How does the regional knowledge base mediate firms' acquisition of external knowledge? *

Damián Tojeiro-Rivero†, Rosina Moreno‡

April 5, 2018

Abstract

Much has been said about the role that the acquisition of external knowledge plays on the innovative performance of firms, but little is known about the importance of contextual factors moderating the channels for accessing such external knowledge. In this article we analyze how the capacity of a region to generate new knowledge and knowledge externalities can mediate the benefit obtained from certain mechanisms through which firms acquire external knowledge. Specifically, we hypothesize that technological cooperation agreements and R&D outsourcing may imply different benefits depending on the knowledge base of the region where the firm is located. For Spanish manufactures in the period 2000-12 and through the use of a multilevel framework, we obtain that after controlling for the firm's characteristics, the regional context is still of certain relevance as a driver of firms' innovation performance, although differently in the case of cooperation and outsourcing. Cooperating in innovation activities is more beneficial for those firms located in a knowledge intensive region, whereas R&D outsourcing seems to be more profitable for firms in regions with a low knowledge pool.

AQR-IREA Research Group, University of Barcelona. Department of Econometrics, Statistics and Applied Economics. Av. Diagonal 690, 08034 Barcelona, Spain.

Keyword: Technological cooperation, R&D Outsourcing, Local Knowledge Spillovers; Multilevel; Panel data; Spanish Firms, Manufactures.

*This article 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).

†Tel. (+34) 934 021 412. Email: dtojeiro@ub.edu

‡Tel. (+34) 934 021 823. Email: rmoreno@ub.edu

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; Jones, 1995). 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 (Grossman and Helpman, 1991; Lucas, 1988; Romer, 1986, 1990) 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. Co-location creates an industrial atmosphere (Becattini, 1979) or local buzz (Storper and Venables, 2004), where ideas flow and knowledge is transferred continuously through informal linkages and serendipitous encounters.

In contrast to this broad belief, some scholars have raised the argument that co-location is not enough to acquire local knowledge, but some kind of formal mechanism such as involvement in networks is needed (Breschi and Lissoni, 2009). According to this view, without denying that knowledge spillovers might be a powerful agglomeration force, formal knowledge exchanges based on market conditions may play an even higher role as a mechanism of knowledge transfer (Breschi and Lissoni, 2001). Among other mechanisms, we can think of technological collaboration agreements or R&D outsourcing, which act as formal, intentional channels through which knowledge is transferred throughout the space allowing for new recombination of ideas (Fratesi and Senn, 2009). These formal mechanisms are not restricted to the knowledge in the region where the firm is located, but firms may build pipelines to benefit from knowledge hotspots around the world (Bathelt et al., 2004; Owen-Smith and Powell, 2004).

However, far less is known about the relationship between formal and informal mechanisms of acquisition of knowledge and its interplay on innovative performance at the firm level. The novelty of the present study and our primary research question is to analyze how regional characteristics, and in particular whether a firm being located in knowledge intensive regions, may extract a higher benefit from the formal mechanisms for acquisition of external knowledge as drivers of firms' innovative performance. In other words, we study to what extent the endowment of knowledge available in the region where the firm is located can influence the effect of different external sources of knowledge, namely technological cooperative agreements and R&D outsourcing, on the innovative performance of firms.

From a methodological perspective, we will 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 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 as well as a distinction between public and private knowledge.

Among the main results, we find that cooperating in innovation activities is more beneficial for those firms located in a knowledge intensive region probably due to the fact that cooperation needs personal contacts, sharing experiences, and dedicating internal resources for developing new solutions to a given problem. Following this, a firm located in a region with more knowledge endowment may have access to more resources available in the region to find these new solutions. On the contrary, R&D outsourcing seems to be more profitable in regions with a low knowledge pool. This is related to the fact that R&D outsourcing implies the use of the knowledge created by others – that is present in the market – to solve the enterprise's needs without implying big changes or adaptions. Therefore, this kind of knowledge needs to be more transferable across organizations, so it is easier for any firm to take advantage of it even in the case that the level of innovativeness found in the region is low.

The article is outlined as follows. In the second section we offer the literature review upon which this article is based. Section three offers the dataset and describes the variables, while the methodology is subsequently presented in section four. The main results are given in the fifth section and the last section concludes.

2 Literature review

2.1 Formal mechanisms for the acquisition of external knowledge

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 formal mechanisms such as cooperation agreements or through outsourcing (OECD, 2008) is gaining weight as an entrepreneurial strategy to become more innovative.

Most of the papers providing empirical evidence at a micro level reach 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), 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 external 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; Nieto and Santamaría, 2007; Van Beers and Zand, 2014). 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 component of 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 (Dhont-Peltrault and Pfister, 2011; Phene and Tallman, 2014; Teirlinck and Spithoven, 2013).

On the other hand, outsourcing part of the innovation process allows an enterprise to gain access to a new source of well-prepared labor, as pointed out by Lewin et al. (2009), as well as to capture external knowledge cheaply. Another relevant advantage of outsourcing is the widening of 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; Grimpe and Kaiser, 2010; Love et al., 2014; OECD, 2008, 20, 91). At the same time, outsourcing may allow the enterprise to gain in productivity and efficiency through an improved reconduction 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).

2.2 The firm's environment: Local knowledge spillovers (LKS)

Firms innovate thanks to the combination and recombination of existing knowledge that goes beyond the limits of their boundaries, accessing external sources of knowledge to expand new visions in their production process (Rosenkopf and Almeida, 2003). However, it is sensible to think that the environment where the firm is located can be essential to recombine and exploit such knowledge. Indeed, at an aggregate level, empirical studies in the geography of innovation (Feldman and Audretsch, 1999; Jaffe et al., 1993) and economic geography literature (Martin and Ottaviano, 1999) highlight that knowledge produced by a firm is only partially appropriated by the producer, whereas part of such knowledge spills over to other firms and institutions. Among the different mechanisms that imply informal exchange of ideas, and as a consequence, knowledge spillovers, we find those of face-to-face interactions between employees and frequent meetings (Allen, 1977; Krugman, 1991), monitoring of competitors (Porter, 1990), spin-offs (Audretsch and Feldman, 2004), trust building (Glaeser et al., 2002), an increased ability to assess and evaluate external knowledge and information collectively within a cluster (Döring and Schnellenbach, 2006), among others.

We stress two key points here. First, a clear assumption within this literature is that knowledge spills over easily from its source to other agents, and this is more the case with physically close actors than with firms located far apart. And second, the informal nature of such knowledge spillovers and the little effort needed to benefit from them since flows are more or less automatically received when being close in the space due especially to the public good definition of knowledge. Indeed, firms often have information on the accomplishments of nearby enterprises even without making any efforts in systematic monitoring (Malmberg and Maskell, 2006).

Previous ideas takes us to the concept of local buzz (Bathelt et al., 2004) consisting of information created by numerous 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 the shared cultural traditions that make interaction less costly. As such, this localized learning may involve spillover effects that take place "through more or less automatic processes of observation, monitoring, benchmarking and informal information exchange such as buzz" (Malmberg and Maskell, 2006, 9).

As a consequence of the existence of local knowledge spillovers, there is broad agreement that firms benefit from being located in regions with a rich knowledge base (Audretsch and Dohse, 2007; Döring and Schnellenbach, 2006). However, while the relevance of local knowledge spillovers for firm performance has been widely analyzed theoretically and empirically, noticeably less is known about what kind of firm benefits most from knowledge spillovers. We turn to this issue in the next subsection.

2.3 Relation between formal and informal mechanisms of acquisition of knowledge

Knowledge acquisition through formal mechanisms, such as technological cooperation and R&D outsourcing, can be assumed to link to the local buzz, so that both become reciprocally supporting. On the one hand, the more advanced the mechanisms of acquisition of external knowledge that bring information about new technologies into the local buzz, the more dynamic the milieu from which local actors profit. On the other hand, a more advanced local buzz presents stronger local interactions that may allow for better selection of external knowledge as well as better translation and integration processes of such knowledge into the firm.

Indeed, formal and informal mechanisms of acquisition of knowledge could complement each other (Malmberg and Maskell, 2006). First, the existence of neighborhood effects could make local buzz reinforce pipelines of knowledge thanks to local capabilities and similar experience in solving specific kinds of problems, allowing a novel recombination/implementation of such external knowledge. Second, knowledge spillovers may signal opportunities for accessing knowledge external to the firm through a more market oriented type of acquisition due to the necessity of sharing a more tacit knowledge, while internalizing the appropriation of such knowledge and building a relationship of trust. This complementarity would imply a self-reinforcing mechanism between knowledge intensive firms and regions.

However, there are contrasting arguments in favor of negative effects coming from 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 newly acquired technologies. 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. Grillitsch and Nilsson (2015) obtain that firms cooperating and located in the periphery get higher profitability of such formal acquisition of knowledge than those in urban areas.

Resulting from the conflicting argument that knowledge intensive firms may also experience negative spillovers, we may think that they may not be as dependent on local knowledge sources as most literature assumes. This being the case, there exist positive and negative effects on the interplay between local knowledge spillovers and firms' knowledge and their impact on firms' performance. Consequently, we argue that this interplay may be different for firms that manage to acquire external knowledge. Initially, particular firms that acquire external knowledge through formal mechanisms (technological cooperation and R&D outsourcing, among the main ones) should, a priori, benefit from a location in regions with a rich knowledge base. However, given that the knowledge acquired through cooperation agreements and through outsourcing present different characteristics, we argue that the result could be different.

The important point here is the explicit differentiation between tacit and codified/explicit knowledge (Polanyi, 1966). Codified knowledge may travel frictionless across the space and across agents through, among other things, information and communication technologies 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 can be of higher relevance in the case of technological cooperation agreements than in the case of R&D outsourcing. 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. That is, 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. In contrast, 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.

3 Dataset and variables

3.1 Dataset

Our main dataset 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. Firms are classified into twenty industries using the two-digit European classification NACE (see Table A1 in the Appendix).[1] As for the regional dataset on the contextual factors affecting innovation, we use Eurostat at the NUTS 2 level. In the Spanish case these territorial units represent administrative and policy authorities. We will consider the 2000-12 period since some of the variables taken from Eurostat are not provided for more recent years.

3.2 Firm level variables

Our dependent variable is the number of product innovations (NIP) as a proxy of the innovative output of the firm. 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; Wixe, 2016) since it takes into account the number of innovations made. Moreover, we have reasons to focus on product instead of process innovations. Building on previous evidence, the external acquisition of knowledge 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 (Phene et al., 2006).[2]

We consider two different strategies for the acquisition of external knowledge. Cooperation is a dummy equal to 1 if the enterprise cooperates with at least one partner and zero otherwise[3]; whereas Outsourcing equals to 1 if the enterprise declares to have external R&D expenditures and zero otherwise.

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)[4] to capture the firm's absorptive capacity

[1] All enterprises with more than 200 workers are enforced to participate, while those in between 10 and 200 employees are selected through a stratified sampling. 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

[2] 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.

[3] The partners can be suppliers, competitors, customers, and universities or research centers.

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

(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, the government tends to be an important player in the innovativeness process in Spain. We try to account for its direct effect through a dummy variable which equals 1 in the case where the firm received public funding from a government – regional, central, or others – for developing R&D and zero otherwise (R&D government). As some enterprises receive very little funding, we decided to re-scale it so that it is finally a dummy equal to one where the enterprise received governmental innovation funding higher than the total average value.

3.3 Regional level variables

We are interested in measuring the knowledge endowment of a region. On the input side, we account for the regional public and private effort on R&D (GERD referring to R&D expenditures) as a driver of firms' innovative performance (Sternberg and Arndt, 2001). In order to account for the accumulative process characterizing innovation and to avoid the influence of punctual shocks, we employ a measure of the stock of such knowledge instead of the flows of expenditure. Thus, we use the perpetual inventory method (as in Peri, 2005) with a geometric mean of the growth rates of R&D spending and a depreciation rate of five percent[5], all measured in purchased power parity at constant prices of 2005. 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).

On the output side of innovation, we propose to use information on the number of patents in each region (Regional patents). Instead of using the raw number of patents we compute the stock using the perpetual inventory method as in the case of expenditures in R&D. Although it would be more appropriate to use the information on the number of product or process innovations, this information is not available at the regional level. In any case, patents embed a high degree of novelty and are mostly generated with a commercial purpose, so that they have frequently been used in previous literature.

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. In addition, we introduce

[5] Other depreciation rates have been used, not affecting the results (see Robustness section 5.2).

sectoral dummies according to the technological sectoral classification (Table A1 in the appendix) and time dummies in order to capture any external shock. All variables in the model are lagged one period in order to lessen simultaneity problems.

4 Methodology

The use of a hierarchical or multilevel model allows for modelling the macro and micro levels simultaneously. Even though it has been used for some time now in other economic fields such as health and educational economics, it is quite recent that researchers in regional economics have realized of the importance of accounting for spatial differences through hierarchical models because of 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 modelling with such amount of regions can be found in López-Bazo and Motellón (2017), 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 those regional characteristics affecting the innovation performance of firms, we plan to use cross interactions between our firm and regional characteristics. In this sense, we follow Snijders and Bosker (2012) who stressed the latter as a more appropriated strategy than using random slopes when having theoretical/empirical reasons for them. Moreover, with so little number of groups, adding random slopes to the model for extending the analysis can bias the estimates; instead, using random intercepts leads to a more robust model.

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 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.[6] On the one hand, due to the poor within variabilities of our set of variables (see Tables A2 and A3 in the 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. Thus, 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 means 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.[7]

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 (see Rabe-Hesketh and Skrondal, 2012). Therefore, the hierarchy is the following: individual observations (time-firms) are nested on firms,

[6] 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).

[7] 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.

and firms are nested on regions.[8] In order to account for this scheme, we first perform a time varying firm-level equation where subscript i refers to the firm, j refers to the region and t refers to time:

$$log\left[E\left(Y_{ijt}|X_{ijt},X_{ij},Z_j,\mu_{0j},\mu_{0ij}\right)\right]=log\left(\eta_{ijt}\right)=\beta_{0ij}+\sum_{m=1}^{s}\beta_{1jm}X_{itjm}+\sum_{m=s+1}^{M}\beta_{2jm}X_{ijtm} \tag{1}$$

Then, the firm as well as region level groups are captured by equations 2 to 5:

$$\beta_{0ij}=\alpha_{00j}+\sum_{k=1}^{K}\gamma_{01k}X_{ijk}+\mu_{0ij} \qquad \mu_{0ij}\sim Normal\left(0,\ \sigma^2_{\mu 0}\right) \tag{2}$$

$$\alpha_{00j}=\gamma_{00}+\sum_{n=1}^{N}\gamma_{10n}Z_{jn}+\mu_{0j} \qquad \mu_{0j}\sim Normal\left(0,\ \sigma^2_{\mu 0}\right) \tag{3}$$

$$\beta_{1jm}=\gamma_{010m}+\sum_{n=1}^{h}\gamma_{11mn}Z_{jn} \tag{4}$$

$$\beta_{2jm}=\gamma_{001m} \tag{5}$$

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, μ_{0j} and μ_{0ij} 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.

Combining all the equations leads to our main equation:

$$log\left(\eta_{ijt}\right) \;=\; \gamma_{00}+\sum_{m=1}^{s}\gamma_{010m}X_{ijtm}+\sum_{m=s+1}^{M}\gamma_{001m}X_{ijtm}+\sum_{k=1}^{K}\gamma_{01k}X_{ijk}+\sum_{n=1}^{N}\gamma_{10n}Z_{jn}+$$

[8] As we want to study 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.

$$+ \sum_{m=1}^{s} \sum_{n=1}^{h} \gamma_{11mn} X_{ijtm} Z_{jn} + \mu_{1j} + \mu_{0ij} \tag{6}$$

where we have M time-varying firm-level characteristics, K time invariant firm-level characteristics and N regional-level variables. Summarizing, we are estimating a multilevel negative binomial random effect model with two random intercepts, one for the firm and another for the region.

Previous literature using multilevel modeling has mainly focused on the impact of regional characteristics – in the sense of social and economic aspects like unemployment, crime rate, regional GDP, etc. – on the innovative performance of the firm (Dautel and Walther, 2014; Naz et al., 2015; Srholec, 2015). More focused on regional innovation, López-Bazo and Motellón (2017) study how regional innovative aspects may influence the internal innovation capacity of enterprises. All these papers use the multilevel modeling for a cross-section dataset. In our case, we estimate a multilevel model using panel data, which to our knowledge, has been done only in two papers on topics related to innovation (Acosta et al., 2012; Naz et al., 2015).

5 Results

5.1 Descriptive analysis

Table 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 capita 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. 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.

[Insert Table 1 around here]

Interesting observations can be extracted when comparing those firms that develop one of the two strategies of acquisition of external knowledge (cooperation and outsourcing) and those that do not. As shown in Table 2, the average internal expenditure on R&D per worker is around fourteen 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 outsourcing if compared with those not engaged (Table 3). In summary, firms engaged in technological cooperation and/or outsourcing use more innovation resources and have a better innovative performance than those non-innovative and innovative enterprises that do not cooperate or outsource R&D.

[Insert Tables 2 and 3 around here]

Table 4 contains seven different estimations in order to analyze how firm and regional characteristics affect firms' innovative performance. We present the incidence rates 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) (see 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.

[Insert Table 4 around here]

This first specification illustrates that all the regressors 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. This is related with the idea stressed in several studies that the development of new products largely depends on the firm's ability to build networks and partnerships as a way to incorporate external knowledge for innovation (Powell and Grodal, 2005; Trigo and Vence, 2012). In particular, collaborative agreements have become a strategy of knowledge sharing and transfer across firms that are largely recognized as an important (quasi-market) mechanism to access such external knowledge (Schilling, 2009). On the other hand, outsourcing could be the best option if the firm wants to reduce management costs while focusing on core activities and taking advantage of the specific knowledge of the external enterprise (Dhont-Peltrault and Pfister, 2011).

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 main hypotheses of the article, specifications 2 to 7 take into account different measures to proxy for the knowledge base of a region.[9] In particular, specifications in columns 2 and 3,[10] include the effect of the regional stock of patents on the number of product innovations at the firm level. Again, we note the relevance of the mechanisms for the external acquisition of knowledge, with the parameters of cooperation and outsourcing being positive and highly significant. 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.

[9]Although not presented in the article, we performed an alternative model with only the firm's characteristics and the interactions of the two mechanisms of acquisition of knowledge with each regional dummy. The reasoning for doing this relies on the expectation of a different regional impact depending on the two sources of external knowledge. The computation of an F-Test for the interactions between cooperation and the regional dummies as well as between outsourcing and the regional dummies leads to significant values for such crossings. This can be taken as an indication of a different impact of the strategies of acquisition of external knowledge depending on the region where the firm is located. This advocates for the use of interactions as will be done subsequently in the article.

[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 A4 in the Appendix).

This is in accordance with the wide agreement that firms benefit from being located in knowledge-intensive regions (Audretsch and Dohse, 2007; Döring and Schnellenbach, 2006).

However, when we look at the cross effect between the regional innovation environment and technological cooperation and/or outsourcing on firms' performance, an interesting result appears. Being in a region with more knowledge capacity (measured through patents) is more beneficial for those enterprises that cooperate, whereas for those firms that outsource R&D it is more beneficial to be 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 LKS 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 (D'Agostino et al., 2013; Dhont-Peltrault and Pfister, 2011) 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.

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 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 provide some evidence on the reason behind this non-significance of the cross-effect, we separate the stock of R&D into its different components, which could reflect a different type of knowledge, 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. The regional stocks of R&D expenditures of the business and government sectors are not significant, while the parameter for the higher education sector is positive and highly significant. However, when crossing the different types of stock of R&D with technological cooperation, we observe that those firms that are cooperating and located in business knowledge-dense regions are in a good position to have more product innovations. 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. Therefore, the positive coefficient – although not significant – found in previous specifications for cooperative firms in regions with a high knowledge pool is, in fact, driven by the amount of R&D expended by private organizations. Moreover, it seems that the non-significance of such cross product could be due to the different directions when splitting R&D expenditures into the public/business sectors canceling the significance of the effect.

In the same manner, we observe that the non-significance of the cross term for outsourcing in knowledge intensive regions could be due to the different sign of such cross effect in the private and public sectors. Several explanations given in the literature review section are in order. First, enterprises in regions where the private knowledge pool is scarce might face a lower degree of competition, so that they can profit more from a less complex and more standard type of knowledge as that acquired from outsourcing. On the other hand, firms in regions with a poor knowledge base do not need to be as innovative as those in high knowledge regions, since an imitation strategy could fit better (Aghion and Jaravel, 2015). That is, R&D outsourcing can be envisaged as a good strategy for firms in low innovative regions compared to firms in more knowledge intensive regions.

On the other hand, a positive interaction between outsourcing and the public knowledge base in the region is observed (although only significant in the case of the government sector). Although we could think that outsourcing can be more beneficial in regions with a high government knowledge pool, it is also true that the regions with a higher share of knowledge made by governmental organizations as well as universities are those with a lower stock of business knowledge. Therefore, it may be the case that the government could be compensating for the lower private knowledge endowment in such regions (Aghion and Jaravel, 2015). Consequently, the possible explanation might not have to do with the type of knowledge developed by those institutions but just because those improvements are made precisely in the regions with a poor private knowledge base.

5.2 Robustness section

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 we may follow the assumption that missing values are random (Snijders and Bosker, 2012).[11] Estimations in Table A5 in the Appendix control for this and show that the results do not change qualitatively and barely change quantitatively for our key variables.

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)[12], instead of 5 percent, the results follow the same pattern (Table A6). Moreover, we have taken Wooldridge (2010, chapter 3) advice, and despite the multicollinearity 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

[11] 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.

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

variable. Table A7 shows 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.

Finally, some enterprises may move from one region to another during the period of analysis, possibly leading to a bias in 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. We re-estimated our model discarding these moving firms, which only represent 3.8 percent of total firms in the sample. Following Chung and Beretvas (2012), the bias due to not controlling 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 to which they move. We expect not to have an important bias in our estimations since the number of firms changing locations in our sample is very low (3.8%) in comparison to theirs (10%). Table A8 shows the results and again, qualitatively speaking, our main results are virtually the same.

6 Conclusion

In this article, we study how the knowledge base of the region where the firm is located affects firms' innovative performance. Specifically, we analyze how the knowledge endowment of the region can mediate the benefit obtained by firms thanks to the acquisition of external knowledge either through technological cooperation agreements or through R&D outsourcing. The evidence provided refers to Spanish manufacturing enterprises in the period 2000 to 2012 and we take explicit account of the multilevel structure of the data as well as its panel structure.

Although firms' characteristics are obtained to be more relevant than regional ones, something already stressed in recent studies (Backman, 2014; López-Bazo and Motellón, 2017; 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. Also, technological cooperation and R&D outsourcing help in explaining firms' innovative performance. However, we observe that this effect is moderated by some regional factors. Indeed, we find evidence of a reinforcement effect between being in a highly knowledge endowed region and the benefits 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.

This could be partly due to the type of knowledge embedded in these two different strategies for the acquisition of external knowledge. For those enterprises cooperating in innovation activities, it is more profitable to be located in a knowledge-dense region, because the type of knowledge shared in cooperation agreements tends to be highly tacit, implies high technicity, and involves a high degree of personal contacts. In this scenario, knowledge externalities coming from other organizations in the region can help the firm in such a process of knowledge processing. Indeed, cooperation needs personal contacts and dedicating internal resources for developing new solutions and new approaches to solve new problems. Following this, a firm located in a region with a rich knowledge base may have access to more resources available in the region to find these new solutions that can only be made through personal contact and sharing experiences.

In the case of R&D outsourcing, the knowledge incorporated is more standard, with a lower technical component, and for which personal contact is less relevant, so that there would be a lower need for knowledge spilling from other firms in the region. Indeed, the outsourcing strategy uses the knowledge created by others – that is present in the market – to solve the enterprise's needs without implying big changes or adaptions. Therefore, this kind of knowledge needs to be more transferable across organizations, and it is easier for any firm to take advantage of it even in the case that the level of innovativeness found in the region is low.

In addition, we analyze if the results are maintained when we consider separately the regional knowledge endowment made by the private sector, the government, and universities and research centers. 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 governmental organizations and universities.

Some policy implications are envisaged. First, governments should not enforce winning or one-size-fits-all types of policy. Firms' innovative performance is likely to differ in terms of knowledge requirements, the kind of problem-solving involved, managerial capabilities, and learning potential (Lucena, 2011; Teirlinck and Spithoven, 2013). Thus, 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.

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). However, in light of our results, in order to improve the innovative performance of firms, policy makers should focus on strengthening the relationship among organizations by encouraging and promoting knowledge transmission among relevant actors, while taking into account the contextual environment in which the firm is located.

Limitations & Future Research

Some limitations of our study are as follows. First, a possible endogeneity problem due to the higher-level variables may arise. However, this problem is resolved thanks to the use of the Mundlak approach as well as by the fact that we estimate a multilevel random effects model augmented with the between-within effects. Indeed, 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). Second, 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 firm is not sufficiently important to affect regional performance. Third, 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. 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. Moreover, the study of the drivers of firms' location is beyond the scope of the article.

Acknowledgments

We thank Antonio Di Paolo, Fernando Bruna, Ernest Miguélez, Enrique López-Bazo, Malcom Fairbrother and Carla Rampichini as well as the participants of the XX Applied Economics Meeting, the 4th Geography of Innovation Conference - GEOINNO 2018, and the 6th PhD-Student Workshop on Industrial and Public Economics (WIPE) for their useful comments on earlier versions. Damián Tojeiro-Rivero gratefully acknowledges financial support from the University of Barcelona (APIF). Rosina Moreno acknowledges financial support provided by the Ministerio de Economía y Competitividad for the project entitled "Innovation and locational factors: Diversification, knowledge and the environmental revolution", ECO2017-86976-R, as well as to the Program ICREA Acadèmia. However, any mistakes or omissions remain the authors' alone.

References

Acosta, M., Coronado, D., and Martínez, M. Á. (2012). Spatial differences in the quality of university patenting: Do regions matter? *Research Policy*, 41:692–703.

Aghion, P., Howitt, P., Brant-Collett, M., and García-Peñalosa, C. (1998). *Endogenous Growth Theory*. MIT Press.

Aghion, P. and Jaravel, X. (2015). Knowledge spillovers, innovation and growth. *Economic Journal*, 125(583):533–573.

Allen, T. J. T. J. (1977). *Managing the flow of technology : technology transfer and the dissemination of technological information within the R&D organization*. [MIT Press].

Audretsch, D. B. and Dohse, D. (2007). Location: A neglected determinant of firm growth. *Review of World Economics*, 143(1):79–107.

Audretsch, D. B. and Feldman, M. P. (1996). R&D Spillovers and the Geography of Innovation and Production. *The American Economic Review*, 86(3):630–640.

Audretsch, D. B. and Feldman, M. P. (2004). Knowledge Spillovers and the Geography of Innovation. In Thisse, V., , and J., H., editors, *Handbook of Urban and regional Economics*.

Backman, M. (2014). Human capital in firms and regions: Impact on firm productivity. *Papers in Regional Science*, 93(3):557–575.

Bathelt, H., Malmberg, A., and Maskell, P. (2004). Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, 28(1):31–56.

Becattini, G. (1979). Dal settore industriale al distretto industriale. Alcune considerazioni sull'unità di indagine dell'economia industriale. *Rivista di economia e politica industriale*, 5(1):7–21.

Belderbos, R., Carree, M., and Lokshin, B. (2006). Complementarity in R & D Cooperation Strategies. *Review of Industrial Organization*, 28(4):401–426.

Belderbos, R., Van Roy, V., and Duvivier, F. (2013). International and domestic technology transfers and productivity growth: Firm level evidence. *Industrial and Corporate Change*, 22(1):1–32.

Bell, A., Fairbrother, M., and Jones, K. (2016). Fixed and Random effects : making an informed choice.

Bell, A. and Jones, K. (2015). Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data. *Political Science Research and Methods*, 3(01):133–153.

Bertrand, O. and Mol, M. J. (2013). The antecedents and innovation effects of domestic and offshore R&D outsourcing: The contingent impact of cognitive distance and absortive capacity. *Strategic Management Journal*, 34:751–760.

Breschi, S. and Lissoni, F. (2001). Localised knowledge spillovers vs . innovative milieux : Knowledge "tacitness" reconsidered. *Papers Reg . Sci*, 80:255–273.

Breschi, S. and Lissoni, F. (2009). Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. *Journal of Economic Geography*, pages 1–30.

Cassiman, B. and Veugelers, R. (2006). In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition. *Management Science*, 52(1):68–82.

Chesbrough, H. (2003). *Open Innovation. The New Imperative for Creating and Profiting from Technology*. Harvard Business School Press, Boston.

Chung, H. and Beretvas, S. N. (2012). The impact of ignoring multiple membership data structures in multilevel models. *British Journal of Mathematical and Statistical Psychology*, 65(2):185–200.

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, 35(1):128–152.

Dachs, B., Kampik, F., Scherngell, T., Zahradnik, G., Hanzl-Weiss, D., Hunya, G., Foster, N., Leitner, S., Stehrer, R., and Urban, W. (2012). Internationalisation of business investments in R&D and analysis of their economic impact. Technical report, European Commission, Luxembourg.

D'Agostino, L. M., Laursen, K., and Santangelo, G. D. (2013). The impact of R&D offshoring on the home knowledge production of OECD investing regions. *Journal of Economic Geography*, 13(1):145–175.

Dautel, V. and Walther, O. (2014). The geography of innovation in a small metropolitan region: An intra-regional approach in Luxembourg. *Papers in Regional Science*, 93(4):703–725.

Dhont-Peltrault, E. and Pfister, E. (2011). R&D cooperation versus R&D subcontracting: empirical evidence from French survey data. *Economics of Innovation and New Technology*, 20(4):309–341.

Döring, T. and Schnellenbach, J. (2006). What do we know about geographical knowledge spillovers and regional growth?: A survey of the literature. *Regional Studies*, 40(3):375–395.

Feldman, M. P. and Audretsch, D. B. (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review*, 43(2):409–429.

Fratesi, U. and Senn, L. (2009). Regional Growth, Connections and Economic Modelling: An Introduction. In *Growth and Innovation of Competitive Regions*, pages 3–27. Springer Berlin Heidelberg, Berlin, Heidelberg.

Glaeser, E. L., Laibson, D., Sacerdote, B., Bowles, S., Haveman, R., Katz, L., Machin, S., Putnam, R., and Shleifer, A. (2002). An economic approach to social capital. *The economic Journal*, 112:437–458.

Grillitsch, M. and Nilsson, M. (2015). Innovation in peripheral regions: Do collaborations compensate for a lack of local knowledge spillovers? *Annals of Regional Science*, 54(1):299–321.

Grillitsch, M. and Nilsson, M. (2017). Firm performance in the periphery: on the relation between firm-internal knowledge and local knowledge spillovers. *Regional Studies*, 51(8):1219–1231.

Grimpe, C. and Kaiser, U. (2010). Balancing internal and external knowledge acquisition: The gains and pains from R & D outsourcing. *Journal of Management Studies*, 47(8):1483–1509.

Grossman, G. M. and Helpman, E. (1991). *Innovation and growth in the global economy*. MIT Press.

Hox, J. (2002). *Multilevel analysis: Thechniques and applications*. Lawrence Erlbaum Associates, New Jersey.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Source: The Quarterly Journal of Economics*, 108(3):577–598.

Jones, C. . (1995). R&D-Based Models of Economic Growth. *Journal of Political Economy*, 103(4):759–784.

Krugman, P. (1991). Increasing Returns and Economic Geography. *The Journal of Political Economy*, 99(3):483–499.

Laursen, K. and Salter, A. (2006). Open for innovation: The role of openness in explaining innovation performance among U.K. manufacturing firms. *Strategic Management Journal*, 27(2):131–150.

Lewin, A. Y., Massini, S., and Peeters, C. (2009). Emerging Global Race for Talent. *Journal of International Business Studies*, (October):2009.

López-Bazo, E. and Motellón, E. (2017). Innovation, heterogeneous firms and the region: evidence from Spain. *Regional Studies*, 3404(October):1–15.

Love, J. H., Roper, S., and Vahter, P. (2014). Dynamic complementarities in innovation strategies. *Research Policy*, 43(10):1774–1784.

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22:3–42.

Lucena, A. (2011). The organizational designs of R&D activities and their performance implications: empirical evidence for Spain. *Industry & Innovation*, 18(2):151–176.

Maas, C. J. and Hox, J. (2005). Sufficient Sample Sizes for Multilevel Modeling. [References]. *Journal of Research Methods for the Behavioral and Social Sciences*, 1:86–92.

Malmberg, A. and Maskell, P. (2006). Localized learning revisited. *Growth and Change*, 37(1):1–18.

Marshall, A. (1890). *Principles of Economics: An introductory volume.* McMillan, Londom.

Martin, P. and Ottaviano, G. I. P. (1999). Growing locations: Industry location in a model of endogenous growth. *European Economic Review*, 43:281–302.

Maskell, P. and Malmberg, A. (1999). Localised learning and industrial competitiveness. *Cambridge Journal of Economics*, 23(2):167–185.

Mihalache, O. R., Jansen, J. J. J. P., Van Den Bosch, F. A. J., and Volberda, H. W. (2012). Offshoring and firm innovation: The moderating role of top management team attributes. *Strategic Management Journal*, 33:1480–1498.

Mundlak, Y. (1978). On the Pooling of Time Series and Cross Section Data. *Econometrica*, 46(1):69–85.

Naz, A., Niebuhr, A., and Peters, J. C. (2015). WhatÂŽs behind the disparities in firm innovation rates across regions? Evidence on composition and context effects. *Annals of Regional Science*, 55(1):131–156.

Nieto, M. J. and Rodríguez, A. (2011). Offshoring of R&D: Looking abroad to improve innovation performance. *Journal of International Business Studies*, 42(3):345–361.

Nieto, M. J. and Santamaría, L. (2007). The importance of diverse collaborative networks for the novelty of product innovation. *Technovation*, 27(6-7):367–377.

OECD (2008). The Internationalisation of Business R&D: Evidence, Impacts and Implications. Technical report, France.

Owen-Smith, J. and Powell, W. W. (2004). Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community. *Organization Science*, 15(1):5–21.

Peri, G. (2005). Determinants of Knowledge Flows and Their Effect on Innovation. *The Review of Economics and Statistics*, 87(2):308–322.

Phene, A., Fladmoe-Lindquist, K., and Marsh, L. (2006). Breakthrough innovations in the U.S. biotechnology industry: The effects of technological space and geographic origin. *Strategic Management Journal*, 27(4):369–388.

Phene, A. and Tallman, S. (2014). Knowledge spillovers and alliance formation. *Journal of Management Studies*, 51(7):1058–1090.

Polanyi, M. (1966). *The tacit dimension.* Doubleday, Garden City N.Y., [1st ed.]. edition.

Porter, M. (1990). *The Competitive Advantage of Nations.* McMillan, London.

Powell, W. W. and Grodal, S. (2005). Networks of innovators. In Fagerberg, J., Mowery, D. C., and Nelson, R. R., editors, *The Oxford Handbook of Innovation*, chapter chapter 3, pages 56–85. Oxford University Press.

Rabe-Hesketh, S. and Skrondal, A. (2012). *Multilevel and longitudinal modeling using Stata.*

Rahko, J. (2016). Internationalization of corporate R&D activities and innovation performance. *Ind. Corp. Change*, pages dtw012–.

Romer, P. M. (1986). Increasing Returns and Long-Run Growth. *Journal of Political Economy*, 94(5):1002–1037.

Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(2):71–102.

Rosenkopf, L. and Almeida, P. (2003). Overcoming Local Search Through Alliances and Mobility. *Management Science*, 49(6):751–766.

Schilling, M. A. (2009). Services, industry evolution, and the copetitive strategies of product firms. *Strategic Management Journal*, 30(3):233–260.

Snijders, T. A. B. and Bosker, R. J. R. J. (2012). *Multilevel analysis : an introduction to basic and advanced multilevel modeling.*

Srholec, M. (2010). A Multilevel Approach to Geography of Innovation. *Regional Studies*, 449:1207–1220.

Srholec, M. (2015). Understanding the diversity of cooperation on innovation across countries: Multilevel evidence from Europe. *Economics of Innovation and New Technology*, 24:159–182.

Stegmueller, D. (2013). How many countries for multilevel modeling? A comparison of frequentist and bayesian approaches. *American Journal of Political Science*, 57(3):748–761.

Sternberg, R. and Arndt, O. (2001). The Firm or the Region : What Determines the Innovation Behavior of European Firms ? *Economic Geography*, 77(4):364–382.

Storper, M. and Venables, A. J. (2004). Buzz: face-to-face contact and the urban economy. *Journal of Economic Geography*, 4:351–370.

Teirlinck, P. and Spithoven, A. (2013). Research collaboration and R&D outsourcing: Different R&D personnel requirements in SMEs. *Technovation*, 33(4-5):142–153.

Trigo, A. and Vence, X. (2012). Scope and patterns of innovation cooperation in Spanish service enterprises. *Research Policy*, 41(3):602–613.

Van Beers, C. and Zand, F. (2014). R&D cooperation, partner diversity, and innovation performance: An empirical analysis. *Journal of Product Innovation Management*, 31(2):292–312.

van Oort, F. G., Burger, M. J., Knoben, J., and Raspe, O. (2012). Multilevel approaches and the firm-agglomeration ambiguity in economic growth studies. *Journal of Economic Surveys*, 26(3):468–491.

Vega-Jurado, J., Gutiérrez-Gracia, A., and Fernández-De-Lucio, I. (2009). Does external knowledge sourcing matter for innovation? Evidence from the Spanish manufacturing industry. *Industrial and Corporate Change*, 18(4):637–670.

Wixe, S. (2016). Neighbourhood related diversity, human capital and firm innovation. *Papers in Regional Science*.

Wooldridge, J. M. (2010). *Introducción a la econometría. Un enfoque moderno.* Cengage Learning, 4a edition.

Table 1: Descriptive statistics of the regional variables

	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

Note: GERD (total, business, government and HES) and Regional patents are measured in per capita terms. Tertiary education is the percentage of people with an undergraduate, master or PhD.

Table 2: Descriptive statistics for enterprises cooperating and not cooperating

	Full Sample					Non Cooperative Firms					Cooperative Firms				
VARIABLES	mean	sd	N	min	max	mean	sd	N	min	max	mean	sd	N	min	max
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
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
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: Descriptive statistics for enterprises doing outsourcing and not doing outsourcing

	No R&D Outsourcing					R&D Outsourcing				
VARIABLES	mean	sd	N	min	max	mean	sd	N	min	max
NIP	0.547	2.404	20,457	0	30	1.931	4.089	6,049	0	30
Cooperation (dummy)	0.160	0.366	20,457	0	1	0.826	0.379	6,049	0	1
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

Table 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)
$InternalRD_{t-1}$	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)
$Size_{t-1}$	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)
$Size^2_{t-1}$	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).

Appendix

Table A1. 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 A2. 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 A3. 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 A4. 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 A5. 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 A6. Using a depreciation rate of 10% 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 A7. 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).

Table A8. Excluding enterprises moving among regions

VARIABLES	(1) NIP	(2) NIP	(3) NIP	(4) NIP	(5) NIP	(6) NIP	(7) 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).