Regional Studies Association
Annual International Conference
Pécs, Hungary-24th 26th May

Measuring the knowledge spillovers in France departments: Comparison to a Spatial Econometrics Approach

Inès MOUSSA[a]

LEREPS Manufacture des Tabacs, Bureau MD 221,21, allée de Brienne 31042 Toulouse CEDEX 09 France
UAQUAP Institut Supérieur de Gestion de Tunis, 41 rue de la liberté, 2000 Le Bardo, Tunisie

Mohamed AMARA[b]

UMR, Géographie-cités 13 rue de Four Paris, 8504 France
UAQUAP Institut Supérieur de Gestion de Tunis, 41 rue de la liberté, 2000 Le Bardo, Tunisie

Abstract

This paper aims to measure knowledge spillovers using two methods across 94 French departments.

In the first part, we estimate the reduced form of the innovation-generating equation for French departments by distinguishing the effects of R&D carried out in several geographic areas (for example from 0 to 200km, from 200 to 400 km, and from more than 400); the purpose of this first method is to measure ***the presence of knowledge spillovers.***

In the second part of our work, the analysis uses spatial econometrics to measure knowledge spillovers and to question the assumptions on the relationship between spatial proximity and innovation. We will first detect the existence of spatial correlation by calculating the Moran's test with different contiguity matrices, and then we use a spatial model to model innovation data; the purpose of this second method is to show ***that knowledge spillovers are localized.***

The mains focus in this study is to compare the results found by using these two methods. This allows us to measure geographical proximity and to show that spillovers are localized.

Keywords: Spillovers, Innovation, spatial econometric

[a] Tel 1 : +33645354398 Tel 2 : +21620030710
E-mail : ines.moussa@iut-tlse3.fr

[b] Tel : +216 97873935
E-mail: Mohamed.Amara@malix.univ-paris1.fr

1. Introduction

Studies that have emerged in the early 90s and who described the geographical pattern of innovative activities within nations are so many in the American context than in the European context (Puga 1999; Amiti 1998; OST, 1998; Paci and Usai 2000 Vertova, 2004, Autant-Bernard et al., 2008, Escribano et al, 2009). At the center of this analysis is often the concept of geographic knowledge spillovers: the positive effect of the geographic proximity is the result of the existence of a limitation on the dissemination of knowledge spillovers in space (Rigby and Zook, 2002 and Escribano et al, 2009).
Recent research, however, has argue that no reason can justify a learning process is territorially limited (O'Brien 1992, Amin and Cohendet, 2004, Giuliani and Bell, 2005, Escribano et al. 2009). Thus, some authors questioned the efficacy and validity of physical space and "They have unwisely supported the thesis of the end of the distance" (Rallet and Torre 2007). Thus, the question is: do we still have faith in the benefits of geographical proximity in the process of innovation? Either we are announcing the end of geography (O'Brien, 1992) and distance (Cairncross, 2001)?
While most studies question the role of geographical proximity in the innovation process, is in a part, because of the existence of other forms of non-geographic proximity. On the other hand, the advent of ICT appears to favor replacing the geographical proximity.
However, measures used in literature to capture spillovers and to reveal the role of geographical proximity in the production of innovation are insufficient. This provided another reason for the underestimation of the role of space in innovation studies.
Thus, the ambiguity of the externality concept has made the empirical interpretation a difficult task. Economists try to use more direct approaches to highlight the externalities, whereas until here, while up here, the most used models do it only partially (Jaffe, Trajtenberg and Henderson, 1993; Autant-Bernard and Massard, 1999; Massard and Torre, 2004). These works are based on estimated innovation production function or on the patent citation and they deduct more than they show the local dimension of spillovers.
Based on this principle, it becomes essential to use an empirical thorough approach and more direct to measure more reliably the role of space in the innovation process. To do it, we will not underestimate or overestimate the role of geographical proximity in the production of innovation.

This paper is organized as follows: Section 2 and 3 provides a short overview of the theoretical results related to the methods for measuring spillovers. Section 4 describes the data and methods. The econometric methodology and results are introduced in Section 5 and 6. The paper ends with some conclusions.

2. Background theory: from patent citation approach to innovation production function approach (IPF)

The purpose of this section is to discuss the advantages and limitations of three approaches presented by authors of the Geography of Innovation to measure knowledge spillovers.
The first is the approach of patent citations[1] (Jaffe, Trajtenberg and Henderson, 1993, Jaffe and Trajtenberg (1999), Almeida and Kogut, 1999). Their experience is to compare the geographic location of patent citations with that of the original. If a patent B cites patent A,

[1] Patent citations are the part of the information contained in patents. Each patent contains references which list all patents describing the state of the art technology combined with previous technology

implies that patent A represents a portion of the existing knowledge, based on which the patent B. Therefore, the number of citations received by each patent by using information from amount of transmitted information and is thus an indicator of knowledge spillovers.
This method was subsequently criticized: (1) too aggregated level of patent classes. Patents controls were selected based on only three levels of the USPTO. (2) The quotations do not always reflect the extent of spillovers where inventors are able to cite patents after completing the invention. (3) The problem of delay on the time gap between the year of publication of the patent and the patent citation. (4) Difficulties in determining the location because an innovation can have several inventors who do not reside necessarily in the same place.
Thus, this method measures only the geographic proximity between the original patent and citation and assumes that patent citations reflect knowledge flows.
Another method is presented to shed light on the interactions between space and innovation: the geographical concentration. The principle of this method is to show that if spillovers are local, then one of their effects will be to stimulate a combination of innovative activities in some places.
Thus, work on the concentration of innovation are essentially static, authors aim to explain the location of innovative activities at a given time and location to connect the phenomena of local technological spillovers.
This second way of modeling considers that the concentration of innovation is the sign of the presence of spillovers and does not measure them with certainty.
The third method is the innovation production function (IPF). Jaffe (1989) is the forerunner in the use of the (IPF). He first studied the impact of the research activity of universities on the innovative capacity of firms in the same area. To capture interactions over local between universities and industries, he then introduced an index of geographic coincidence between public and private research (corresponding to the correlation between the number of employees in R & D within a metropolitan area of a State and the volume of public spending on research conducted in the same geographical area).
This approach has been taken up and expanded by Anselin, Varga and Acs (1997). This authors constructed models based on spatial interaction: this led to move from an "indirect" which infers the existence of externalities to an approach "direct".
This is the most commonly used approach since it has the advantage to measure the interaction between neighbouring units and relatives. It is therefore a measure of geographical space in which knowledge spillovers should occur but the spatial dimension of the phenomena is set a priori.

3. Innovation production function and spatial interactions: the extensions

Researches on measures of knowledge spillovers are varied and could identify the role of geographical proximity in the capture of spillovers. Overall, we find a consensus around the idea of a local dimension of knowledge spillovers. However, despite the interest of each, none of the methods used in the literature appears sufficient to measure externalities: the analysis on the concentration measures the local dimension of externalities and does not confirm their attendance. In contrast, modeling studies knowledge spillovers treat poorly the geographic dimension.
Thus, to measure the externalities it is important to test two main assumptions:
Hypothesis 1: the presence of knowledge spillovers
Hypothesis 2: knowledge spillovers are localized

Therefore it seems desirable to use with the innovation production function approach a second method that can test the local nature of knowledge spillovers.

3.1 Approach by geographic areas[2]

The model proposed here is based on a study by geographical areas. We use an IPF for measuring externalities in intervals of 200 km. Next, to better confine the spatial extent of externalities, we measure the externalities by interval of 100km (see Annex 1). This study was conducted by Bottazzi and Peri (2003) on a sample of 86 European regions. The authors distinguish the effects of R & D carried out in 5 geographic areas (from 0 to 300km, from 300 to 600 km, from 600 to 900, from 900 to 1300 and from 1300 to 2000 km). On a study of 86 European regions, they find that there are flows of knowledge, but only between regions separated by less than 300 km. When expenditure on R & D in a region doubles the number of patents filed in other regions in this interval will increase by 2-3%, while it increases the innovations of the same region of 80-90%. Using this method, we can test the first hypothesis:
H1: The presence of knowledge spillovers

3.2 Spatial Econometrics approach

The second approach based on the tools of spatial econometrics is also used to study the role of space in the process of innovation. Through this approach we find a notion of geographical proximity to both more accurate and more dynamic: modeling of spatial autocorrelation makes it possible to capture the existence, scope and influence of geographic spillovers.
We use spatial econometrics in our work to measure the geographical dimension of spillovers and to show their spatial character. We can then verify the second hypothesis of our study:

H2: knowledge spillovers are localized

4. Data and variables

Applied to the French case, our study proposed to measure the effect of knowledge spillovers in the production of innovation through a knowledge production function of Griliches-Jaffe type. We mobilize the survey data R&D (2002-2004) to identify resources necessary for innovation. Several reasons justify our choice of survey R&D:

- R&D is representative at regional level (as opposed to Community Innovation Survey CIS that is not representative at regional level).

- The R&D data are available by establishments (CIS survey has only data by enterprise level, the distribution of R&D by establishments is calculated by using the share of employments in theestablishment concerned in the total number of employees in the department)

[2] Autant-Bernard (2001a,b) for a study on France has used another method: Order of contiguity between spatial units to test the impact on the level of innovation from a French department, characteristics (R&D and private Public human capital) of neighboring departments on the one hand, and the neighboring departments of these same districts bordering other.

Moreover, the availability of zip code of each enterprise has avoided merging this survey with other since we have all the information necessary for the construction of our exogenous variables.

The variables used in our work are:

Patents

We used patent data calculated at the departmental level (2004-2006) to measure the output of innovation. These data are from the base of INPI-IPO (Observatory of Industrial Property) which identifies all patents filed by firms and financial institutions. They are identified by the address of residence of inventors and non-depositors.
This takes into account the spatial dimension. In addition, these data have the advantage to identify from French origin, the inventions arising from research conducted on French territory and also by international patents. This variable measures the number patents in each department and is subsequently divided by the area of each department. Therefore, it measures the intensity of innovation in a square kilometer of each department (see Appendix 3). Using patent activities such as measuring of innovation was not without controversies. But there is no alternative indicators such as rich in information regarding the location of people or firms that are the source of innovation (Paci and Usai, 1999). The data is expressed in logarithms because the model is specified in logarithms. The coefficients thus indicate the elasticity of innovation with respect to each of the inputs. This choice also appears to be the most appropriate.

R&D

We chose to shift in time the dependent variable (patents) and the independent variables (Expenditure R&D). At this point, we refer the work of Crepon, Duguet and Mairesse (1998): Expenditure on R&D is measured in 1985 while the dependent variable measures the output of innovation for the period 1986-1990. This is explained by the fact that the fruits of innovation are shifted relative to investment in R&D. (Cf. Feldman, 1994; Audretsch and Feldman, 1999, for long shifts or Hall, Griliches and Hausman, 1984, for the choice of a short lag of one to two years).
This variable represent the total R&D/km2 of each department (see Appendix 2
In addition, the R&D is measured by performing a smoothing over three years. Otherwise, we take into account the sum of expenditures for three years. This smoothing is that several years of cumulative R&D can accumulate knowledge over several years and thus produce a result in terms of innovation.

Khi

The indicator of human capital used here relates the number of researchers to the total spent on R&D. This variable measures for each area the proportion of researchers in relation to all staff employed in the research (researchers, technicians, administrative staff, etc.).

Specialization

It is measured by the ratio of the share of expenditure on R&D of a sector k in the department i share the same set at the national level.

Sectoral specialization is defined by the ratio of the share of R&D expenditure in the department k i in the total expenditure of the department i divided on the same set at national level:

$$\mathrm{Spe}_{i,k} = \frac{\mathrm{rdi,k/rdi}}{\mathrm{rdk/rd}}$$

Where rdk represents the R&D expenditure of sector k at national level. And rd is the national total expenditures for that year. A positive effect of this variable on the local industry to innovate would be perceived as indicating the existence of externalities type MAR.

Diversification

Diversity is measured by the inverse of Herfindhal index. This is captured by the part of all sectors in total R&D department with the exception of sector k analyzed. It is also standard on the same principle to the national level:

$$\boldsymbol{div\ i,k} = \frac{1}{\sum_{k'=1,k'\neq k}^{k} \left(\frac{\mathrm{rdi,k'}}{\mathrm{rdi-rdi,k}}\right)2} \Bigg/ \frac{1}{\sum_{k'=1,k'\neq k}^{k} \left(\frac{\mathrm{rdk'}}{\mathrm{rd-rdk}}\right)2}$$

Where k is the total number of sectors. This indicator takes important values when the sizes of the sectors, other than sector k are relatively close: the numerator is maximized when all sectors have the same level of local spending. A positive influence of this variable would reflect the existence of externalities like Jacobs.

Size

This variable measures the average size in terms of number of R&D companies and department i divided on the average size of firms in this sector nationally.

$$Size_{\ i,k} = \frac{eff\,i,k}{nbi,k} \Bigg/ \frac{effk}{nbk}$$

Where *eff* denotes the effective of R&D and nb the number of companies in the sector k. A negative influence of the variable *eff* confirms the important role of small firms in the dynamics of local externalities while a positive role would be to affirm the existence of increasing returns from research and should therefore relate more to the sectors with high costs Fixed search (Massard and Riou, 2002).

5. Econometric Modeling and Results

Before presenting our results, we specify the allocation of departments by interval of 200 km:

	Mean	Min	Max
Average number of departments in [0 :200[	16.29787	3	25
Average number of departments in [200 :400[	33.08511	11	58
Average number of departments in [400 :600[	29.42553	16	40
Average number of departments for more than 600 km	14.21277	0	47

Table 1: of departments by interval 200 km

5.1 Endogeneity problem

The estimation of our model by the OLS has been marked by an endogeneity problem. Our R&D exogenous variable is correlated with the error term which can lead to bias on the OLS estimators.
Hausman (1978) proposed a test to detect the presence of endogeneity. The results found are as follows:

Instrumented: $\ln$(R&D)i			
Instruments: $DIV_{i,k}$ $Taille_{i,k}$ $Spe_{i,k}$ $\ln[_{i\ [0\text{-}200[}(R\&D)_i]$ $\ln[_{i\ [200\text{-}400[}(R\&D)_I$ $\ln[_{i\ [400\text{-}600[}(R\&D)_i$			
$\ln[_{i\ [morethan600[}(R\&D)_i$ Kh			
Tests of endogeneity of: R&D			
H0: Regressor is exogenous			
Wu-Hausman F test:	550.20949	F(1,464)	P-value = 0.00000
Durbin-Wu-Hausman chi-sq test:	257.14539	Chi-sq(1)	P-value = 0.00000

Table 2: Haussman test

The test of endogeneity is significant at 1% indicating the rejection of H0 (no endogeneity) and the acceptance of H1 (the presence of endogeneity in the model).

To find the best instrumental variable, we choose the linear combination that is most strongly correlated with our variable R&D.
Our variable measuring expenditure on R&D is endogenous so as it can be explained by the variable of human capital which is thus the instrumental variable in our model. Once our instrumental variable is chosen, then we estimate the model by the double least square method (2SLS) or two-stage least squares

5.2. Basic specification using 200 km distance interval

We have established a robust estimate to account for problems of heteroscedasticity in the model. We present below a comparison of results found by OLS and the results found using 2SLS:

	MCO		2SLS	
Bvt	**Coef.**	**Std.**	**Coef.**	**Std.**
ln (R&D)	0.629***	(0.015)	1.021***	(0. 024)
Kh	0.543***	(0.032)		
Spe	0.018***	(0.008)	0.083***	(0.017)
DIV	-0.029***	(0.015)	-0.012	(0.019)
Taille	-0.062***	(0.023)	-0.245***	(0.049)
ln $[_{i\ [0-200[}$(R&D)]	0.060***	(0.018)	0.090***	(0.02)
ln $[_{i\ [200-400[}$(R&D)]	0.036***	(0.014)	0.037	(0.012)
ln $[_{i\ [400-600[}$(R&D)]	0.015	(0.021)	0.024	(0.011)
ln $[_{i\ [morethan600[}$(R&D)]	0.011	(0.017)	0.027	(0.024)
Cste	-1.973	(0.67)	-8.080	(0.453)
R-squared	0.966		0.888	
Root MSE	0.860		0.629	

Coefficient significant at the 10%, ** coefficient significant at the 5%, * coefficient significant at the 1% standard deviation between parenthesis.*

Table 3: Estimation using 200 km distance interval This table shows a very significant and positive impact (at the 1%) of R&D measured in a department i on the production of innovation in the same department. Our results are similar to those found by the economic theorists of innovation carried out on both American and European data (Jaffe et al. 1993; Feldman 1994; Lung (1997), Moreno, Paci and Usai (2005) ...).
The coefficient of this variable becomes more significant in the second model. The elasticity of innovation to R&D is 1.021.

We have found a significant and positive relationship with R&D measured in the range 000-200 and 200-400. Using 2SLS method, only the coefficient of the first interval which remains significant. Therefore, the spatial extent of externalities related to the total R&D is 200km. Here we have similar results to those obtained by Bottazzi and Peri (2003), who found that the coefficients become insignificant beyond 300 km for a study on European regions.

The elasticity of innovation to R&D departments located in the interval (0-200) is 0.090 while it becomes insignificant for the departments most distant (200-400).
The effect of R&D spillovers therefore decreases with distance.

To further limit the extent of externalities, we will proceed to the following estimate where externalities are measured in intervals of 100 km.

5.2 Basic specification using distance interval of 100 km

We complete our analysis by measuring externalities interval of 100 km. We present a descriptive analysis of the distribution department at intervals of 100 km and then we present the results of our second estimate.

The following table gives the observed average number of departments at intervals of 100 Km.

	Mean	Min	Max
Average number of departments in[0 :100[	4.638298	0	12
Average number of departments in[100 :200[	11.65957	3	20
Average number of departments in[200 :300[	15.46809	5	32
Average number of departments in[300 :400[	17.61702	6	33
Average number of departments for more than 400 km	43.6383	16	79

Table 4: of departments by interval of 100 km

Regression 2 identify whether there are externalities of knowledge in intervals of less restrictive. The estimation of Model 2 gives us the following results:

Tableau 1 Résultats d’estimation du modèle 2

	MCO		2SLS	
Bvt	**Coef.**	**Std.**	**Coef.**	**Std.**
ln(R&D)	0.628***	(0.014)	1.096***	(0. 034)
Kh	0.566***	(0.033)		
Spe	0.021***	(0.008)	0.097***	(0.018)
DIV	-0.032***	(0.013)	-0.012	(0.20)
size	-0.068***	(0.023)	-0.267***	(0.054)
ln[$_{i[0-100[}$(R&D)]	0.048***	(0.009)	0.055***	(0.019)
ln[$_{i\ [100-200[}$(R&D)	0.036***	(0.009)	0.057***	(0.025)
ln[$_{i\ [200-300[}$(R&D)	0.018	(0.009)	0. 033	(0.018)
ln[$_{i\ [300-400[}$(R&D)	0.008	(0.007)	0.026	(0.019)
ln[$_{i\ [morethan500[}$(R&D)	0.015	(0.012)	-0.078	0.022
Cste	-1.674 (0.406)		-8.157	(0.494)
R-squared	0.964		0.852	
Root MSE	0 .350		0.717	

** Coefficient significant at the 10%, ** coefficient significant at the 5%, *** coefficient significant at the 1% standard deviation between parenthesis*

Table 5: Estimation using 100 km distance interval

As we found earlier, the implied spatial spread of R&D related to the acquisition of external knowledge is 200 km since the coefficients 1.096, 0.055 and 0.057 are significant at 1%.

By estimating our model with 2SLS, we also note that the specialization variable has significant and positive influence on the production of innovation. Regarding the diversification variable, the regression shows no influence on innovation.

Many recent econometric studies have tried to distinguish and evaluate the effects of specialization and sectoral diversity of the innovative activities of enterprises.

Our finding is similar to study of Henderson, Kuncoro and Turner (1995) who see the positive role of specialization while diversity has no significant impact.

But beyond that, it is appropriate to measure the spatial dimensions of spillovers and show their spatial character. It will target the next section will measure the spatial character of the spillover using the tools of spatial econometrics.

5.3 Estimation using the tools of spatial econometrics

5.3.1 Spatial data analysis

Modeling spatial autocorrelation allows us to capture the existence and the influence of geographical spillovers. The most commonly used index detecting global autocorrelation of a variable of interest (brevet) is Moran's I index. Roughly speaking the Moran index is a cross product correlation measure that incorporates `space' through a spatial weight matrix W which reflects geographical proximity. Formally, let n the number of elementary spatial unit `departments', breveti (xi); i = 1,..., n, the brevet at the department i. The Moran's index is defined as:

$$I = \frac{N \sum_i \sum_j W_{ij} \, (x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_i (x_i - \bar{x})^2}$$

Where xi is the value of the x variable at location i, $\bar{x}$ is the sample mean, wij is the corresponding element of the spatial weight matrix W expresses the degree od interdependence between location I and location j and $S_0 = \sum_i \sum_j W_{ij}$. N is the total number of areas or observations.

At this stage a remark is in order. It is important to select an appropriate spatial weighting matrix when calculating the spatial autocorrelation statistic since it assigns weights to each pair of observation locations. The simplest weight matrix for area data is a set of binary weights that assigns the value one if two localities have a common border and zero otherwise [see Anselin, 1988 and Anselin et al., 2004 for other forms of the weight matrix]. These weights are then summarized in the spatial weights matrix W. Since each observation by convention can't be its own neighbor the diagonal consists of zeros. 1 Note that by construction I ∈ [-1,1] ; I close to 1 denotes a strong spatial autocorrelation (positive or negative).

Table 6 reports the Moran's I statistics. Test result of Moran is calculated using the distance matrix d = 200 km are as follows:

Moran's I					
Variables	I	E(I)	sd(I)	z	p-value*
brevet	0.515	-0.001	0.010	53.876	0.000

Table 6: Moran test

The Moran test rejects the null hypothesis of no spatial autocorrelation (critical probability of less than 1%).

5.3.2 Spatial econometric models

Taking into account the spatial autocorrelation is a necessary precaution to do any empirical mobilizing spatial data. This dependence can be introduced into the model in several ways: In terms of the dependent variable in the spatial autoregressive model (SAR), and spatial error model (SEM).

5.3.2.1 Spatial autoregressive model (SAR)

One way to incorporate spatial autocorrelation in a model is as follows:

$$y = \rho W y + W\beta + \varepsilon$$

Where W is matrix defining the neighborhood structure and ρ is the spatial auto-regressive parameter. This model is appropriate in the case of spatial dependence between the dependent variable of near localities giving rise to spatial auto-regressive problem.

5.3.2.2 Spatial error model (SEM)

The most used specification is in a spatial error model. The structural model is:

$$y = X\beta + \varepsilon$$

$$\varepsilon = \lambda W\varepsilon + u$$

λ measures the intensity of the interdependence between the residuals from the regression, u is the error term as : $u \sim iid\ (0,\sigma^2 I)$.

Not use spatial autocorrelation of errors can produce unbiased but inefficient statistical inference based on OLS is biased (Le Gallo, 2002). This is explained by the fact that errors are not spherical.

Results are presented in the following table:

	SEM		SAR	
Bvt	**Coef.**	**Std.**	**Coef.**	**Std.**
R&D	0.588***	(0.007)	0.589***	(0. 005)
Kh	0.555***	(0.017)	0.625***	(0. 005)
Spe	0.017***	(0.006)	0.08	(0.005)
DIV	-0.0314***	(0.012)	-0.014	(0.01)
Taille	-0.053***	(0.023)	-0.245	(0.018)
CSTE	-0.468		-0.018	
Rho	0.003	6.68		
Lambda			0.044	35.10

Table 7: Estimation using SEM and SAR models

The explanatory variables keep the same effects as model (2). Indeed, in the SEM model, the variables R&D, kh and Spe have a positive effect on the Bvt. however, the size of the company as well as a diversified industrial structure have a negative effect. We note also, that rho and lambda are positive and significant indicating the presence of auocorrelation level, spatial error term and the level of the dependent variable.

6. Conclusion

Endogenous growth theories have emphasized the importance of knowledge spillovers. These spillovers appear because of the partially public good characteristic of knowledge, allowing diffusion of many knowledge-related innovations (Parent and Riou, 2005). Thus, part of this new knowledge is sensitive to distance in its diffusion. This would explain the reasons why innovative activity tends to be agglomerated. This paper takes exactly this issue.

Based on the teachings of spatial econometrics and on the work of several decades of economic geography of innovation, we have asked in this paper the question of geographical proximity and knowledge spillovers in the innovative process of French departments.
In the first part, we proposed a measure that deviates to other studies in how to measure knowledge spillovers by intervals of different size. This allowed us to study the degree of influence of neighboring departments on the production of a neighboring department. This method allowed us to measure knowledge spillovers interval of 200 km and 100 km range.
In a second part, we have used the tools of spatial econometrics to compare the results with previous results found using spatial econometrics.
This method allowed us to test the localized nature of knowledge spillovers using the test Moran we could detect the presence of spatial autocorrelation between observations. This allowed us to measure the geographical dimension of spillovers and their spatial characteristics.
The result of our analysis shows that the spatial heard R & D is 200Km. Beyond this distance the effects of knowledge spillovers on the production of innovation is zero.

References

Acs, Z J., Audretsch, D. B. & M. P. Feldman, 1992 “Real Effects of Academic Research”, *American Economic Review*, 82, 363.367.
Anselin., L, 1988. *Spatial econometrics: Methods and models*. Boston: Kluwer Academic Publishers.
Anselin L. & Varga A & Acs, Z, 1997 "Local Geographic Spillovers between University Research and High Technology Innovations" *Journal of Urban Economics*, vol. 42(3), pp 422-448.
Adams J.D., & Jaffe B.A, 1996 “Bounding the Effects of R&D: An Investigation Using Matched Establishment-Firm Data” *Rand Journal of Economics* vol.27, n°.4, pp.700-721.
Audretsch, D. B. & Feldman M. P., 1996 “R&D spillovers and the geography of innovation and production”, *American Economic Review* 86(4): pp 253-273.
Autant-bernard C., & Massard N., 1999,"Econométrie des externalités technologiques locales et géographie de l’innovation: une analyse critique ", *Revue d’Economie Appliquée*, Tome LII, n° 4, pp.35-68.
Autant-Bernard, C., 2001a, “Science and knowledge flows: evidence from the French case”, *Research policy*, 30, pp. 1069-1078.
Autant-Bernard, C., 2001b, “The geography of knowledge spillovers and technological proximity”, *Economic of Innovation and New Technology*, 10, pp. 237-254.
Almeida P., Kogut,B., 1999, “Localization of knowledge and the mobility of engineers in regional networks”, *Management Science*, 45(7), pp. 905-917.
Baldwin W.L & J.T.Scott 1987, *Market Structure and technological Change.*, A volume in the Economics of Technological Change section edited by F.M. Scherer, Harwood Academic Publishers, Chur, London, Paris, New York. Melbourne.
Boschma, R.A., 2005. “Proximity and innovation: a critical assessment”. *Regional Studies* 39, 61-74.
Bottazzi L. & Peri G., 2003 “Innovation and spillovers in regions: evidence from European patent data” *European Economic Review* 47 (7), 687.710.
Breschi, S.,& Lissoni, F., 2003. “Mobility and Social Networks: Localized Knowledge Spillovers Revisited”, CESPRI working paper N°. 142, Centre for Research on Innovation and Internationalisation Process, Universita Bocconi, Milan.

Cohen, W.M & D. A. Levinthal, 1989, “Innovation and learning: the two faces of R&D”, *The Economic Journal*, 99, pp.S 569-96.

Crepon B., Duguet E., Mairesse, 2000, « Mesurer le rendement de l’innovation », *Economie et statistique* n° 334.

De Rass De Rassenfosse, G., Van Pottelsberghe B., 2009 “A Policy Insight into the R&D-Patent Relationship”,*Research Policy* 38, 779.792.

Esccribano A., Fosfuni A. And Tribo J. A. 2009, “Managing external knowledge flows: the moderating role of absorptive capacity”, *Research Policy* 38, 96-105.

Feldman M. P, 1994a, *The Geography of Innovation Kluwer Academic Publishers*, Boston.

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

Feldman M., & Kelley M. 2006, “The exante assessment of knowledge spillovers: Government R&D policy, economic incentives and private firm behaviour*”*, *Research Policy* vol 35, pp 1509-1521.

Fischer M & Varga A., 2001 "*Production of Knowledge and Geographically Mediated Spillovers from Universities: Spatial Econometric Perspective and Evidence from Austria* "ERSA conference papers ersa01p182, European Regional Science Association.

Griliches, Z., 1979 “Issues in assessing the contribution of research and development to productivity growth” *Bell Journal of Economics* 10 (1), pp 92.116.

Griliches, Z., 1990, “Paten statistics as economic indicators: A survey”, *Journal of Economic Literature* XXVIII, pp 1161.1707.

Gertler, M.S., 2003, “Tacit knowledge and the economic geography of context, or the indefinable tacitness of being (there)”, *Journal of Economic Geography* vol 3, pp 75-99.

Guellec D., 1999 *Économie de l’innovation*, Paris, la découverte, Collection Repères.

Guellec D., &Van P., 1999, «*Les brevets comme indicateurs de l’innovation*», Programme CNRS : les enjeux économiques de l’innovation, Les Cahiers de l’Innovation, n° 99024.

Jaffe, A., 1989, “Real Effects of Academic Research”, *American Economic Review*, vol 79, pp 957-970.

Jaffe, A., Trajtenberg, M., Henderson, R., 1993, “Geographic localization of knowledge spillovers as evidenced by patent citation”. *Quarterly Journal of Economics* 108 (3), pp 577-598.

Jaffe, A., Trajtenberg, M., 1999, “International knowledge flows: evidence from patent citations”, *Economic of Innovation and New Technology*, 8, pp. 105-136.

Jones, C., 1995. “R&D based models of economic growth”. *Journal of Political Economy* 103, 739-784.

Kogut, B., Zander, R., 1996, “What firms do? Coordination, identity and learning” *Organisation Science*, vol 7, pp 502.518.

Le Gallo., J., 2002, Econométrie spatiale : l’autocorrélation spatiale dans les modèles de régression linéaire, Economie et Prévision, 155 (4), pp. 139-158.

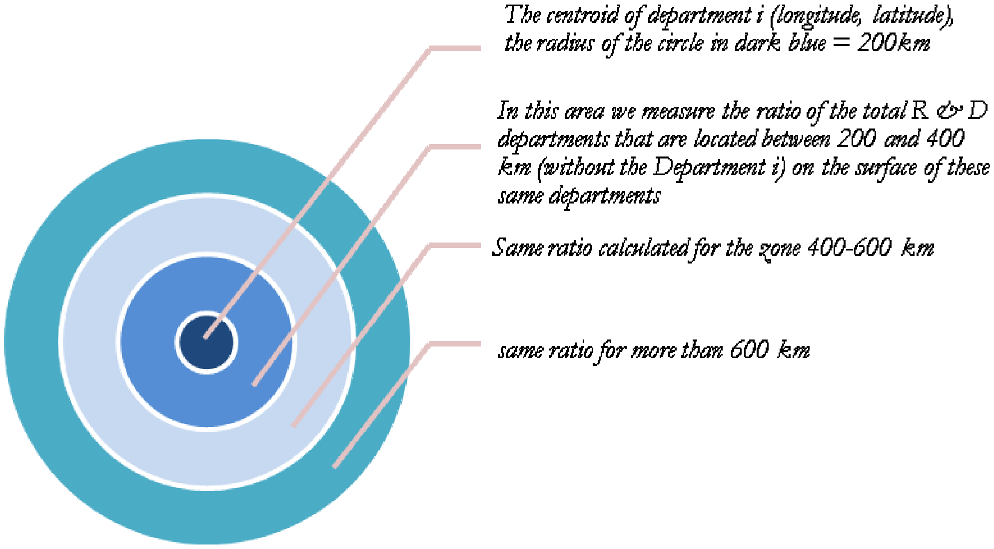
Le Goff Pronost M. et Lethiais V., TIC, 2007, « besoins de coordination et d’information et de proximité géographique: une analyse sur des données bretonnes », *Cahier de recherche*, février, numéro 4.

Lesage J.P., M. Fischer and T. Scherngell, 2007, “Knowledge spillovers across Europe. Evidence from a Poisson spatial interaction model with spatial effects”, *Papers in Regional Science*, vol 86, pp. 393-421.

Mairesse, J. & Mulkay B, 2008, “An Exploration of local R&D Spillovers in France”, *Cahier du GRES* n° 15.

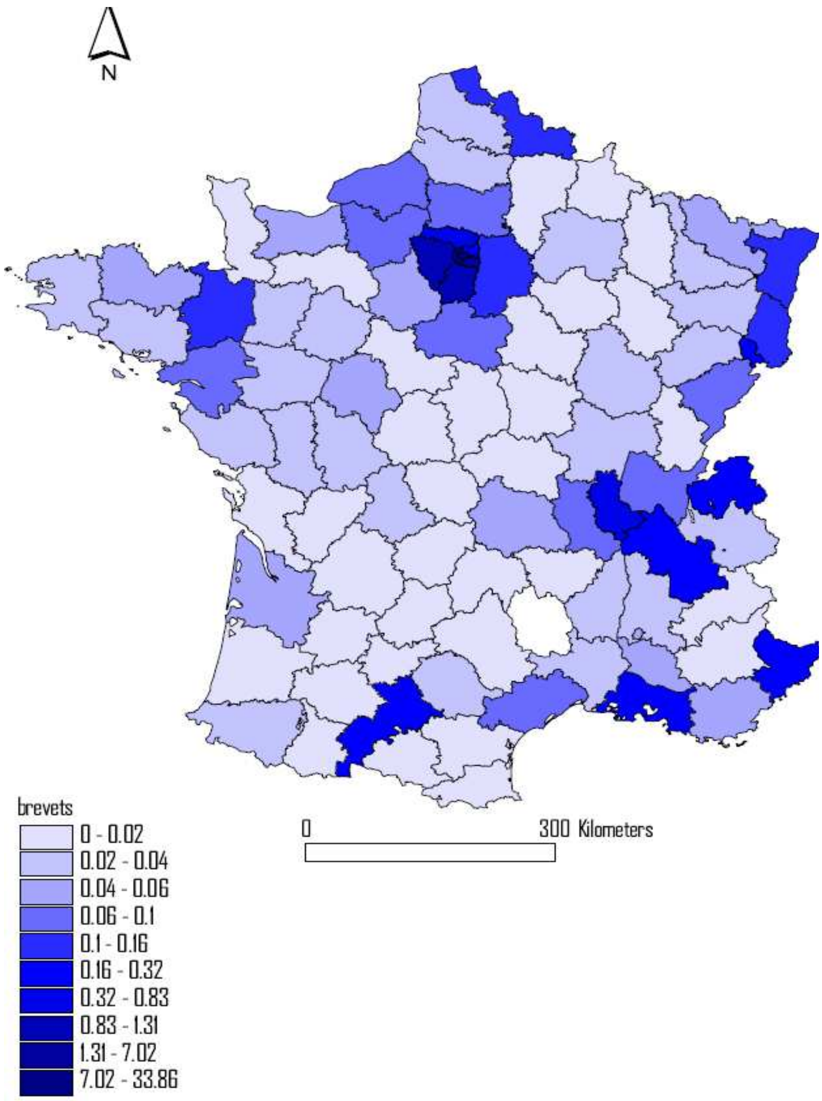
Maryann P. Feldman And Maryllen R. Kelly, 2006,"The ex ante assessment of knowledge spillovers government R&D policy, economic incentives and private firm behaviour", *Research Policy* vol 35, pp. 109-1521.
Massard N., Mehier C. 2005, "*Proximity, Accessibility to Knowledge and Innovation*" 10th International Conference of The Regional Studies Association on .Regional Growth Agendas., Denmark, 28th - 31st May.
Maurseth, P.B., & Verspagen, B., 2002, "Knowledge Spillovers in Europe: A Patent Citations Analysis," *Scandinavian Journal of Economics*, 104(4), pp. 531-545.
Mohnen P., 1992, "International R&D Spillovers*" Cahiers de recherche du Département des sciences économiques »*, UQAM 9208, Université du Québec à Montréal, Département des sciences économiques.
Moreno R., Paci R. and Usai S. 2005, "Spatial spillovers and innovation activity in European Regions", *Environment and Planning A*, 37, 1793-1812.
O.Mahony And Vecchi, 2009, "R&D, knowledge spillovers and company productivity performance", *Research Policy* 38, pp. 35-44.
Paci R. & Usai S., 2007, "Knowledge flows across European regions", Working paper.
Parent O. And Riou S., 2005, "Bayesian analysis of knowledge spillovers in European regions", *Journal of regional science*, vol. 45, No. 4, pp. 747-775
Rallet A. & Torre, 2000, "Is geographical proximity necessary in innovation networks in the era of global economy?*" GeoJournal* 49, pp. 373-380.
Rallet A. & Torre A. (Dir.) 2007, Quelles proximités pour innover? L'harmattan.
Rigby, D., Zook, C., 2002, Open-market innovation, Harvard Business Review (October).
Romer, P.1990, "Endogenous Technological Change", *Journal of Political Economy*, 98, 71.S102.
Scherer F. M. 1965,"Firm size, market structure, opportunity, and the output of patented innovations" *American Economic Review*, 55, 1097-1123.
Schumpeter J. 1942, Capitalisme, socialisme et démocratie, Paris, Payot.
Vega-jurado,J.&Guti´errez-Gracia,A.,Fern´andez-DE-Lucio,I.,Manjarr´es-henr´iquez, L., 2008 "The effect of external and internal factors on firms product innovation " *Research Policy* 37, pp616-632
Von hipple, E., 1994, "Sticky Information and the Locus of Problem Solving: Implications for Innovation", *Management Science*, 40, pp 429-439.
Weterings A., Boschma R., 2009, "does spatial proximity to customers matter for innovative performance? Evidence from the Dutch software sector", *Research Policy* , vol 38, pp. 746-755.

Appendix 1



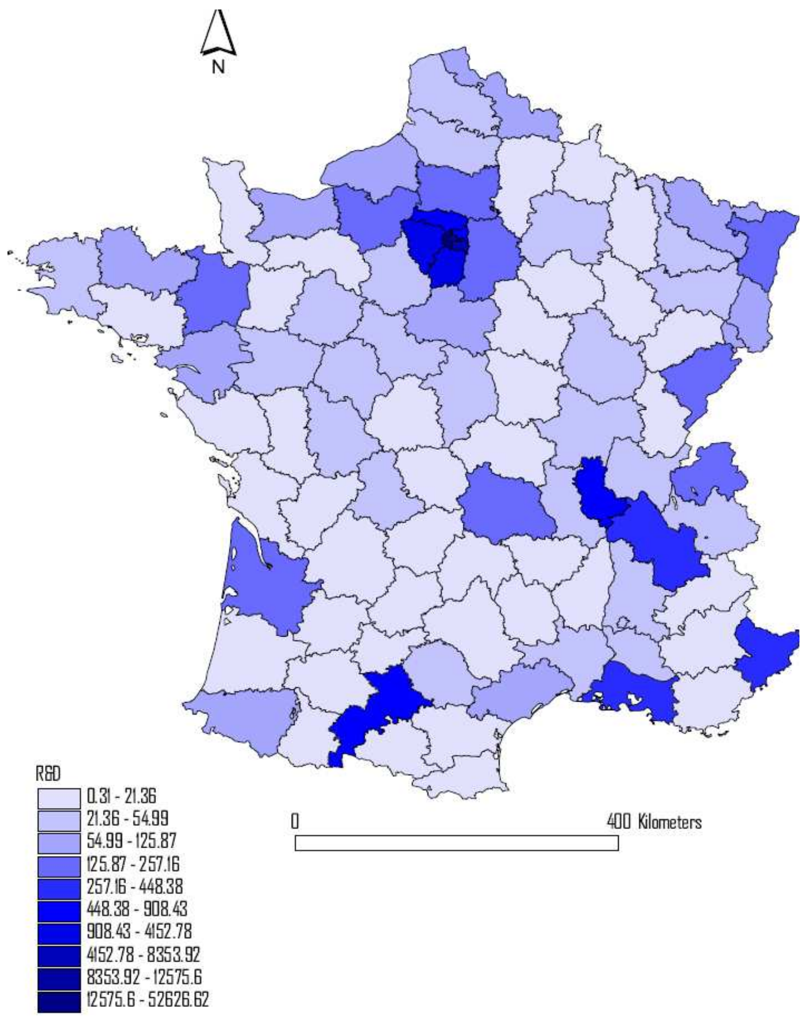
Measuring externalities using a geographical interval (interval of 200 km)

Appendix 2



Distribution of total patent by department

Appendix 3



Distribution of total R&D by department