"Everything is related to everything else,
but near things are more related than distant things"
Tobler (1976)

GEOGRAPHY OF INNOVATIONS AND GEOGRAPHY OF RESEARCH: THE FRENCH EXPERIENCE

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HIGHLY PRELIMINARY VERSION
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Abstract:
In the literature, innovation is the outcome of spatial interactions between the innovative structure of a district and its knowledge structure: innovations tend to concentrate in the locations where they find knowledge that is necessary for the development of innovating activities. Thus, proximity increases the chance of developing new ideas (Feldman, 1999). Starting from this theoretical hypothesis, in this paper we analyze the relationship between the spatial distribution of the main research fields and the spatial distribution of innovations for the main industrial activities, for the French case. For analyzing both repartitions, we use the 94 French departments as our basic spatial units. The local level of innovation is measured by the number of patents, by activity. The local level of research is measured by the production of research articles published by local research institutions.

Using data mining and spatial exploratory statistics, we find evidence of concentration of innovations in regions where one finds the necessary knowledge to develop the innovating activity. Then, we estimate a model with spatial interaction, thereby taking into account the technological spillovers. The core of the model is an innovation function, where the level of innovation depends upon the local level of research, of the level of research in neighboring areas, and of the local industrial specialization. Our results show that there is a polarized spatial structure for innovations as well as for research activities.

Moreover, we find that the emergence of patents is locally influenced by the global research activity, as well as by the specific structure of local research activities. In addition, we have taken into account that proximity increases the chances for the diffusions of ideas, even though the space concentration of French patents does not seem to be seriously affected by research spillovers.

Keywords : Innovation, research, localization

Classification : JEL R12, O31

I . INTRODUCTION

If the spatial repartitions of innovation and research have been extensively studied, there is much less work on the links between the two spatial repartitions. Analysing this link may however shed some light on the influence of research on innovation. This influence is at the core of the standard endogenous growth literature (Romer, 1990; Grossman and Helpman, 1991), where growth is fostered by innovation and innovation uses knowledge produced by research. Growth models have no spatial dimension, however, and then consider that knowledge entirely diffused into the economy.

Nevertheless, empirical evidence reveals that technology and the dissemination of information remain delimited geographically (Autant-Bernard, 2001). Knowledge creation and knowledge diffusion are highly localized, as research activities benefit from local networks facilitating the exchange of information. Furthermore, these may constitute an important basis for the competing advantages of these areas, and thus for their potential attraction. The spatial agglomeration of innovating activities may then be explained through a process of creation and dissemination of information, which is still influenced by:

- the devices of research and the degree of specialization of research;
- the width of industrial specialization (or Marshallian externalities) of the area which affects the innovating output in a particular local industry;
- the geographical range of the externalities of science and the way these knowledge spillovers attenuate in space. The innovations are represented as a function of knowledge inputs of local districts and that of the neighbors, while controlling the size of the market.

Therefore, the main questions we raise in this paper are: How far the local level of research activity influences the local level of innovation? Is this influence a purely quantitative one, or do the local research structure matters? What is the extent of diffusion and then do neighboring areas matter? In order to answer these questions, we estimate an econometric model using data on the French *departements*, where the local level of innovation is explained by the local and neighboring level of research activity and its structure.

The remainder of the paper is as follows. The next section provides a description of the data we will be using and discusses econometric issues. In the third section, we present the spatial repartitions of both innovation and research, using the standard tools of exploratory spatial data analysis. In the fourth section, we present the results of econometric estimation. The last section concludes.

II. DATA AND METHODOLOGY

II.1 Data

We analyze the link between the spatial repartition of innovative activity and the spatial repartition of research activity for the French case. The basic territorial units we use for measuring both the local level of innovation and the local level of research activity are the French "departement". The *departements* are the NUTS 3 French territorial units.

Our measure of local innovative activity is the number of patents produced by local organizations during the period 1998-2000. The data are averaged for three years in order to have the long-term values [1]. We use a "fractional account" where the global weight of every patent equals unity and, when a patent is multi-authored, this unit weight is evenly divided among the authors: if there are n author, each author accounts for $1/n$. We know the repartition of these patents across 7 activities: electronics & electricity,

[1] The method was used by Autant-Bernard C, 2001 and Moreno, R et alii 2004

mechanical engineering, chemistry & materials, pharmacy & biotechnologies, industrial processes, machinery & transport, and household consumption.

Our measure of local research activity is the number of scientific articles published by local organizations. Every article is assigned to the institution (university, research centre) where its authors work. If an article is multi-assigned, every institution accounts for one.

We know the repartition of these articles across the following research fields: food/nutrition; animals breeding; astronomy-astrophysics; biomedical engineering; cellular and molecular biology; oncology; analytical chemistry; chemistry; medical chemistry/pharmacy; ecology; endocrinology; general biology; chemical engineering; genetics; earth sciences; general medicine; mechanical engineering; immunology; computer science, hospital medicine, mathematics-statistics; materials; bacteriology; other medical specialties; multidisciplinary; neuroscience; optics and spectroscopy; chemical physics; general physics; applied physics; agronomy and public health.

II.2 Methodology

We start analyzing separately the spatial repartitions of both innovation and the research activity. Our main aim here is to measure the spatial concentration of these activities and to identify the main clusters. Moreover, as we know the repartition of patents by activity and the number of articles by research field, we examine how far patents are correlated across activities and articles are correlated across research fields. For analyzing the spatial repartition, we rest upon the now standard tools of spatial descriptive analysis: spatial correlograms, Moran diagrams and LISA maps. For the study of correlations, we use principal components analysis.

Then, we move to the analysis of the quantitative relation between research activity and local innovative activity. Therefore, we estimate econometric models where the dependant variable is the local quantity of patents, either globally or for each of the seven main activities. Our explained variable, the number of patents, is non-negative, discrete, and often takes a zero value. Therefore, for estimation purposes, we use the negative binomial model. Let us remind that this model is an extension of the well-known Poisson model. Let us remind that, in the later case, the number of patents for observation i, n_i, follows the probability distribution

$$\Pr\{n_i\} = e^{-\lambda_i}\frac{(\lambda_i)^{n_i}}{n_i!}$$

where the parameter λ_i, is linked to the explanatory variables in a log-linear form:

$$\ln\lambda_i = X_i^{'}b$$

The disadvantage if the Poisson is that it imposes the restriction that the mean and the variance equal each other (both equal the parameter value). Usually, this restriction is not met by the data, the variance being larger than the mean[2]. The negative binomial model relaxes this restriction by adding a random term:

$$\ln\lambda_i = X_i^{'}b + \ln\varepsilon_i \qquad (1)$$

where ε_i follows a gamma distribution with parameter θ. Integrating, one finds

$$\Pr\{n_i\} = \frac{\Gamma(\theta + n_i)}{\Gamma(n_i + 1)\Gamma(\theta)}\left(\frac{\lambda_i}{\lambda_i + \theta}\right)^{n_i}\left(\frac{\theta}{\lambda_i + \theta}\right)^{\theta}$$

Because we are interested in the impact of local research, as an input of innovation, our primary explanatory variable of interest is the local level of published articles[3]. For controlling the size of the *departements* we used the census data on employment by sector of activity[4]. After controlling the size of

[2] Chada, A., Trips And Patenting Activity : Evidence From Indian Pharmaceutical Industry, Working Paper 512, 2005

[3] Source of data set OST 1998-2000 (Observatoire de Sciences et des Technologies)

[4] Source of data set: INSEE 1999

the market, we want to test the differential impact of specific research fields on specific activities, so as to compare the importance of global versus specific research. We do this by the use of likelihood ratio test, which provides us evidence to use not only the global level of research activity, but also its measure for each research field.

To test the validity of a priori restriction that the coefficients of specific research are zero, the likelihood test obtains the following statistics:

$$\lambda = 2(ULLF - RLLF)$$ [5]

where ULLF is the unrestricted log-likelihood function that is, it includes also the specific research, and RLLF restricted log-likelihood function that is, it accounts only for the global research(while the coefficients of the specificity of research are zero). Asymptotically, this is distributed as the chi-square distribution with usually 30 degrees of freedom (32 fields of science-2 variables of size) and the p-value of the chi-square of almost zero.

In addition, the spatial diffusion of innovation is highly sensitive to distance, and thus we cannot exclude spillovers between *departements*. On one side, for these spillovers, distance also matters and they are much more likely to be observable between *departements* that are close to each other. Therefore, following Autant-Bernard (2001), we introduce spatially lagged values of the explanatory variables in the model, using a spatial weights matrix. Our weights matrix is the usual row standardized contiguity matrix. On the other side, these spillovers might be sensitive to the technological distance. Consequently, we construct a technological matrix following Moreno, R et alii (2004) approach. Once more the incorporation of neighboring variables is tested by the use of Likelihood Ratio test.

III. STYLISED FACTS ON THE SPATIAL DISTRIBUTIONS OF PATENTS AND ARTICLES

In this section, we analyse the spatial distributions or patents and articles across *departements*, using the standard tools of exploratory spatial data analysis, Moran correlograms and Moran indices, Moran diagrams and LISA indices. This analysis of patterns is done for each activity, while the analysis of articles is done separately for each research field.

III.1 The spatial distribution of patents

The spatial distribution of innovation, measured by the number of patents (all activities being grouped), is displayed on the left hand side map of Figure 1. Innovation looks to be highly concentrated, *departements* where patenting activity is high tending to cluster close to each other. There are three main areas where patenting activities tend to concentrate. The first one has Ile-de-France as its core and extends to the neighbouring *departements* and, further, to Northern *departements*. The second one has the urban areas of Lyon and Grenoble as their core and mainly includes Northen Alps[6]. The third one corresponds to the Mediterranean cost.

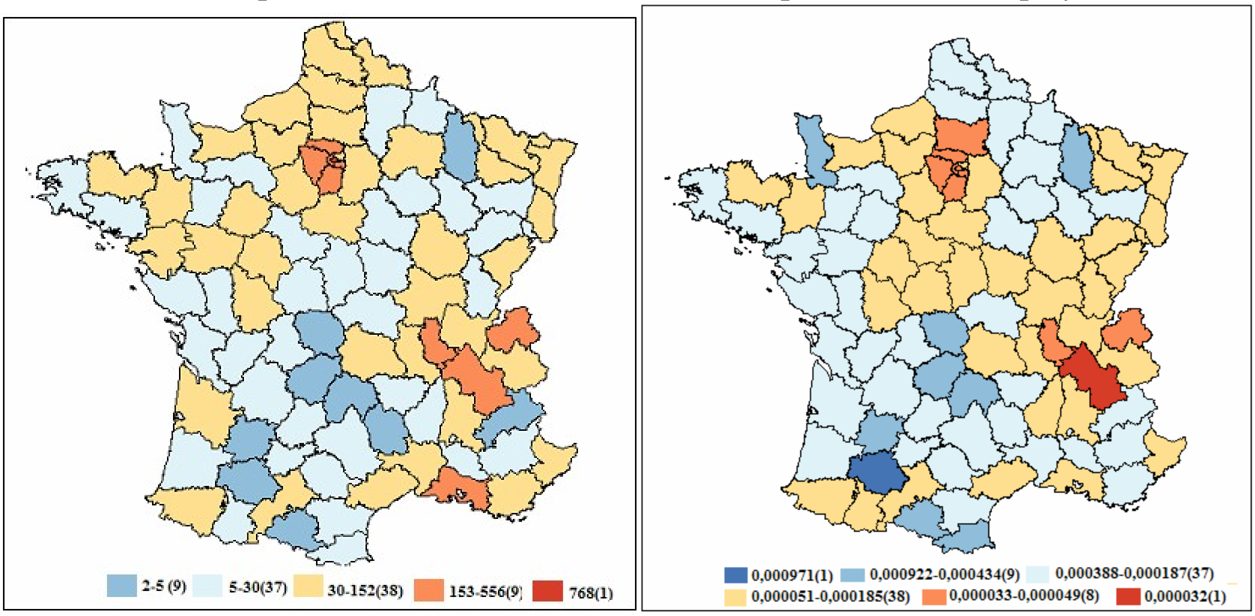
One can expect this distribution to be heavily influenced by area size. The larger a *departement*, the higher are population and employment, the larger the basis for innovative activity. We take account for this size effect calculating patent rates with respect to employment. The spatial distribution of these rates is displayed on the right hand side map of Figure 1.

[5] Gujarati, D, Basic Econometrics, forth edition, Unites States Military Academy, West Point,

[6] which concords to the evidence of european innovation clustering found by Moreno&Paci 2004

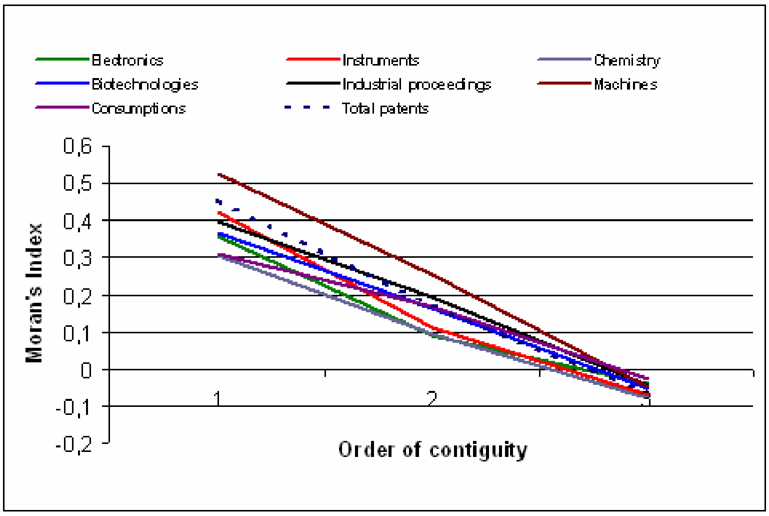
Figure 1: the spatial distribution of patents

Number or patents **Rate of patents (w.r.t. employment)**



The main areas with high innovation rates rest still Ile de France and the Northern Alps (mainly around Grenoble and Lyon). The Mediterranean cost is not an area with high rates of patenting activity. This tendency of *departements* with high patents levels to cluster can also be observed for each of the seven activities. Figure 2 displays Moran indices for all the patents and for the seven activities, using standard row-normalized contiguity matrices at contiguity orders 1, 2 and 3. At orders 1 and 2, one rejects the null hypothesis of no spatial autocorrelation. Spatial autocorrelation is highest for the machinery and transportation activity, and is slightly lower for other activities.

Figure 2: Moran indices on patent levels, by activity



Despite their differences, the seven activities display similar spatial patterns, as one can see on table 1 and figures 3 and 4. Table 1 displays correlations between activities. Most of these correlations are high. Therefore, we can expect departments with a high patenting level and departments with a low patenting level to be fairly the same across activities.

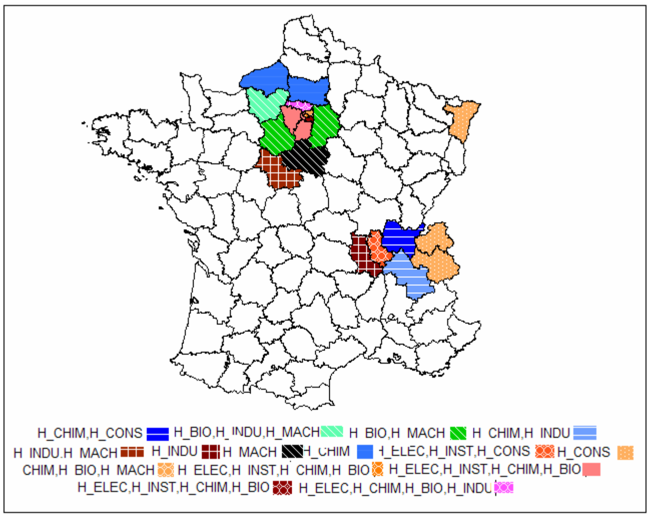
Table 1: Patterns: Correlation between activities (rate of patents)

	Electronics	Instruments	Chemistry	Biotech nologies	Industrial processes	Machines	Consumption
Electronics	1.00	0.83	0.43	0.54	0.36	0.40	0.27
Instruments	0.83	1.00	0.55	0.67	0.39	0.47	0.38
Chemistry	0.43	0.55	1.00	0.62	0.51	0.40	0.34
Biotechnologies	0.54	0.67	0.62	1.00	0.38	0.52	0.27
Industrial processes	0.36	0.39	0.51	0.38	1.00	0.45	0.33
Machines	0.40	0.47	0.40	0.52	0.45	1.00	0.36
Consumption	0.27	0.38	0.34	0.27	0.33	0.36	1.00

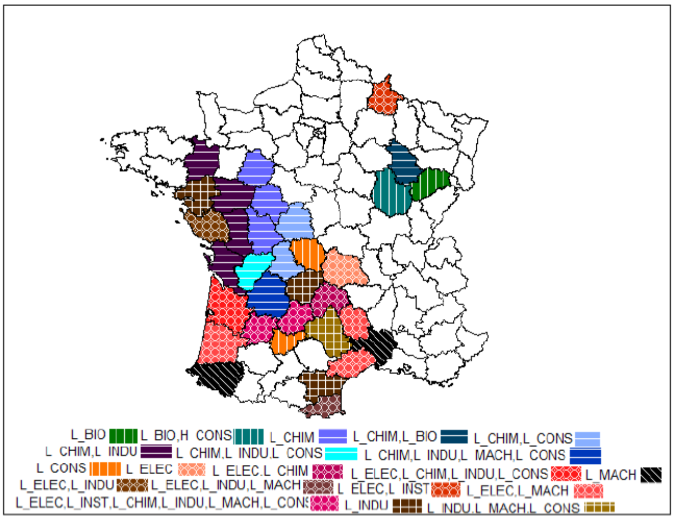
The two maps of Figure 3 use LISA statistics. These statistics test whether a *departement* can be significantly considered of the High-High type (High local patenting level, surrounded by similar *departements*) or of the Low-Low type (Low local patenting level, surrounded by similar *departements*) For all the activities, *departements* of the High-High type are mainly concentrated in two areas. The first one is the Ile-de France region and its neighbouring *departements*. It is slightly more oriented toward Electronics and instruments. The second one includes the Northern Alps, with the urban areas of Lyon, Grenoble and Saint Etienne and is slightly more oriented toward electronics and industrial processes. There is more dispersion of *departements* of the Low-Low type. However, most of them are in Western and South Western France. The only Western *departements* that are not of the low-low type for any industry are in Western Brittany. And the only South-Western *departements* that are not of the low-low type for any industry correspond to the city of Toulouse and its hinterland.

Figure 3: Patents, departements with a significant position

High-High



Low-Low

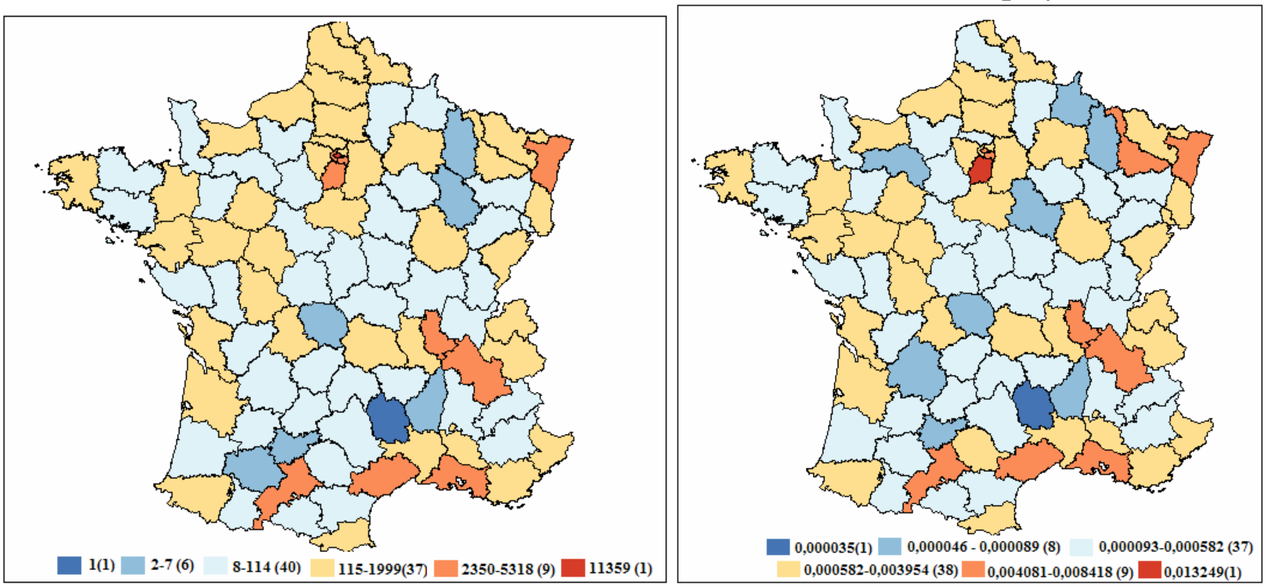


III.2 The spatial distribution of research articles

The spatial distribution of research activity, measured by the quantity of research articles published by local organisations and by the rate with respect to employment, is displayed in figure 4. The comparison with the maps of Figure 1 shows some strong similarities. These similarities are confirmed by correlation coefficients: the correlation between the number of patents and the number of published articles is 0.83. Of course, this correlation is influenced by size effects; but, after removing the size effects using rates with respect to employment, we still have a correlation of 0.57. Research activity is well developed in the Ile de France region, the Lyon and Grenoble area, and along the Mediterranean coast. It is also well developed in Alsatia and in the Toulouse area.

Figure 4: the spatial distribution of research articles

Number of articles **Rate (w.r.t. employment)**



This spatial repartition also applies to most of the 32 research fields. When looking at the number of published articles, the correlations across research fields are very high. This was expected, however, as all the research fields share the same size effect. However, when one takes account of this size effect using rates of published articles with respect to employment, all correlations are still positive and most are highly significant (see the correlation matrix in appendix). Therefore, when research is well developed in a *departement*, it is well developed in most research fields and there are few cases where some research fields are well developed and other research fields are not developed. There is few evidence of a high degree of local specialisation in specific research fields and, in most cases, the aggregate spatial repartition displayed in Figure 4 also applies to specific research fields. This weakness of local specialisation is confirmed by a principal component analysis of the series of specificity coefficients.[7] The share of the variance explained by the first 10 principal components is provided below (Table 2). These share are quite low, implying that there is very low correlation across research fields and that it is impossible to define local specialisations combining several research fields.

Table 2: Specifities of research fields : Share of variance explained by the main principal componants

Number	Percentage
1	11.45
2	9.17
3	8.35
4	6.27
5	5.63
6	5.41
7	5.13
8	4.88
9	4.70
10	4.16

[7] The specificity of the research field *i* in area *n* is the ratio $\frac{x_{in}/x_{.n}}{x_{i.}/x_{..}}$, where a dot stands for a sum on the relevant dimension.it is the ratio of the share of research field *i* in the publications originating from area *n* to the share of research field *i* in all the publications.

Moreover, whatever the research field, the spatial repartition of research fields displays a low level of spatial autocorrelation. Two research fields apart (general medicine and hospital medicine), all first rank autocorrelations lie below 0.15.

IV. ESTIMATION RESULTS

IV. 1. Global determinants

We first look at global determinants of innovative activity, without any reference to the structure of employment or research. As French *departements* are highly heterogenous with respect to size, we have first to take account of size differences. Once controlled for size, we can look into the analytical structure of the factors of innovation. Therefore, we start estimating a simple version of (1), where S_i is a size variable:

$$\ln\lambda_i = b_0 + b_1 \ln S_i + \ln\varepsilon_i \qquad (2)$$

The coefficient b_1 is a measure of scale effects. When b_1 equals unity, $\lambda_i = E[n_i]$ is proportional to size and then the expected rate of innovation, $\lambda_i = E[n_i/S_i]$ is constant across areas. When b_1 is higher than unity, the expected rate of innovation, $\lambda_i = E[n_i/S_i]$ increase with area size and then innovation tends to concentrate in larger areas.

Model (2) has been estimated using three size variables: local employment, the local size of the pool of researchers and a global measure of the local research activity (the number of published research articles). Estimation results are displayed in table 3. When size is measured by local employment, its coefficient is significantly higher than unity: the larger the *departement*, the higher the rate of innovation. When size is measured by the local number of researchers or by the local research activity (the quantity of published articles), its coefficient is significantly lower than unity: the higher the level of research activity, the higher the level of innovation, but the lower the rate of innovation.

Table 3: Estimated impact of size on the local level of innovation

Size measured by employment

	Electronics	Instruments	Chemistry	Biotech nologies	Industrial processes	Machines	Consumption
Employment (logged)	1.92 [.000]	1.85 [.000]	1.91 [.000]	2.38 [.000]	1.34 [.000]	1.30 [.000]	1.27 [.000]
Intercept	-21.40 [.000]	-20.97 [.000]	-21.83 [.000]	-28.12 [.000]	-14.5861 [.000]	-13.56 [.000]	-13.77 [.000]
Negative binomial parameter	0.94 [.000]	0.43 [.000]	0.67 [.000]	0.58 [.000]	0.35 [.000]	0.36 [.000]	0.42 [.000]
R-squared	0.51	0.52	0.39	0.75	0.65	0.48	0.55

Note: P-values within brackets

Size measured by the number of researchers

	Electronics	Instruments	Chemistry	Biotechn ologies	Industrial processes	Machines	Consumption
Number of researchers (logged)	0.66 [.000]	0.61 [.000]	0.72 [.000]	0.88 [.000]	0.43 [.000]	0.42 [.000]	0.40 [.000]
Intercept	-1.79 [.000]	-1.95 [.000]	-2.74 [.000]	-4.37 [.000]	-0.64 [.037]	-0.05 [.861]	-0.49 [.118]
Negative binomial parameter	1.11 [.000]	0.57 [.000]	0.90 [.000]	0.60 [.000]	0.63 [.000]	0.56 [.000]	0.64 [.000]
R-squared	0.59	0.72	0.48	0.72	0.47	0.48	0.39

Note: P-values within brackets

Size measured by research activity

	Electronics	Instruments	Chemistry	Biotech nologies	Industrial processes	Machines	Consumption
Research activity[8] (Quantity, logged)	0.64 [.000]	0.61 [.000]	0.64 [.000]	0.77 [.000]	0.41 [.000]	0.42 [.000]	0.41 [.000]
Intercept	-1.05 [.001]	-1.41 [.000]	-1.60 [.000]	-2.83 [.000]	-0.16 [.499]	0.33 [.119]	-0.20 [.412]
Negative binomial parameter	1.00 [.000]	0.46 [.000]	0.95 [.000]	0.69 [.000]	0.57 [.000]	0.48 [.000]	0.55 [.000]
R-squared	0.58	0.70	0.51	0.73	0.50	0.47	0.43

Note: P-values within brackets

Another interesting result is the difference between two groups of sectors. Electronics, instruments, chemistry and biotechnologies form the first group; the second group includes industrial processes, machinery and consumption. The first group is much more sensitive to size than the second group: the coefficients of the size variables are much higher in the former case than in the later.

Of course, as size may not be a one-dimensional attribute and then, it may be useful to combine several size variables instead of using them separately. We are now using the following variants of equation (1):

$$\begin{aligned} \ln\lambda_i &= b_0 + b_1 \ln E_i + b_2 \ln A_i/E_i + \ln\varepsilon_i \\ \ln\lambda_i &= b_0 + b_1 \ln E_i + b_2 \ln R_i/E_i + \ln\varepsilon_i \qquad (3) \\ \ln\lambda_i &= b_0 + b_1 \ln E_i + b_2 \ln R_i/E_i + b_3 \ln A_i/R_i + \ln\varepsilon_i \end{aligned}$$

where E_i is local employment, R_i is the local size of the pool of researchers and A_i is the global measure of the local research activity (the number of published research articles).

In all three models, as in (2), the coefficient b_1 is a measure of scale effects; it does not significantly differ from unity when there are no scale effects. The coefficients b_2 and b_3 measure the specific influence of the other size variables, independently of their correlation to employment. When they do not significantly differ from zero, the relevant variable has no significant effect. Moreover, if the null hypothesis $b_1 = b_2$ is accepted, then employment is not the relevant size variable and we have to measure size using R_i or A_i.

Estimation results are displayed in table 4, for the three equations. They can be compared to the first panel of table 3. All of them lead to a lower value of the scale parameter, b_1, however still significantly higher than unity. Moreover, the differences between the two groups of innovation sectors are less clear. Scale effects are still very high for chemistry and biology and lowest for machines and consumption. But there are no marked differences between electronics, instruments, and industrial processes. If differences in scale effects are less clear, they are very important when we look at the impact of local research. The last panel of table 4 shows that the number of published articles does not have an impact once the number of local researchers is taken account of: the coefficient b_3, measuring the effect of the local rate of publication, is not significantly different of zero. And all three panels show that, once size has been taken account of, the local research activity has an effect for the first group of sectors only. When we look at the second panel, the coefficient of the rate of researchers significantly differs from zero for all three sectors of the first group. It is highest for biology (0.46), intermediate for chemistry (0.32) and lowest for electronics and instruments (0.25 and 0.23, respectively). For the three sectors of the second group, the null hypothesis of a zero coefficient is accepted.

[8] Research activity is measured by the number of published articles.

Table 4: Combined effect of size variables on the local level of innovation

Employment and research activity

	Electronics	Instruments	Chemistry	Biotech nologies	Industrial processes	Machines	Consumption
Employment (logged)	1.45 [.000]	1.37 [.000]	1.64 [.000]	1.85 [.000]	1.42 [.000]	1.18 [.000]	1.22 [.000]
Research activity[9] (Rate, logged)	0.28 [.009]	0.29 [.000]	0.17 [.103]	0.31 [.002]	-0.05 [.530]	0.08 [.266]	0.04 [.692]
Intercept	-13.68 [.000]	-13.12 [.000]	-17.29 [.000]	-19.51 [.000]	-15.95 [.000]	-11.47 [.000]	-12.83 [.000]
Negative binomial parameter	0.85 [.000]	0.34 [.000]	0.66 [.000]	0.46 [.000]	0.35 [.000]	0.35 [.000]	0.42 [.000]
R-squared	0.58	0.63	0.43	0.80	0.64	0.50	0.56

Note: P-values within brackets

Employment and number of researchers

	Electronics	Instruments	Chemistry	Biotech nologies	Industrial processes	Machines	Consumption
Employment (logged)	1.57 [.000]	1.53 [.000]	1.57 [.000]	1.80 [.000]	1.35 [.000]	1.22 [.000]	1.29 [.000]
Rate of researchers[10] (Rate, logged)	0.25 [.015]	0.23 [.002]	0.32 [.001]	0.46 [.000]	0.00 [.954]	0.07 [.313]	-0.01 [.876]
Intercept	-15.55 [.000]	-15.69 [.000]	-15.79 [.000]	-18.34 [.000]	-14.68 [.000]	-12.17 [.000]	-14.04 [.000]
Negative binomial parameter	0.87 [.000]	0.35 [.000]	0.58 [.000]	0.37 [.000]	0.35 [.000]	0.35 [.000]	0.42 [.000]
R-squared	0.60	0.63	0.45	0.85	0.65	0.50	0.55

Note: P-values within brackets

Employment, number of researchers, and publication rate

	Electronics	Instruments	Chemistry	Biotech nologies	Industrial processes	Machines	Consumption
Employment (logged)	1.42 [.000]	1.36 [.000]	1.66 [.000]	1.84 [.000]	1.41 [.000]	1.17 [.000]	1.23 [.000]
Rate of researchers (Rate, logged)	0.32 [.005]	0.31 [.000]	0.27 [.010]	0.44 [.000]	-0.04 [.668]	0.09 [.232]	0.02 [.826]
Publication rate[11] (logged)	0.20 [.150]	0.21 [.064]	-0.10 [.448]	-0.05 [.704]	-0.07 [.470]	0.06 [.519]	0.07 [.521]
Intercept	-13.04 [.000]	-12.96 [.000]	-17.30 [.000]	-18.97 [.000]	-15.77 [.000]	-11.32 [.000]	-12.98 [.000]
Negative binomial parameter	0.84 [.000]	0.33 [.000]	0.56 [.000]	0.37 [.000]	0.35 [.000]	0.35 [.000]	0.42 [.000]
R-squared	0.61	0.65	0.44	0.85	0.65	0.51	0.55

Note: P-values within brackets

IV. 2. The impact of research and industrial structures

We start by evaluating the impact of employment structure in the research of the agglomeration effects. Afterwards we move our analysis to the impact of the structure of research

[9] The rate of research activity is the ratio of the number of published articles to employment.
[10] The rate of researchers is the ratio of the number of researchers to employment.
[11] The publication rate is the ratio of the number of published articles to the number of researchers.

IV.2.b. Employment structure

Another obvious candidate for explaining the structure of local innovation is employment structure. One can expect a *departement* specialized in a specific industry to generate more innovation in the fields corresponding to this industry. We are following the intuition of Krugman (1991b)[12] who attributes the concentration of innovation to the concentration of production. In the empirical literature it is attested that knowledge is on of the most important agglomeration externalities (Feldman M., Audretsch, D., 1996). Thus, industries using the same knowledge would concentrate more and thus, we expect innovation to be more concentrated in R&D intensive industries. The results of section 3 of spatial exploratory analysis support this hypothesis, showing a Moran index is higher for machines, installation and biotechnologies than for consumption.

In order to test this hypothesis, we consider the following model

$$\ln\lambda_i = b_0 + b_1 \ln E_i + b_2 \ln R_i/E_i + \sum_j b_{3,j} \ln E_{i,j}/E_i + \ln\varepsilon_i \qquad (4)$$

Where $E_{i,j}$ is local employment in the activities corresponding to the research field j.

Estimation results are displayed in table 6. There is some evidence of an influence of the industrial structure. This influence looks weak, however. A higher share in industries liked to electronics has a significant positive effect on innovation in the field of electronics. Similarly, a higher share in industries linked to biotechnologies has a significantly positive effect on innovation in this field. However, the other coefficients of interest are non significant or have the wrong sign.

Table 6: Employment structure and the local level of innovation

	Electronics	Instruments	Chemistry	Biotech nologies	Industrial processes	Machines	Consumption
Employment (logged)	1,51 [.000]	1,47 [.000]	1,45 [.000]	1,62 [.000]	1,20 [.000]	1,14 [.000]	1,09 [.000]
Rate of researchers (Rate, logged)	0,03 [.744]	0,12 [.134]	0,31 [.001]	0,28 [.008]	-0,06 [.416]	0,00 [.951]	0,03 [.678]
Employment share in electronics (logged)	1,02 [.000]	0,28 [.092]	0,12 [.586]	0,32 [.118]	0,08 [.579]	0,06 [.677]	0,00 [.983]
Employment share in instruments (logged)	-2,31 [.049]	-2,18 [.028]	1,01 [.394]	0,24 [.848]	-0,07 [.938]	-1,23 [.101]	0,31 [.732]
Employment share in chemistry (logged)	-0,37 [.032]	-0,37 [.012]	0,23 [.235]	-0,06 [.725]	-0,03 [.797]	-0,10 [.398]	-0,10 [.501]
Employment share in biology (logged)	-0,07 [.503]	-0,11 [.248]	0,14 [.231]	0,44 [.001]	0,12 [.138]	0,14 [.064]	-0,06 [.531]
Employment share in mechanics (logged)	-0,99 [.002]	-0,26 [.311]	0,13 [.680]	-0,65 [.030]	-0,14 [.519]	-0,14 [.501]	0,12 [.659]
Employment share in machines (logged)	-1,70 [.029]	-1,58 [.018]	-0,17 [.848]	-0,28 [.741]	-0,75 [.226]	-0,13 [.819]	-0,38 [.587]
Employment share in consumption (logged)	-11,44 [.012]	-11,58 [.002]	-4,85 [.330]	-3,92 [.407]	-9,15 [.009]	-7,79 [.018]	-9,16 [.026]
Intercept	-30,66 [.000]	-30,07 [.000]	-11,31 [.160]	-17,47 [.032]	-17,84 [.002]	-17,21 [.001]	-14,88 [.021]
Negative binomial parameter	0,39 [.000]	0,19 [.000]	0,35 [.000]	0,19 [.003]	0,17 [.001]	0,19 [.000]	0,26 [.000]
R-squared	0,71	0,85	0,71	0,86	0,82	0,75	0,62

Note: P-values within brackets

IV. 2.2. The impact of local neighbourhood and similar research structures

[12] « What is the feature of the geography of economic activity? the short answer is surely production is remarkably concentrated into space »(Krugman 1991b)

In the literature, most of the results are contradictory, but all the authors agree upon the fact that urbanization fosters the emergence of innovations [13]. Once controlling for the size of the market we look at the specificity of knowledge.

IV.2.2a Local Research specialisation

The complexity of innovative activity implies that inventors must set in place procedures using various types of knowledge to find specific information. The source of information could be:

- a very specialized one, within the framework of each discipline,
- or, conversely, a mix of fields of science, (Autant-Bernard, C. 2001) that is a typical property of the evolutionary environments.

Then, innovation is analyzed as an activity emerging out of clustering economic activities of comparable nature, as well as out of complementary activities using various knowledges (MP. Feldman, D.B. Audretsch, 1999). Consequently, we add the impact of the specialization of research through a location quotient, in order to identify, if possible, the specific source of information which determines the emergence of innovation. we start from the second equation of formula (3), introducing the log of the share of each research field in the total number of articles published by local researchers:

$$\ln\lambda_i = b_0 + b_1 \ln E_i + b_2 \ln R_i/E_i + \sum_k b_{3,k} \ln A_{i,k}/A_i + \ln\varepsilon_i \qquad (4)$$

where $A_{i,k}$ is the number of articles published by researchers of *departement i* in research field *k* and A_i is the total number of articles published by researchers of *departement i*. Then, $\ln A_{i,k}/A_i$ is the logarithm of the share of research field *k* in articles published by researchers of *departement i*. We expect the coefficient $b_{3,k}$ to be more positive if knowledge produced by research field *k* is a more important input of the innovation sector. Estimation results of (4) are displayed in Table 5. Only the coefficients differing from zero at the 10% level have been kept.

In a patent citation analysis, Jaffe Trajtenberg (1996) found evidence that the fields of electronics and chemistry are subject of cross citation. Even though in our analysis we do not find results that support these connections, we can not ignore that the chemical patents are the most susceptible to be influenced by other fields of research.

We test the joint significance of all the specialization variables using a standard likelihood ratio statistic:

$$LR = 2(ULLF - RLLF)$$

where ULLF is log-likelihood of the unrestricted model, (4), and RLLF the log-likelihood of the restricted model, (3). For all seven innovation sectors, the P-value is less than 1%. Then, we can conclude that research specialization matters for innovation.

However, few specialization variables have an individually significant effect. The only variable that has a significant effect is research specialization in the field of ecology and environment. The effect is significantly negative in all the sectors, machinery and transport apart. Moreover, there is no straightforward interpretation of some significant effects. For example, it is difficult to understand why specialization of local research in the field of endocrinology has a positive effect on innovation in machines; or why a specialization in the field of general physics has a positive effect on consumption. Therefore, there is no obvious description of the influence of local research specialization on the type of innovations.

[13]Gallaus, D., Knowledge Production And Patterns Of Proximity: French Sme's Biotechnology, Paper to be presented at the DRUID Summer Conference on "Industrial Dynamics of the New and Old Economy - who is embracing whom?" Copenhagen/Elsinore 6-8 June 2002

Table 5: Effect of the research specialisation on the local level of innovation

	Electronics	Instruments	Chemistry	Biotechnologies	Industrial processes	Machines	Consumption
Employment (logged)	1,50 [.000]	1,32 [.000]	1,66 [.000]	1,57 [.000]	1,49 [.000]	1,21 [.000]	1,06 [.000]
Rate of researchers (Rate, logged)	0,32 [.002]	0,24 [.001]	0,29 [.000]	0,48 [.000]	0,01 [.831]	0,04 [.542]	-0,05 [.479]
Alimentation					0,20 [.038]		
Biomedical Engineering			-0,47 [.027]				
Analytical chemistry		-0,44 [.003]					
Chemistry						-0,48 [.002]	
Medical chemistry					-0,32 [.023]	0,43 [.003]	
Ecology, environment	-0,58 [.000]	-0,42 [.000]	-0,40 [.001]	-0,22 [.095]	-0,47 [.000]		-0,20 [.054]
Endocrinology			0,58 [.001]			0,28 [.049]	
General biology			0,48 [.025]				-0,27 [.036]
Chemical engineering	-0,41 [.010]						
Genetics			-0,32 [.036]				
Earth sciences			-0,29 [.007]				
Mechanical engineering		0,37 [.003]	0,94 [.000]		0,43 [.001]		
Hospital medecine			-0,79 [.000]				
Optics	0,39 [.008]						
General physics							0,32 [.000]
Applied physics			-0,50 [.000]	-0,52 [.002]			
Public Health						-0,66 [.000]	
Intercept	-14,34 [.000]	-14,27 [.000]	-19,01 [.000]	-17,41 [.000]	-16,42 [.000]	-13,21 [.000]	-12,13 [.000]
Negative binomial parameter	0,53 [.000]	0,20 [.000]	0,13 [.012]	0,29 [.001]	0,18 [.000]	0,28 [.000]	0,27 [.000]
R-squared	0,72	0,81	0,82	0,87	0,75	0,61	0,67
LR CHISQ Test: (DF)	35,77 (6) [0.000]	29,77 (6) [.000]	54,44(10) [.000]	9,46 (2) [.009]	40,52(10) [.000]	18,36 (5) [.002]	24,56 (3) [.000]

Note: P-values within brackets

IV.2.2b Geographic neighbourhood of research

The results of exploratory spatial descriptive analysis displayed in section (3) give support to the hypothesis that neighbors influence local innovation. Thus, following Autant-Bernard (2001), we introduce spatially lagged values of the explanatory variables in the model, using a spatial weights matrix. Our weights matrix is the usual row standardized contiguity matrix. We start from the third equation of formula (4), introducing the log of the share of research field in the total number of articles published by neighboring researchers:

$$\ln\lambda_i = b_0 + b_1 \ln E_i + b_2 \ln R_i / E_i + \sum_k b_{3,k} \ln A_{i,k} / A_i + \sum_k b_{4,k} \ln AN_{i,k} / A_i + \ln\varepsilon_i \quad (5)$$

where $AN_{i,k}$ is the number of articles in research field *k* published by researchers located in the neighbourhood of *departement i,* and A_i is the total number of articles published by researchers of *departement i*. We expect the coefficient $b_{4,k}$ to be more positive if knowledge produced by research field *k* is a more important input of the innovation sector. Estimation results of (5) are displayed in Table 6. As before, only the coefficients that significantly differ from zero have been kept.

Table 6: Neighbourhood effects on the local level of innovation

	Electronics	Instruments	Chemistry	Biotechnologies	Industrial Processes	Machines	Consumption
Employment (Logged)	1,25 [.000]	1,53 [.000]	1,64 [.000]	1,95 [.000]	1,54 [.000]	0,72 [.000]	1,12 [.000]
Rate of Researchers (Rate, Logged)	0,11 [.294]	0,23 [.001]	0,23 [.032]	0,43 [.000]	-0,09 [.233]	0,02 [.662]	0,01 [.923]
Local Animals Breeding				0,22 [.048]			
Biomedical Engineering							-0,35 [.004]
Local Endocrinology						0,45 [.000]	
Local Chemical Engineering	-0,62 [.000]						
Local Materials	0,51 [.011]		0,41 [.026]				
Local General Physics					0,15 [.102]		
Local Applied Physics			-0,51 [.006]			-0,18 [.033]	
Local Biology, Agronomics	-0,25 [.032]					-0,42 [.000]	
Local Public Health			-0,29 [.093]			-0,51 [.000]	
Neighbourhood Food, Nutrition	-0,19 [.012]			-0,11 [.000]			
Neighbourhood Astonomy, Astropysics				0,07 [.011]			
Neighbourhood Analytical Chemistry						0,22 [.000]	
Neighbourhood Immunology	0,12 [.063]						
Neighbourhood Neurosciences						-0,16 [.003]	
Neighbourhood Biology, Agronomics						-0,20 [.000]	
Neighbourhood Public Health		-0,03 [.096]					
Negative Binomial Parameter	0,62 [.000]	0,32 [.000]	0,50 [.000]	0,32 [.000]	0,25 [.000]	0,14 [.000]	0,36 [.000]
Intercept	-14,63 [.000]	-16,06 [.000]	-18,25 [.000]	-20,86 [.000]	-17,17 [.000]	-8,72 [.000]	-13,59 [.000]
Likelihood Ratio Chisq Test(Ndl)	25,38 (5) [0,000]	2,67 (1) [0,102]	11,62 (5) [0,040]	6,48 (3) [0,090]	21,79 (4) [0,000]	59,02 (8) [0,000]	11,45 (4) [0,022]
R-squared	0,79	0,71	0,48	0,90	0,73	0,76	0,57

We test the joint significance of all the neighbourhood variables using a standard likelihood ratio statistic:

$$LR = 2(ULLF - RLLF)$$

where ULLF is log-likelihood of the unrestricted model, (5), and RLLF the log-likelihood of the restricted model, (3). The sector of instruments apart, the null hypothesis of no joint effect is rejected at the 5% level. Then, we can conclude that neighboring areas influence innovation. Very few neighborhood variables have a significant effect, however. Therefore, it is difficult to describe how the local level and type of innovation is influenced by the neighboring areas.

IV.2.2c Technological neighbourhood of research

Is local innovation influenced by research in areas with a similar research structure? For measuring similarity in research structure, we use the following index, proposed by Moreno R., Paci, R., Usai, S.,(2004) in their analysis of the distribution of patents in the European regions.

$$P_{ij} = \frac{\sum_{k=1}^{K} f_{ik} f_{jk}}{\sqrt{\sum_{k=1}^{K} f_{ik}^2 \sum_{k=1}^{K} f_{jk}^2}} \qquad (6)$$

where f_{ik} is the share of analytical research of *departement i* in the total research of the *departement i*, where f_{jk} is the share of analytical research of *departement j* in the total research of the *departement j*.

Using this formula we build a technological matrix that has 94 rows and 94 columns. Each cell has a value in the [0,1] interval, $0 \leq P_{ij} \leq 1$, measuring the degree of similarity between the research structures of two departments. The closer is P_{ij} to zero, the more dissimilar are the research structures of the two regions. Then, we build similarity variables similar to neighborhood, the degree of similarity playing the same role as proximity:

$$AS_{i,k} = \sum_{j \neq i} P_{ij} A_{jk} \qquad (7)$$

Then, we estimate the following model

$$\ln \lambda_i = b_0 + b_1 \ln E_i + b_2 \ln R_i / E_i + \sum_k b_{3,k} \ln A_{i,k} / A_i + \sum_k b_{5,k} \ln AS_{i,k} / A_i + \ln \varepsilon_i \qquad (8)$$

Estimated results are displayed in Table (7). As before, coefficients that doe not significantly differ from zero at the 10% level are ignored. We also test the joint significance of all the similarity variables using a standard likelihood ratio statistic:

$$LR = 2(ULLF - RLLF)$$

where ULLF is log-likelihood of the unrestricted model, (8), and RLLF the log-likelihood of the restricted model, (3).

Moreno, and Paci (2004) found that, at the level of European regions, there is little influence of the similar technological neighbors for the emergence of patents. In our estimation, the likelihood ratio tests lead to the conclusion that, globally, similarity variables have a significant effect of 5 sectors out of 7; the exceptions being chemistry and biotechnologies. However, as for specialization and neighborhood variables, very few variables have a significant effect and then the influence of similar *departements* cannot be described.

Table 8: Effect of the similar technological research on the local level of innovation

	Electronics	Instruments	Chemistry	Biotechnologies	Industrial Processes	Machines	Consumption
Employment (Logged)	10,28 [.000]	10,38 [.000]	10,63 [.000]	10,88 [.000]	10,47 [.000]	0,79 [.000]	10,18 [.000]
Rate Of Researchers (Rate, Logged)	0,26 [.009]	0,22 [.001]	0,32 [.000]	0,43 [.000]	0,034 [.635]	0,03 [.666]	-0,01 [.861]
Local Animals Breeding					-0,04 [.625]		
Local Analytical Chemistry	-0,37 [.080]	-0,15 [.206]					
Local General Biology	0,55 [.016]						-0,34 [.021]
Local Chemical Engineering					0,31 [.003]		
Local Earth Sciences			-0,21 [.088]				
Local Ecology, Environment		-0,38 [.000]					
Local Endocrinology						0,51 [.000]	
Local Other Medical Specialties	-0,40 [.031]					-0,33 [.019]	
Local Biology, Agronomics						-0,36 [.000]	
Similar Technological Neighbours Biomedical Engineering	0,137 [.014]						
Similar Technological Neighbours Ecology, Environment	-0,23 [.000]						
Similar Technological Neighbours Computer Science							0,05 [.086]
Similar Technological Neighbours Hospital Medecine	-0,15 [.057]						
Similar Technological Neighbours Bacteriology, Virology	0,20 [.068]						
Similar Technological Neighbours Chemical Physics		0,006 [.038]					
Similar Technological Neighbours Public Health						-0,007 [.018]	
Negative Binomial Parameter	0,52 [.000]	0,23 [.000]	0,53 [.000]	0,36 [.000]	0,31 [.000]	0,26 [.000]	0,32 [.000]
Intercept	-130,89 [.000]	-140,55 [.000]	-160,20 [.000]	-190,37 [.000]	-150,28 [.000]	-90,25 [.000]	-120,71 [.000]
Likelihood Ratio Chisq Test (DF)	31.15 (8) [0,000]	22.83 (3) [0,000]	4.55 (2) [0,103]	1.48 (2) [0,477]	9.02 (3) [0,029]	22.15 (5) [0,000]	14.44 (4) [0,006]
R-Squared	0,74	0,76	0,46	0,85	0,69	0,64	0,61

V. CONCLUSION

The objective of this paper was to test the extent to which innovations are explained by the local level and specialization of research. Using data mining and exploratory statistics we find evidence of spatial concentration of innovations in spaces where one finds the necessary knowledge to develop the innovating activity. Moreover, a polarized spatial structure appears.

Econometric analysis leads to three main results.
Our main result is that, even when taking account of size effects, local innovation is influenced by local research activity, all the research fields being grouped.
The second one is that this influence is far from being uniform across sectors. The influence of the level of local research is highly significant in four sectors, electronics, instruments, chemistry and biology. If is weak and insignificant for industrial processes, machines and consumption.
The third result is that there is that there is almost no impact of the research and employment structures at the local level, in neighbor areas and in regions with a similar structure.

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Appendix 1 : Rates of published articles with respect to population ; Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Food, nutrition	1,00	0,52	0,13	0,48	0,49	0,50	0,49	0,52	0,56	0,60	0,58	0,58	0,50	0,51	0,49	0,40
2	Animals breeding	0,52	1,00	0,16	0,43	0,34	0,47	0,22	0,32	0,47	0,34	0,75	0,40	0,28	0,40	0,36	0,37
3	Astonomy, Astropysics	0,13	0,16	1,00	0,64	0,70	0,33	0,67	0,70	0,55	0,30	0,29	0,53	0,40	0,62	0,73	0,34
4	Biomedical Engineering	0,48	0,43	0,64	1,00	0,85	0,82	0,80	0,78	0,80	0,52	0,75	0,78	0,73	0,80	0,74	0,81
5	Cellular biology	0,49	0,34	0,70	0,85	1,00	0,72	0,83	0,90	0,83	0,64	0,64	0,91	0,71	0,94	0,83	0,67
6	Oncology	0,50	0,47	0,33	0,82	0,72	1,00	0,53	0,56	0,80	0,47	0,77	0,70	0,57	0,68	0,49	0,91
7	Analytical chemistry	0,49	0,22	0,67	0,80	0,83	0,53	1,00	0,84	0,67	0,55	0,47	0,74	0,71	0,77	0,82	0,48
8	Chemistry	0,52	0,32	0,70	0,78	0,90	0,56	0,84	1,00	0,76	0,57	0,54	0,81	0,66	0,83	0,84	0,49
9	Medical chemistry	0,56	0,47	0,55	0,80	0,83	0,80	0,67	0,76	1,00	0,58	0,73	0,79	0,67	0,77	0,70	0,76
10	Ecology, environment	0,60	0,34	0,30	0,52	0,64	0,47	0,55	0,57	0,58	1,00	0,51	0,83	0,64	0,67	0,69	0,41
11	Endocrinology	0,58	0,75	0,29	0,75	0,64	0,77	0,47	0,54	0,73	0,51	1,00	0,71	0,52	0,69	0,49	0,77
12	General biology	0,58	0,40	0,53	0,78	0,91	0,70	0,74	0,81	0,79	0,83	0,71	1,00	0,69	0,92	0,78	0,66
13	Chemical engineering	0,50	0,28	0,40	0,73	0,71	0,57	0,71	0,66	0,67	0,64	0,52	0,69	1,00	0,61	0,70	0,50
14	Genetics	0,51	0,40	0,62	0,80	0,94	0,68	0,77	0,83	0,77	0,67	0,69	0,92	0,61	1,00	0,77	0,65
15	Earth sciences	0,49	0,36	0,73	0,74	0,83	0,49	0,82	0,84	0,70	0,69	0,49	0,78	0,70	0,77	1,00	0,46
16	General Medecine	0,40	0,37	0,34	0,81	0,67	0,91	0,48	0,49	0,76	0,41	0,77	0,66	0,50	0,65	0,46	1,00
17	Mechanical engineering	0,32	0,22	0,74	0,80	0,76	0,46	0,86	0,78	0,63	0,48	0,40	0,65	0,73	0,68	0,79	0,42
18	Immunology	0,42	0,32	0,42	0,73	0,81	0,81	0,52	0,61	0,77	0,60	0,71	0,84	0,57	0,82	0,59	0,83
19	Computer science	0,43	0,35	0,73	0,82	0,80	0,51	0,77	0,79	0,64	0,57	0,50	0,71	0,70	0,69	0,87	0,50
20	Hospital medecine	0,48	0,45	0,35	0,85	0,74	0,95	0,56	0,59	0,83	0,51	0,83	0,73	0,60	0,71	0,53	0,96
21	Mathematics	0,43	0,31	0,73	0,85	0,82	0,54	0,87	0,85	0,67	0,53	0,54	0,75	0,60	0,80	0,82	0,56
22	Materials	0,32	0,15	0,63	0,74	0,74	0,44	0,82	0,75	0,58	0,45	0,37	0,62	0,72	0,60	0,71	0,42
23	Bacteriology, virology	0,67	0,55	0,43	0,81	0,83	0,82	0,65	0,70	0,82	0,78	0,84	0,91	0,65	0,87	0,69	0,79
24	Other medical specialties	0,49	0,48	0,35	0,81	0,73	0,87	0,53	0,59	0,82	0,53	0,84	0,74	0,62	0,70	0,55	0,91
25	Multidisciplinary	0,37	0,27	0,75	0,84	0,96	0,64	0,80	0,86	0,77	0,60	0,60	0,88	0,66	0,92	0,83	0,65
26	Neurosciences	0,45	0,38	0,50	0,85	0,85	0,83	0,67	0,75	0,81	0,53	0,79	0,83	0,59	0,85	0,63	0,84
27	Optics	0,22	0,17	0,79	0,68	0,69	0,33	0,80	0,74	0,50	0,31	0,28	0,54	0,41	0,61	0,67	0,31
28	Chemical physics	0,38	0,18	0,73	0,79	0,85	0,48	0,94	0,88	0,64	0,50	0,43	0,74	0,68	0,79	0,79	0,42
29	General physics	0,21	0,09	0,77	0,62	0,71	0,25	0,79	0,75	0,43	0,28	0,25	0,55	0,40	0,67	0,65	0,22
30	Applied physics	0,23	0,11	0,71	0,64	0,72	0,30	0,75	0,72	0,46	0,36	0,28	0,55	0,57	0,56	0,68	0,26
31	Biology, Agronomics	0,77	0,35	0,28	0,50	0,65	0,46	0,58	0,62	0,63	0,82	0,51	0,77	0,60	0,68	0,65	0,38
32	Public Health	0,47	0,52	0,29	0,85	0,67	0,93	0,53	0,51	0,77	0,45	0,85	0,67	0,60	0,65	0,49	0,94

		17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
1	Food, nutrition	0,32	0,42	0,43	0,48	0,43	0,32	0,67	0,49	0,37	0,45	0,22	0,38	0,21	0,23	0,77	0,47
2	Animals breeding	0,22	0,32	0,35	0,45	0,31	0,15	0,55	0,48	0,27	0,38	0,17	0,18	0,09	0,11	0,35	0,52
3	Astonomy, Astropysics	0,74	0,42	0,73	0,35	0,73	0,63	0,43	0,35	0,75	0,50	0,79	0,73	0,77	0,71	0,28	0,29
4	Biomedical Engineering	0,80	0,73	0,82	0,85	0,85	0,74	0,81	0,81	0,84	0,85	0,68	0,79	0,62	0,64	0,50	0,85
5	Cellular biology	0,76	0,81	0,80	0,74	0,82	0,74	0,83	0,73	0,96	0,85	0,69	0,85	0,71	0,72	0,65	0,67
6	Oncology	0,46	0,81	0,51	0,95	0,54	0,44	0,82	0,87	0,64	0,83	0,33	0,48	0,25	0,30	0,46	0,93
7	Analytical chemistry	0,86	0,52	0,77	0,56	0,87	0,82	0,65	0,53	0,80	0,67	0,80	0,94	0,79	0,75	0,58	0,53
8	Chemistry	0,78	0,61	0,79	0,59	0,85	0,75	0,70	0,59	0,86	0,75	0,74	0,88	0,75	0,72	0,62	0,51
9	Medical chemistry	0,63	0,77	0,64	0,83	0,67	0,58	0,82	0,82	0,77	0,81	0,50	0,64	0,43	0,46	0,63	0,77
10	Ecology, environment	0,48	0,60	0,57	0,51	0,53	0,45	0,78	0,53	0,60	0,53	0,31	0,50	0,28	0,36	0,82	0,45
11	Endocrinology	0,40	0,71	0,50	0,83	0,54	0,37	0,84	0,84	0,60	0,79	0,28	0,43	0,25	0,28	0,51	0,85
12	General biology	0,65	0,84	0,71	0,73	0,75	0,62	0,91	0,74	0,88	0,83	0,54	0,74	0,55	0,55	0,77	0,67
13	Chemical engineering	0,73	0,57	0,70	0,60	0,60	0,72	0,65	0,62	0,66	0,59	0,41	0,68	0,40	0,57	0,60	0,60
14	Genetics	0,68	0,82	0,69	0,71	0,80	0,60	0,87	0,70	0,92	0,85	0,61	0,79	0,67	0,56	0,68	0,65
15	Earth sciences	0,79	0,59	0,87	0,53	0,82	0,71	0,69	0,55	0,83	0,63	0,67	0,79	0,65	0,68	0,65	0,49
16	General Medecine	0,42	0,83	0,50	0,96	0,56	0,42	0,79	0,91	0,65	0,84	0,31	0,42	0,22	0,26	0,38	0,94
17	Mechanical engineering	1,00	0,44	0,82	0,51	0,88	0,88	0,58	0,45	0,78	0,62	0,79	0,90	0,80	0,79	0,45	0,48
18	Immunology	0,44	1,00	0,54	0,84	0,57	0,42	0,85	0,85	0,80	0,84	0,33	0,50	0,33	0,34	0,54	0,78
19	Computer science	0,82	0,54	1,00	0,55	0,85	0,81	0,62	0,55	0,81	0,60	0,77	0,76	0,66	0,77	0,52	0,53
20	Hospital medecine	0,51	0,84	0,55	1,00	0,61	0,51	0,84	0,92	0,70	0,87	0,35	0,51	0,28	0,35	0,49	0,95
21	Mathematics	0,88	0,57	0,85	0,61	1,00	0,78	0,68	0,59	0,85	0,73	0,83	0,89	0,80	0,72	0,53	0,57
22	Materials	0,88	0,42	0,81	0,51	0,78	1,00	0,52	0,43	0,76	0,57	0,81	0,84	0,74	0,92	0,45	0,46
23	Bacteriology, virology	0,58	0,85	0,62	0,84	0,68	0,52	1,00	0,85	0,78	0,86	0,43	0,62	0,41	0,41	0,75	0,81
24	Other medical specialties	0,45	0,85	0,55	0,92	0,59	0,43	0,85	1,00	0,68	0,84	0,33	0,47	0,23	0,27	0,49	0,91
25	Multidisciplinary	0,78	0,80	0,81	0,70	0,85	0,76	0,78	0,68	1,00	0,83	0,73	0,85	0,75	0,76	0,58	0,63
26	Neurosciences	0,62	0,84	0,60	0,87	0,73	0,57	0,86	0,84	0,83	1,00	0,50	0,69	0,52	0,49	0,53	0,83
27	Optics	0,79	0,33	0,77	0,35	0,83	0,81	0,43	0,33	0,73	0,50	1,00	0,83	0,87	0,84	0,33	0,31
28	Chemical physics	0,90	0,50	0,76	0,51	0,89	0,84	0,62	0,47	0,85	0,69	0,83	1,00	0,88	0,83	0,54	0,47
29	General physics	0,80	0,33	0,66	0,28	0,80	0,74	0,41	0,23	0,75	0,52	0,87	0,88	1,00	0,83	0,32	0,23
30	Applied physics	0,79	0,34	0,77	0,35	0,72	0,92	0,41	0,27	0,76	0,49	0,84	0,83	0,83	1,00	0,36	0,28
31	Biology, Agronomics	0,45	0,54	0,52	0,49	0,53	0,45	0,75	0,49	0,58	0,53	0,33	0,54	0,32	0,36	1,00	0,42
32	Public Health	0,48	0,78	0,53	0,95	0,57	0,46	0,81	0,91	0,63	0,83	0,31	0,47	0,23	0,28	0,42	1,00