40th CONGRESS OF THE EUROPEAN REGIONAL SCIENCE ASSOCIATION
BARCELONE – 30th August-2nd September, 2000

Scientific interactions, geographic spillovers and innovation
An empirical study on the French case

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Section 1: Introduction

There is a general consensus that geography is important in determining an economy's capacity to innovate. However we have only partial understanding of the reasons why innovation varies across space. Knowledge spillovers and interactions among agents are often set at the heart of the understanding of innovation process (C. Antonelli, 1995). But, the association between externalities, interaction and location of innovation is not obvious and deserves to be specified. Within the recent empirical literature, two ways of analysis can be distinguished.

The first one comes from the current of the new geography of innovation (M. Feldman, 1994, 1998). It attempts to measure directly the impact of geographic proximity on technological spillovers, which are themselves supposed to enhance innovation performances. In that stream of work there have been many attempts to test the local dimension of externalities generated by innovative activity[1]. The majority of those studies deal with the American case. They generally conclude that there is a significant localisation of spillovers. However, this result may be strongly linked to the American institutional system. Besides, it is difficult for those econometric studies to model externalities on the one hand and their geographic dimension on the other. Studies that model externalities cannot give a clear indication of the spatial dimension. Conversely, the measure of a geographic dimension is carried out at the expense of a precise measure of spillovers. Proximity is modelled in terms of distance or geographical coincidence of units of research inside the boundaries of a state or of a metropolitan area (A. Jaffe, 1989; Anselin, Varga et Acs, 1997). However, nothing is said about the specific mechanisms of knowledge transmission.

The second way of analysis puts the stress on the role of interactions as sources of knowledge transfers (I. Cockburn and R. Henderson, 1998; L. Zucker, M. Darby and J. Armstrong, 1994; P. Almeida and B. Kogut, 1997). In that prospect, the studies measure the impact of interaction and communication on innovative performances. However, we can observe that, in this framework, analysis have generally no geographic implications[2] and, once more, solely concern the American case.

The proposed communication provides an empirical study that will inform the discussion of innovation and location by analysing the links between geographic dimension, interactions and knowledge spillovers in the French context. Thus, we test empirically the following hypothesis: spillovers are mediated by interactions and those interactions are themselves facilitated by geographic proximity.

In this aim, we study innovation and interactions inside French regions. We measure interactions by co-authoring (published articles signed by authors from different institutions). Indeed, co-authored publications generates a paper trail which can be used to quantify some aspects of "connectedness" in an objective, albeit limited way. Our study appeals to two methods. First, thanks to a pretopologic approach[3], the co-authoring structure is compared to the geographic structure. In this way, we investigate if interactions are favoured by proximity, in other words, if face to face

[1] Cf. C. Autant-Bernard and N. Massard (1999) for a detailed survey of the econometric literature on geographical spillovers.
[2] Even when they have (cf. L. Zucker, M. Darby a,d J. Armstrong, 1994; P. Almeida and B. Kogut, 1997), they postulate the geographic dimension and do not really test it.
[3] Cf. L. Bonnevay and alii (1998).

contacts are easier when people belong to neighbouring areas. Then, we explicit the relations between interactions and local spillovers, by means of an econometric approach.

The structure of the paper is as follows. Section 2 wonders about the way by which knowledge spills over in the local context and particularly it tries to find evidence that interactions are favoured by geographic proximity using co-authoring as a measure of interactions. The pretopologic approach enables us to compare co-authoring and geographic structure of the relations. Section 3 comes back to the econometric approach so as to explicit the relations between interactions and local spillovers. It presents a new model to test at the same time, the local dimension of externalities and the need to face to face contacts to benefit from these externalities. Results are also presented in this section. Concluding remarks are in section 4.

Section 2: The geographic structure of co-authorship between French "departements".

At this stage, the question is: are scientific interactions favoured by geographic proximity?

In order to answer this question, we use data on co-authorship of scientific papers between the French « departements » (French administrative units). As noted in previous works[4], a departement wishing to take advantage of research conducted outside its boundaries may need to develop « absorptive capacity » in the sense of accumulating themselves research means, knowledge and skills. But it seems necessary to expand upon this idea. While it is certainly necessary to invest in basic and applied research inside the departement, we believe that it is also important for the departement to be actively connected to the outside sources of knowledge. We thus build on an important stream of work developed by Zucker, Darby and Armstrong (1994) or Zucker, Darby and Brewer (1997), who have shown the importance of face to face contact with university scientists as an explicative variable of the innovative efficiency of the firms. In that context, highlighting the key role of the necessary interactions between users and

[4] For instance, Cohen and Levinthal (1989) ; Cockburn and Henderson (1998).

producers of new knowledge helps understanding the « collective character of technologic knowledge » (C. Antonelli, 2000). In that sense, the characteristics of the established connections and the structure of the communication networks play a key role in the innovative capabilities of agents.

Among the different communication channels which allow the interactions between the participants to the knowledge production, scientific collaborations take recently a fundamental part. During the last twenty years, scientific collaborations have notably increased. This reveals the role of men in the process of knowledge diffusion as collaborations can be seen as a specific form of mobility of the scientists. Moreover, scientometrics studies suggest also that such connectedness is often favoured by geographic proximity.

Here, we wish to set up these ideas by the mean of a quantitative analysis on French data. In that prospect, we use co-authorship of scientific papers between French departements.

In scientometrics analysis, co-authorship are often used as a measure of scientific collaboration. Joint co-authorship is indeed a good indicator of scientific interactions. By contrast with cross-citations (often used in American studies), co-authorship is costly. For effective collaborations to take place, systematic efforts and a long time spell are often required. Moreover, this kind of data evidences a qualitatively different kind of interactions than do citations. Joint co-authorship reflects joint research, which is an important opportunity for the exchange of tacit knowledge. By contrast, citations may be seen as an acknowledgement of the exchange of codified knowledge (I. Cockburn, R. Henderson, 1998) and do not necessarily imply real relations between scientists.

The data we use come from OST (Observatoire des Sciences et des Techniques) and are extracted from the Science Citation Index (SCI). For each year (1992 and 1997), we have a matrix $C = [c_{xy}]_{x,y\in\{1,\ldots,n\}}$, where c_{xy} gives the number of co-authored publications written by at least one author belonging to departement x and at least one author belonging to departement y. First, a simple statistical analysis enables us to differentiate the main co-authorship behaviours of the departements and some characteristics of the two by two relations. Then, thanks to a pretopologic approach we could extract structural informations from the whole data.

2.1/. First statistical analysis

Globally, the number of co-authored publications between French departements has strongly increased between 1992 and 1997 (from 10 280 during 1992 to 14 335 in 1997). The distribution of the departements according to their co-authorship activities shows a high concentration. In 1997, the first 14 (on a total of 101 departements) represent 90% of the co-authoring in France while, at the opposite, 51% of the departements represent less than 1% of the total co-authoring.

The major part of co-authoring occurs between scientists who belong to the same department. In 1997, 9 618 publications have been written by scientists whom institutions are located in the same departement, while only 4 717 co-authored publications imply distinct departements.

The externalisation index is defined for each departement as the part of its co-authored publications implying other departements compared to its total co-authoring[5]. Thus we can have an idea of the tendency of each departement to mainly publish with partners belonging to the same departement or conversely to choice external partners.

According to the externalisation indicator, departements can be clearly distinguished in two groups. In the first one we can find the departements with a high co-authoring activity. They generally correspond to the main university centres. In that group the externalisation rates are below the average rate. The second group brings together the smallest departements in terms of scientific activities. They generally present a very high externalisation rate. In distinct terms, after exponential adjustment, we find a negative correlation between the number of co-authored publications and the externalisation rate of the departements[6](cf. figure 1). Small departements, carrying out very few scientific activities inside their boundaries, need to get the competencies they are missing from the outside. And conversely, when it is possible, the departements make primarily the choice of internal co-authorship. This is a first indication concerning the role of geographic proximity but now we need to go ahead and try to determine the role of geographic dimension in the case of external co-authoring publications. When authors belonging to a departement choice external partner, do they work primarily with their neighbours or not?

[5] Externalization index = e_x / $c_{x.}$ where $e_x = c_{x.} - c_{xx}$ and $c_{x.}$ is the total number of co-authoring of the departement x.
[6] Coefficient R = -0,728 and R^2 = 0,53.

A first answer can be given in calculating the following ratio:

$$\sum_{x=1} CDxy \;/\; \sum_{x=1} Cx.$$

where *CD xy* is the number of co-authored publications between a departement x and a departement y located at a distance D from x and *Cx.*, the total number of outside co-authored publications of the departement x. The distance is measured as the number of departements boundaries it is necessary to pass through to go from the departement x to the departement y. Inside the French territory, *Dxy* is bounded between 1 (bordering) and 12. For each distance D = 1,…,12, we construct the indicator presented above and we normalised it by the part of the cells of the matrix corresponding to the distance concerned in the total of the possible cells, that is to say

$$\sum_{x=1} D_{x.} \;/\; TOT$$

where $D_{x.}$ is the number of cells where D = 1(respectively 2,…12) and *TOT* = 8742 is the number of cells in the matrix.

Thus an index higher than 1 reveals a tendency to privilege the relations with departements situated to the distance analysed compared to what we may expect in regarding the part of these departements in the total number of possible partners.

The results obtained are presented in Table 1:

Table 1:

	$\Sigma CD_{xy}/\Sigma C_{x\cdot}$	$[\Sigma CD_{xy}/\Sigma C_{x\cdot}]/[\ \Sigma D'_{x}/8742]$
Dxy =1	0,1793	3,2668594
Dxy=2	0,1261	1,25045159
Dxy=3	0,0795	0,59253701
Dxy=4	0,1156	0,7670199
Dxy=5	0,1335	0,85975526
Dxy=6	0,1245	0,87543207
Dxy=7	0,0750	0,669181
Dxy=8	0,0775	0,99057964
Dxy=9	0,0683	1,4786376
Dxy=10	0,0176	0,87903932
Dxy=11	0,0025	0,5549315
Dxy=12	2,5366E-05	0,1108731
Total	1	

This table shows clearly that, within the French scientific community, the number of collaborations rapidly decreases as a function of the distance separating the departements. This is consistent with the results obtained by J.S. Katz (1994), in the UK, Canadian and Australian cases. Moreover, in relative terms, departements have a very high tendency to co-publish with their neighbours as the part of co-authored publications between bordering departements appears very high relatively to the part of bordering (D = 1) in the total matrix of distances (ratio = 3,26).

One notices also that departements co-publish much more with other departements located at distance D = 2 (bordering of the bordering) since the coefficient is higher than 1.

Surprisingly, the coefficient corresponding to D = 9 is equally higher than 1. We think that this may reveal the specific role of Paris which attract many departements (specifically university departements) which are often located at a distance D = 9. It is, for example, the case for Herault (university of Montpellier), Haute-Garonne (university of Toulouse) or Bouches du Rhône (university of Marseille).

Up to now, the analysis of co-authorship helps us identifying co-authorship behaviours of the departements. However, it doesn't supply any global view of the structure of the relations established on the French territory and we are not able to situate each departement from each others in that sense. To this aim, we propose to turn to a pretopologic analysis in order to extract more structural informations of the scientific relations between departements.

2.2/. Co-authorship structural analysis

In this section, we give a rapid introduction of the pretopologic method used. Then, we present the result for French co-authoring.

A complete description of the method used can be found in Bonnevay and alii (1999) and Largeron and alii (2000). The aim of this method, based on pretopological closed subsets, is to bring out the structure of a space E according to the pseudoclosure a(.) defined on E. In this way, closed subsets are of particular interest within the context of structural analysis. They enable the representation of the homogenous subsets of E in regard to the pseudoclosure retained. Indeed, there are significant connections in regard to a(.) between elements of a closed subset F, and there are no significant connections between these elements and those outside of F. Thus, in view to extract structural informations of a space E, we display relations between some closed subsets with the structural algorithm described in Bonnevay and alii (1999).

In the case of co-authorship between departements, we have $E = \{1,\ldots,n\}$, with $n = 89$ (number of French departments) and C, composed of c_{xy}, the matrix of co-authored publications between departements x and y. There are of course several methods in which a pretopologic structure on E can be constructed from C. Here, we use the following:

Let P(E) be the family of subsets of E. A mapping a(.) is defined from P(E) to P(E) such as:

(P1) : $a(\emptyset) = \emptyset$

(P2) : $\forall\ A \in P(E)\ ,\ A \subset a(A)$

(P3) : $\forall\ A, B \in P(E)\ ,\ A \subset B \Rightarrow a(A) \subset a(B)$

In that study, a(.) is constructed starting from the relation R defined on E such as :

$R(x) = \{y \in E\ ,\ xRy\ \} \cup \{x\}$

$\forall\ A \in P(E),\ a(A) = \{x \in E\ ,\ R(x) \cap A \neq \emptyset\}.$

Where R(x) is the set of departements with which x mainly publish. So, by definition of R, a departement x belongs to the pseudoclosure a(A) of a set of departements A, if and only if x has mainly published with one departement of A. F(x) is the set of departements which have mainly published either with x directly or with other elements which have mainly published with x, directly or not.

So, one of the main differences between this pseudoclusure and a topological closure is that the set a(a(A)) is not always equal to a(A). According to this property, it is possible to apply a successive mapping a(.) on a set A. These successive spreading of A can model expansions corresponding to different types of phenomena (dilation, propagation, influence…).

The result obtained for the matrix of co-authored publications in 1997 is illustrated in the figure 1 (cf. appendix)[7].

An elementary closed subset F(x) reduced to a one-element set {x} corresponds to a departement such that F(x) = a({x}) = {x}. This means it does not exist any departement that has mainly published with x. This refers for example to elements 61 and 62 (Orne and Pas-de-Calais). An element y, such that $y \in F(x)$, with $x \in E-\{y\}$, corresponds to a departement y which has connections with x, either directly, or indirectly through other departements. For example, departement 52 (Haute-Marne) has mainly published with 60 (Oise), so $52 \in F(60)$. As well, 30, 66, 84, $82 \in F(34)$ and 82, 16, 24, 40, 64 and $101 \in F(33)$.[8]

One notices that Paris (75) and Essonne (91) are very strong attractors as they include the whole set of other departements. It means all departements have directly or indirectly published with Paris and Essonne. Globally the structure is not very overlapping; it is constituted of separated groups around an attractor (single element inside the group), i.e. an element with which the other members of the group mainly publish. These departements correspond to the main French University centres. They generally attract the smallest departements that are located close to them. Indeed, the large university departements do not privilege the relations between them; they publish much in-house and often choose Paris as partner. They are, on the other hand, selected as main partners by the departements that surround them. The latter, having rather little publishing activities, do it primarily outside and with the closest great university centre.

Thus, plotted on a map, this structuring enables us to clearly find groups (sometimes connected to each other) around the principal regional university centres (Lille, Strasbourg, Clermond-Ferrand, Toulouse, Bordeaux, Lyon, Grenoble, Marseille, Nice and Montpellier).

Finally, it is clear, in the French case, that, globally, scientific interactions are favoured by geographic proximity even if the role of Paris and some other large university centres seems rather determined by a proper attractive effect than by any geographic factor.

At this stage, the remaining question for us is: does this geographic dimension of individual interactions or face to face contacts play a key role in the process of diffusion of knowledge externalities? Indeed, answering such a question will enable us to complete our analysis of the relations between geographic dimension, interactions and knowledge spillovers in the French context.

[7] The structuration obtained with the co-authored publications in 1992 is not very far from the one of 1997 so we present only the latter in the appendix.

Section 3: Interactions and local dimension of knowledge externalities

This section studies the link between interactions and local externalities. In this aim, we construct a model that allows to test the presence of local knowledge and to measure in what extent they are enhanced by inter-personal relations.

3.1/. Model

Empirical studies of spillover phenomena have developed over the past ten years.[9] They conclude that there is a significant localisation of spillovers. However, as we noted in introduction, it is difficult for those econometric studies to model externalities on the one hand and their geographic dimension on the other.

The production function of innovation used here tries to overcome these difficulties. Besides modeling externalities, the study puts forward a method to test the impact of spatial dimension, by confronting distinct geographic levels.

Spillovers are introduced in the production function of innovation as an external stock of knowledge. The local characteristic of externalities is studied by taking into account not only R&D conducted within a geographic area but also R&D carried out nearby and finally R&D conducted in a more distant neighbourhood.[10] If research spillovers are geographically limited, then the level of local innovation must be even more affected by neighbouring research than by research carried out at a distance.

The general equation is as follows:

$$(1)\quad I_{gi} = \alpha + \beta_1 RD_{gi} + \beta_2 RD_{vi} + \beta_3 RD_{v'i} + \beta_4 \Sigma RD_{gj} + \beta_5 \Sigma RD_{vj} + \beta_6 \Sigma RD_{v'j} + u_g + v_{gi}$$

with $j = 1, \ldots J$ and $i \neq j$.

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[8] The list of the French administrative departements and the corresponding numbers are given in the appendix (table 2).

[9] Cf. especially A. Jaffe [1989], Z. Acs, D. Audretsch, M. Feldman [1991], A. Jaffe, M. Trajtenberg, R. Henderson [1993], M. Feldman [1994], D. Audretsch and M. Feldman [1996a and 1996b], L. Anselin, A. Varga and Z. Acs[1997].

[10] In many other studies (Antonelli, 1994, Acs, Anselin and Varga, 1997), only a local stock of knowledge is considered. But such a bounding of the geographic area in which spillovers can occur does not seem fully satisfactory. At the most, it allows us to determine if spillovers are geographically bounded. But it does not prove that their diffusion is constrained by distance. To demonstrate the impact of geographic distance, we must be able to affirm that an agent is more affected by his neighbours' activity than by the activity of agents that are physically distant. This is why it would seem better to do a comparative analysis of different geographic levels. The localization of spillovers could then be tested by comparing the impact of the close neighborhood with the impact of a more distant neighborhood.

I is an indicator of innovation output, RD measures the stock of knowledge. g is the geographic area considered, v is the close neighbourhood of this area and v' is a more distant neighbourhood. i and j are the sector indexes. This way, we consider both infra and inter sectoral spillovers. α is a constant and u_g is the geographic effect. v_{gi} is the random disturbance.[11] Thus, we test the presence of technological spillovers by looking at the relation between the innovative output of area g and the research carried out in the neighbourhood. Local knowledge spillovers will be highlighted if $\beta_2 > \beta_3$ for infra sectoral analysis and if $\beta_4 > \beta_5 > \beta_6$ for intersectoral analysis. Then, this model allows testing the impact of human interactions on spillovers. In this aim, the coefficients of external knowledge variables are considered as functions of co-authoring relations.

3.2/. Data description

The number of patents approximates the innovative output. For the inputs, there are several ways of measuring the stocks of knowledge RD. First of all, we may assume that it is the level of knowledge that prevails. There may be more innovation when R&D expenditure is high and R&D staff numerous. To account for this relation, an indicator of R&D level is used. It is measured by R&D expenditures. However, what we are interested in is the place of human interactions.[12] Thus, we also introduce an indicator of human capital. It will allow testing if externalities are more supported by people or if knowledge flows freely. The indicator used here is the ratio between the number of researchers and the total research staff. So, the human capital variable (noted KH) represents the proportion of researchers relatively to the total research staff. [13]

The geographic area g is the French administrative "departement", v represents all the bordering "departements" of g and v', the bordering "departements" of v. In this way, we can observe the relation between the production of innovation for each "departement" and the research effort carried out in its periphery, defining concentric

[11] The model is expressed in logarithms. In addition to the interest it implies for the interpretation of the results, this functional form appears to be the more suitable. The Bera and McAleer test suggests a preference for the semi-log form to the linear one. Then, comparing explanatory power of log-log form and semi-log form shows a superiority of the log-log one. Consequently, it is relevant to specify the model in logarithms.

[12] In endogenous growth models (R. Lucas[1988]) as in geography of innovation (L. Zucker, M. Darby and J. Armstrong [1994]), some studies emphasize the human capital factor. Consequently, the percentage of the population devoted to research becomes the determining variable of innovative output, and no longer the level of R&D.

[13] Data come from the R&D inquiry of the French Ministry of National Education, Research and Technology and from the Observatoire des Sciences et Techniques (O. S. T.).

areas around each “departement”.[14] A control variable noted VAg is introduced. It accounts for the economic size of area g. This way, we aim at controlling for the unequal spatial distribution of economic activities.

Data are available over the period 1991-1996.[15] The triple dimension of the data (geographic, temporal and sectoral) allows controlling for the individual heterogeneity. Geographic specific effects are introduced. The average temporal effect on innovation is accounted thanks to a variable TREND. It takes the value 0 for year 1991, value 1 for year 1992 etc., up to 5 for year 1996. The third dimension (the sectoral one) is accounted by introducing sectoral dummies. Eleven industrial sectors are considered: Chemistry; Medicines; Energy; Electricity; Computer and Electronics; Instruments; Mechanics; Building and materials; Aerospace; Agriculture and Food; Transport. [16]

Table 1 gives indications about the variables. There are 6204 observations corresponding to the 94 geographic areas observed over 6 years and 11 industrial fields. As we can notice, the sectoral partition leads to a small level of analysis. Consequently, there is a large number of null observations. It is especially the case for the dependent variable.[17] Only few departments have patented each year in every technological field whereas almost all of them have carried out research spending and used human capital.[18] Thus, the Tobit method with random effects appears as the most fitted one.

3.3/. Results

Results are summarised in table 2. Column 1 gives the results obtain without local interactions. Two main results appear. Firstly, human capital is the main source of knowledge spillovers. Secondly, spillovers, both infra and inter sectoral, are geographically bounded. Columns 2, 3 and 4 give the results when we introduce

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[14] It is nonetheless uncertain that this geographic level is the most relevant to give an account of local externalities. If some local technological consequences exist, it is likely that, concerning a certain number of cases at least, they don’t occur between departments but at a subtler level. Nevertheless, departments constitute a satisfactory geographic level. It is the smallest administrative division for which the whole data is available. It is besides a relatively coherent level in the sense that departments represent essentially a large town and its urban agglomeration. This scale presents therefore a certain homogeneity.

[15] More precisely, data are available over the period 1989-1996, but we assume a lag structure between the moment research is done and the moment it comes out as an innovation. Consequently, patents observed for the years 1991 to 1996 are explained by R&D and human capital of the period 1989-1994. All the data are computed with a smoothing procedure (an average on three years is used).

[16] In order to avoid perfect colinearity, only 10 dummies are introduced.

[17] In order to allow logarithm transformation, 0.001 is added to all the patents data. The censure is thus on -6.90776. (For R&D data, to allow logarithm transformation, 1 is added to all R&D spending.)

[18] More than 16% of the 6204 observations equal 0 for the dependent variable whereas none of them equal 0 for all the independent variables.

interactions in the model. The positive impact of local interactions on knowledge spillovers is highlighted.

3.3.1. Knowledge spillovers and human capital

Not surprisingly, innovation is first of all affected by internal activity. The significant coefficients are essentially those of variable internal to area g. RDgi, RDgj, KHgj and VAg have a positive and a significant impact on local innovation. In this context, the negative sign of KHgi is unexpected. It may come from the particular construction of the human capital variable and from the small level of observation that result from a sectoral analysis. When geographic areas have a low level of activity, the number of scientists in a given field is often identical to the number of total staff since there is only one person. In this case, the proportion of scientists equals 100% of the total research staff. However, this does not mean human is really high. Consequently, the human capital in one field and one geographic area is often all the more high that the area has a low level of innovative activity. Thus, the variable KHgi has a slightly different meaning than the one expected which explain its negative coefficient.

Except this variable, innovation of a given area is essentially linked to the research activity carried out inside this area. This may result from firms' own research, but also from spillover phenomena. The number of patents granted in sector i and area g significantly depends on R&D carried out in the same area, but in other sectors. Positive interregional spillovers also occur since local innovation is positively affected by research carried out outside. Those spillovers stem from both human capital and R&D spending. But the coefficients of human capital variables indicate that the major part of externalities spread through human capital. This result may validate the place of individuals in the process of knowledge transfers. Knowledge, embodied into people, would require face to face contact to spill over.

3.3.2. The local dimension of knowledge diffusion

Both infra and inter sectoral spillovers occur. This result is consistent with other studies (Glaeser and al., 1992; Henderson and al., 1995). These spillover effects are localised.

If we look at spillovers stemming from R&D spending, the local dimension depends on the sectoral origin. Rdvi has a positive and significant coefficient. Thus, local innovation is positively linked with the R&D carried out in the same field by the contiguous areas. On the opposite, between contiguous area, there is a negative effect from RDvj on Ig. Thus intersectoral spillovers occur only inside the “departement” boundaries and interregional externalities are negative. A high level of research in the close periphery may produce “shadow” effects that lower innovation inside the area considered.

Positive R&D spillovers between regions are thus essentially infrasectoral. Technological and geographical proximity seems to set off each other. At a distance, infrasectoral spillovers are more likely to occur. Conversely, geographic proximity enhances knowledge flows between sectors. Thus infrasectoral spillovers seem spreader through geographic areas than intersectoral spillovers. But they are not totally diffused phenomena either since RDv’i is not significant.

However, those results must be considered cautiously. Local spillovers combine with more global phenomena, at the geographic scale as well as at the sectoral level. Indeed, KHvj and KHv’j produce positive effects on the innovation of area g. These human capital externalities seems more diffused than R&D spillovers. However, they have also a spatial dimension. Their coefficients are decreasing with geographic distance.

Thus, this first analysis validates knowledge spillovers hypothesis. Innovation in a given sector and a given geographic area does not only depend on the research carried out inside this area and this sector. It also benefits from external research, carried out in other sectors or in other places. Those spillovers are higher when they stem from close geographic areas.

But showing the local dimension of spillovers is not sufficient to understand why the geographic dimension matters. What we would like to investigate now is why those spillovers are localised. The larger influence of human capital indicates that people play a great part in knowledge diffusion. This may be the reason why location matters.

3.3.3. Local interactions as channel of knowledge diffusion

Spillovers may be influenced by location because skills and knowledge are embodied into people. Then, knowledge requires personal interactions to spill over. Now, as the structuration method highlighted interactions are more likely to occur when people are geographically closed. To test this hypothesis, we rewrite the model presented above. We allow the coefficients of RDvi, KHvj, KHv'j to vary with the level of copublications between regions.

The following model is estimated:

$$(2)\ Igi = \delta + \gamma_1\ RD_{gi} + F_1\ (REL_{gvi})\ RD_{vi} + \gamma_2\ RD_{v'i} + \gamma_3\ RD_{gj} + \gamma_4\ RD_{vj} + \gamma_5\ RD_{v'j} +$$

$$\gamma_6\ KH_{gi} + \gamma_7\ KH_{gj} + \gamma_8\ KH_{vi} + F_2\ (REL_{gv})\ KH_{vj} + \gamma_9\ KH_{v'i} +$$

$$F_3\ (REL_{gv'})\ KH_{v'j} + u'_g + v'_{gi}$$

We test if the impact of the external stock of knowledge is a function of the interactions between the region g and its neighbours v. RDvi, is related to the co-authoring publications between areas g and v in sector i. KHvj is related to the co-authoring between g and v in all technological fields. And KHv'j is related to co-authoring between g and v in all technological fields. For more convenience, we assume these functions take the following form:[19]

$F = a\ \mathit{log}(REL_{g.}) + b$

Consequently, it consists in introducing three join variables to the model: RDvi*RELgvi, KHvj*RELgv and KHv'j*RELgv'j. The results are given in table 2, column 2, 3 and 4.

For R&D spillovers, the coefficients of both RDvi and RDvi*RELvi are positive and significant at 1% threshold. According to estimation (2), function F is as follow:

F (RELvi) = 0.002 log (RELvi) + 0.035

Externalities stemming from R&D carried out in area v and benefiting to innovation of area g depend on the level of co-authoring between the two areas. However, this link is very low. A doubling of co-authoring will result only in a 0.2% increase in externalities.

The link between spillovers and local interactions is higher for human capital externalities. The coefficient of KHvj*RELgv is positive and significant. The more people interact, the more knowledge spills over. This result is less clear for distant interactions. Co-authoring between area g and area v' has a low impact on knowledge spillovers between g and v'. The parameter of KHgv'*RELgv' equals 0,01 in regression (3) and it is not significantly different from zero in regression (4). Spillovers depend more on interactions when they are local.

[19] This functional form gives the higher explanatory power to the model.

Thus, spillovers seem to have a local dimension because they need face to face contacts and because these interactions are enhanced by geographic proximity. But geography matters also because face to face contacts are more incline to generate spillovers if interactions are local.

However, we must notice the weakness of the results. When we account for interactions, several coefficients are disturbed. Especially, RDv'i and RDv'j become positive and significant when co-authoring is introduced at the level of human capital spillovers. This result is not consistent with those of estimations (1) and (2). Thus, further analysis should be necessary

Section 4: Concluding remarks

The aim of the communication was to understand why spillovers are geographically bounded. In order to test this idea, we studied the link between innovation, technological spillovers and local interactions. The two following questions were addressed: Do spillovers require face to face contact? And is face to face contact favoured by geographic proximity? We answer both questions positively. It supports the idea that spillovers are local because they require personal interactions and these interactions are favoured by geographic proximity.

But these results should be considered cautiously. Firstly, as we mentioned above, some results are not consistent. Secondly, the data used to account for inter-personal relations are not fully satisfying. Publications reflect mainly public research activity. Consequently, co-authoring accounts only for interactions between public scientists and only for a special kind of those interactions. Using co-authoring as an indicator of the global level of interactions between two areas is a simplifying assumption. It should be necessary to find a more general indicator associating, for instance, different ways of interactions. Especially, the results suggest that human capital spillovers are more distant in geographic and technologic space than R&D spillovers. This may rely on scientists' mobility. An analysis of the impact of such mobility should then be interesting to improve the understanding of knowledge flows in space and between different technological fields.

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APPENDIX :

Figure 1: Externalisation index and total number of co-authored publications of the departements in 1997.

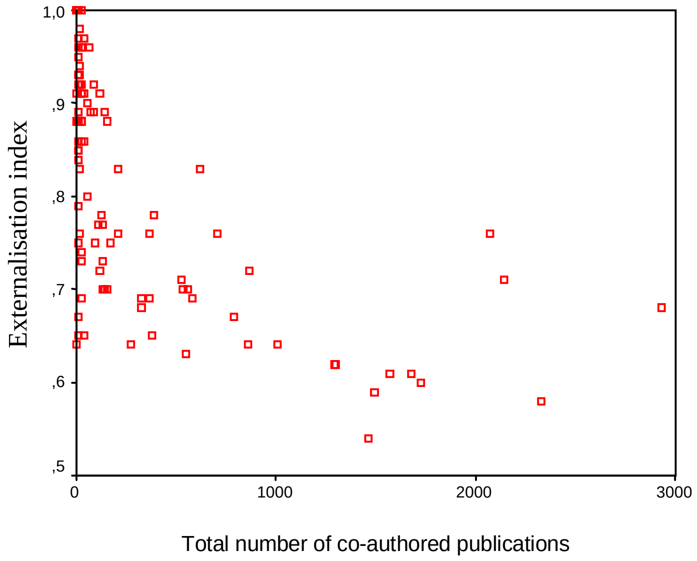

Table 2: French administrative "departements"

AIN	1	DEUX-SEVRES	79	INDRE-ET-LOIRE	37	PYRENEES-	
AISNE	2	DORDOGNE	24	ISERE	38	ATLANTIQUES	64
ALLIER	3	DOUBS	25	JURA	39	PYRENEES-	
ALPES-DE-HAUTE-		DROME	26	LANDES	40	ORIENTALES	66
PROVENCE	4	ESSONNE 91		LOIRE	42	RHONE	69
ALPES-		EURE	27	LOIRE-		SAONE-ET-LOIRE	71
MARITIMES	6	EURE-ET-LOIR	28	ATLANTIQUE	44	SARTHE	72
ARDECHE 7		FINISTERE29		LOIRET	45	SAVOIE	73
ARDENNES	8	GARD	30	LOIR-ET-CHER	41	SEINE-ET-MARNE	77
ARIEGE	9	GERS	32	LOT	46	SEINE-MARITIME	76
AUBE	10	GIRONDE 33		LOT-ET-GARONNE	47	SEINE-	
AUDE	11	GUADELOUPE	97	LOZERE	48	SAINT-DENIS	93
AUTRES-		GUYANE		MAINE-ET-LOIRE	49	SOMME	80
OUTRE-MER	99	100		MANCHE	50	TARN	81
AVEYRON 12		HAUTE-CORSE		MARNE	51	TARN-ET-	
BAS-RHIN 67		101		MARTINIQUE	96	GARONNE 82	
BOUCHES-		HAUTE-GARONNE	31	MAYENNE 53		TERRITOIRE-DE-	
DU-RHONE	13	HAUTE-LOIRE	43	MEURTHE-ET-		BELFORT 90	
CALVADOS	14	HAUTE-MARNE	52	MOSELLE 54		VAL-DE-MARNE	94
CANTAL	15	HAUTES-ALPES	5	MEUSE	55	VAL-D'OISE	95
CHARENTE	16	HAUTE-SAONE	70	MONACO 98		VAR	83
CHARENTE-		HAUTE-SAVOIE	74	MORBIHAN	56	VAUCLUSE	84
MARITIME17		HAUTES-		MOSELLE 57		VENDEE	85
CHER	18	PYRENEES65		NIEVRE	58	VIENNE	86
CORREZE 19		HAUTE-VIENNE	87	NORD	59	VOSGES	88
CORSE-DU-SUD		HAUT-RHIN	68	OISE	60	YONNE	89
102		HAUTS-DE-SEINE	92	ORNE	61	YVELINES 78	
COTE-D'OR	21	HERAULT 34		PARIS	75		
COTES-D'ARMOR	22	ILLE-ET-VILAINE	35	PAS-DE-CALAIS	62		
CREUSE	23	INDRE	36	PUY-DE-DOME	63		

Figure 3 : Structuration of the co-authorship between French departements in 1997.

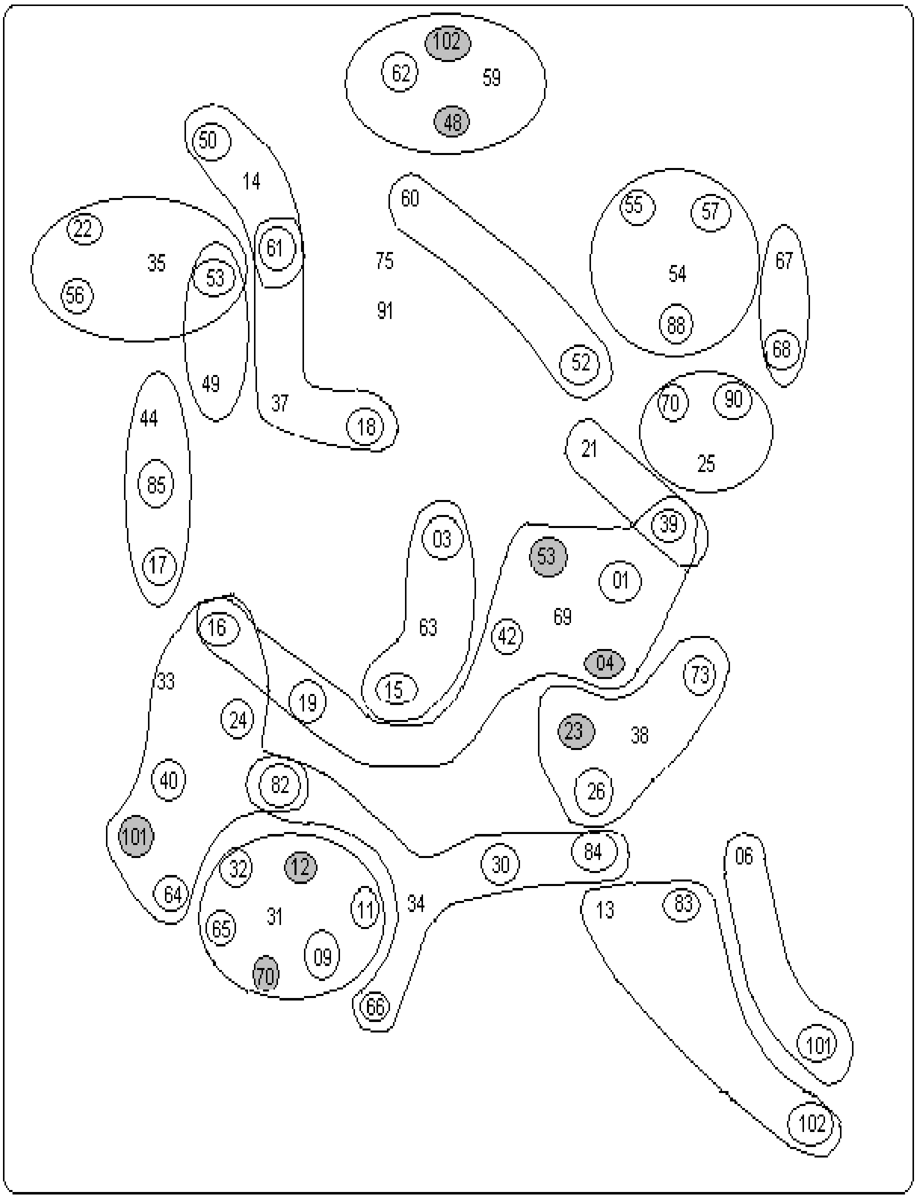

Table 3: Data description

Variable	Mean	Standard error	Min	Max	Obs.
Igi	-0,78	3,09	-6,91	5,12	6204
RDgi	9,29	4,46	0	16,93	6204
RDgj	13,23	1,98	0	18,04	6204
Rdvi	13,07	2,10	0	17,43	6204
RDvj	15,62	1,27	10,62	18,72	6204
RDv'i	14,07	1,64	0	17,62	6204
RDv'j	16,41	1,10	13,29	18,85	6204
KHgi	2,94	1,37	0	5,181	6204
KHgj	3,47	0,31	0	4,605	6204
KHvi	3,47	0,41	0	4,604	6204
KHvj	3,49	0,24	1,918	4,176	6204
KHv'i	3,55	0,37	0	4,605	6204
KHv'j	3,52	0,17	2,812	4,111	6204
VAg	10,81	0,85	8,72	13,59	6204

Table 4: Function of production of innovation with knowledge spillovers and local interactions

6204 observations, Tobit estimation with random effects

Dependent variable: patents logarithm

Variables	(1)	(2)	(3)	(4)
Constant	-10,53***	-10,19***	-14,85***	-12,09***
	(0,35)	(0,40)	(0,16)	(0,17)
RDgi	0,19***	0,19***	0,05***	0,07***
	(0,01)	(0,01)	(0,00)	(0,00)
RDgj	0,18***	0,14***	0,05***	0,05***
	(0,01)	(0,01)	(0,00)	(0,00)
RDvi	0,03***	0,03***	-0,33^{E-2}	0,62^{E-2}
	(0,01)	(0,01)	(0,00)	(0,00)
RDvi*RELgvi	-	0,20^{E-3}***	-	0,82^{E-2}***
		(0,00)		(0,00)
RDvj	-0,04***	-0,06***	0,04***	0,21^{E-2}
	(0,01)	(0,01)	(0,01)	(0,03)
RDv'i	0,02*	0,02**	0,02***	0,03***

	(0,01)	(0,01)	(0,00)	(0,01)
RDv’j	0,00	0,01	0,10***	0,11***
	(0,02)	(0,02)	(0,01)	(0,01)
KHgi	-0,20***	-0,19***	-0,05***	-0,09***
	(0,01)	(0,01)	(0,01)	(0,01)
KHgj	0,50***	0,40***	0,15***	0,14***
	(0,05)	(0,05)	(0,02)	(0,02)
KHvi	0,03	-0,02	-0,03**	0,00
	(0,03)	(0,03)	(0,01)	(0,01)
KHvj	0,35***	0,30***	0,15***	0,22***
	(0,07)	(0,07)	(0,03)	(0,03)
KHvj*RELgv	-	-	0,07***	0,09***
			(0,01)	(0,01)
KHv’i	-0,03	-0,04	0,04*	0,04**
	(0,03)	(0,03)	(0,02)	(0,02)
KHv’j	0,17**	0,17*	0,12***	0,04
	(0,08)	(0,09)	(0,03)	(0,03)
KHv’j*RELgv’	-	-	0,01***	-0,81 $^{E-2}$
			(0,00)	(0,00)
VAg	0,68***	0,71***	1,13***	0,89***
	(0,02)	(0,03)	(0,01)	(0,01)
TREND	-0,06***	-0,05***	-0,04***	-0,03***
	(0,01)	(0,01)	(0,00)	(0,00)