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The trilogy of knowledge spillovers in French regions: a history of nature, channels and boundaries

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Abstract:
We suggest three theoretical propositions on the nature, channels and boundaries of knowledge spillovers, and we test them with knowledge production functions estimated on French NUTS 3 regions over 2002–2008. Several novelties are introduced. First, we quantify external R&D to complement the usual internal R&D variable and assess the effect of knowledge nature on knowledge spillovers. Second, we construct several measures of the quantity and quality of regional knowledge diffusion channels and introduce them in our knowledge production functions. Third, we test several spatial panel specifications to assess robustness and evaluate the geographical boundaries of various types of knowledge spillovers. All methods converge to provide evidence for the following: 1) spillovers from internal R&D are larger than spillovers from external R&D; 2) the quantity and quality of regional knowledge transmission channels are important determinants of regional innovation; and 3) industrial and technological diversity produce positive knowledge externalities, not only locally but also in the neighbourhood of French regions.

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1. Introduction

Knowledge spillovers amplify the social benefits of R&D and stimulate the geographical clustering of innovative activities, thereby leading some cities, regions and even nations to acquire a technological competitive advantage. However, because they are not directly observable and use different channels to diffuse, they raise many questions and debates. One can sort these interrogations in three series of questions. A) Do knowledge spillovers happen only at a small distance, such as within cities, or do they also exist at longer distances, such as between regions or even between nations? B) What are the channels through which knowledge diffusion occurs and are they geographically bounded? Is it important for regional innovation to be endowed with numerous and efficient knowledge diffusion networks? C) What are the factors influencing knowledge diffusion processes through these channels and do they produce spatial clustering or spatial dispersion of knowledge spillovers?

One can provide answers to the first series of questions using spatial econometrics methods, but neglecting questions B) and C) can result in under-specification biases in the econometric estimates and incorrect economic interpretations of the evidence. Therefore, rigorous studies of knowledge spillovers between agents/places confront a complex challenge because they have to account for the channels of knowledge diffusion and control for the numerous characteristics of agents/places suspected to influence knowledge flows: competitive pressure, Marshall-Arrow-Romer specialisation externalities, Jacobs diversity externalities, technological endowments and absorptive capacities. Most recent studies introduce part of these control variables, but bringing them together is rarely tractable. Moreover, only a few recent studies introduce variables capturing at least one of the three main channels of knowledge diffusion identified in the theoretical literature: labour force mobility, spin-offs and formal or informal networks (see, e.g., Breschi and Lissoni, 2006, Boufaden and Plunket, 2008, Ponds et al., 2010).

The goal of this paper is to study the nature, channels and boundaries of knowledge spillovers using an integrative knowledge production function (KPF) framework applied to French regions. More precisely, we aim to provide answers to three questions: 1) the *nature* question: what is the effect of the nature of knowledge and of the type of knowledge spillovers on innovation productivity? 2) the *channels* question: Is the abundance and efficiency of knowledge diffusion channels an effective determinant of regional innovation productivity? and 3) the *boundaries* question: What are the short distance determinants of innovation productivity and what are the ones that remain effective over longer distances?

The KPF framework correlates R&D activities of some agents/places with the innovative output of possibly different and distant agents/places. We propose to account for both the nature and the channels of knowledge spillovers within a panel data framework, and we use spatial econometrics to assess whether each of them acts at short or long distance, that is to say, whether they produce localised or distant knowledge spillovers. To the best of our knowledge, this is the first study on French NUTS 3 regions in which the nature, the channels and the boundaries of knowledge spillovers are accounted for together. Considering that in-house and outsourced R&D have very different contents of tacit and codified knowledge, we assess separately their influence on innovation productivity and we test whether they spill over different distances. We use an index of industrial and technological diversity to capture Jacobs externalities. We also use a synthetic measure of the abundance and quality of knowledge diffusion channels to assess whether they are important determinants of a region's innovation productivity. We compare the impact of this synthetic variable to density measures regarding more specific research networks. Our econometric framework is twofold. First, we employ panel econometrics that seriously address heterogeneity and endogeneity problems using the estimator proposed by Amemiya and MaCurdy (1986). We then test our model with spatial econometric techniques for panel data, which provides explicit treatment of spatial dependence and allows us to assess the boundaries of spillovers evidenced in the first stage panel estimations.

The paper is organised as follows. In section 2, we review the existing literature on knowledge spillovers and argue in favour of an integrative approach accounting for the nature, channels and boundaries of knowledge diffusion. In section 3, we describe the data and the research design. Section 4 discusses the results and section 5 assesses their robustness. Section 6 concludes.

2. Nature, channels and boundaries of knowledge spillovers

There is now a growing consensus on the idea that knowledge spillovers are neither completely localised and bounded in space nor completely free to diffuse at any distance and between any kind of agents/places (see, e.g., Breschi and Lissoni, 2001, Amin and Cohendet, 2004, Boschma, 2005, Rallet and Torre, 2007). Indeed, it is widely acknowledged that the geographical scale of knowledge diffusion processes depends on three factors: 1) the type of knowledge at stake; 2) the kind of diffusion channel it uses; and 3) the characteristics of the agents, organisations or places involved in the knowledge exchange process.

The first series of factors was originally inspired by the seminal work of M. Polanyi (1966) on tacit knowledge, revived by Nelson and Winter (1982) and applied by Gertler (2003) to show the importance of contextualisation as a determinant of production, appropriation and exchange of tacit knowledge. Nevertheless, the distinction between tacit, person-embodied, knowledge and codified, explicit knowledge is difficult to operationalise in econometric frameworks. The tacitness argument is used everywhere to explain why knowledge spillovers appear to be bounded in space, but one cannot find a study that compared how strongly and how far tacit and codified knowledge spill over. On the contrary, many studies differentiate public and private R&D, or academic and entrepreneurial R&D. One generally considers that basic knowledge is the main product of the former whereas applied knowledge is the main outcome of the latter, but this division of knowledge-producing labour tends to become less relevant in the age of mode 2 science (Gibbons et al., 1994). Moreover, the distinction between basic research and applied research does not seem very fertile to understand why some knowledge flows are localised whereas others are able to diffuse at longer distances. In theory, the main determinant of the geographical extension of knowledge spillovers remains the need for face-to-face contacts to transfer tacit knowledge and the use of codification to diffuse knowledge over longer distances. Therefore, we propose to employ a twofold R&D measure that differentiates outsourced R&D and in-house R&D as an operational approach to account for the differences in tacit and codified knowledge contents. Indeed, several authors (e.g., Cowan and Foray, 1997, Cantwell and Santangelo, 1999 or Narula, 2001) argued that outsourced R&D is less frequent than in-house R&D because it requires a high level of codification that is never perfectly attained. For the residual tacit knowledge embedded in outsourced R&D, the property rights are difficult to establish and outsourcing may generate unintended spillovers. As a consequence, firms seeking to take advantage of tacit knowledge will prefer in-house R&D authorising face-to-face contacts and avoiding unintended knowledge transfers to competitors: “The benefits of such tacit knowledge arise only through a culture of trust and knowledge-sharing within an organization” (Cowan, David and Foray, 2000, p. 223). This is not exclusive of the presence of codified knowledge in internal R&D activities. On the contrary, outsourced R&D relies very strongly on codified knowledge that is more easily transferable but also less idiosyncratic and novel. We use these arguments to infer one hypothesis and one proposition that will be assessed empirically.

Hypothesis 1: In-house R&D makes use of both tacit and codified knowledge whereas outsourced R&D involves a much greater proportion of codified knowledge. Consequently, using distinct measures for internal and external R&D is a fairly good approach to assess whether the nature of knowledge, tacit versus codified, determines the intensity and the boundaries of knowledge spillovers.

Proposition 1: *The nature of knowledge has a significant impact on the magnitude of knowledge spillovers. Consequently, in-house R&D has higher innovation productivity than outsourced R&D because it takes advantage of both tacit and codified knowledge. On the contrary, outsourced R&D has weaker innovation productivity because it utilises a great proportion of codified knowledge with lesser novelty content.*

The French R&D survey offers a clear distinction between firms' internal and external R&D. Therefore, it provides an opportunity to test proposition 1.

Concerning the second series of factors, three knowledge diffusion channels are now widely acknowledged by the theoretical literature: labour force mobility, spin-offs and networks of knowledge exchange, whether formal or informal. Geographical and occupational mobility is the channel through which skilled engineers and researchers diffuse their tacit, person-embedded knowledge in the organisations that successively employ them. Strong empirical evidence supports this mechanism of knowledge diffusion (e.g., Almeida and Kogut, 1999, Breschi and Lissoni, 2009, Corredoira and Rosenkopf, 2010). A spin-off is the practice through which a new company is created from a parent organisation. It is not only one important means of transferring and commercialising innovations but also a channel for circulation of person-embodied knowledge: some employees leave the parent organisation, taking with them knowledge that will enter a new organisation but not necessarily in a new place because spin-offs tend to stay near parent organisations (Buenstorf and Geissler, 2009). Most frequently driven by strategic disagreements (Klepper, 2007), spin-offs have been very important in the development of places like Silicon Valley, but they also allowed long distance knowledge transfers between core developed countries and emergent peripheral economies (Saxenian, 2007). Finally, the third knowledge diffusion channel is made of various types of networks that can support knowledge flows. Social networks offer numerous channels of informal knowledge transfers and there is now evidence that they are effective at stimulating regional knowledge spillovers, making social capital an important transmission channel for tacit knowledge exchanged at short distance (Tappeiner et al., 2008). More formal collaborations are also an essential means of transferring knowledge more intentionally and over longer distances. For example, strategic alliances and research joint ventures have been recognised as an important vector of knowledge transmission since the mid-nineties (e.g., Mowery et al., 1996). Recent empirical evidence shows that inter-firm research partnerships have become one of the most effective tools for knowledge creation (e.g., Hagedoorn, 2002), and there is also growing evidence for the effectiveness of the university-industry channel of knowledge diffusion (Ponds et al., 2010). One could also argue that networks produce interregional knowledge exchanges through interregional trade flows. Indeed, there is evidence that business and social networks stimulate trade flows between regions (Combes and Lafourcade, 2005).

Therefore, any kind of network allowing either face-to-face or distant interactions between highly skilled researchers or engineers may contribute to knowledge diffusion. That is why we suggest the following hypothesis and proposition.

Hypothesis 2: Clusters endowed with the most various and effective networks of knowledge transmission are characterised by higher innovative performance because they benefit from more important knowledge spillovers arising from various channels. In high-tech clusters, these knowledge channels are complementary and cumulative rather than substitutable.

Proposition 2: *The various channels of knowledge diffusion have cumulative effects on innovation productivity. Consequently, high-tech clusters endowed with a wealth of good-quality knowledge networks will have higher innovation productivity.*

In other words, some regions have more clusters than others, and these clusters have more numerous and more efficient knowledge transmission channels. Therefore, they will have greater innovative performance because they are highly endowed with the three kinds of knowledge diffusion channels (labour mobility, spinoff opportunities and efficient formal and informal networks) and because these channels have cumulative effects on knowledge diffusion.

In France, the cluster policy is based on identification of the most highly gifted clusters that are labelled "Pôles de compétitivité mondiaux ou à vocation mondiale" ("world-class clusters" in the sequel). This label is obtained by places endowed with regional, national and international research collaboration networks, with labour markets that can attract highly skilled engineers and researchers from abroad, and with a high level of innovative entrepreneurship. However, assessing whether the presence of world-class clusters in a region is a source of higher innovation productivity remains difficult because of the endogeneity bias generated by the reverse causation between the regions' innovation production and obtaining 'world-class cluster' labels (Martin, 2003). This cannot be disentangled without explicit treatment of endogeneity in the econometric setting. Moreover, testing proposition 2 requires to compare the effect of particular knowledge diffusion channels considered alone to the cumulated effect of several knowledge diffusion channels that can be present in some gifted regions.

The third array of factors possibly determining the geographical scale of knowledge diffusion is made of the characteristics of agents/places that transfer and receive knowledge when it spills over. Indeed, various factors may affect the learning capacity of agents and places (Asheim, 1996). Theory and empirical evidence generally show that the ability to extract benefits from knowledge spillovers is positively correlated to the size of the firm/place, the intensity of the competitive pressure that characterises its business environment, and the level of the technological and human capital endowments (Porter, 1990, 2003). More controversial is the specialisation/diversification debate. Marshall (1890) argued that industrial districts could benefit from more efficient knowledge transfer mechanisms because of their high degree of industrial specialisation leading to the co-localisation of numerous engineers endowed with the same technological skills. This debate spawned the so-called Marshall-Arrow-Romer view (MAR in the sequel), stating that knowledge flows occur mainly between firms in the same or similar industries. On the contrary, Jacobs (1969) argued that firms' most important sources of new knowledge are located out of their own industry and come from agents specialised in different technological fields. Because major cities are characterised by an important technological diversity, they are privileged places for extracting these diversity externalities. This plea for knowledge diversity received empirical support recently in studies providing evidence that too much cognitive proximity lowered firms' innovative performance (e.g., Broekel and Boschma, 2012).

A comparison of the empirical tests designed to settle this issue (Beaudry and Schiffauerova, 2009) shows that most of the contradictory empirical findings can be explained by methodological differences. When empirical studies use highly aggregated industrial data, they detect MAR externalities but do not necessarily find Jacobs' ones. Datasets characterised by a high degree of industrial detail show the opposite result. Moreover, Frenken et al. (2007) show that the concept of mere diversity is not necessarily relevant and that measures of related variety may prove to be more effective in explaining regional growth (see also Boschma and Ianmarino, 2009 and Neffke et al., 2011). The maturity of products and technologies may also determine whether MAR or Jacobs externalities are more effective (Duranton and Puga, 2004). In addition, the meta-study by Beaudry and Schiffauerova (2009) shows that the level of geographical disaggregation strongly influences the results, suggesting that specialisation/diversity externalities may influence knowledge diffusion at different distances. New knowledge may be more difficult to find in a highly specialised local environment so that the quest for novelty may require distant interactions with agents possessing related or unrelated pieces of new knowledge. Consequently, if technological and industrial diversity is not large enough in a region, the latter may however benefit from the diversity of its neighbouring regions. We summarize these arguments in one hypothesis and one proposition.

Hypothesis 3: Because similar industries tend to choose similar locations, a phenomenon sometimes called "homophilic location strategies", the search for new knowledge in other sectors may require distant interactions with knowledge holders located in neighbouring regions. It is therefore important for regional innovation that neighbouring regions be diversified rather than highly specialised.

Proposition 3: *When they are technological or industrial rather than urban, diversity externalities are effective within but also beyond regional borders. Diversified regions provide novelty potential to their neighbours as well as to themselves.*

To correctly assess the extent of these diversity externalities, one has to construct a relevant diversity indicator of course, but it is also necessary to control for the urban effect that may explain why industrial diversity is correlated to innovation productivity.

3. Research design

The knowledge production function approach introduced by Jaffe (1986) is highly appreciated as a means of detecting and quantifying knowledge spillovers. The main reason for this success is that it provides measures of innovation productivity in a framework in which one can assess whether the R&D effort of some agents/places influences the innovative output of other agents/places. The alternative patent citation approach is more useful to precisely track the direction and intensity of knowledge flows, but it only captures flows of codified (patented) knowledge. Moreover, one cannot easily assess from patent cites whether they detect true knowledge externalities or simply exchanges of knowledge at market prices.

To test propositions 1, 2 and 3, we need to build a knowledge production function that includes three key elements. First, we have to introduce a distinction between flows of tacit knowledge and flows of codified knowledge. In this study, we propose to proxy this distinction by differentiating in-house and outsourced R&D. As already argued, there are good reasons to consider that a great part of the knowledge involved in external R&D is codified whereas tacit knowledge is much more present in internal R&D. Second, we need to differentiate the places where R&D activities are implemented using variables that measure the quantity and quality of their knowledge transfer channels. Ideally, one would like to account for the three types of channels acknowledged by the literature: spin-offs, networks and labour force mobility. Gathering comprehensive data on each of these three channels is virtually impossible but an indirect identification of the efficiency of these knowledge transfer channels in various territories is possible. In France, the cluster policy is based on the differentiation between "world-class clusters" and "national clusters". This labelling procedure provides us with a means to identify the regions endowed with more knowledge transfer channels than the other regions. We also want to detect Jacobs externalities and assess at what distance they are effective. Therefore, we will introduce a diversification measure in the knowledge production function.

3.1. Sample and variables construction

We estimate our model on the so-called French "départements" between 2002 and 2008. These administrative units created in 1789 correspond to NUTS 3 regions in the Eurostat classification. We exclude overseas «départements», as well as southern and northern Corsica, to circumvent discontinuity problems. Consequently, we work with 94 metropolitan «départements» observed during seven years. Contrary to most previous studies on French regions, we do not average the variables over the time span because we want to maintain the panel data structure. The descriptive statistics of the variables are presented in Table 1.

3.1.2. The dependent variable: innovation output

Despite its imperfections, the patent count indicator is a widely accepted proxy for the innovative output. The caveats are well known: some valuable innovations are not patented, and many patents will prove to have low economic value. In addition, the design of the patent system, the type of R&D implemented (e.g., business versus basic R&D), and the variety of science and technology policies may all influence the patenting performance through a propensity to patent effect (de Rassenfosse and van Pottelsberghe de la Potterie, 2009). Nevertheless, there are means to control for the propensity to patent effect. Furthermore, the novelty content of patented innovations is warranted by the patenting procedure, whereas it is much more problematic to assess the newness of the product or process innovations added up in innovation surveys (Griliches, 1990).

The French National Institute of Industrial Property (INPI) provided us with a count of all published patents of French origin between 2002 and 2008. These figures have been distributed across the French NUTS 3 regions ("départements") according to the address of the inventor. They include all patents of French origin published by any possible patent office, that is to say, the national one (INPI), the European one (EPO), the American one (USPTO), the international one (WIPO), and so on. They also include all applications filled under the Patent Cooperation Treatise (PCT). To avoid multiple counting, only non-priority fillings are considered. All industries are covered, including, for instance, the patenting of financial innovations. Counting all possible sorts of patents is interesting because it softens the propensity to patent problem: some unobserved regional characteristics may influence the propensity to file patents at one office rather than the others, but they will not necessarily influence the total number of patent applications. Moreover, PCT patents are much less affected by this problem (de Rassenfosse and van Pottelsberghe de la Potterie, 2009). To further alleviate the noise possibly remaining in the patent count, we smooth the regional patent count variable over three years, replacing the number of patents filed by inventors from department i at time t by the average of t-1, t and t+1. We also checked that averaging over the years t-2, t-1 and t does not change significantly the results.

3.1.2. Independent variables

The main independent variables are internal and external R&D expenses of region i over the year t. The figures come from the R&D survey implemented yearly by the French Ministry of Research. Given the perspective of this paper, this survey has three interesting advantages over the community innovation survey (CIS). First, R&D figures are collected both at the firm level and at the establishment level. The latter statistics are necessary if one seeks to trace precisely the locus of R&D activities. Second, the R&D survey data are representative of firms' sizes and sectors both at the national and at the regional level, that is to say, in the territorial units called "«départements»". A third advantage of this survey is that in-house and outsourced R&D are clearly differentiated, the latter being divided into public external R&D and private external R&D. However, only internal R&D is available at the establishment level. Because we want to account for all R&D implemented in each of the 94 considered regions, we need to recount the R&D expenses of all business units present in each region. This is straightforward for in-house R&D because the figures are available at the establishment level, but external R&D has to be redistributed across firms' business units. The R&D survey provides the number of R&D employees in each business unit. Therefore, we can compute the share of each establishment in the total R&D labour force of the parent firm and use it as a repartition key to distribute outsourced R&D across firms' business units[2]. Summing up over all business units present in a region then provides the total external R&D expense of each region, divided into public external R&D and private external R&D.

We finally end up with three R&D variables: internal R&D, external R&D outsourced to private organisations and external R&D outsourced to public organisations. As usual, we consider that there is a time lag between R&D expenses and innovation. We choose a one-year lag to avoid excessive reduction of the time dimension in the panel estimates. As underlined in section 2, we suppose that internal R&D relies on both tacit and codified knowledge whereas external R&D involves principally codified knowledge. Consequently, according to proposition 1, we expect that in-house R&D has higher innovation productivity than external R&D.

To test proposition 2, we construct a variable aimed at synthesising the quantity and quality of regional knowledge transmission channels. The French cluster policy is a labelling policy that provides subsidies to firms and research organisations belonging to selected high-tech clusters, labelled "Pôles de compétitivité". Among these labelled clusters, some of them are deemed "world-class clusters" by the French ministry of economics, a label that explicitly recognises and encourages the formation of international knowledge networks. They are considered particularly innovative because of their numerous research collaboration networks, and because they have a highly skilled and mobile workforce. Firms and organisations belonging to these "world-class" clusters are granted supplementary funds when they build collaborative research networks in response to specific call for tenders launched by two public agencies, the FUI (Fond Unique Interministériel) and the ANR (Agence National de la Recherche). We therefore assume that "world-class" clusters are more channel-gifted than the others, that is to say, we suppose that they have more numerous and more efficient knowledge networks. A French NUTS 3 region can obtain several "world-class cluster" labels in various technological domains. We thus consider that a region's number of world-class clusters is a good synthetic proxy for the quality and quantity of its knowledge diffusion channels. To construct this proxy, we have to consider that a "world-class" cluster generally brings together companies belonging to several distinct regions. For example, the French department "Ille-et-Vilaine" has been granted two "world-class cluster" labels, one for a cluster specialised in ICT and multimedia (called "Pôle Images et réseaux") and the other for a cluster dedicated to high-tech activities related to the maritime environment (called "Pôle Mer-Bretagne"). The workforce of the cluster "Images et réseaux" is mainly located in three French *départements*: "Ille-et-Vilaine", "Loire-Atlantique" and "Finistère". The workforce of the cluster "Mer-Bretagne" is principally localised in the *départements* "Finistère", "Morbihan" and "Ille-et-Vilaine". During the time period studied in this paper (2002-2008), seventeen French clusters have been labelled "world-class"[3]. Workforce localisation of these clusters is provided by the Industry Directorate-General of the Ministry of Economics and Finance[4]. To compute the number of "world-class" clusters that can be attributed to each region, we localise each "world-class" cluster in the three NUTS 3 regions where its workforce is mainly located. We end up with 29 regions endowed with at least one "world-class cluster". The average number of such clusters per NUTS 3 region is 0.54, and the maximum number is 8. All these "world-class cluster" labels have been granted in 2005, except one in 2006 and another in 2007. Anyway,

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[2] This is the only tractable way to redistribute external R&D across firms' business units. It is relevant if external and internal R&D are complementary, or if one can reasonably assume that external R&D is ordered and exploited mainly by the business units that concentrate most of the R&D workforce of the parent firms.

[3] A eighteenth "world-class" label has been granted in 2010 to the cluster "EAU" dedicated to ecological water resource management and mainly located in regions "Hérault", "Haute-Garonne" and "Gard".

[4] http://competitivite.gouv.fr/poles-en-action/annuaire-des-poles-20.html

we consider that a place labelled "world-class cluster" in 2005, 2006 or 2007 was already endowed with the required channels of knowledge transmission in 2002, 2003 and 2004. As a consequence, for a region *i* that obtained, for example, two world-class clusters in 2005, our cluster variable $PoleM_i$ is set to 2 during all the estimation period (2002–2008). Transforming the variable into a time-invariant one has two main advantages. First, it is more realistic to consider that the knowledge diffusion channels acknowledged by the label "world-class cluster" were already there before the granting of the label. Second, it mitigates the endogeneity affecting this variable. Indeed, there is probably a reverse causation issue since the label "world-class cluster" may have been attributed to the clusters that have the highest innovation productivity measures . As a consequence, we will also use a specific econometric technique to account for this potential endogeneity bias.

Proposition 2 states that channels of knowledge diffusion have cumulative rather than substitutable effects on innovation productivity: the more channel-gifted is a region, the higher should be its innovative output. If this proposition is correct, the variable $PoleM_i$ summarising the quantity and quality of regional knowledge channels should have a larger coefficient than any variable measuring the connectivity of a particular knowledge diffusion network of region *i*. To test this prediction, we construct two supplementary network variables measuring the connectivity of two different kinds of collaborative networks. First, we introduce the variable $intercopubliscore_i$ measuring the size of international co-publication networks in region *i*. To construct this latter variable, we exploit a survey implemented by the DGCIS[5] to evaluate the impact of the French cluster policy on the evolution of collaboration networks[6]. This survey provides the total number of co-publications produced by each "world-class cluster" between 2002 and 2009. The share of international co-publications among total co-publications is also computed. This percentage is a good quantification of the connections between the cluster's researchers and their foreign colleagues. When a NUTS 3 region have several "world-class clusters", we average international co-publication percentages over each "world-class cluster" present in region *i*. We compute the deciles of these international co-publication shares, we rank the regions according to these deciles and we give them a score based on this ranking. This score variable $intercopubliscore_i$ is scaled between 0 and 8, so that its coefficient in the regressions can be compared to the coefficient of $PoleM_i$. We also pay attention to another collaborative network that can be identified in "world-class clusters": the network of partnerships generated by FUI call for tenders. These collaborative projects funded by the "Fond Unique Interministériel" have created linkages between "world-class cluster" members and other organisations mostly belonging to the regional neighbourhood or to more distant French regions. Thus, contrary to the one formed by international co-publications, the FUI network is a regional-national one. The DGCIS survey provides information on all the FUI funded projects obtained by each "world-class cluster". For a given cluster, the survey displays the number of organisations involved in at least one of its FUI projects. These are the nodes of the cluster's FUI network. The DGCIS survey also provides the number of dyads that have been created by the series of FUI financed projects between 2006 and 2008[7]. We use these two figures to compute the density of the FUI network in each of the seventeen "world-class" clusters. For a region with several clusters, we average the FUI network densities. We then use the resulting regional network densities to construct a score ranging from 0 to 8, using the method describe above for the international co-publications score. The resulting variable

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[5] "Direction Générale de la Compétitivité, de l'Industrie et des Services": the directorate-general of the French Ministry of Economics and Finance that is in charge of competitivity and innovation policies.

[6] "L'impact de la politique des poles de compétitivité sur le développement des collaborations entre acteurs du processus d'innovation", DGCIS-EUROLIO survey, October 2011. We thank Nadine Massard, Rachel Lévy and the European Localized Innovation Observatory (http://www.eurolio.eu/) for granting us access to this survey.

[7] A dyad is formed between two organisations when they belong to the same FUI project.

densityfuiscore$_i$ is a measurement of the density of the regional-national research network of region *i*. Finally, we also create a variable *allnetworks*$_i$ equal to the regional average of *intercopubliscore*$_i$ and *densityfuiscore*$_i$. It will allow us to assess the cumulativeness of the knowledge spillovers resulting from these two different networks.

To test proposition 3, we construct two variables designed to account for Jabobs' externalities. The construction of an indicator of industrial diversity first requires choosing the level of industrial aggregation of the data. Data limitation forced us to opt for an aggregation into five sectors: manufacturing activities, trade, construction, agriculture and services plus transport. It is also necessary to choose the data used in the diversity index formula. Since we want to capture cognitive diversity in our industrial diversity index, we use R&D employment shares rather than total employment or value-added shares. Then, we have to choose the type of diversity indicator. We do not use a simple Herfindahl index because it would not account for the heterogeneity of business units' dispersion across regions. We therefore prefer an Ellison-Glaeser index (Ellison and Glaeser, 1997). It follows the formula:

$$EGindex_{it} = -\frac{G_{it} - H_i}{1 - H_i}$$

with:

$$H_i = \sum_e \left(\frac{RD_e}{RD_i} \right)^2 \text{ and } G_{it} = \frac{\sum_k (S_{ik} - S_k)^2}{1 - \sum_k S_k^{\ 2}}$$

where S_{ik} is the share of sector *k* R&D in region *i* R&D employment, S_k is the share of sector *k* R&D in national R&D employment, RD_e is establishment *e* R&D employment and RD_i is region *i* R&D employment.

Regions with a high *EGindex* display a high diversity of their R&D activities. In contrast, regions with a low *EGindex* are characterised by R&D activities that are more concentrated on some specific sectors. A significantly positive *EGindex*$_{it}$ provides evidence that Jacobs' diversity externalities are at work. However, there might be a positive correlation between a region's cognitive/industrial diversity and its urbanisation degree. We therefore introduce a control for the probable positive effect of urbanisation. This control variable is a dummy *largecity*$_i$ equal to one whenever region *i* has a city of more than two hundred thousand inhabitants in its territory. Nearly 12% of our regions have such a major city in their territory. We also compute the diversity index over regions neighbouring region *i*, in order to assess the boundaries of diversity externalities (proposition 3). We select neighbouring regions in the 0-100 km circle for the variable *EG100*$_{it}$, and in the 0-200 km circle for the variable *EG200*$_{it}$.

Table 1: Variables definitions and descriptive statistics							
Variable	***Definition***		***Mean***	***Std. Dev.***	Min	Max	***Observations***
		Overall	0.259	1.440	.0000968	12.661	N=658
pat_{it}	The total number of patents per km^2 by region *i* at year *t*	Between		1.434	.0003556	11.713	n =94
		Within		0.189	-1.682	3.149	T=7
		Overall	432.755	2990.634	0.031	56192.03	N =564
$RDint_{it-1}$	The total in-house R&D per km^2 by region *i* at year *t-1*	Between		2568.578	0.187	24111.25	n =94
		Within		1550.77	-6868.6	32513.54	T =6
	The total R&D per km^2 outsourced to public	Overall	9.815	79.165	0.000	1278.26	N =564
$RDextpub_{it-1}$	organisations by region *i* at year *t-1*	Between		69.553	0.002	670.166	n =94
		Within		38.371	-267.484	617.908	T =6
	The total R&D per km^2 outsourced to private	Overall	154.611	1118.929	0.001	16801.64	N =564
$RDextpriv_{it-1}$	organisations by region *i* at year *t-1*	Between		955.486	0.036	9038.134	n =94
		Within		589.199	-4428.942	7918.119	T =6
	Ellison-Glaeser index: sector diversity of region *i*'s R&D	Overall	-0,060	0,675	-11,416	4,114	N=658
$EGindex_{it}$	at year *t*	Between		0,433	-3,307	0,920	n =94
		Within		0,519	-8,169	3,535	T=7
	The *$EGindex_{it}$* computed over regions neighbouring	Overall	-0,328	5,017	-83,624	61,575	N=658
$EG0100_{it}$	region *i* in the 0-100 km circle	Between		1,014	-3,901	5,981	n =94
		Within		4,915	-81,872	55,266	T=7
	The *$EGindex_{it}$* computed over regions neighbouring	Overall	0,210	0,677	-0,601	4,479	N=658
$EG0200_{it}$	region *i* in the 0-200 km circle	Between		0,543	-0,335	1,982	n =94
		Within		0,409	-1,799	2,707	T=7
	Number of officially labelled "word-class clusters" in	overall	0.543	1.156	0	8	N=658
$poleM_i$	region *i*	between		1.161	0	8	n =94
		within		0	0.543	0.543	T=7
	Score based on the deciles of the share of international	overall	1.65	2.710	0	8	N=658
$intercopubliscore_i$	co-publications of region *i*'s world-class clusters	between		2.723	0	8	n =94
		within		0	1.65	1.65	T=7
	Score based on the deciles of the densities of FUI	overall	1.681	2.732	0	8	N=658
densityfuiscorei	networks of region *i*'s world-class clusters	between		2.744	0	8	n =94
		within		0	1.681	1.681	T=7
$allnetworks_i$	Average of *$intercopubliscore_i$* and *$densityfuiscore_i$*	overall	1.665	2.556	0	7.5	N=658
		between		2.568	0	7.5	n =94
		within		0	1.665	1.665	T=7
	Dummy=1 if there is a city in region *i* whose number of	overall	0.117	0.321	0	1	N=658
$largecity_i$	inhabitants is higher than 200.000	between		0.323	0	1	n =94
		within		0	0.117	0.117	T=7

Although a significant portion of regional heterogeneity is accounted for by the three series of independent variables just described, we also introduce yearly fixed effects to obtain differences-in-differences estimates and individual-level random effects to correct the biases possibly generated by unobserved regional characteristics.

3.2. Econometric Methodology

The equation that we estimate to test propositions 1, 2 and 3 is the following:

(Equation 1)

$$\begin{aligned} ln(pat_{it}) &= \alpha + \beta_1 ln(RD\,int_{it-1}) + \beta_2 ln(RDextpub_{it-1}) + \beta_3 ln(RDextpriv_{it-1}) \\ &+ \gamma_1 EGindex_{it} + \gamma_2 EG0200_{it} + \lambda_1 network\,score_i + \lambda_2 largecity_i \\ &+ \sum_t \mu_t \, time_t + u_i + \varepsilon_{it} \end{aligned}$$

where:

- pat_{it} is the total number of patents per square kilometre filed by region *i* at year *t*,
- $R\&Dint_{it-1}$ is the total in-house R&D per square kilometre of region *i* at year *t-1*,
- $R\&Dextpub_{it-1}$ is the total R&D per square kilometre outsourced to public organisations by region *i* at year *t-1*,
- $R\&Dextpriv_{it-1}$ is the total R&D per square kilometre outsourced to private organisations by region *i* at year *t-1*,
- $EGindex_{it}$ is a measure of industrial-technological diversity of region *i* at year *t*, namely the Ellison-Glaeser index defined above,
- $EG0200_{it}$ is the same measure of diversity as EGindex_{it} computed over regions neighbouring region *i*; we select neighbouring regions in the 0–200 km circle and also construct and test a variable $EG100_{it}$ with neighbouring regions in the 0–100 km circle,
- $networkscore_i$ stands either for $poleM_i$, $intercopubliscore_i$, $densityfuiscore_i$ or $allnetworks_i$:
  - $poleM_i$ is the number of officially labelled "world-class" clusters of region *i*. For a region that obtained, for example, two "world-class" clusters in 2005, $PoleM_i$ is set to 2 for all the estimation period (2002–2008),
  - $intercopubliscore_i$ is a score ranging from 0 to 8 and based on the deciles of the average share of international co-publications among co-publications of region *i*'s "world-class" clusters between 2002 and 2009,
  - $densityfuiscore_i$ is a score ranging from 0 to 8 and based on the deciles of the average densities of FUI networks of region *i*'s "world-class" clusters,
  - $allnetworks_i$ is the average of $intercopubliscore_i$ and $densityfuiscore_i$,
- $largecity_i$ is a dummy equal to 1 if there is a city in region *i* whose number of inhabitants is higher than 200.000,
- $time_t$ is a time dummy equal to 1 at years t=2004…2008; year 2002 is dropped to avoid multicolinearity, and year 2003 is dropped because the R&D covariates are lagged one year, and
- u_i is an unobserved individual effect and ε_{it} is the usual idiosyncratic error term.

We take advantage of the panel structure of our dataset to address heterogeneity and endogeneity biases. We cannot introduce the time-invariant variables $PoleM_i$, $intercopubliscore_i$, $densityfuiscore_i$, $allnetworks_i$ and $largecity_i$ in fixed-effects regressions. Therefore, random-effects estimations are more suitable. However, simple random-effects estimators would not address the potential endogeneity bias generated by the variables $PoleM_i$, $intercopubliscore_i$, $densityfuiscore_i$, $allnetworks_i$ if they are correlated with the unobserved individual effect u_i. To address this issue, we use the Amemiya-MaCurdy (1986) estimator. This is an improvement of the Hausman-Taylor (1981) estimator for panel-data random effects models with correlations between some covariates and the unobserved individual-level random effect. It assumes however that the covariates are independent of the idiosyncratic error term ε_{it}. Hausman-Taylor models are GLS instrumental variables regressions supplying consistent and efficient estimators of the coefficients, provided that the instruments respect some validity conditions. Amemiya MaCurdy estimators are more efficient but place stricter restrictions on the set of instruments. We validate the assumption that the covariates are independent of the idiosyncratic error term ε_{it} with the Sargan-Hansen overidentifying restrictions test.

4. Results of instrumental variables panel estimates

Table 2 presents the results of the Amemiya-MaCurdy regressions for equation (1). The different columns display estimation results using four alternative variables to measure regional research networks' quality and quantity: $densityfuiscore_i$, $intercopubliscore_i$, $allnetworks_i$, and $PoleM_i$.

Levels, signs and significance of variables are coherent with comparable empirical studies on French regions (Autant-Bernard, 2001a&b, Massard and Riou, 2002, Autant-Bernard and Lesage, 2011), and they are also in line with elasticities found in similar studies on other European regions (e.g., Bottazzi and Peri, 2003, Fischer and Varga, 2003, Ponds et al., 2010). Sargan-Hansen statistics show that the instruments are valid in all regressions.

The elasticity of in-house R&D ranges between 0.13 and 0.14 and is strongly significant in all specifications. Only the R&D outsourced to public organisations is (slightly) significant, with an elasticity of 0.022. The Ellison-Glaeser index is strongly significant across all estimations with the expected positive sign meaning that a research structure more diversified across industries is beneficial to regional innovation productivity. The Ellison-Glaeser index of neighbouring regions in the 0-200km circle is also positive and significant, but with a coefficient divided by two.

The instrumented network variables $densityfuiscore_i$, $intercopubliscore_i$, $allnetworks_i$, and $PoleM_i$ are all significant with the expected positive signs. The density of FUI networks formed by regional "world-class clusters" is positively correlated to innovation productivity; so is the share of international co-publications among co-publications of the regions' "world-class clusters". The average of the these two scores does not display a higher coefficient than the variable $densityfuiscore_i$ alone but *poleMi*, the synthetic measurement of the quantity and quality of all regional research networks, displays a much higher coefficient (1.292 instead of 0.521).

These results provide quite satisfying evidence in favour of propositions 1, 2 and 3. Regarding proposition 1, we unambiguously find that in-house R&D has higher innovation productivity than outsourced R&D. The elasticities of in-house R&D are always much larger than those of private or public outsourced R&D, and the Wald tests always reject the hypothesis that the differences between these coefficients are zero. Because in-house R&D takes advantage of tacit knowledge, it has a six times higher impact on innovation productivity than outsourced R&D which mainly draws on codified knowledge.

Table 2: Amemiya-MaCurdy estimations of the French Knowledge Production Function[1]				
	$ln(pat_{it})$	$ln(pat_{it})$	$ln(pat_{it})$	$ln(pat_{it})$
$ln(R\&Dint_{it-1})$	0.131****	0.131****	0.133****	0.143****
	(0.030)	(0.030)	(0.030)	(0.031)
$ln(R\&Dextpub_{it-1})$	0.022*	0.022*	0.022*	0.021*
	(0.011)	(0.011)	(0.011)	(0.012)
$ln(R\&Dextpriv_{it-1})$	0.021	0.021	0.021	0.022
	(0.014)	(0.014)	(0.014)	(0.014)
$EGindex_{it}$	0.108****	0.108****	0.108****	0.108****
	(0.025)	(0.025)	(0.025)	(0.026)
$EG0200_{it}$	0.053*	0.053*	0.053*	0.051*
	(0.028)	(0.028)	(0.028)	(0.029)
$densityfuiscore_i$	0.521**			
	(0.181)			
$intercopubliscore_i$		0.443**		
		(0.199)		
$allnetworks_i$			0.521***	
			(0.184)	
$poleM_i$				1.292****
				(0.200)
$largecity_i$	-0.135	-0.272	-0.365	-0.397
	(1.034)	(1.216)	(1.058)	(0.544)
intercept	-5.371****	-5.211****	-5.340****	-5.195****
	(0.384)	(0.398)	(0.371)	(0.189)
Observations	564	564	564	564
Sargan-Hansen statistic	11.867 Chi-sq(29) *p-value* = 0.9979	12.930 Chi-sq(29) *p-value* = 0.9956	13.714 Chi-sq(29) *p-value* = 0.9927	20.531 Chi-sq(29) *p-value*= 0.8757
Wald Chi2 test [a]	10.40***	10.60***	10.75***	12.55****
Wald Chi2 test [b]	9.33***	9.52***	9.62***	10.79***

[1] The instrumented variables are respectively $densityfuiscore_i$, $intercopubliscore_i$, $allnetworks_i$ and $poleM_i$.
To save space, coefficients of year fixed effects are not displayed.
[a] $\chi 2$ statistic for hypothesis that the difference of marginal effects of $ln(R\&Dint_{it-1})$ and $ln(R\&Dextpubi_{t-1})$ is zero
[b] $\chi 2$ statistic for hypothesis that the difference of marginal effects of $ln(R\&Dint_{it-1})$ and $ln(R\&Dextprivi_{t-1})$ is zero
Standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$, $^{****}p < 0.001$

Proposition 2 is clearly validated by the positive and significant coefficients of the instrumented variables $densityfuiscore_i$, $intercopubliscore_i$, $allnetworks_i$, and $PoleM_i$. Regions endowed with "world-class clusters" characterised by higher network scores have higher innovative performance. Moreover, the coefficient is obviously higher for the variable $PoleM_i$ which synthesises the quality and quantity of all networks present in the region's "world-class clusters". However, this result suggesting cumulativeness of the positive effects of regional knowledge channels must be considered cautiously since the variable $PoleM_i$ might still capture some other regional characteristics than networks quantity and quality, even though we think that we have controlled for most of them.

Proposition 3 states that industrial-technological diversity externalities should be significantly positive, and effective beyond regional borders. What we obtain here is, first, that a regional research structure more diversified across industries is unambiguously beneficial to innovation productivity. We also obtain that the diversification index of neighbouring regions is positive and significant, but its coefficient is of a lower magnitude. Surprisingly, we could not validate the latter finding using the 0-100km circle instead of the 0-200km circle for the measurement of the Ellison-Glaeser index of neighbouring regions. A more thorough investigation of spatial dependence may prove particularly useful on this point.

These results on propositions 1, 2 and 3 seem to be robust because we have cautiously dealt with heterogeneity and endogeneity. However, innovation and R&D data are also subject to spatial autocorrelation, which may have biased these estimates. To check this point, we now propose a modification to equation 1 and replace it with various spatial panel specifications robust to spatial dependence.

5. Robustness test: accounting for spatial dependence

We now estimate three spatial specifications of equation 1: the spatial errors model with spatial random effects (RE-SEM in the sequel), the spatial lag model with spatial random effects (RE-SAR in the sequel) and the spatial Durbin model with spatial random effects (RE-SDM in the sequel)[8]. The latter specification has received far less attention than the others but it is gaining popularity (Baltagi et al., 2003; Beer and Riedl, 2010). Because the SDM model includes a spatial lag on the dependent and independent variables, it provides estimates of spillovers arising from different sources.

Even if spatial heterogeneity is already accounted for in the previous estimates presented in section 4, thanks to the regional variables, we have not yet accounted for spatial autocorrelation. Therefore, we have to check whether this form of spatial dependence biased our results. Moreover, recall that we made a prediction in proposition 3 about the geographical distribution of the effect of industrial-technological diversity. The RE-SDM specification is, therefore, particularly interesting here because it introduces spatially lagged independent variables in equation 1, which provides direct estimates of the boundaries of knowledge spillovers captured by these variables. To implement such spatial regressions, one has to choose a type of spatial weight matrix. Because French NUTS 3 regions are rather large geographical areas, we do not expect that 'very' distant regions j will provide significant externalities to a region i. These externalities will, at best, be limited to adjacent regions.

[8] Detailed equations and properties of these models can be found in Anselin (1988), Anselin et al. (2008) and Elhorst (2009).

Moreover, 42 of the 94 French regions considered have foreign or coastal borders. The *k*-nearest neighbours and inverse distance matrixes would attribute them quite distant 'neighbours' and would consequently tend to minimise the importance of externalities stemming from directly adjacent regions (Le Gallo, 2002). That is why we only provide the results of estimates implemented with contiguity matrixes. Classically, we use row standardised matrixes, which implies that the spatially lagged variables are weighted averages of the variables measured in neighbouring regions.

The results of these panel spatial estimates are displayed in Table 3. The hypothesis of spatial dependence is validated in each regression, but the RE-SDM model shows that only a few variables have significant effects beyond a region's borders and they are small. However, the spatial specifications do not challenge the results described in section 4. According to the Akaike Information Criterion (AIC) the RE-SAR and RE-SDM models perform better than the RE-SEM model. In comparison to the non-spatial panel econometrics implemented in section 4, these spatial regressions produce a slightly lower coefficient for internal R&D, around 0.09 instead of 0.13, and an identical coefficient for the two types of outsourced R&D. The evidence in favour of proposition 1 is confirmed: the coefficient of internal R&D is always much higher than the coefficient of both types of external R&D. The coefficient of the Ellison-Glaeser diversity index is slightly higher in the spatial estimates, but the variable $EG0200_{it}$ is no longer significant in the RE-SEM and RE-SAR specifications. However, the Ellison-Glaeser of adjacent regions $W{\times}EGindex_{it}$ appears to have a significant positive impact on regional patenting activity in the RE-SDM model. We interpret this result as evidence in favour of proposition 3 stating that diversity externalities should be effective beyond a region's borders. These spatial models also confirm the evidence in favour of proposition 2: the abundance of international co-publication linkages measured by $intercopubliscore_i$ and the quantity and quality of regional knowledge diffusion channels synthesised in $PoleM_i$ are still strongly and positively correlated to regional patenting activity. However, the coefficients of these two variables are much lower than in the Amemiya-MaCurdy estimations: the former is divided by nearly three, and the latter is divided by two. Furthermore, the urban effect measured by the variable $largecity_i$ if now positive and significant in all but one spatial panel models whereas it was not significant in the Amemiya-MaCurdy regressions. We think that these differences come from the fact that our spatial panel regressions with random effects do not account for the endogeneity bias of the variables $intercopubliscore_i$ and $PoleM_i$, whereas the Amemiya-MaCurdy estimator do not account for spatial autocorrelation. However, the two estimators produce results that validate proposition 2, even if one has to acknowledge that the coefficients of the three variables $intercopubliscore_i$, $PoleM_i$ and $largecity_i$ would probably be better estimated in a model accounting for endogeneity and spatial autocorrelation at the same time. Lastly, the coefficients of $W\times intercopubliscore_i$ and $W\times PoleM_i$ in the RE-SDM model are significant and negative, which may seem surprising since it means that the networks of neighbouring regions have a negative impact on regional innovation. However, it can easily be understood if one considers that regions endowed with numerous and efficient knowledge networks may divert knowledge flows in their direction and dry up the neighbouring regions as a consequence. However, this finding would need to be further investigated in an econometric setting accounting for the possible endogeneity of these spatially lagged network variables.

Table 3: Spatial panel specifications of the knowledge production function.
Dependent variable: ln(patent per squared kilometre). 94 French regions; 2002-2008.

Model	*RE-SEM*		*RE-SAR*		*RE-SDM*	
$ln(RDint_{it-1})$	0.183****	0.185****	0.089****	0.099****	0.091****	0.098****
	(0.025)	(0.025)	(0.018)	(0.019)	(0.018)	(0.018)
$ln(RDextpubi_{t-1})$	0.025**	0.022*	0.023**	0.022**	0.024**	0.023**
	(0.012)	(0.012)	(0.010)	(0.011)	(0.010)	(0.010)
$ln(RDextprivi_{t-1})$	0.037***	0.037***	0.018	0.022**	0.015	0.020*
	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)	(0.011)
$EGindex_{it}$	0.119****	0.121***	0.131****	0.134****	0.134****	0.135****
	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)
$EG0200_{it}$	0.015	0.012	0.025	0.025		
	(0.031)	(0.031)	(0.022)	(0.023)		
$intercopubliscore_{i}$	0.162****		0.140****		0.139****	
	(0.047)		(0.040)		(0.040)	
$poleM_{i}$		0.697****		0.586****		0.586****
		(0.088)		(0.077)		(0.077)
$largecity_{i}$	0.671*	0.308	1.078***	0.750***	1.077***	0.764***
	(0.395)	(0.308)	(0.337)	(0.272)	(0.334)	(0.270)
$W{\times}ln(RDint_{it-1})$					-0.021	-0.016
					(0.021)	(0.022)
$W{\times}ln(RDextpubi_{t-1})$					0.012	0.016
					(0.014)	(0.015)
$W{\times}ln(RDextprivi_{t-1})$					0.025	0.025
					(0.020)	(0.020)
$W{\times}EGindex_{it}$					0.015*	0.015*
					(0.008)	(0.008)
$W{\times}\ intercopubliscore_{i}$					-0.004*	
					(0.002)	
$W{\times}\ PoleM_{i}$						-0.013*
						(0.007)
$W{\times}largecity_{i}$					0.006	-0.002
					(0.020)	(0.019)
rho			0.630***	0.549***	0.633***	0.547***
			(0.080)	(0.088)	(0.08)	(0.088)
Lambda	0.229**	0.234**				
	(0.093)	(0.093)				
AIC criteria	623.832	584.720	598.294	564.537	599.941	564.856

$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
(To save space, coefficients of year fixed effects are not displayed.)

6. Conclusions

This paper estimated knowledge production functions on French NUTS 3 regions observed between 2002 and 2008. We introduced several novelties in this classical approach. First, we constructed measures of R&D outsourced to public and private organisations to complement the usual internal R&D measure. At best, all of the studies found differentiate between public and private R&D, or academic versus corporate R&D. Secondly, we used a synthetic variable to proxy the quality and quantity of regional knowledge diffusion channels. This variable is an index equal to the number of regional clusters officially labelled "world-class clusters" by the French Ministry of Economics. We compared this synthetic network variable to other variables measuring the density of more specific research networks. These comparisons were implemented using the instrumental variable estimator proposed by Amemiya and MaCurdy (1986). On top of that, we also tested robustness with various spatial panel specifications. All of these techniques converge to provide evidence on three propositions related to the nature, channels and boundaries of knowledge spillovers.

Proposition 1 predicts that, because it contains more tacit knowledge, internal R&D will have a stronger impact on innovation productivity than external R&D. We obtain clear evidence for this proposition.

Proposition 2 states that regions endowed with more numerous and more efficient knowledge diffusion channels will produce more innovations. We validate this proposition using several regional network variables that prove to have strong positive effects on regions' patenting activity.

Proposition 3 predicts that technological and industrial diversity externalities should spread beyond regional borders. Again, we obtain results in favour of this proposition. The Ellison-Glaeser index used to measure the diversity of R&D activities is significant both in the region and in adjacent regions. Therefore, regional innovation seems to benefit from positive diversity externalities that stem not only from the region itself but also from its direct neighbours.

Of course, these results obtained from a panel of 94 French NUTS 3 regions observed over seven years would need to be further investigated using other data samples. An extension of the number of time periods would be helpful to reinforce the robustness of the panel estimates. An extension to other countries would require access to data that explicitly distinguish external and internal R&D, which may prove difficult in some countries. In addition, it would certainly be useful to study the effect on regional innovation of a wider range of knowledge networks. However, real-life networks are so numerous that it may prove very arbitrary to select a few of them and consequently neglect the others.

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