' innovative performance; and up to what extent this relation might be non-linear. I argue that a relative increase in industrial R&D offshoring has a positive influence in firms' innovativeness, but only until an intermediate threshold; thereafter, higher levels of offshoring may end in pervasive forces inducing negative returns.

Second, I investigate whether the return firms take from the offshoring at the sectoral level is also a matter of firms' characteristics. With regard to this, the benefits and cost of the aggregate R&D offshoring may have an important firm level component that moderates the hypothesized non-linear relation with respect to firm's innovativeness. For instance, firms having a broader internal knowledge base present a higher innovative performance, reducing the negative effects from firms' over-outsourcing (Grimpe and Kaiser, 2010; Steinberg et al., 2017).

Third, contrary to previous studies focusing only on particular industries using one level of aggregation as posit by Malerba (2002), I use a rich dataset covering not just manufacturing but also service sectors. Most of the literature analyzing R&D offshoring at firm level is based on cross sectional analysis using CIS-type surveys. Indeed, using an inter-sectoral analysis through a hierarchical model, the present chapter gives a step forward in studying to what extent the R&D offshoring is equally/unequally relevant in certain industries, while controlling by other sectoral as well as enterprises' characteristics, something unexplored in the literature.

Using the technological innovation panel (PITEC) for Spanish firms in the period 2005-15 as well as a multilevel framework, I find an inverted U-shape relation between the aggregate sectoral R&D offshoring and the enterprises' innovative performance. However, I also find this relationship is heterogeneous with respect to firms' internal characteristics, changing the return they obtain from their sectoral environment.

The outline of the chapter is as follows: In section 4.2, I provide the literature review as well as the conceptual framework of the study. Next, in section 4.3, I offer the dataset while the methodology is given in section 4.4. Section 4.5 presents the main results of the study, and finally, I conclude.

4.2. Literature review and conceptual framework

4.2.1. Firm's R&D offshoring. One of the advantages of the internationalization of the offshoring strategy comes from the fact that firms—thanks to the new information and communication technologies (ICT)—get access to resources owned by foreign enterprises or foreign institutions, as well as gain access to international talent (Youngdahl and Ramaswamy, 2008). Therefore, it is expected that R&D offshoring improves firms' productivity and gives a better access to a well prepared and cheaper labor force (Belderbos et al., 2013; Lewin et al., 2009).

Previous studies have identified R&D offshoring as a mechanism by which firms could not just complement internal sources of knowledge (Añón-Higón et al., 2014; Cassiman and Veugelers, 2006), but also improve the likelihood as well as the intensity to innovation (Arvanitis et al., 2015; Bertrand and Mol, 2013; Nieto and Rodríguez, 2011). For instance, Martinez-Noya et al. (2012) stress that the higher the international experience of the manager, the higher the likelihood of success of the offshoring strategy, suggesting that the international experience allows to detect in a finer way, the specific locations from which it may be more profitable for firms to take advantage of knowledge specificities.

Another relevant advantage is the access to a new and different way of thinking and making, that is, to a different national innovation system (NIS). This is very important in the sense of not being trapped by the knowledge developed at home while being in contact with the newest ideas in the international markets. The fact of being in contact with institutions presenting national differences in education and training, in market regulations, in industry specializations, culture and preferences, etc. (Phene et al., 2006) makes that the combination/implementation of such a knowledge may end in new products having higher returns for the enterprise (Tojeiro-Rivero et al., 2018). The latter is more pronounced when technological and cognitive proximities between firms exist due to the improved efficiency in the recombination of knowledge (Cohen and Levinthal, 1990). For instance, Phene et al. (2006) find that in presence of technological proximities, the international outsourcing between two given enterprises generates breakthrough innovations.

4.2.2. Firm's R&D offshoring: the more the better? Recent contributions highlight that too much offshoring can lead to a decrease of the marginal return of this external R&D acquisition. One reason behind is that geographical distance could imply an opportunistic behavior, increases the transmission cost and increase the cultural and institutional distance, leading to a difficulty at the time of implementing the foreign knowledge (Larsen et al., 2013; Mol, 2005; Teece, 1987). Another reason is the fact that when a firm relies strongly on external knowledge, it can lose its specific resources hampering its internal capabilities, while implying a greater difficulty in case of dealing with many contractual actors (Kotabe et al., 2007).

Following the latter, the hollowing out concept Kotabe (1989) stresses that the dependency on external knowledge implies a reduction of the internal capabilities of the firm. In part, because of the substitution effect of the former over the latter, but also because the company loses its control on the R&D process, and the cultural and institutional distance harms the implementation of such external knowledge. In addition, not having the control on the R&D process may encompass a lower quality of the technology acquired since the contracting firm cannot follow all the steps of the process.

It is clear that going further in the internationalization of the acquisition of knowledge has an incorporated cost, since wider differences in organizational and internal capabilities lead to a more difficult understanding of the foreign knowledge. At the same time, it can take resources from the internal investment in R&D taking into account that outsourcing is time consuming and most of the time need renegotiation as highlighted by Weigelt (2009). Specifically, in those cases in which the contracted firm fails in the development of the project being the manager of the contracting enterprise the one taking control of the offshored process, implying less time for monitoring core activities (Grimpe and Kaiser, 2010).

Studying the same non-linear behavior coming from the firm's R&D offshoring but from a managerial perspective, Baier et al. (2015) found a threshold level of offshoring beyond which organizational management is more complex. Even more, they stress the idea that making R&D offshoring can be detrimental for those enterprises that have a local network in the sense of losing the local connections with suppliers and/or customers.

4.2.3. The importance of the sectoral context. The benefits of R&D offshoring might depend not just on the firm specificities, but also on the sectoral context. Nonetheless, based on the analytical and conceptual studies of Sectoral Innovation System (SIS) (Malerba, 2005, 2002), some authors have argued that aspects like the knowledge base, the technological regime, that is, opportunity, appropriability, and cumulativeness, historical and institutional characteristics, as well as the economies of scales or path dependence processes, may be sectoral specificities (Edquist, 1998, chapter 6).

It is important to notice that because of similar knowledge base, problem-solving techniques, and interpretative schemes of new knowledge, an enterprise placed in one region is in some way expected to be connected with other firms within the same industry but located in other regions or in the same region. Therefore, as stated by Malerba and Adams (2014) "firms within the same sector face the same set of technologies, search within a similar knowledge base, will undertake similar production activities, and will be embedded in the same institutional setting". The result of this is that within a given sector, firms will show similar learning patterns, as well as will present similar behaviors in terms of product generation, while being bounded by similar organizational forms. All this, linked to a standard and easy to codify type of knowledge, that tend to be the case in R&D offshoring, will make geographical proximity less relevant—as in the opposite case of technological collaboration with the need of more tacit knowledge (Teirlinck and Spithoven, 2013).[1] Therefore, other types of proximities, like cognitive and organizational (Boschma, 2005), have a higher relevance here since the ICT allow this type of knowledge to travel easily across geographical borders. Hence, the common knowledge, technological trajectories, and learning processes, may propitiate closeness among the firms pertaining to a given sector.

From the company point of view, it is important to understand how firms' innovative performance take advantage from their sectoral context. Ornaghi (2006) studies how sectoral spillovers affect firms' productivity, building an externality measure—using the R&D activity of firms—based on firm's size and sector. He finds that sectoral R&D externalities have a positive role in explaining firm's productivity for Spanish manufacturing enterprises. Industries with a higher share of R&D intensity performs better not just at the industry level but also at the firm level, being a direct determinant of firm's performance (Short et al., 2006). For instance, Amoroso (2017) studies how firms' collaboration strategies as well as firms' innovative output could be affected by sectoral heterogeneity for the case of the Netherlands, finding that sectoral level of concentration and legal protection, as well as sectoral heterogeneity in government R&D funding, are positively associated with firms' collaborations strategies and innovative output.

Consequently, it is sensible to think that the aggregate industrial level of offshoring to which the firm belongs to, might be highly beneficial for firms seeking to take advantage of market novelties. The latter can be translated into complementarities between the firm's internal knowledge and the one coming from abroad, generating synergies through better relations based on trust, and the improved experience and skills of those firms pertaining to a given industry. On top of that, Short et al. (2006) find that an industry with more experience/level of R&D may present a higher firm's performance. The latter connects with the access to a higher pool of different and novel type of ideas coming from dissimilar

[1] Studies of the national or regional contexts have the aim of understanding the role of local institutions, government policies, among others, in influencing the innovative performance of firms. However, they do not analyze how the innovation across geographical boundaries are affected by sectoral characteristics (Malerba and Adams, 2014). Unfortunately, geographical location of firms is not present in the PITEC database.

NIS possibly ending in more externalities within the industry through the interchange of such a knowledge through other mechanisms, like the firm's networking strategies or knowledge spillovers. Thus, building on previous evidence, firms' innovative performance may depend positively on the firm's acquisition of R&D offshoring (Laursen and Salter, 2006; Mihalache et al., 2012; Nieto and Rodríguez, 2011) as well as on the pool of general knowledge it has access to in a given sector (Amoroso, 2017; Goya et al., 2016; Ornaghi, 2006).

However, even though the entrance in the sector of a dissimilar pool of knowledge thanks to R&D offshoring may imply a way of taking advantage of foreign knowledge, not just for firms going abroad in search of such a knowledge but also for those firms not having the means for it but taking profit through internal interchange of knowledge. There is a real possibility of underinvestment in basic research at the industry level diminishing the pool of knowledge to guarantee long-term industry growth when doing too much offshoring (Chesbrough, 2003). Therefore, the more a sector relies in knowledge acquisition from abroad, the less knowledge base and internal capabilities are developed by the home firms putting in check the whole sector.[2]

Taking the above evidence, I believe that sectors presenting a relative increase in sectoral R&D offshoring has a positive influence in its firms' innovativeness, but only until an intermediate threshold; thereafter, the deterioration of the sectoral internal capacity might be determinant for sectors with high level of R&D offshoring inducing negative returns. Therefore, my first hypothesis arises.

H1. The relation between sectoral R&D offshoring and its firms' innovative performance follows an inverted U-shape.

4.2.4. The role of firms' heterogeneity. The latter is open to criticisms, since it assumes that all firms in a given sector can take the same benefit/damage from their industrial context. However, the return coming from the industrial R&D offshoring may well depend on the firm's internal capacity to build and recombine new ideas. For instance, elaborating on Malerba and Adams (2014), firms pertaining to the same industrial context will be more alike than firms from different industries, due to among other things, the share of similar technologies,

[2] The reader must notice that this is different from the hollowing-out concept in Kotabe (1989), since in that case it was stated for multinationals having a subsidiary abroad, also known as captive offshoring; while the present study also focuses on knowledge acquisition coming from a third party as well as public research centers abroad. Therefore, contrary to Kotabe's case, an enterprise may end losing internal capabilities—and therefore the whole sector—since the knowledge may not be generated by a subsidiary abroad and thus, the enterprises' know how is lost.

same labor market policies, and the same product life-cycle (van Oort et al., 2012). However, this does not preclude the heterogeneity among enterprises from within sectors. Therefore, despite the technological proximity; differences in the learning processes, in competences, as well as in managerial capabilities, will induce heterogeneity within the context (Malerba, 2002; Phene et al., 2006).

The extent to which firms benefit from R&D offshoring, may depend on their scale, their internal capabilities, and their networking strategies to strengthen firms' absorptive capacity. Smaller firms, which on average have lower resources—for instance, researchers, R&D funding, laboratories—may have a disadvantage over larger firms for going abroad in search of novel technologies. Therefore, if resource constraint is an important obstacle to innovation, then, smaller firms will have a handicap with respect to larger firms since their smaller innovative project portfolios on the one hand, and their higher risk for technological stealing on the other (Narula, 2004) will reduce their opportunity to access directly to R&D offshoring processes. Besides, smaller firms might depend more on their context externalities as evidenced by Backman (2014) for the case of industries and López-Bazo and Motellón (2018) and Tojeiro-Rivero and Moreno (2019) for the case of regions. Thus, they could take more profit from an increasing pool of knowledge in their industries coming from foreign sources with respect to LEs, since LEs might be less dependent on their contextual environment.

However, an important issue is that the firm might need at the same time certain level of internal capacity and experience in R&D processes as evidenced by Grimpe and Kaiser (2010) and Steinberg et al. (2017) in order to develop the necessary skills to understand and implement such dissimilar knowledge. Therefore, it may be that the larger the firm is—large firms have more resources and are more open than smaller firms—the better, since it would imply a higher internal knowledge base (Teirlinck and Spithoven, 2013). These firms are more prone to re-elaborate and benefit from this specific type of knowledge present in their context. Nonetheless, they may present a higher availability of internal resources, thus, presenting a higher level of recruitment of specialized workers, as well as a higher level of management experience in networking which help in identifying the best choice among different knowledge sources. On the other side of the coin, larger firms may be too much exposed to this knowledge spillover precisely because its scale advantage and therefore, present higher negative returns coming from their sectoral externalities when the industry presents the highest levels of such spillovers. In such a case, the greater industrial reliance on this externality may induce the loss of those necessary skills and investments to adopt foreign market novelties.

These arguments lead to the following hypothesis.

H2. At low-to-intermediate levels of industrial offshoring, large enterprises in such a sector obtain higher returns from industrial offshoring. However, they will be more affected (showing lower returns) in those industries presenting the highest levels of industrial offshoring.

Previous studies have identified R&D offshoring as a mechanism by which firms could complement internal sources of knowledge and the other way around (Añón-Higón et al., 2014; Cassiman and Veugelers, 2006). This is because, according to the complementary relationship, the marginal increase of adding one activity—offshoring—when already performing the other—internal R&D—is larger than the marginal increase from performing only one activity—offshoring. Therefore, a company with higher levels of internal R&D could take more advantage of the entire pool of offshored knowledge in a given sector. Additionally, if enterprises in a given industry are developing new ideas/knowledge internally, then, the danger posit by high levels of industrial R&D offshoring may be mitigated. Furthermore, the industry keeps building new capabilities, and this is done through learning by doing and training processes which foster the generation of tacit knowledge (Grimpe and Kaiser, 2010).

Firms with more levels of human capital might have an advantage due to a more likely novel recombination of incoming knowledge thanks to their experienced routines and skills (Grimpe and Kaiser, 2010; Martinez-Noya et al., 2012). This is especially true since the knowledge embedded in individuals can be thought as a tacit type of knowledge, which is hard to codify and share, and thus, highly profitable for firms looking for internalizing their knowledge spilling over. Hence, the level of education and training present in the workforce of enterprises might lead to an increase in the capacity of managers and employees to identify certain type of knowledge specificities, acquire information, as well as to implement innovations developed elsewhere as highlighted by Backman (2014).

Therefore, I expect higher levels of absorptive capacities of firms to positively influence the inverse U-shape pattern of industry R&D offshoring, as posit in the next hypothesis.

H3. At high levels of industrial offshoring, enterprises with higher levels of absorptive capacity obtain higher returns from such industrial offshoring.

Some scholars have pointed the fact that internal capabilities goes beyond the absorptive capacities characterized by Cohen and Levinthal (1990); for instance, Spithoven and Teirlinck (2015) highlight that on top of internal R&D efforts, networking is key for strengthening firm's internal capabilities. Hence, firms having collaborative and offshoring relations with other institutions will be more open to external knowledge (Laursen and Salter, 2006). Therefore, they might be less dependent on their sectoral context since they can more easily go abroad and explore new sources of knowledge while acquiring it directly from knowledge suppliers. The latter is linked to the idea that an enterprise that can access directly foreign knowledge through networking strategies, might be less dependent on the pool of a similar knowledge generated in their sectors, since it may be redundant. On the opposite, those firms with lower degrees of openness showing lower levels of experience in such strategies may be more prone to take advantage of such knowledge spillover generated in their sector. However, lower degrees of networking experience also imply that firms will present lower capacity to develop novel innovations since as suggested by Chesbrough (2003) they may end trapped in internal ways of doing not able to adopt novel insights developed elsewhere. Consequently, those firms presenting lower networking experience will have lower capacities to get rid of too much R&D offshoring in their sector not because they do not want to, but probably because they cannot manage such amount of information, with higher costs for searching, detecting, and implementing such technologies, and thus, not able to benefit from the highest levels of such externalities.

Given the above arguments, I expect that technological collaboration and R&D offshoring experiences at the firm level influence the relationship between industrial R&D offshoring and firms' innovative performance. Therefore, the next hypothesis arises.

H4. At high levels of industrial offshoring, enterprises with higher levels of firm's networking experiences will obtain higher returns from such industrial offshoring.

4.3. Dataset and variables

4.3.1. Dataset. The dataset I use is the Technological Innovation Panel (PITEC) which is an unbalanced panel tracing the innovation activity of Spanish enterprises from 2003 until 2015. It uses two surveys: the first—Survey on Technological Innovation of Firms—is the Spanish counterpart to the Community Innovation Survey (CIS) from the Eurostat, following the guidelines of the Oslo Manual; the second is the Statistics on R&D Activities. The PITEC database offers direct measures of the innovation output as product and process innovations—instead of relying only on measures of semi-output, such as patents, or on inputs, such as R&D expenditures.

The PITEC is representative of small and medium-size as well as large firms; enterprises with internal R&D expenditures, as well as those with external R&D expenditures without having internal R&D; and finally, those small and medium-size firms without any expenditures on innovation. The stratification of the sample is for all the business sectors that are included in the National Classification of Economic Activities (NACE two-digit level) (see Table 1); and the representativeness of the panel is assured thanks to the annual inclusion of firms with similar characteristics to those that disappear from the sample. The response rate is very high due to the fact that it is mandatory for firms, and the territorial covering is the whole Spanish Economy.[3] The PITEC is a survey in which values are self-reported, however, in this kind of survey, where anonymity is a legal concern, there is not a systematic propensity for over- or under-reporting the innovation that is carried out by the enterprise (Aarstad et al., 2016).

My sample covers the period 2005-15,[4] with around 12,000 enterprises. However, after deleting missing values, considering only companies with more than 10 workers, dropping those observations for firms that declare having products innovations while not presenting innovative expenditures, as well as those outliers with more than 20 percent of market share in a given sector,[5] the final sample is around 8,200 enterprises.

4.3.2. Firm level variables. In the PITEC survey, firms are asked whether they have developed product innovations in the current year or in the previous two years. Using this information, I proxy for the innovative output of enterprises which is my dependent variable (PI) equal to one in case the enterprise developed product innovations in the current year or in the previous two years, and zero otherwise (López-Bazo and Motellón, 2018; Naz et al., 2015; Srholec, 2010). Moreover, building on previous evidence, the reason to focus on product instead of process innovations is that the acquisition of knowledge external to the firm

[3]More details on the sample, the quality and validation of the information can be obtained from: https://www.ine.es/dynt3/metadatos/es/RespuestaDatos.html?oe=30061

[4]Due to a methodological change, the year 2003 is discarded, some variables do not present data for the year 2004, so that I have decided to discard it too.

[5]Firms with more than 20 percent of the market share in a given sector represent around 0.05 percent of total observations in the sample. The threshold of 20 percent of the market share was chosen following previous evidence that is also based on the PITEC survey, such as López-García and Montero (2010). Additionally, in the case of those observations for which internal R&D expenditures are more than two times the volume of sales, I have replaced such values with a maximum value of 2—representing around 0.5 percent of total observations. Although the selection of a value of 2 is arbitrary, other smaller values did not imply any change in the results. These additional estimates are available upon request.

through R&D offshoring has a higher impact on product rather than on process innovations (Bertrand and Mol, 2013; Nieto and Rodríguez, 2011). The latter has to do with the type of knowledge required, which for product innovations tends to be more explicit, while for process innovations, organizational closeness among the enterprises is also required (Phene et al., 2006), which is more difficult. Therefore, as the knowledge embedded on R&D offshoring is assumed standard and codified and is less bounded by geographical proximities, it is expected to impact more on product rather than on process innovations.

Firms' R&D *Offshoring* is measured as a dummy variable equal to one in case the enterprise presents external R&D expenditures in knowledge generated abroad, and zero otherwise (Arvanitis et al., 2015; Bertrand and Mol, 2013; Cusmano et al., 2009). To control for other firm characteristics I use *Collaboration*, which has been observed to have an important role on product innovation (Robin and Schubert, 2013). It captures whether the firm acquires external knowledge through other channels, and it is measured as a dummy variable equal to one if the firm cooperates in the current year or in the previous two years with other organizations and zero otherwise. For accounting for internal capabilities of firms (Cohen and Levinthal, 1990), I use the amount of *internal R&D* as proportion of total sales (Cassiman and Veugelers, 2006; Spithoven and Teirlinck, 2015). However, previous scholars recognize that this is a limited way of accounting for the internal capabilities of enterprises. Therefore, I include also the amount of workers with tertiary education and/or training in R&D (as proportion of total workforce), *Human capital*. This way, I intend to take into account the effort and productivity in the innovation process, something not accounted by the internal R&D variable alone, as posit by Griffith et al. (2006).

In addition, *Size* is a categorical variable accounting for the number of total workers, going from 10-49 (*small*), 50-200 (*Medium*), 201-499 (*LEs*), and 500 or more (*very large*) taking small firms as the base category. For controlling by cohort effects, I use the firm's *Age*, which is measured as the current year minus the born year. Additionally, *Foreign* measures the fact that the company belongs to a multinational group of enterprises implying better financial and innovative environments being a dummy variable equal to one in case the firm belongs to a multinational group with more than 50 percent of its capital from abroad and zero otherwise (Belderbos et al., 2013; Srholec, 2010). Finally, the variable *Market* tries to capture the importance of accessing foreign markets with the idea that a firm facing more competition tends to be more innovative and more competitive.

This variable is a categorical variable representing *Regional, National, EU,* and *Rest of the World* firm's markets with Regional being the base category.

4.3.3. Sectoral variables. The interest of the present study is on the relation between the industrial context, and specifically, the industrial acquisition of foreign knowledge and the firms' innovative performance. Therefore, including sectoral-level variables allows me to capture variations in the product innovation of firms not captured by firm's characteristics. However, the information on the external R&D expenditure—offshoring—at the industry level is not present in any other sectoral representative database as for instance, Eurostat or the Spanish National Institute of Statistics (INE). Therefore, since the PITEC is stratified at the industry level, I can aggregate the R&D offshoring at the NACE two digit level (see Amoroso, 2017; Goya et al., 2016; Ornaghi, 2006). Consequently, *Sec. Offshoring* measures the percentage of firms doing R&D offshoring in a given industry. With this, I proxy for the amount of units acquiring foreign knowledge at the industry level, which helps me to study if too much offshoring may have a pervasive effect on the likelihood of generating new product innovations.

In addition, on top of accounting for industry heterogeneity using sectoral random effects, as will be commented in section 4.4, it is highly important to control for other industry characteristics in order to isolate specifically the relation between the two variables of interest, avoiding the bias due to confounding with other context specific characteristics (Manski, 1993). Thus, I account for the industrial investment on internal R&D (*Sec. Internal R&D*) which is measured as the average industrial share of internal R&D over the total industrial sales in the whole period. This is an important control since everything else equal, sectors with higher share of internal R&D expenditures may show a higher propensity to develop more innovations; however, it may also serve as an entry barrier, and thus, reduce the opportunity and incentive to innovate. Besides, higher levels of concentrations may also induce knowledge diffusion since firms can better internalize knowledge externalities (Amoroso, 2017). Therefore, for measuring industry competitiveness, a Simpson/Herfindahl-Hirschman Index (*HHI*) of concentration is used for each industry in a given year using the firm's market share, where t is the time, i is the firm, and j is the sector.

$$ms_{tij} = \frac{sales_{tij}}{\sum_{j=1}^{J} sales_{tij}} \qquad \forall t = 1...T \tag{4.1}$$

$$HHI_{tj} = \sum_{i=1}^{I} (ms_{tij})^2 \qquad \forall t = 1...T; \forall j = 1...J \tag{4.2}$$

Thereafter averaging for the whole period as follow:

$$HHI_j = T^{-1} \sum_{t=1}^{T} HHI_{tj} \tag{4.3}$$

Finally, as stated by Malerba (2002), I account for the industry level of appropriation which on the one hand is measured as the industry percentage of firms using other ways of proprietary methods as utility models, trademarks, and/or Copyrights (*Appropriation*); and on the other hand, it is measured as the industry percentage of firms patenting (*Patents*).

In addition, I introduce time and technological sectoral fixed effects for accounting for the technological level of the industries, as well as one year lagged explanatory variables for lessening simultaneity problems.[6]

It is important to highlight that all industrial variables do not vary at lower levels if analyzing inter-sectoral differences using the multilevel methodology as it is the aim of the present study. Therefore, I averaged for the industry the ones having a yearly variation (Short et al., 2006). Otherwise, you may end analyzing an average of the within- and between-sector with an erroneous effect without an economic interpretation (Bell and Jones, 2015).

4.4. Methodology, empirical strategy, and specification

4.4.1. Methodology. Even though hierarchical models have been used for some time now in other economic fields such as health economics and education economics, it is quite recent that researchers have realized of its importance for accounting for context's differences to analyze sectoral/regional effects (Corrado and Fingleton, 2012). With this, I expect to consider the hierarchical structure of the dataset for the effect of those sectoral characteristics affecting/moderating the measure of innovative performance of the firm. There are some theoretical and empirical reasons that drive me to consider the use of the multilevel model, also known as hierarchical or mixed models.

[6]Especially at the firm level, since the sectoral classification is high enough to guarantee no reverse causality, and thus, it is unlikely that a single firm can affect the whole sectoral environment (see section 4.5.3 for a robustness check using two lags of the explanatory variables).

First, the hierarchical structure of the data is not taken into consideration if using an OLS estimation assuming independence of units, since the correlation among those observations pertaining to a given firm (different years), as well as those firms pertaining to a given sector due to the presence of common factors, is left out.[7] This is highly important since the standard errors would be artificially lower ending with a more likely false positive—type error I—in the coefficients (Snijders and Bosker, 2012). Second, the multilevel approach allows to model variances instead of means, which helps to identify the role of firm and industry characteristics separately on the firm's innovative performance using random intercepts for both levels.

Third, in order to guarantee causal estimations as in the Fixed effects approach, I follow Mundlak (1978); this way I estimate the same within—causal—effects as in the Fixed effects case. Due to the fact of possible correlation between the fixed part of the model and the random part of the model, this correction is highly important, otherwise leading to inconsistent estimations (Rabe-Hesketh and Skrondal, 2012). Moreover, the Fixed effect estimation only looks for within variability which in the present study is the lowest (see Tables A.1-A.2 in the appendix A), reason why the Hausman test adds no information. On the one hand, the Mundlak correction permits the model to give within effects, and on the other hand, the use of higher-level variables—not varying for lower level units—invalidate the results of the Hausman test since it does not account for the effect of time and firm invariant population parameters. In fact, running a Wald Test on the means of firm level variables is equivalent to the Hausman test (Rabe-Hesketh and Skrondal, 2012). On top of that, the traditional approach—Fixed effects—excludes the sectoral variation controlling for it using sectoral dummies (Bell and Jones, 2015). Instead, the aim here is to explain such variation.

4.4.2. Empirical strategy. Even though the reader may think that the decision to start an enterprise in a given sector is not random, as there is not any planner that decides in which sector to put a given firm, it is also true that owners of firms do not decide to start a company in a given sector because such an industry is performing better in terms of R&D offshoring. The latter might be related to other reasons; for instance, having previous knowledge/experience in the sector, market, etc. which can be taken as independent of the offshoring performance in

[7] Notice that this might be solved with cluster robust errors. However, the latter does not allow to study the heterogeneity among groups but to control for it, possibly leading to a misspecified model. On top of that, it is less efficient and requires homogenous clusters (which is not the case here) (Snijders and Bosker, 2012).

a given sector. Therefore, I do not expect a huge selection problem. Unfortunately, random assignments cannot be done, nor to control for self-selection using observed information in the model due to unavailable information on the reason behind the change of sectors in the database. However, the multilevel structure helps me to control for unobserved heterogeneity at firm and sectoral levels, thus, controlling for sorting issues.

Moreover, as the objective of the chapter is the study of inter-sectoral differences, using leave-out means—leaving the firm i out of the industrial R&D offshoring average—instead of total group averages, is nearly the same in econometric terms when the number of firms in a group is high (Angrist, 2014), as it is the present case. However, the leave-out mean is a measure that vary between and within industries, while the total group averages varies just between industries being more appropriate for the aim of the chapter.

4.4.3. Empirical specification. The structure of the data in the present study follows a three-level hierarchy starting with time (t first level) which is nested in firms (i second level) and these are nested in industries (j third level). Besides, instead of assuming a representative firm, and therefore that all firms take on average the same profit from R&D offshoring as in previous studies, it is allowed that the effect of such strategy varies from firm to firm. Therefore, not all firms in different industries should take the same profit from R&D offshoring. The latter is done through a random coefficient for R&D offshoring at the firm level which following Stegmueller (2013) posit no problem in the estimation since the number of higher level units is above 30.

To account for this scheme, the multilevel logit model's reduced form is as follows:

$$y_{tij} = \begin{cases} 1 & if \quad y^*_{tij} > 0 \\ 0 & if \quad y^*_{tij} \leq 0 \end{cases} \tag{4.4}$$

$$\begin{aligned} logit\left\{Pr\left(y_{tij} = 1 | x_{tij}, x_{ij}, z_j, \mu_{0ij}, \mu_{0j}, \mu_{1ij}\right)\right\} = log\left(\tfrac{y_{tij}}{1-y_{tij}}\right) = \beta_0 + \\ + \sum_{m=1}^{M} \beta_{1m} x_{tijm} + \sum_{n=1}^{N} \beta_{2n} x_{ijn} + \sum_{k=1}^{K} \beta_{3k} z_{jk} + \sum_{k=1}^{K}\sum_{n=1}^{N} \beta_{4nk} x_{ijn} z_{jk} + \\ + \sum_{k=1}^{K}\sum_{m=1}^{M} \beta_{5mk} x_{tijm} z_{jk} + \mu_{0ij} + \mu_{0j} + \mu_{1ij} x_{tij} \end{aligned} \tag{4.5}$$

Where y^*_{tij} is a continuous unobserved latent variable (propensity to innovate) that is related to the observed y_{tij}, which refers to the outcome variable; x_{tij}

represents M time-varying firm level variables, x_{ij} are N time-invariant firm level variables as for instance means fixed effects (Mundlak)[8] and technological fixed effects, and z_j are the K sectoral variables. Moreover, $\mu_{0ij} \sim N(0, \sigma_{\mu 0})$, and $\mu_{0j} \sim N(0, \sigma_{\mu 0})$ are the random parts of the model accounting by the unobserved heterogeneity at firm and sectoral level respectively, while $\mu_{1ij} \sim N(0, \sigma_{\mu 1})$ is the random coefficient for the firm's R&D offshoring allowed to vary between different firms with covariance $\sigma_{\mu 01}$.[9] These random effects are assumed independent of each other, of the covariates, across sectors, and μ_{0ij} and μ_{1ij} are assumed independent across firms as well.[10]

However, for the ease of the interpretation I will estimate the model using a linear multilevel specification since the parameter can be directly interpreted as marginal effects. This way, since the study aims is not on the prediction but on the parameters itself, this does not posit a problem. However, in the robustness section (4.5.3), a logit model will be estimated for comparison purposes.

4.5. Results

4.5.1. Descriptive analysis. Table 4.1 shows summary statistics for the sectoral variables. First thing to notice is that the percentage of firms doing R&D offshoring within sectors varies substantially across sectors. Fourteen industries present values above the national average, not presenting the same dynamics through time, that is, having a higher share of firms doing offshoring at the beginning of the period does not guarantee these sectors will maintain such a level time along.[11] More impressive is the size of the differences; sectors like Pharmaceutical or R&D Services present nearly six and four times more of firms acquiring foreign knowledge than national averages, being this independent of the sector's size. With regard to market concentration, it is clear that few sectors are highly concentrated even though the Naval Construction sector presents the highest levels of concentration through all the period. Moreover, the Pharmaceutical industry presents the highest industrial level of appropriation, and the Scientific

[8]Which will be used in the estimation to proxy for the firms' experience in certain characteristics (Offshoring and Collaboration). These parameters will not be shown for space restriction unless necessary.

[9]The covariance between the two random effects at firm level measures the relation between both, therefore not restricted to be zero.

[10]The random part of the first-level, equivalent to ε_{tij} is fixed $\frac{\pi^2}{3}$ since I am estimating a latent class model (see Rabe-Hesketh and Skrondal, 2012).

[11]Because of space restriction, Table 4.1 only reports average values without time evolution.

Research and Development industry presents the highest formal appropriation of knowledge, while presenting different trends throughout the period.

Table 4.1. Descriptive analysis of sectoral-level variables

Sectors	Sec. Offshoring	Sec Internal R&D	HHI	Appropriation	Patent
High tech manufacture					
Pharmaceutical products (21)	27.07	7.38	0.029	36.87	31.06
Computer, electronic and optical products (26)	6.03	12.18	0.037	22.90	15.56
Medium tech					
Chemicals products (20)	6.75	3.28	0.015	26.02	12.15
Rubber and plastic products (22)	7.24	1.73	0.033	19.08	14.81
Other non-metallic mineral products (23)	4.20	1.66	0.018	20.60	8.45
Metallurgy (24)	7.52	0.76	0.033	8.66	9.51
Metal products, excepts machinery and equipment (25)	2.45	1.98	0.014	16.36	12.86
Electrical machinery and material (27)	7.63	3.53	0.040	26.36	22.09
Other machinery and equipment n.e.c. (28)	3.33	3.43	0.014	19.80	19.37
Motor vehicles (29)	13.54	1.93	0.067	12.30	14.77
Naval construction (301)	4.77	9.92	0.158	14.98	6.56
Aircraft and spacecraft (303)	15.49	12.61	0.117	9.41	18.84
Other transport equipment (30)	13.86	2.94	0.118	16.65	21.26
Repair and installation of machinery and equipment (33)	0.68	2.74	0.040	9.35	8.58
Low tech					
Food, beverages, and tobacco products (10-12)	3.12	1.39	0.009	25.86	6.44
Textile (13)	4.93	2.01	0.019	16.28	8.08
Wearing apparel (14)	2.56	2.20	0.089	22.49	4.11
Leather and related products (15)	0.96	1.55	0.069	14.18	5.60
Wood and cork (16)	0.87	0.87	0.075	12.28	5.62
Cardboard and Paper (17)	5.79	0.50	0.043	14.56	7.88
Graphic arts and reproduction (18)	1.10	1.53	0.056	12.15	7.02
Furniture (31)	1.22	1.24	0.030	26.82	14.81
Other manufacturing (32)	6.60	6.05	0.046	32.51	22.95
Knowledge intensive sectors KIS					
Telecommunications (61)	5.54	10.01	0.149	27.16	9.63
Computer programming, consultancy and related activities (62)	2.24	16.67	0.059	22.01	6.60
Information and communications (58-63)	2.27	8.88	0.053	29.23	3.79
Financial and insurance activities (64-66)	2.02	0.83	0.036	19.46	2.35
Scientific research and development (72)	16.10	94.96	0.045	27.89	39.58
Other activities (69-71, 73-75)	2.48	13.47	0.023	15.14	8.83
Education (85 excluding 854)	0.76	7.76	0.075	20.57	1.49
Health activities and social services (86-88)	0.23	4.10	0.037	10.18	3.55
Arts, entertainment and recreation	0.61	1.46	0.090	12.72	1.36
Non-knowledge intensive sectors NKIS					
Wholesale trade (45-47)	1.52	1.10	0.025	16.67	4.78
Transport (49-53)	0.96	0.45	0.038	7.25	2.50
Accommodation and food service activities (55-56)	0.21	0.06	0.022	7.78	0.58
Real estate activities (68)	1.00	3.66	0.076	11.68	2.75
Administrative and support services activities (77-82)	0.45	1.53	0.023	6.73	1.79
Other services (95-96)	2.58	11.82	0.036	16.41	2.87
National averages	4.91	6.84	0.051	18.09	10.29

Offshoring, Appropriation, and Patent are the percentage of firms developing the characteristic in a given sector. Internal R&D is the average industrial share of Internal R&D over the industrial sales (in percentage), and HHI is the concentration index defined in section 4.3.3. In parenthesis is the CNAE09 sectoral code.
Source: Eurostat and PITEC (see page 19 for the industrial classification):
http://www.ine.es/en/daco/daco43/metoite2013_en.pdf

Interesting facts can be extracted from Table 4.2, which describe patterns of firm characteristics in the sample. Enterprises seeking to obtain foreign knowledge present strong differences with respect to knowledge inputs and output when compared to those not purchasing foreign knowledge. When differentiating with regard to this, it is clear that these offshorer enterprises dedicate around three times more internal resources to R&D and they export beyond Europe around 65 percent more than non-offshoring firms. In addition, they present around three times more a workforce with tertiary education dedicated to R&D. Finally, on average they are more innovative presenting almost the double of product innovations. Therefore, it is sensible to think that offshoring firms are in a better position in terms of knowledge inputs/output with respect to other innovative firms not developing an offshoring strategy.

TABLE 4.2. Descriptive analysis of firm-level variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non Offshoring Firms				**Offshoring Firms**			
VARIABLES	Mean	Sd	Min	Max	Mean	Sd	Min	Max
Innovative Performance								
Product innovation (dummy)	0.482	0.500	0	1	0.801	0.399	0	1
Controls								
Collaboration (dummy)	0.359	0.480	0	1	0.649	0.477	0	1
Internal R&D	0.050	0.201	0	2	0.167	0.406	0	2
Human Capital	0.031	0.089	0	1	0.088	0.150	0	1
Size	361.0	1,649	10	41,509	410.9	1,027	10	21,905
Age	27.19	21.19	0	551	30.79	21.89	0	170
Foreign (dummy)	0.109	0.312	0	1	0.291	0.454	0	1
Regional Market (dummy)	0.949	0.218	0	1	0.928	0.258	0	1
National Market (dummy)	0.259	0 .438	0	1	0.069	0.254	0	1
EU Market (dummy)	0.163	0.369	0	1	0.121	0.326	0	1
Rest of the World Market (dummy)	0.480	0.499	0	1	0.794	0.404	0	1

4.5.2. Empirical results. Table 4.3 contains different specifications for studying the influence of the sectoral level of offshoring on the innovative performance of firms. The first specification is the empty model, and only includes the intercept with the objective of determining how relevant firm and industry levels on the firms' product innovations are. For this, the model divides the random part into three[12] and calculates the variance related with firms' as well as with industries' characteristics. Column 1 shows the relevance of using mixed models, thus, since part of the variability of product innovation is due to the statistically significant influence of the industrial context, it is necessary to account for that.

[12]See footnote 10.

Therefore, the model accounts for the similarity between the observations coming from the same firm as well as for the similarity between firms pertaining to the same sector, as shown by the ICC at the bottom of column 1. Similar to previous studies, and even though both are relevant, the model shows firms characteristics being more important than industrial ones for the innovative process (Backman, 2014; van Oort et al., 2012).[13]

The second specification (column 2) includes just firm level variables showing that when accounting by firm characteristics, the industrial context still matters,[14] even though the decrease of the between-sector variance suggests that the distribution of some of the firm variables varies across sectors as illustrated by Figure A.1 in Appendix A. With regard to the fixed part of the model, it is clear that on average offshoring is an important strategy for increasing the probability of product innovations. Looking at the random coefficient variance, we see that it is statistically significant, showing evidence of variability in the effectiveness of offshoring across enterprises. The estimated covariance suggests that offshoring is more effective in firms where product innovation rates are below average having above average effects of acquiring foreign knowledge.

In addition, the rest of controls at the firm level present the expected sign; for instance, collaborating with other institutions is beneficial for engaging in product innovations. With regard to the size, there is evidence of a non-linear effect since larger firms are the most prone to develop a product innovation, even though medium-sized firms are also more likely in developing new products than small firms. Enterprises with export activities, especially to the rest of the world present a higher likelihood of innovating, while younger firms are also more likely to innovate than older ones. Moreover, increasing the amount of R&D workers with tertiary education is highly convenient for the enterprise as stressed by Backman (2014) for the case of firms' productivity, as well as increasing the amount of euros dedicated to internal R&D as proportion of sales. Besides, belonging to an international group of firms does not contribute to increasing the likelihood of product innovations.

Lastly, technological, time, and means fixed effects are jointly significant respectively. This guarantees that the firm level characteristics are not correlated with the firm random effects, which would lead to unbiased parameters. Finally,

[13]See appendix B for the calculation of the Variance Partition Coefficient (VPC) in case of a logit estimation. For the case of the linear models the term $\frac{\pi^2}{3}$ should be substituted by ε_{tij}.

[14]Showing a statistically significant sectoral variance as shown by the LR test as well as an economic significance, since the sectoral standard deviation is more important than the effect of the collaboration parameter pointing to significant economic differences across sectors.

Table 4.3. Effect of Sectoral R&D externalities on firms' product innovation (PI)

VARIABLES	(1) PI	(2) PI	(3) PI	(4) PI
Offshoring (dummy)		0.019*	0.019*	0.019*
		(0.010)	(0.010)	(0.010)
Collaboration (dummy)		0.074***	0.074***	0.074***
		(0.004)	(0.004)	(0.004)
Internal R&D		0.033**	0.033**	0.033**
		(0.014)	(0.014)	(0.014)
Human Capital		0.247***	0.247***	0.248***
		(0.031)	(0.031)	(0.031)
Size (Medium)		0.047***	0.047***	0.047***
		(0.008)	(0.008)	(0.008)
Size (LEs)		0.069***	0.069***	0.069***
		(0.013)	(0.013)	(0.013)
Size (very LEs)		0.116***	0.116***	0.116***
		(0.018)	(0.018)	(0.018)
Foreign (dummy)		-0.016	-0.016	-0.016
		(0.011)	(0.011)	(0.011)
Age (log)		-0.013***	-0.013***	-0.013***
		(0.004)	(0.004)	(0.004)
National market		0.022*	0.021*	0.022*
		(0.012)	(0.012)	(0.012)
EU market		0.038***	0.038***	0.038***
		(0.013)	(0.013)	(0.013)
Rest of the World market		0.057***	0.057***	0.058***
		(0.014)	(0.014)	(0.014)
Sec. Offshoring			0.023***	0.014**
			(0.007)	(0.006)
Sec. Offshoring^2			-0.001***	-0.001***
			(0.000)	(0.000)
Sec. Internal R&D				-0.004***
				(0.001)
HHI				0.257
				(0.286)
Appropriation				0.006***
				(0.001)
Patent				0.004*
				(0.002)
Constant	0.582***	0.305***	0.245***	0.262***
	(0.021)	(0.037)	(0.041)	(0.061)
Technological fixed effects	No	No	No	Yes
Observations	57,649	57,649	57,649	57,649
Number of Sectors	38	38	38	38
Variance (sector)	0.0162	0.0088	0.0067	0.0012
Variance (firm)	0.0966	0.0874	0.0874	0.0873
Variance (Offshoring)		0.0194	0.0194	0.0195
Covariance (random intercept-coefficient)		-0.0154	-0.0154	-0.0156
ICC Sector	0.0678	0.0410	0.0315	0.0058
ICC Firm	0.472	0.446	0.441	0.426
LR test Firm random intercept- coefficient	18814***	17049***	16837***	16009***
LR test Sector random intercept	808.4***	425.2***	348.2***	68.85***
Wald Test Mean values (Mundlak)		318.4***	331.1***	376.7***
Wald Test Time dummies		998.7***	998.7***	998.5***

*** p<0.01, ** p<0.05, * p<0.1. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi 2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89). ICC is conditional on zero values of random-effects covariates.

the industrial variance is reduced in specifications 3-4 with respect to specifications 1 and 2, meaning that the sectoral characteristics included in the model are catching up a great part of the industrial variability.

To start analyzing the first hypothesis, the model includes the percentage of firms doing offshoring in a given sector and its quadratic term (column 3). First thing to notice is that both are statistically significant, being positive in the linear part of the term, and presenting a negative quadratic shape, pointing to a decrease or even negative return for industries presenting high levels of offshoring.

In column 4, the model also controls for other sectoral characteristics. For instance, the average internal R&D expenditure as percentage of sales in a sector presents a counterintuitive result, being negative and statistically significant, suggesting that it may be acting as an entry barrier to those firms willing to innovate in the sector. Besides, firms working in sectors with higher usages of informally and formally methods for appropriating knowledge, are the ones taking the most advantage from its context, while the level of concentration, even though positive, do not seem to benefit product innovation engagement. Therefore, all else equal, and in light of the specification in column 3, firms in sectors with low-to-intermediate aggregated levels of R&D offshoring are benefiting more from its environment than similar firms established in sectors with high levels of offshoring. To illustrate this, Figure 4.1 presents the marginal effects as well as the predictions for the continuum of values. The left-hand side of Figure 4.1 presents the average marginal effects, that is, the derivative, in which all else equal, sectoral offshoring has a positive but decreasing effect, thereafter, showing negative returns. As a result, while certain industries take profit from low-to-intermediate levels of offshoring, those with high levels of offshoring incur in negative returns. Looking at the right-hand side of Figure 4.1 (predictive margins), the probability of obtaining a new product increases with the increment in the percentage of firms in a given sector that are doing offshoring. The latter reach its maximum at around 9 percent, from which it starts to show a negative tendency for higher values of sectoral offshoring, showing and inverted U-shape, and thus, confirming hypothesis 1.

FIGURE 4.1. Average marginal effects and Predictive margins of Sec. Offshoring on product innovation

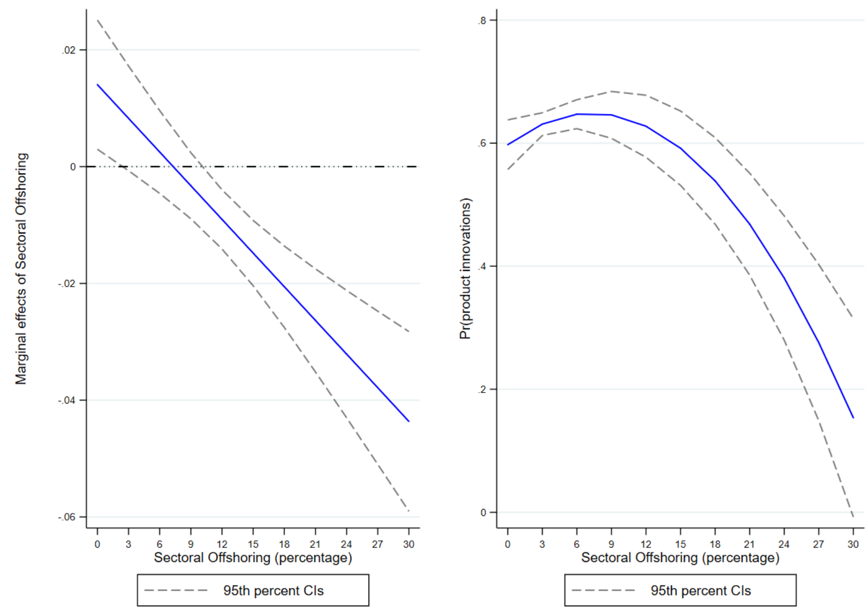
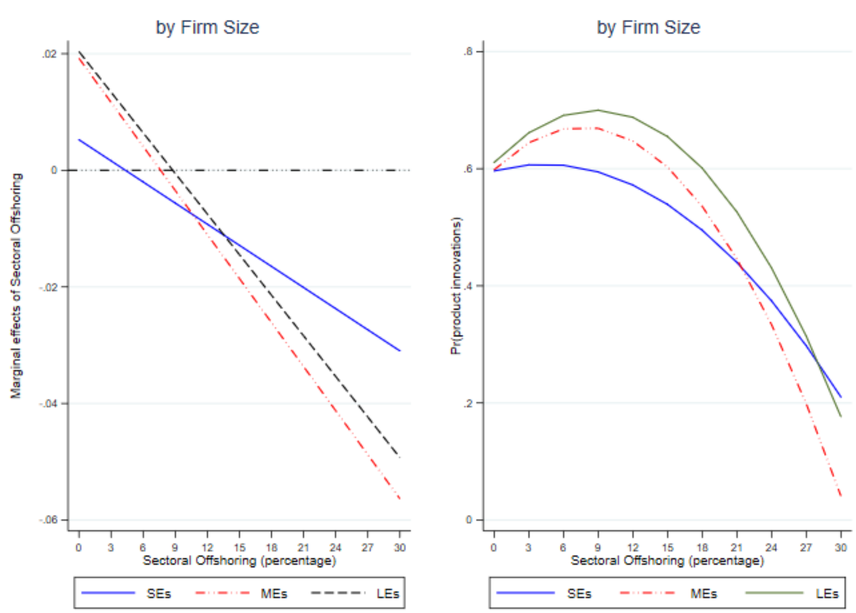


FIGURE 4.2. Average marginal effects and Predictive margins of Sec. Offshoring on product innovation by firm's size



For disentangling the extent to which firms benefit differently from the aggregate R&D offshoring from the industry to which they belong to, I present Table A.4 in appendix A. However, for the ease of interpretation, and in light of Figure 4.1, Figures 4.2 to 4.4 present the average marginal effects as well as the predictive margins of the interactions for validate hypotheses 2 to 4. Figure 4.2 suggests that as stated in H2, larger firms are the ones benefiting the most from their sectoral externalities showing higher positive returns than smaller firms in a given sector with low-to-intermediate levels of R&D offshoring. However, as stated in H2 they are also more dependent from these knowledge spillovers and thus, are more damaged by the highest level of sectoral R&D offshoring. In addition, when comparing two similar firms of equal size, those in sectors with lower/higher share of offshoring are the ones presenting lower probabilities for innovate with respect to those with intermediate levels. Being the latter more extreme in case of larger firms, thus, supporting the non-linear behavior across industries captured by H1. Therefore, H2 is also confirmed.

Furthermore, the extent to which the sectoral environment may differ depending on the internal capabilities of firms is tested through Figures 4.3 and 4.4. Starting by Figure 4.3 and using the information present in Table A.4 (column 3), there are no differences in the firms' internal R&D in a given sector with high level of externality. However, enterprises in sectors with low-to-intermediate levels of offshoring that increase their internal R&D, do show lower returns even though it is marginally significant. With regard to the firms' level of human capital, it influences the return of sectoral offshoring to product innovation engagement, showing a positive and statistically significant effect. Therefore, H3 is supported for those enterprises increasing the level of education and training present in their workforce. In other words, firms with more level of human capital are less affected by a high knowledge spillover content in their sectors.

Next, looking at Figure 4.4, enterprises with higher experience in networking with other organizations through R&D offshoring and technological collaborations are taking a lesser damage from their environment in those sectors with the highest knowledge spillovers. Therefore, they are in a better position than enterprises with lower experience in working with other institutions when their context relies too much on R&D offshoring for being a product innovator, and thus, H4 is supported.

FIGURE 4.3. Average marginal effects and Predictive margins of Sec. Offshoring on product innovation by firm's absorptive capacity

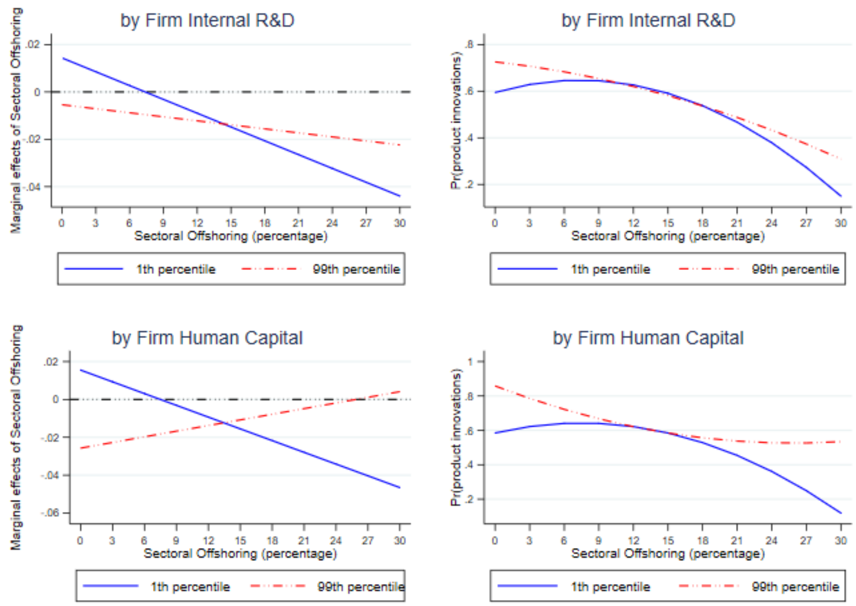
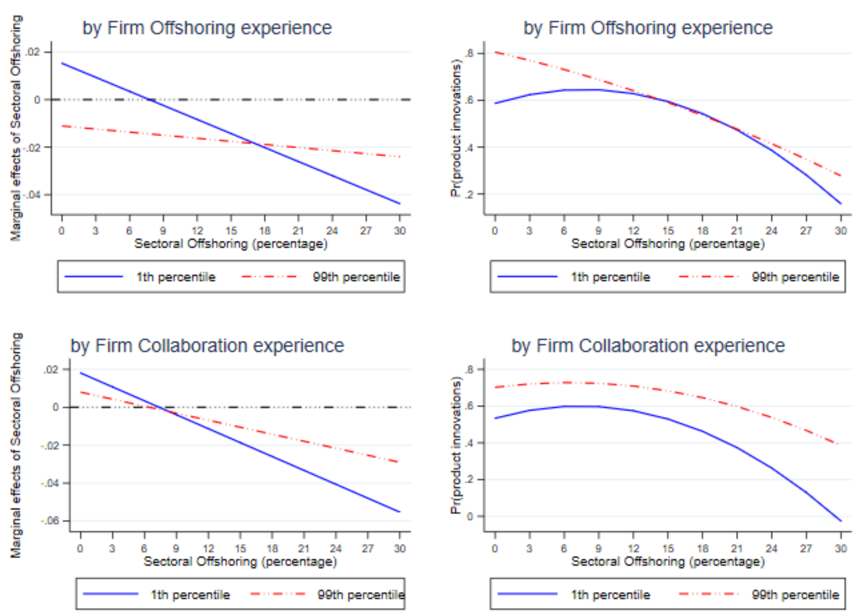


FIGURE 4.4. Average marginal effects and Predictive margins of Sec. Offshoring on product innovation by firm's networking strategies



4.5.3. Robustness. Until now, the offshoring strategy has been considered as a dummy just accounting for the fact of firms doing or not doing such strategy at the firm level as well as the share of firms doing offshoring in a given industry at the sectoral level. However, it may be the case that the important decision is not just to do or not to do, but how much to do. Therefore, in order to account for this, I use the expenditures in foreign R&D as percentage of total R&D present in the survey at the firm level. At the sectoral level, I use the industrial average of the offshoring expenditures as percentage of total R&D. Table A.5 in appendix A, shows that when accounting for the amount expended in firms and sectors, none of the variables are significant and therefore, they do not affect the decision to innovate. The same conclusion remains for the rest of specifications testing hypotheses 2 to 4, indicating that it is the number of firms developing an offshoring strategy within sectors and not the amount expended what affect the firm's likelihood to innovate.

An important concern is whether the results are biased due to the possibility of firms deciding to change from one sector to another within the period of analysis generating a possible self-selection of firms. In addition, it posits another problem which is the non-hierarchy of firms nested within a sector not accounting for the importance of previous sectors' characteristics in the firm's likelihood of becoming a product innovator. I investigate this, re-estimating the model just for those firms not changing sectors through all the period, which implies discarding around 16.5 percent of firms from the sample. Table A.6 in appendix A, evidences that sorting issues within the analyzed period are not influencing the results, since the conclusions are unchanged. On top of that, looking at the average born year of firms (around 28 years) for those not changing between sectors, sorting can be assumed as an exogenous decision since on average it was taken three decades ago, and thus, not expected to influence today's sectoral characteristics effects.

Another concern relates to the time lapse between the outcome and the explanatory variables. Since the outcome variable includes a three-years period, while some of the explanatory variables—specifically the quantitative ones—refers to the current year of the period, it may be the case that the time lag used does not properly capture the effects of knowledge inputs. For studying this, I re-estimate the model and instead of using one lag, I use two lags for the explanatory variables. The evidence presented in Table A.7 in appendix A points to most of the same conclusions as those in Table 4.3, and thus, supporting hypotheses 1 to 4.

Finally, since the interest of the present chapter relies on the parameter and not on the predictions of the model, I use a linear model for the ease of the interpretation since it gives directly the marginal effects. However, it is true that the linear model can give results in which the predicted probability may be outside the range 0-1, and thus, I also estimate the logit model in table A.8 in the appendix A. It shows the odd ratios, which can be interpreted as the ratio of the probability of success over the probability of fail with respect to the different values of the covariates, being positive (if the coefficient is greater than one) or negative (if lower than one). The results are qualitatively pretty much the same as those presented in Table 4.3.

4.6. Conclusions

This chapter analyses the influence R&D offshoring has on the innovative performance of firms. The main idea behind is that offshoring strategy is not just profitable for the firm implementing it, but also for the rest of firms in its sectoral context. The latter connects with the access to a higher pool of different and novel type of ideas coming from dissimilar NIS possibly ending in more externalities within the industry. Such knowledge spillover may lead to higher sectoral as well as firm's innovative performance as stressed by Short et al. (2006). Thus, building on previous evidence, firms' innovative performance may depend positively on the firm's acquisition of R&D offshoring (Laursen and Salter, 2006; Mihalache et al., 2012; Nieto and Rodríguez, 2011) as well as on the pool of general knowledge it has access to in a given sector, that is, knowledge spillover (Amoroso, 2017; Goya et al., 2016; Ornaghi, 2006). However, too much R&D offshoring may have negative consequences. Most studies tend to analyze R&D offshoring at the firm level. Nevertheless, the problem is that the context also affect firms' performance (van Oort et al., 2012), and focusing on just one level may generate an incomplete analysis (Backman, 2014). I argue that a relative increase in industrial R&D offshoring has a positive influence in firms' innovativeness, but only until an intermediate threshold; thereafter, higher levels of offshoring may end in pervasive forces inducing negative returns.

The study controls for firm and industrial heterogeneity using a multilevel approach including characteristics at both levels. The evidence provided for Spanish firms from 2005 to 2015 indicates that R&D offshoring is key for enrolling in product innovation, while also indicates that it varies substantially across firms. An important feature of the chapter is that firms' characteristics are the most important ones for innovativeness, a results also found in recent literature (Backman, 2014). However, propensity to innovate is also positively affected by the industrial level of offshoring. Hence, confirming the relevance that the pool of knowledge coming from a different NIS has for firms' innovative processes.

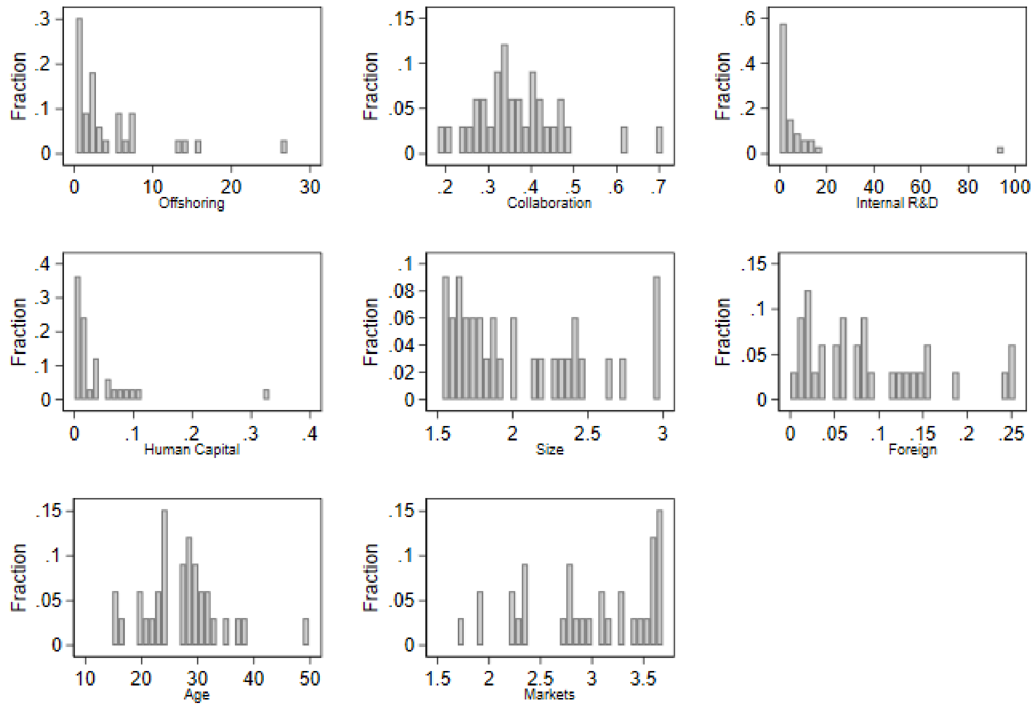
Yet, too much of this industry externality generates negative returns. As the literature points, going abroad in search of new and different knowledge is not an easy task, it requires attention from the managers and is time consuming, which may end in organizational problems (Baier et al., 2015). Also, domestic companies may lack the ability to efficiently implement foreign knowledge at higher degrees of R&D offshoring (Steinberg et al., 2017), even losing their networking of knowledge suppliers at home. Therefore, as suggested by Chesbrough (2003), it seems that too much offshoring at the industry level may posit a damage into its firms' innovativeness which is supported by these results.

The chapter also finds empirical support for the heterogeneity present among firms pertaining to the same industry. Therefore, smaller firms, as well as those enterprises presenting higher levels of collaboration and offshoring experience with other organizations are the ones less harmed when the sectoral R&D offshoring is high. Besides, those enterprises increasing their internal capacity through a more skilled workforce are the ones benefiting the most from their industrial context presenting positive returns coming from sectors with the highest sectoral spillovers.

The evidence provided suggests that some sectors are beyond the optimal percentage of firms developing an offshoring strategy. However, on average, manufacturing and services sectors have around 4.9 percent of firms doing offshoring (see Table 1), while the results reported show around 9 percent as the optimal value for the Spanish Economy (see Figure 1). Therefore, it seems that a strategy that is highly beneficial for all enterprises individually might be also optimal for the whole economy since still there is space for accessing foreign knowledge trough R&D offshoring.

Appendix A

FIGURE A.1. Distribution of firm-level variables across sectors



Note: Calculated as the avergage firm-level characteristics for each sector

TABLE A.1. Descriptive statistics for sectoral-level variables

Variable		Mean	Std. Dev.	Min	Max	Observations	
Sec. Offshoring	Overall	0.049	0.058	0	0.321	N	456
	Between		0.056	0.002	0.271	n	38
	Within		0.015	-0.041	0.102	T	12
Sec. Internal R&D	Overall	0.068	0.153	0.0001	1.011	N	456
	Between		0.153	0.0003	0.949	n	38
	Within		0.022	-0.027	0.209	T	12
HHI	Overall	0.051	0.040	0.0001	0.176	N	456
	Between		0.036	0.009	0.157	n	38
	Within		0.018	-0.055	0.119	T	12
Appropriation	Overall	0.182	0.091	0	0.484	N	456
	Between		0.075	0.067	0.368	n	38
	Within		0.052	0.034	0.339	T	12
Patent	overall	0.102	0.091	0	0.441	N	456
	between		0.086	0.006	0.399	n	38
	within		0.032	-0.018	0.279	T	12

Table A.2. Descriptive statistics for the firm-level variables

Variable		Mean	Std. Dev.	Min	Max	Observations	
PI (dummy)	Overall	0.496	0.499	0	1	N	97,751
	Between		0.392	0	1	n	10,841
	Within		0.324	-0.420	1.412	T-bar	9.01
Offshoring (dummy)	Overall	0.045	0.208	0	1	N	97,751
	Between		0.146	0	1	n	10,841
	Within		0.146	-0.871	0.962	T-bar	9.01
Collaboration (dummy)	Overall	0.377	0.484	0	1	N	72,156
	Between		0.361	0	1	n	9,421
	Within		0.331	-0.539	1.294	T-bar	7.65
Internal R&D	Overall	0.055	0.215	0	2	N	97,751
	Between		0.210	0	2	n	10,841
	Within		0.097	-1.607	1.886	T-bar	9.01
Human Capital	Overall	0.033	0.093	0	1	N	89,340
	Between		0.087	0	1	n	10,578
	Within		0.043	-0.730	0.873	T-bar	8.44
Size (categorical)	Overall	2.013	1.041	1	4	N	97,751
	Between		0.995	1	4	n	10,841
	Within		0.283	-0.652	4.763	T-bar	9.01
Foreign (dummy)	Overall	0.117	0.321	0	1	N	97,751
	Between		0.280	0	1	n	10,841
	Within		0.134	-0.799	1.033	T-bar	9.01
Age (log)	Overall	3.131	0.662	0	551	N	93,718
	Between		0.658	0	546	n	9,505
	Within		0.194	1.377	3.987	T-bar	9.85
Markets (categorical)	Overall	3.056	1.056	0	1	N	97,751
	Between		0.976	0	1	n	10,841
	Within		0.441	0.306	5.806	T-bar	9.01

Table A.3. Correlation matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Offshoring	1												
(2) Collaboration	0.14	1											
(3) Internal R&D	0.10	0.16	1										
(4) Human Capital	0.10	0.18	0.65	1									
(5) Size	0.11	0.11	-0.14	-0.18	1								
(6) Foreign	0.13	0.03	-0.07	-0.07	0.27	1							
(7) Age (log)	0.03	0.01	-0.20	-0.21	0.26	0.09	1						
(8) Markets	0.11	0.07	-0.06	-0.01	0.01	0.12	0.17	1					
(9) Sec. Offshoring	0.22	0.11	0.25	0.21	0.01	0.12	0.02	0.20	1				
(10) Sec. Internal R&D	0.09	0.15	0.67	0.55	-0.11	-0.06	-0.21	-0.08	0.39	1			
(11) HHI	0.04	0.05	0.13	0.13	0.06	0.01	-0.11	-0.08	0.16	0.18	1		
(12) Appropriation	0.09	0.05	0.16	0.18	-0.15	0.01	0.001	0.20	0.43	0.25	-0.08	1	
(13) Patent	0.16	0.09	0.39	0.31	-0.15	0.03	-0.04	0.24	0.74	0.59	-0.01	0.48	1

Table A.4. Studying firms' heterogeneity

VARIABLES	(1) PI	(2) PI	(3) PI	(4) PI	(5) PI
Offshoring (dummy)	0.019*	0.019*	0.019*	0.019**	0.019*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Offshoring (experience)	0.249***	0.092***	0.095***	0.093***	0.091***
	(0.064)	(0.028)	(0.028)	(0.028)	(0.028)
Collaboration (experience)	0.146***	0.169***	0.148***	0.147***	0.146***
	(0.013)	(0.023)	(0.013)	(0.013)	(0.013)
Sec. Offshoring	0.015***	0.018***	0.014**	0.016***	0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Sec. Offshoring^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sec. Internal R&D	-0.003***	-0.004***	-0.003***	-0.003***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HHI	0.279	0.280	0.251	0.279	0.229
	(0.287)	(0.286)	(0.284)	(0.281)	(0.284)
Appropriation	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Patent	0.005**	0.004*	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Offshoring (experience)*Sec. Offshoring	-0.030**				
	(0.012)				
Offshoring (experience)*Sec. Offshoring^2	0.001**				
	(0.000)				
Collaboration (experience)*Sec. Offshoring		-0.010			
		(0.006)			
Collaboration (experience)*Sec. Offshoring^2		0.001**			
		(0.000)			
Internal R&D*Sec. Offshoring			-0.013*		
			(0.007)		
Internal R&D*Sec. Offshoring^2			0.000		
			(0.000)		
Human Capital*Sec. Offshoring				-0.076***	
				(0.017)	
Human Capital*Sec. Offshoring^2				0.003***	
				(0.001)	
Size (Medium)*Sec. Offshoring					0.014***
					(0.004)
Size (Medium)*Sec. Offshoring^2					-0.001***
					(0.000)
Size (LEs)*Sec. Offshoring					0.015***
					(0.005)
Size (LEs)*Sec. Offshoring^2					-0.001***
					(0.000)
Constant	0.255***	0.255***	0.256***	0.251***	0.267***
	(0.061)	(0.062)	(0.061)	(0.060)	(0.061)
Technological fixed effects	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Observations	57,649	57,649	57,649	57,649	57,649
Number of Sectors	38	38	38	38	38
Variance (sector)	0.0012	0.0012	0.0011	0.0011	0.0011
Variance (firm)	0.0873	0.0872	0.0873	0.0871	0.0873
Variance (Offshoring)	0.0195	0.0196	0.0194	0.0192	0.0193
Covariance (random intercept-coefficient)	-0.0158	-0.0157	-0.0157	-0.0157	-0.0153
ICC sector	0.0058	0.0058	0.0056	0.0054	0.0056
ICC firm	0.426	0.426	0.426	0.425	0.426
LR test Firm random intercept- coefficient	16001***	15991***	16002***	15948***	15984***
LR test Sector random intercept	69.30***	68.16***	65.11***	61.55***	66.11***
Wald Test Mean values	363.9***	231.9***	365.7***	373.6***	338.2***
Wald Test Time dummies	998.1***	998.1***	997.6***	995.5***	1002***

*** p<0.01, ** p<0.05, * p<0.1. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi 2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89). ICC is conditional on zero values of random-effects covariates.

Table A.5. Measuring Offshoring as percentage of total R&D expenditures

VARIABLES	(1) PI	(2) PI	(3) PI	(4) PI	(5) PI	(6) PI	(7) PI
Offshoring (expenditure)	0.032	0.032	0.106	0.031	0.032	0.032	0.030
	(0.026)	(0.026)	(0.071)	(0.026)	(0.026)	(0.027)	(0.026)
Collaboration (experience)	0.128***	0.127***	0.127***	0.114***	0.127***	0.127***	0.127***
	(0.013)	(0.013)	(0.013)	(0.029)	(0.013)	(0.013)	(0.013)
Sec. Offshoring (expenditure)	0.016	-0.020	-0.019	-0.019	-0.000	-0.021	-0.021
	(0.027)	(0.021)	(0.021)	(0.022)	(0.000)	(0.021)	(0.022)
Sec. Offshoring (expenditure)^2	-0.001	0.002	0.002	0.001	0.000	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.003)	(0.000)	(0.002)	(0.003)
Offshoring (expenditure)* Sec. Offshoring (expenditure)			-0.056				
			(0.043)				
Offshoring (expenditure)* Sec. Offshoring (expenditure)^2			0.006				
			(0.004)				
Collaboration (experience)*Sec. Offshoring (expenditure)				0.001			
				(0.022)			
Collaboration (experience)*Sec. Offshoring (expenditure)^2				0.002			
				(0.003)			
Internal R&D*Sec. Offshoring (expenditure)					-0.000		
					(0.000)		
Internal R&D*Sec. Offshoring (expenditure)^2					0.000		
					(0.000)		
Human Capital*Sec. Offshoring (expenditure)						-0.049	
						(0.074)	
Human Capital*Sec. Offshoring (expenditure)^2						0.021*	
						(0.011)	
Size (Medium)*Sec. Offshoring (expenditure)							-0.002
							(0.013)
Size (Medium)*Sec. Offshoring (expenditure)^2							0.001
							(0.002)
Size (LEs)*Sec. Offshoring (expenditure)							0.016
							(0.016)
Size (LEs)*Sec. Offshoring (expenditure)^2							-0.000
							(0.002)
Constant	0.279***	0.215***	0.213***	0.217***	0.216***	0.215***	0.198**
	(0.048)	(0.078)	(0.078)	(0.079)	(0.078)	(0.079)	(0.078)
Technological fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54,700	54,700	54,700	54,700	54,700	54,700	54,700
Number of Sectors	38	38	38	38	38	38	38
Variance (sector)	0.0075	0.0027	0.0027	0.0027	0.0027	0.0028	0.0027
Variance (firm)	0.0843	0.0843	0.0843	0.0842	0.0842	0.0841	0.0844
Variance (Offshoring)	0.0648	0.0648	0.0639	0.0649	0.0651	0.0655	0.0647
Covariance (random intercept-coefficient)	-0.0229	-0.0232	-0.0232	-0.0239	-0.0231	-0.0234	-0.0232
ICC sector	0.0357	0.0132	0.0131	0.0133	0.0134	0.0136	0.0134
ICC firm	0.433	0.420	0.420	0.420	0.420	0.420	0.420
LR test Firm random intercept- coefficient	15646***	15033***	15028***	16254***	16264***	16254***	16277***
LR test Sector random intercept	339.2***	124.4***	123.6***	126.1***	127.9***	128.9***	127.1***
Wald Test Mean values	227.1***	244.1***	244***	172.2***	331.4***	331.2***	325***
Wald Test Time dummies	954.2***	954.1***	954.6***	999.6***	998.9***	999.5***	1003***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi 2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89). ICC is conditional on zero values of random-effects covariates.

Table A.6. Excluding firms moving across sectors

VARIABLES	(1) PI	(2) PI	(3) PI	(4) PI	(5) PI	(6) PI	(7) PI	(8) PI	(9) PI
Offshoring (dummy)		0.024**	0.024**	0.024**	0.024**	0.024**	0.024**	0.024**	0.023**
		(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Offshoring (experience)		0.093***	0.091***	0.090***	0.283***	0.085***	0.089***	0.088***	0.086***
		(0.031)	(0.031)	(0.031)	(0.072)	(0.031)	(0.031)	(0.031)	(0.031)
Collaboration (experience)		0.153***	0.153***	0.151***	0.149***	0.175***	0.151***	0.151***	0.150***
		(0.014)	(0.014)	(0.014)	(0.014)	(0.025)	(0.014)	(0.014)	(0.014)
Sec. Offshoring			0.023***	0.013**	0.015**	0.018***	0.014**	0.014**	0.003
			(0.008)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
Sec. Offshoring^2			-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.000*
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Offshoring (experience)*Sec. Offshoring					-0.035**				
					(0.013)				
Offshoring (experience)*Sec. Offshoring^2					0.001**				
					(0.000)				
Collaboration (experience)*Sec. Offshoring						-0.011			
						(0.007)			
Collaboration (experience)*Sec. Offshoring^2						0.001**			
						(0.000)			
Internal R&D*Sec. Offshoring							-0.016*		
							(0.008)		
Internal R&D*Sec. Offshoring^2							0.000		
							(0.000)		
Human Capital*Sec. Offshoring								-0.052**	
								(0.020)	
Human Capital*Sec. Offshoring^2								0.002*	
								(0.001)	
Size (Medium)*Sec. Offshoring									0.016***
									(0.004)
Size (Medium)*Sec. Offshoring^2									-0.001***
									(0.000)
Size (LEs)*Sec. Offshoring									0.016***
									(0.005)
Size (LEs)*Sec. Offshoring^2									-0.001***
									(0.000)
Constant	0.583***	0.312***	0.249***	0.260***	0.252***	0.252***	0.249***	0.247***	0.276***
	(0.022)	(0.041)	(0.046)	(0.069)	(0.069)	(0.069)	(0.068)	(0.068)	(0.068)
Technological fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral-level controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,813	46,813	46,813	46,813	46,813	46,813	46,813	46,813	46,813
Number of Sectors	38	38	38	38	38	38	38	38	38
Variance (sector)	0.0176	0.0101	0.00785	0.00145	0.00147	0.00145	0.00139	0.00135	0.00142
Variance (firm)	0.0972	0.0884	0.0884	0.0883	0.0882	0.0882	0.0883	0.0882	0.0883
Variance (Offshoring)		0.0174	0.0174	0.0175	0.0175	0.0177	0.0175	0.0174	0.0175
Covariance (random intercept-coefficient)		-0.0171	-0.0170	-0.0174	-0.0177	-0.0177	-0.0176	-0.0176	-0.0171
ICC sector	0.0733	0.0462	0.0365	0.0069	0.0070	0.0069	0.0066	0.0065	0.0068
ICC firm	0.479	0.453	0.447	0.430	0.430	0.430	0.430	0.430	0.430
LR test Firm random intercept- coefficient	15719***	14175***	13995***	13223***	13213***	13201***	13215***	13183***	13200***
LR test Sector random intercept	719.9***	381.4***	314.2***	65.44***	66.24***	64.68***	61.06***	59.47***	64.01***
Wald Test Mean values		248.7***	259***	292.2***	286.8***	177.9***	283.1***	286.1***	278.1***
Wald Test Time dummies		759.7***	759.6***	759.4***	759***	759.3***	758.8***	757.3***	761.8***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89). ICC is conditional on zero values of random-effects covariates.

Table A.7. Two lags of explanatory variables

VARIABLES	(1) PI	(2) PI	(3) PI	(4) PI	(5) PI	(6) PI	(7) PI
Offshoring (dummy)	0.019*	0.019*	0.019*	0.019*	0.019*	0.020**	0.019*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Offshoring (experience)	0.102***	0.101***	0.265***	0.099***	0.100***	0.098***	0.095***
	(0.029)	(0.029)	(0.067)	(0.029)	(0.029)	(0.029)	(0.029)
Collaboration (experience)	0.195***	0.194***	0.192***	0.208***	0.194***	0.193***	0.193***
	(0.013)	(0.013)	(0.013)	(0.023)	(0.013)	(0.013)	(0.013)
Sec. Offshoring	0.023***	0.016***	0.017***	0.019***	0.016***	0.017***	0.010
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Sec. Offshoring^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Offshoring (experience)*Sec. Offshoring			-0.030**				
			(0.013)				
Offshoring (experience)*Sec. Offshoring^2			0.001*				
			(0.000)				
Collaboration (experience)*Sec. Offshoring				-0.007			
				(0.006)			
Collaboration (experience)*Sec. Offshoring^2				0.000			
				(0.000)			
Internal R&D*Sec. Offshoring					-0.013*		
					(0.008)		
Internal R&D*Sec. Offshoring^2					0.000		
					(0.000)		
Human Capital*Sec. Offshoring						-0.057***	
						(0.018)	
Human Capital*Sec. Offshoring^2						0.002*	
						(0.001)	
Size (Medium)*Sec. Offshoring							0.008**
							(0.004)
Size (Medium)*Sec. Offshoring^2							-0.000**
							(0.000)
Size (LEs)*Sec. Offshoring							0.013***
							(0.005)
Size (LEs)*Sec. Offshoring^2							-0.000**
							(0.000)
Constant	0.133***	0.160**	0.153**	0.155**	0.150**	0.147**	0.151**
	(0.041)	(0.064)	(0.065)	(0.065)	(0.064)	(0.063)	(0.064)
Technological fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral-level controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,585	51,585	51,585	51,585	51,585	51,585	51,585
Number of Sectors	38	38	38	38	38	38	38
Variance (sector)	0.0070	0.0014	0.0014	0.0014	0.0013	0.0013	0.0013
Variance (firm)	0.0904	0.0903	0.0903	0.0903	0.0903	0.0901	0.0903
Variance (Offshoring)	0.0113	0.0114	0.0114	0.0115	0.0113	0.0106	0.0113
Covariance (random intercept-coefficient)	-0.0091	-0.0093	-0.0096	-0.0093	-0.0096	-0.0092	-0.0091
ICC sector	0.0325	0.0068	0.0068	0.0068	0.0064	0.0062	0.0065
ICC firm	0.452	0.437	0.437	0.437	0.437	0.436	0.437
LR test Firm random intercept- coefficient	15290***	14555***	14547***	14548***	14547***	14494***	14520***
LR test Sector random intercept	345.9***	75.90***	76.41***	75.06***	69.80***	66.81***	73.12***
Wald Test Mean values	505.9***	550.5***	527.1***	311.8***	540***	546.4***	518.2***
Wald Test Time dummies	1073***	1072***	1072***	1073***	1074***	1071***	1078***

*** p<0.01, ** p<0.05, * p<0.1. Means, time, and technological Fixed effects included. The null hypothesis for the likelihood ratio tests does not follow a $\chi 2$ distribution because it is not on the boundary of the parameter space. I corrected for this following Rabe-Hesketh and Skrondal (2012, pp. 88-89). ICC is conditional on zero values of random-effects covariates.

Table A.8. Logit estimation

VARIABLES	(1) PI	(2) PI
Offshoring (dummy)	1.986***	2.038***
	(0.310)	(0.322)
Collaboration (dummy)	1.828***	1.819***
	(0.070)	(0.069)
Internal R&D	1.358**	1.357**
	(0.183)	(0.182)
Human Capital	11.115***	10.838***
	(3.326)	(3.219)
Size (Medium)	1.434***	1.407***
	(0.096)	(0.093)
Size (LEs)	1.670***	1.688***
	(0.183)	(0.185)
Size (very LEs)	2.415***	2.413***
	(0.379)	(0.377)
Foreign (dummy)	0.844*	0.843*
	(0.085)	(0.085)
Age (log)	1.267	1.275
	(0.198)	(0.199)
National market	1.136	1.152
	(0.113)	(0.115)
EU market	1.300**	1.328***
	(0.140)	(0.144)
Rest of the World market	1.543***	1.566***
	(0.170)	(0.173)
Sec. Offshoring		1.317***
		(0.050)
Sec. Offshoring^2		0.985***
		(0.002)
Sec. Internal R&D		0.958***
		(0.005)
HHI		0.003***
		(0.005)
Appropriation		1.037***
		(0.008)
Patent		1.079***
		(0.011)
Constant	0.555***	0.347***
	(0.124)	(0.120)
Technological fixed effects	No	Yes
Time fixed effects	Yes	Yes
Mundlak (mean fixed effects)	Yes	Yes
Observations	57,649	57,649
Number of Sectors	38	38
Variance (sector)	1.0239	0.5334
Variance (firm)	5.3501	5.2475
Variance (Offshoring)	3.3375	3.4111
Covariance (random intercept-coefficient)	0.5773	0.6331

*** p<0.01, ** p<0.05, * p<0.1. Odd ratios. Means, time, and technological Fixed effects included.

Appendix B. Variance Partition Coefficient (VPC)

It measures the proportion of the total residual variance in the propensity to develop a product innovation due to differences between groups going from zero (meaning no group differences) to one (no within-group differences). In the present case, it should be noted that the unconditional VPC and Intra-class Correlation (ICC) coincide for the highest level (sector), while they do not coincide for lower levels. However, when conditional on characteristics, the inclusion of offshoring in the random part of the model imply differences in the calculation of both.[15] Since R&D offshoring is a dummy variable, it will be two VPC for the firm, one for values of offshoring equal to one and another when offshoring is zero.

$$VPC_{firm} = \frac{\sigma^2_{\mu 0ij}}{\sigma^2_{\mu 0j} + \sigma^2_{\mu 0ij} + \left(\frac{\pi^2}{3}\right)} \tag{4.6}$$

$$VPC_{sector} = \frac{\sigma^2_{\mu 0j}}{\sigma^2_{\mu 0j} + \sigma^2_{\mu 0ij} + \left(\frac{\pi^2}{3}\right)} \tag{4.7}$$

(4.8)

$$VPC_{firm} = \frac{\sigma^2_{\mu 0ij} + 2\,(offshoring)\,\sigma_{\mu 01ij} + \sigma^2_{\mu 1ij}\,(offshoring)^2}{\sigma^2_{\mu 0j} + \left[\sigma^2_{\mu 0ij} + 2\,(offshoring)\,\sigma_{\mu 01ij} + \sigma^2_{\mu 1ij}\,(offshoring)^2\right] + \left(\frac{\pi^2}{3}\right)}$$

(4.9)

$$VPC_{sector} = \frac{\sigma^2_{\mu 0j}}{\sigma^2_{\mu 0j} + \left[\sigma^2_{\mu 0ij} + 2\,(offshoring)\,\sigma_{\mu 01ij} + \sigma^2_{\mu 1ij}\,(offshoring)^2\right] + \left(\frac{\pi^2}{3}\right)}$$

Making use of the notation introduced in section 4.4.3, the first two VPC correspond to those of column 1 of Table 3, and thus, are the unconditional ones. These will divide the proportion of the total residual variance in the propensity to develop a product innovation due to differences between sectors on the one hand, and between enterprises on the other. Consequently, replacing the values in Table 3 (column 1) in those formulas, firm-level variation (40 percent) in the proportion of product innovations is higher than the sectoral one (7 percent) and thus, more important. The last two VPC correspond to those of the firm and sectoral levels (columns 3-4 of Table 3) but differentiating with respect to R&D

[15]Unconditional VPC is based on the observed response, while the conditional VPC is based on the residual, and thus, it measures the proportion of outcome variation unexplained by the variables in the model.

offshoring equal to one or equal to zero. In any case, it should be noted that irrespective of conditional/unconditional VPC, the firm-level variation is more important than the sectoral one.

CHAPTER 5

Conclusions

5.1. Concluding thoughts and policy implications

The present dissertation consists of three different empirical studies which represent new contributions to the empirical research of firms' R&D offshoring, one of the most relevant research issues in the area of Open Innovation literature. The acquisition of external knowledge connects the firm with an array of know-how and new knowledge, which are necessary to develop new processes and products. This leads the enterprise to avoid being locked in and to gain access to new ideas, especially if coming from abroad. However, as other scholars highlight, there are other relevant players apart from the firm in the process of innovation, like for instance, institutions, being the latter understood in a broad sense (Edquist, 1998).[1] Indeed, the context in which firms operate is crucially influencing firms' innovative processes. As also suggested by previous literature, these contextually backgrounds can be thought to be on the one hand the geographical location, and on the other hand the industrial environment of the firm (Amoroso, 2017; Backman, 2014; van Oort et al., 2012).

As stressed by Crescenzi and Gagliardi (2018) in a recent paper, the geography of innovation has often adopted a more aggregate perspective neglecting firms' heterogeneity. Moreover, differences in technological performance cannot be explained by firms in isolation but at the regional level (Uyarra, 2009). Besides, and without denying the importance of geographical proximity for knowledge diffusion, other scholars point to the necessity of incorporating the industrial context. Aspects like learning patterns, organizational processes, knowledge base, or technological regimes, among others, are recognized as sectoral specificities (Edquist, 1998; Malerba, 2002; Malerba and Adams, 2014). Therefore, this thesis makes two empirical contributions to the Economics of Innovation literature through the study of the influence the regional as well as the industrial contexts have on firms' innovative processes.

[1]Universities, research centers, R&D laboratories, patent systems, labor market organizations, government agencies, but also, norms, habits, practices, routines, etc.

The three studies that constitute the dissertation focus on the Spanish case for several reasons. First, as already said, Spain is an open economy that is well integrated in a trade and monetary union with some of the world's technology leaders (García-santana et al., 2016). Second, being part of the European Union (EU) implies solid laws of intellectual property rights, which leads to a substantial benefit from offshoring strategies as suggested by Tübke and Bavel (2007). Finally, Spain is also one of the four European countries presenting the widest regional heterogeneity in innovation (European Commission, 2014), having competencies and financial autonomy in terms of innovation policies, and presenting important socio-cultural differences that could lead to different learning process (Cooke et al., 1997). As far as the author knows, this is the first attempt in studying R&D offshoring beyond firm-level characteristics. The dissertation shows empirical evidences of regional as well as industrial differences in the return enterprises can get from the acquisition of foreign knowledge through R&D offshoring, while studying the contextual characteristics affecting such a process.

In chapter two, I analyze the relation between firms' economic return to innovations and their acquisition of foreign knowledge through R&D offshoring. Previous studies have focused their attention on the role of R&D offshoring in the generation of product and/or process innovations, focusing mainly on the manufacturing sectors and on the relation that multinational enterprises have with their subsidiaries abroad. I am interested in the innovative performance that a firm obtains with regard to the intensity of radical innovations in the manufacturing as well as in the service sectors when knowledge is acquired from subsidiaries as well as third party agents. This second chapter contributes to the literature of Open Innovation in the study of the heterogeneity in the influence of R&D offshoring according to the nature of the agents, as well as to the phase of the economic cycle, aspects unexplored in previous literature.

The evidence for Spanish firms between 2004 and 2013 shows that R&D offshoring influences significantly the intensity of radical but not of incremental innovations. This influence is apparently smaller when external knowledge comes from universities or research institutions rather than from the business sector. With regard to the economic cycle, the recent financial crisis also exerted a detrimental effect on this influence, as compared with the previous period of economic growth. The chapter studies empirically the differences between LEs and SMEs with respect to the impact of R&D offshoring on the innovative performance of the firm. The results indicate that LEs are the ones obtaining most benefits from seeking knowledge from abroad. Following the arguments of Di Gregorio et al.

(2008) and Nieto and Rodríguez (2011), LEs have greater financial, technological, and internal resources, so they are more able to implement and recombine the knowledge from abroad, while they face less risk of appropriation, information asymmetry, and opportunism, and therefore profit more from such knowledge.

Several implications for policy makers follow: First, policy makers should focus less on innovation agreements between national firms and foreign public research institutes; at least, these agreements should not be encouraged at all costs. Instead, firms should also be helped to gain access to foreign knowledge.

Second, our results shed light on the lesser influence of R&D offshoring on the intensity of radical product innovation in periods of financial constraints. As stressed by the OECD (2012, p. 48), the Spanish Government diminished the budget that was devoted to R&D, which resulted in a decrease in the funds that were reserved for private R&D projects. However, as observed in our results, purchasing R&D from foreign countries can allow firms to achieve good innovation performance. Therefore, given the complementary relationship between internal and external R&D that has been found in many papers Añón-Higón et al. (2014); Cassiman and Veugelers (2006), it would be desirable for governments to show greater commitment to maintaining expenditures on innovation even in crisis periods to avoid reducing the return that firms can gain from external R&D strategies.

In chapter three, I investigate whether the regional innovative environments affect the innovative performance of enterprises through networking activities (technological collaboration and R&D outsourcing); and on the other hand, if the knowledge structure of regional stakeholders affects such a process. To answer this question, I analyze how the knowledge endowment of the region can influence the return of the networking activities carried out by the firm, explicitly technological cooperation agreements and R&D outsourcing. I estimate a multilevel framework that combines information at the firm as well as the regional level for the case of Spanish manufactures in the 2000-2012 period, allowing to take explicit account of the multilevel structure of the data as well as its panel structure.

Explicitly, we find evidence of a reinforcement effect between being in a highly knowledge endowed region and the returns obtained from cooperating technologically with other organizations. In contrast, enterprises that are located in a region with a lower knowledge endowment have a higher return of the acquired external knowledge through an outsourcing strategy.

In addition, we analyze if the results are maintained when we consider separately the regional research effort made by the private sector as compared to the public one. It seems that the benefits obtained from technological cooperative agreements are higher in regions with a high endowment of knowledge made by the private sector. On the other hand, the R&D outsourcing strategy is more efficient in regions where the knowledge pool available is mainly due to public institutions. All in all, we can conclude that a firm's ability to exploit external knowledge acquired through networking activities depends crucially on the endowments of the region in which it operates.

Some policy implications are envisaged. First, as previously stressed, our results illustrate that although firms' characteristics are of clear importance for innovative outcomes, firms are also influenced by the regional environment in which they are located. Consequently, the mechanism to incorporate new knowledge into the firm needs to fit with the requirements of the enterprise but also take into account the regional context. Otherwise, policies used in an undifferentiated manner for all kinds of regions may be misleading. More specifically, in the case of the firms located in regions where innovation is primarily not research based, our results have shown that R&D outsourcing is an efficient way to generate innovation. Thus, a sensible regional policy priority could be to redesign local labour-training systems fostering human capital formation for the new knowledge needs of the region's traditional industries which are starting to introduce R&D developed by other agents within or beyond the borders of the region. A good matching between supply of skills training and region's skills demand in regions with a weak knowledge base should follow the logic of the smart specialization strategy: since low-endowed knowledge regions tend to have more specialized industry structures, controlled by a small group of sectors highly embedded in the region, the training programmes should be strongly related to the requirements of the local industries (McCann and Ortega-Argilés, 2015). This greater local skills match would, in addition, reduce labour outflows, which is a main handicap in policies of human capital carried out in less-developed regions. Another regional policy priority to enhance R&D outsourcing is the promotion of university-industry linkages that would allow the firm to incorporate appropriately the knowledge outsourced from other firms. In Spain, the government has paid much attention to the public-private innovation relationship, being one of the most important objectives in terms of public policy (Vega-Jurado et al., 2009). Our results would support this type of intervention in regions with a low knowledge base.

Chapter four evidences that while most studies tend to analyze R&D offshoring at firm level, the downside is that the context also affects firms' performance (van Oort et al., 2012), and focusing on just one level may generate an incomplete analysis (Backman, 2014). As previously said, the main idea behind this chapter is that the offshoring strategy is not just profitable for the firm implementing it, but also for the rest of firms in its sectoral context. The latter connects with the access to a higher pool of different and novel type of ideas coming from dissimilar NIS possibly ending in more externalities within the industry. Such knowledge spillover may lead to higher sectoral as well as firm's innovative performance as stressed by Short et al. (2006). Thus, building on previous evidence, firms' innovative performance may depend positively on the firm's acquisition of R&D offshoring (Laursen and Salter, 2006; Mihalache et al., 2012; Nieto and Rodríguez, 2011) as well as on the pool of general knowledge it has access to in a given sector, that is, knowledge spillover (Amoroso, 2017; Goya et al., 2016; Ornaghi, 2006).

The evidence provided for Spanish firms from 2005 to 2015 indicates that R&D offshoring is key for enrolling in product innovation, while also indicates that it varies substantially across firms. An important feature of the chapter is that firms' characteristics are the most important ones for innovativeness, a results also found in recent literature (Backman, 2014). However, propensity to innovate is also positively affected by the industrial level of offshoring. Hence, confirming the relevance that the pool of knowledge coming from a different NIS has for firms' innovative processes.

Yet, too much of this industry externality generates negative returns. As the literature points, going abroad in search of new and different knowledge is not an easy task, it requires attention from the managers and is time consuming, which may end in organizational problems (Baier et al., 2015), even losing their networking of knowledge suppliers at home. Therefore, as suggested by Chesbrough (2003), it seems that too much offshoring at the industry level may posit a damage into its firms' innovativeness which is supported by these results.

The chapter also finds empirical support for the heterogeneity present among firms pertaining to the same industry. Therefore, smaller firms, as well as those enterprises presenting higher levels of collaboration and offshoring experience with other organizations are the ones less harmed when the sectoral R&D offshoring is high. Besides, those enterprises increasing their internal capacity through a more skilled workforce are the ones benefiting the most from their industrial context presenting positive returns coming from sectors with the highest sectoral spillovers.

These results have some policy implications; on the one hand, the government might want to increase the innovativeness of firms through a better access to foreign technologies promoting for example, transfer agencies. In particular, policy-makers might also see these results as an indication for encouraging firms to strengthen their internal innovative capacity, through collaboration with other institutions and especially increasing their levels of human capital through training processes and hiring personnel with tertiary education. On the other hand, externalities coming from R&D offshoring, even though positive, seem to deter firms' innovativeness at high levels. The latter points to a lower social optimal level (sectoral R&D offshoring) than the private return (firm-level R&D offshoring) in such sectors with the highest externalities levels. Two possible interventions may be at hand. (i) For those sectors with the highest shares of offshorers, government should encourage firms not to look just abroad but also within the national context for purchasing new technologies. This way, the risk of losing internal capacities of sectors might be minimized. (ii) Since most of the sectors are below the optimal level of R&D offshoring, it seems that they still have space to increase the foreign acquisition of technologies through R&D offshoring, and thus, should also be encouraged by governmental institutions.

5.2. Limitations and future research

Certainly, the empirical research conducted in this thesis must be seen as an open door to future projects derived and connected with the current analysis. There are certain limitations that this thesis faced that are worth recognizing and which, at the same time, can serve to identify interesting lines for future research. A common obstacle when dealing with survey data facing anonymity laws as in the case of Spain is data availability. Regardless of this, it is also worth to mention the quality of the datasets used, that allowed me to address panel analyses as in the contrary case of most of previous literature studying innovativeness at firm level.

Considering the second chapter, I tried to analyze the R&D offshoring strategy from a geographical point of view: I argued for the existence of differences in the knowledge that comes from other national innovation systems, which could have a considerable impact on radical innovations. It would be interesting to identify which type of knowledge, with respect to its geographical origin, could be more profitable: either that from a technological leader country, such as the United States, or that from a country that is not at the technological frontier, such as India. However, with the information available we cannot address such issue. Another limitation comes from an absence of different categories of R&D offshoring in the data—such as R&D, design, and marketing, among others—that might account for their different impacts.

Chapter three suffers a number of shortcomings worth to mention. First, a possible endogeneity problem due to the higher-level variables may arise. However, this problem is solved thanks to the use of the time averaged regional variables as well as by the fact that we estimate a multilevel random effects model augmented with the between-within effects. According to the literature, this is the best choice to produce within effects with lower bias due to omitted higher-level variables (Bell et al., 2016). As in most previous studies, the present research assumes that spatial sorting is exogenous to the firm. Therefore, the interpretation of the model must account for the fact that firms' location choice does not influence the impact of our measures of regional knowledge endowment. Besides, the robustness analyzing how the model behaves when accounting just for those firms not moving to other regions through all the period, allows us to see that sorting into different regions seems not to be an important issue here. However, even though panel data may help to control for this, we do not have information on the location of the enterprises before the beginning of the survey or about the reasons to move. Moreover, the study of the drivers of firms' location is beyond the scope of the chapter.

Another important limitation regards the measurement we use for the innovative output as the number of product innovations. Although widely considered in previous literature, it may not capture the profitability of the innovation. It would be desirable to consider the economic return of innovation proxied, for instance, with the share of sales due to new or significantly improved products. However, this measure has being criticized by other scholars (Efthyvoulou and Vahter, 2016; Mairesse and Mohnen, 2010) and it is not available in our dataset (ESEE); in any case other alternatives could be explored in the future. Also concerning the measurement of key concepts in chapter three such as the regional knowledge base, we acknowledge that R&D expenditures and patents do not fully capture it despite they have been widely used in the literature. Although other measures might be used,[2] they also present their own limitations, such as data availability for the Spanish case. Finally, there is previous evidence on the importance of distance as a barrier to knowledge sharing in case of collaborations while offering the possibility to access different knowledge (Acosta et al., 2011; Hoekman et al., 2010). It would be interesting to analyze how the regional context conditions the returns to both regional and international collaboration, separately. Due to the lack of data

[2] This study also uses the employment in high and medium-high tech manufactures as suggested by the European Commission (2014) and Feldman and Audretsch (1999) for accounting for regional knowledge base.

on the geographical extent of the networking activities in the survey used in this paper, I cannot address this study empirically and I leave it in the future agenda with the use of a different database.

Chapter four is limited in several respects, but mainly by the lack of geographical information of firms. In the study, it is argued that other types of proximities may be at work, since the type of knowledge accessed is more of a standard nature and easy to codify diminishing the geographical proximity relevance. However, having the location of the firm might enrich the research, something I plan to explore in further analysis. Another important limitation is the fact of not having access in the survey to the sector from which firms buy the knowledge in order to incorporate into the study Marshalian/Jacobian type of externalities. When seeking specific information, as the disaggregation of the sectoral classification at three digit level and/or the geographic location for firms, most requests were rejected on the grounds of "anonymity laws" and the possible identification of the units, which of course the author understands.

As previously said, this dissertation has left an open door to future research. Therefore, with regard to the second chapter and in light of our results for LEs and SMEs, it would be interesting to analyze empirically which characteristics allow LEs to take more advantage of R&D offshoring than is true for SMEs. It would also be remarkable to study the fact that the service sector is apparently different from manufacturing when dealing with the impact of R&D offshoring. With regard to my third chapter, an insteresting future project is to study if firms invest in innovation less than the socially-desirable level, basically because of knowledge externalities. Policies may mitigate this plausible effect by subsidising private R&D and by encouraging firms to collaborate in R&D activities in order to partially internalize these externalities. Policy intervention could be addressed to specic areas of interest, such as environmental issues, with the aim to create some critical mass by putting together the brightest minds in the field. What is argued is that the innovation of local firms may be positively affected by the involvement of local organizations in international research networks supported by public funding specifically designed to boost transnational cooperation in environmental research. Finally, it would be interesting to replicate the analysis in chapter 4 for other countries at three digit level disaggregation of the industrial structure in order to incorporate relatedness among industries into the study. The latter is also connected to Marshalian/Jacobian type of externalities which I plan to proxy in a future study by input-output linkages in order to answer how important the own industrial knowledge generation is versus other industrial technologies for firms' innovativeness.

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