LAMETA
Laboratoire Montpelliérain d'Economie Théorique et Appliquée
UMR
Unité Mixte de Recherche

DOCUMENT de RECHERCHE

« Convergence, Patenting Activity and Geographic Spillovers: A Spatial Econometric Analysis for European Regions »

Karine PELLIER

DR n°2007-14

Faculté de Sciences Economiques - Espace Richter
Avenue de la Mer - Site de Richter C.S. 79606
34960 MONTPELLIER CEDEX 2
Tél: 33(0)467158495 Fax: 33(0)467158467
E-mail: lameta@lameta.univ-montp1.fr

Université Montpellier 1
agro Montpellier Ecole Nationale Supérieure Agronomique
CNRS Centre National de la Recherche Scientifique
INRA

Convergence, Patenting Activity and Geographic Spillovers: A Spatial Econometric Analysis for European Regions

Karine PELLIER*

This version: December 2007

Abstract

In this paper, we investigate the impact of geographical spillovers in the patenting activity and convergence process for a sample of 131 European regions over the 1981-2001 period. Using spatial econometrics methods (Anselin, 1988, 2001), we detect spatial autocorrelation and heterogeneity in the regional distribution of patent applications to the European Patent Office. Then, we include successively these spatial effects in a convergence analysis. A first specification taking into account the spatial dependence reveals a global convergence process between European regions as also a positive effect of geographical spillovers on this convergence process. Secondly, the spatial heterogeneity is taking into account by a specification with two spatial regimes, a "Core-Periphery" type. Finally, ours results show that the global convergence process is hiding disparities and different convergence processes for the two regimes. Only regions that belong to the "Core" of the EU are converging.

Keywords: Patents, Convergence, Spatial effects, European regions, Spatial Econometrics
JEL Classification: C21, O33, O52, R11

Résumé

Nous analysons les contributions des effets de débordement géographique sur l'activité inventive et le processus de convergence des régions européennes sur la période 1981-2001. L'application des outils de l'économétrie spatiale (Anselin, 1988, 2001) à la distribution des demandes de brevets déposées à l'Office Européen des Brevets révèle la présence d'effets spatiaux (autocorrélation et hétérogénéité spatiale) que nous intégrons successivement dans notre analyse de la convergence. L'estimation, dans un premier temps, d'un modèle avec autocorrelation spatiale des erreurs montre que les effets de débordement géographique contribuent favorablement au processus de rattrapage des régions les moins performantes. Dans un second temps, l'hétérogénéité spatiale est prise en compte et modélisée par une spécification à deux régimes spatiaux, de type "cœur-périphérie". Finalement, nos résultats permettent de conclure que le processus de convergence globale mis en évidence masque des disparités au sein des régions européennes, où seulement les régions appartenant au centre de l'Europe convergent.

Mots-clés : brevets, convergence, effets spatiaux, régions européennes, économétrie spatiale.
Classification JEL : C21, O33, O52, R11

*LAMETA, Université Montpellier I, UFR des Sciences Economiques, Espace Richter, Avenue de la Mer, C.S. 79606, 34960 Montpellier Cedex 2, France. E-mail : pellier@lameta.univ-montp1.fr.
I am grateful to Jalal El Ouardighi for his valuable comments. All mistakes or omissions are mine.

1 Introduction

Although the spatial dimension of knowledge spillovers is a recent field of the literature, the number of publications increased rapidly these last ten years, stressing the significant interest in this field. According to Endogenous Growth Theory, technological progress and knowledge externalities are crucial factors explaining economic performance and long term growth (Romer, 1990, Grossman et Helpman, 1991, Coe et Helpman, 1995). These spillovers exist because of the particular nature of knowledge, which is defined as a non-rival economic good and partly non-excludable (Arrow, 1962). The empirical literature relative to the geography of innovation investigated the two main sources of these spillovers: the geographic proximity and the technological proximity. Jaffe (1986) was one of the first interested in the idea that a clustering of activities of the same nature would be in favour of innovation. From an indicator of technological proximity, he shows that the R&D productivity of a firm is increased by the R&D of "technological neighbours", i.e. neighbours firms which belong to the same technological domain.

Differently from that, several empirical works suggested that geographical clustering of innovative activities facilitates knowledge transmission. These works underline the fact that spillovers are localized and also sensible to the proximity. By introducing a "Geographic Coincidence Index" in the knowledge production function formalized by Griliches (1979), Jaffe (1989) finds a positive impact from university research to innovative activity of firms located in the same geographic area. Theses studies attempted to measure the spatial dimension of spillovers were refocused and developed by Jaffe, Trajtenberg and Henderson (1993), Audretsch and Feldman (1996), Anselin, Varga and Acs (1997) and others.

From an econometric point of view, traditional econometrics techniques are no longer appropriate to provide correct estimations in presence of spatial dependence. A recent line of research uses spatial econometrics tools to model spatial externalities and investigate the role of geography in innovation (Fisher and Varga, 2003, Dettori, Paci and Usai, 2005). In the spirit of these works, the aim of this paper is to show the impact of geographical spillovers in the regional patenting activity. Our contribution is different from previous ones since we include these spatial effects into a convergence analysis. We study the extend to which spatial effects contribute to the convergence process of the innovative activities of regions. The debate on convergence of economies, i.e. if poorer countries catch up richer ones, has been widely studied in the macroeconomic literature. Our approach of the convergence of innovation activities is based on cross section data analysis proposed by Barro and Sala-I-Martin (1991, 1995). The choice of the period of study, from 1981 to 2001, can by justifies first of all by a context of extension of Europe, fast technological changes as well as the will of the European Commission to build a European Research Area. Our choice is also constrained by the data availability. Because of the lack of data, we are not able to provide an analysis over a longer period or with more regions.

The paper is organized as follows: the next section provides a short description of the econometrics tools we use for our empirical analysis. In section 3, we present our database and perform the exploratory spatial data analysis to European regional patents applications. Section 4 presents the beta convergence analysis which includes spatial autocorrelation and spatial heterogeneity detected in the previous section. A summary and final remarks conclude the paper.

2 Exploratory Spatial Data Analysis

Exploratory Spatial Data Analysis (ESDA) is a set of techniques aimed at describing, visualizing spatial distribution, detecting patterns of spatial association, identifying atypical localizations or at suggesting some forms of spatial heterogeneity (Anselin, 1988). These methods are based on various indicators such as Moran'I statistic, Moran Scatterplot and local indicators of spatial association to provide both measures of global and local spatial autocorrelation.

Spatial autocorrelation is the correlation of a variable with itself through space. According to Anselin & Bera (1998), spatial autocorrelation can be defined as "coincidence of value similarity with locational similarity". Spatial autocorrelation is said positive when similar (high or low) values of a random variable tend to cluster in space whereas patterns in which neighbouring areas are unlike reveal a negative spatial autocorrelation. Random patterns exhibit no spatial autocorrelation. Spatial dependence is often due to some processes which connect different areas. Factors such as trade, knowledge diffusion or more generally geographical spillovers lead to spatial interactions between regions.

The use of econometrics techniques for the analysis of Georeferenced data is relatively recent (Cliff and Ord, 1981; Anselin and Florax, 1995) and majority of studies investigate the dynamics of European regional per capita product over time and space (Le Gallo and Ertur, 2003; Dall'erba and Le Gallo, 2005).

2.1 The Spatial weight matrix

This matrix contains the information about the relative spatial dependence between the N regions i of the sample. A spatial weight matrix W has a dimension equal to the number of observations. Each element w_{ij} indicates the way that the region i is spatially connected to the region j. By convention, the diagonal elements of the weight matrix are set to zero. There are various types of weight matrix, such as matrix of proximity to model interactions between regions having a common border. Others weight matrix are based on the number of k nearest neighbours or on the great circle distance between the regional centroids. In this last case, intensity of the interaction between regions is then supposed to depend on the distance which separates the centroids of regions. Given that the European context of our study contains islands, we choose a weight matrix W based on the great circle distance between centroids of the European regions. This distance-based weight matrix is useful to ensure the space connections of the United Kingdom to the European continent. Moreover, the fact that it contains pure geographical distance makes sure its exogeneity (Anselin and Bera, 1998). The functional form of this matrix is the inverse of the squared distance:

$$\begin{cases} w_{ij}^*(k) = 0 \; if \; i = j \\ w_{ij}^*(k) = 1/d_{ij}^2 \; if \; d_{ij} \leq D(k) \\ w_{ij}^*(k) = 0 \; if \; d_{ij} > D(k) \end{cases} \tag{1}$$

$$w_{ij} = \frac{w_{ij}^*}{\sum_i w_{ij}^*} \text{ for } k = 1, 3, 2 \tag{2}$$

The intensity of interactions between spatial units is negatively correlated to the distance which separates them[1]. The matrix is row-standardized such that the element of each row sum up to one an then it is the relative and not absolute distance that matters. w_{ij} is an element of the unstandardized weight matrix W, w_{ij}^* is an element of the standardized weight matrix, d_{ij}^* is the great circle distance between centroids of regions i and j. $D(k)$ is the cut-off parameter above which interactions are assumed negligible, in others words, it gives the geographic limit to the diffusion of externalities. $D(1) = Q1$, $D(2) = Q2$ and $D(3) = Q3$ where $Q1, Q2$ and $Q3$ are respectively the lower quartile, the median and the upper quartile of the great circle distribution. For our sample, $D(1) = 273$ miles, $D(2) = 462$ miles and $D(3) = 711$ miles.

2.2 Moran'I

The most widely known measure of spatial clustering is the Moran'I statistic (Cliff and Ord, 1981). The statistic can be expressed in the following matrix notation:

$$I = \frac{N}{S_0} \frac{y'Wy}{y'y} \text{ with } S_0 = \sum_i \sum_j w_{ij} \tag{3}$$

S_0 is a scaling factor equal to the sum of all elements of W, y is a vector of the N observations in deviation from the mean, and Wy is the spatially weighted average of the neighbouring values (also called spatial lag vector). Moran'I statistic gives a formal indication on the degree of linear association between the vector of observed values, y, and the associate spatial lag vector, Wy. A positive (respectively negative) spatial autocorrelation occurs when I is larger (respectively

[1] According to Tobler in his First Law of Geography (1979): "Everything is related to everything else, but near things are more related than distant things".

smaller) than the expected value $E(I) = -1/(N-1)$. Statistic inference is based a permutation approach with 10 000 permutations.

Moran'I statistic can detect global spatial autocorrelation but it is not able to appreciate the regional structure of spatial autocorrelation. The analysis must go on to detect possible local clusters of strong or weak values, which regions contribute more to the global spatial autocorrelation and which regions deviate from the global pattern of positive spatial autocorrelation. Among techniques most frequently used, we will choose the Moran scatterplot (Anselin, 1996) and the Local Indicators of Apatial Association (LISA) (Anselin, 1995a).

2.3 Moran Scatterplot

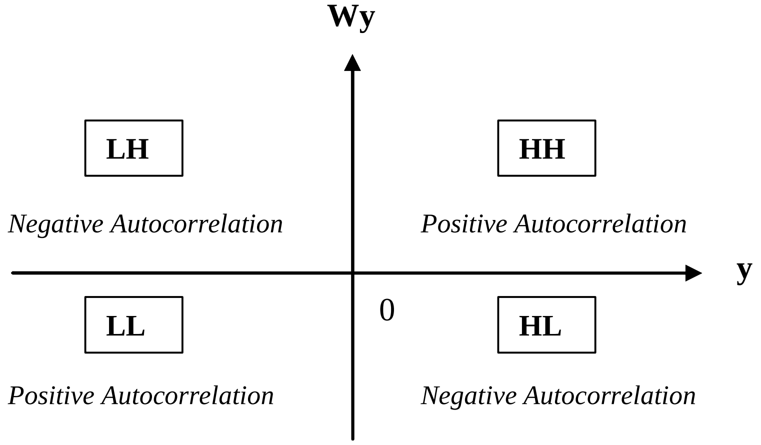
Local spatial instability is carried out by the mean of the Moran Scatterplot (Anselin, 1996). The scatterplot (figure 1) display on the horizontal axis the vector y (in our case, the standardized patent applications for each region) against the spatial lag vector Wy (standardized spatial weighted of the neighbours' patent applications) on the vertical axis. Moran scatterplot is divided into four quadrants corresponding to the four types of local spatial association between a region and its neighbours. The HH quadrant shows that regions with high patent applications are surrounded by regions with high patent applications. In the LL quadrant, regions with low values are surrounded by regions with low values. In the LH quadrant, regions with low values are surrounded by regions with high values. Finally, regions belonging to the quadrant HL with high values are surrounded by regions with low values. HH and LL quadrants indicate a spatial clustering of similar values and therefore a positive spatial autocorrelation. In the opposite, LH and HL quadrants represent a negative spatial autocorrelation, i.e. a spatial clustering of dissimilar values.

Moran Scatterplot is useful to detect « atypical localization » i.e. group of regions which deviate from the global pattern of spatial autocorrelation. These regions are located in the LH or HL quadrants of the Moran scatterplot. Finally, global spatial autocorrelation may also be visualized on this graph since the Moran's I statistics is formally equal to the slope coefficient of the linear regression of Wy on y. Moreover, the use of standardized values allows the Moran scatterplots to be comparable across time.

2.4 Local Indicators of Spatial Association (LISA)

Moran scatterplot does not give any information about the significant spatial clustering put in evidence. Therefore, we have to calculate particular indicators: the local indicators of association spatial or LISA statistics defined by Anselin (1995b). These indicators are used as well for the detection of significant spatial clusters or "hot spots", significant regimes or outliers. According to Anselin (1995), LISA statistics satisfies two requirements. The first one is that the LISA

Figure 1: Moran scatterplot



gives for each observation an indication of significant spatial clustering of similar values around that observation. The second is that the sum of LISA is proportional to a global indicator of spatial association. The local version of Moran's I for every region i and for every year t is:

$$I_{i,t} = \frac{y_{i,t}}{m_0} \sum_j w_{ij} y_{j,t} \text{ with } m_0 = \frac{\sum_i y_{i,t}^2}{N} \tag{4}$$

$y_{i,t}$ and $y_{j,t}$ are observations of region i et j at the year t (in deviation from the mean). The summation over j is such that only neighbouring values of i are included. In our study, we use standardized spatial weights matrix, therefore $S_0 = N$ and $I_t = \frac{1}{N} \sum_i I_{i,t}$, which implies that the global statistics of Moran's I is equivalent to the average of the local statistics of Moran. A positive value of LISA indicates a spatial cluster of similar values whereas a negative value indicates a spatial cluster of dissimilar values.

3 Exploratory analysis of the distribution of patent applications

3.1 The database

We apply the Exploratory Spatial Data Analysis to patent applications to the European Patent Office per million inhabitants. The data are extracted from the EUROSTAT REGIO databank and include 131 regions for 12 European countries over the 1981-2001 period. The countries are: Danmark (1), Irland (1), Luxembourg (1), Italy (21), Spain (6), United Kingdom (10), Austria (9), Belgium (11), Germany (31 regions, East Germany regions are exclude for historical reasons), France (22), Netherlands (12), Sweeden (6). For our analysis, we prefered the level 2 of The Nomenclature of Territorial Units for Statistics[2] because it is the level used by member states to apply their regional policy. However, we had to use NUTS 1 level of aggregation for Spain and the United Kingdom because of unavailability of data at the level 2. The regions of the Scotland and London (United Kingdom), Smaland med öarna and Västsverige (Sweden) are excluded due to the lack of availability of the data. We also exclude the Canarian Islands (Spain) and the French overseas departments and territories because of their geographical removal.

We choose patent applications to the EPO as a proxy for innovative activity of a region[3]. Patent applications are recorded by priority year. The statistics concern applications directly filed under the Patent Convention or applications filed under the Patent Co-operation Treaty and designating the EPO (Euro-PCT). The regional distribution of patent applications is assigned according to the inventor's region of residence, what is preferred to attribute the spatial localisation of each innovation. If one application has more than one inventor, the application is divided equally among all of them and among their region of residence, thus avoiding double counting. In this paper, tests are carried out on the ratio patent / million inhabitants and the series are exclusively extracted from the REGIO database.

3.2 Empirical Results

The choropleth maps in appendix 1 and 2 display the spatial distribution of regional patent applications level relative to the European average. In 1981, the innovative performances are not dispersed in a homogeneous way over the European space, which highlights a strong disparity between regions but also between countries. A central-periphery pattern appears in the map. The most innovative regions are grouped together for the greater part in the middle of Europe (regions of West Germany, Austria, Luxemburg, some regions of Netherlands, east of France). Some regions of the North of Europe are also leading regions, these regions are located in the South of the United Kingdom and Sweden. The least innovative regions are mainly located in the periphery or in the South of Europe: Spain, the South of Italy, some French regions, the North of the United Kingdom. Although this pattern is stable over in 2001, we can note that innovation activity has considerably increased during the last twenty years. The European average of patents per million inhabitants has almost quadrupled (42 patents per million inhab. in 1981 against 167 patents per million inhab. in 2001). These choropleth maps offer a general

[2] The territorial breakdown established by Eurostat is the Nomenclature of Territorial Units for Statistics (NUTS). This one provides a single and uniform breakdown of territorial units for the production of regional statistics for the European Union. The NUTS is a hierarchical classification with five levels comprising three regional levels (NUTS 1-3) and two local levels (NUTS 4 and 5). So, according to this classification, every member state is subdivided into an integer of level 1 regions, each of which is subdivided into an integer of level 2 regions, and so on.

[3] Acs, Anselin et Varga (2002) provide some insight into the reliability of the patent data as a proxy for regional innovative activity. See also Griliches (1990) and Basberg (1987) for the advantages and drawbacks to use patents statistics as indicators of innovative activity.

approach of the distribution of the patent applications but it do not indicate in any case if this spatial concentration of the activities of innovation generates a process of spatial dependence. That is why the AEDS tools are mobilized.

We start the spatial analysis by computing three weights matrix $D1$, $D2$ and $D3$ based on the three distances thresholds defined in the section 2.1. The Moran's I statistics are then calculated to realize the test of the global spatial autocorrelation. The table 1 report, for each year and each weights matrix, the value of Moran's I, the standard deviation and the standardized value of Moran's I. Whatever the weight matrix and the year, all statistics are significant[4] (p-value=0.0001). According to the decision rule, the null hypothesis of no spatial autocorrelation is thus rejected. Patent applications are positively and spatially correlated in 1981 and in 2001. In other words, regions depositing a relatively high number (respectively low) of patents are located near regions also depositing a high number (respectively low) of patents. This result confirms the visual impression of spatial concentration given by choropleth maps. It is worth mentioning that the standardized values of Moran's I increase slightly in 2001, what lets suppose a persistent tendency to the geographical concentration of similar regions.

Table 1 : Moran's I statistics

		Moran's I	**Std. dev.**	**Z(I)**
1981	D1	0,5591	0,0468	12,0723
	D2	0,5031	0,0400	12,7243
	D3	0,4310	0,0369	11,8553
2001	D1	0,6038	0,0471	12,9468
	D2	0,5379	0,0402	13,5500
	D3	0,4651	0,0370	12,7426

Notes: The expected value of Moran's I is constant for each year: E(I)=-0,007.
Z(I) is the standardized value of Moran's I.

Subsequently of the analysis, we will keep the weights matrix $D2$, the one for which the standardized value of Moran'I is maximized[5]. These first results show that innovation performance of a region is not independent from it geographical location and the patenting activity in a region appears correlated to the one in neighbouring regions. To refine the analysis and provide an evaluation of the local structure of the autocorrelation, we represent the Moran scatterplots in 1981 and 2001. The standardized patent applications for each region appear on the horizontal axis and their spatial lag standardized on the vertical axis. These scatterplots, diplayed in figures 2 and 3, confirm the presence of positive spatial autocorrelation: more than 70 % of regions belong to HH or LL quadrants (cf. table 2). Some atypical regions which deviate from the global pattern are also bringing to the fore. These regions are characterized by an association

[4] The robustness of results is also tested by using others distance-based matrix.
[5] All estimations were carried out by means of the SpaceStat 1.91 software (Anselin, 1995b).

of dissimilar values and belong to the quadrants HL or LH. The pattern of association LH is more important that the pattern HL what indicates that some regions meet with difficulties in spite of a favourable environment. The temporal comparison of Moran scatterplots reveals that pattern of spatial association seem to be stable over time, indicating some persistence of spatial disparities between European regions. These results also suggest the existence of spatial heterogeneity and more precisely a "core-periphery" pattern because the majority of the center regions are belonging to the HH quadrant whereas the peripheral regions are belonging to the BB quadrant.

In spite of the remaining of the dominant spatial pattern, it is interesting to analyze the dynamics of the spatial associations by comparing the Moran's scatterplot of patent applications growth rates with the Moran's scatterplot of the patent applications in 1981. The existence of an inverse relationship between the growth rates and the initial level of patent applications would imply a possible decrease of the disparities and would plead in favour of a convergence hypothesis of regions towards the same steady state.

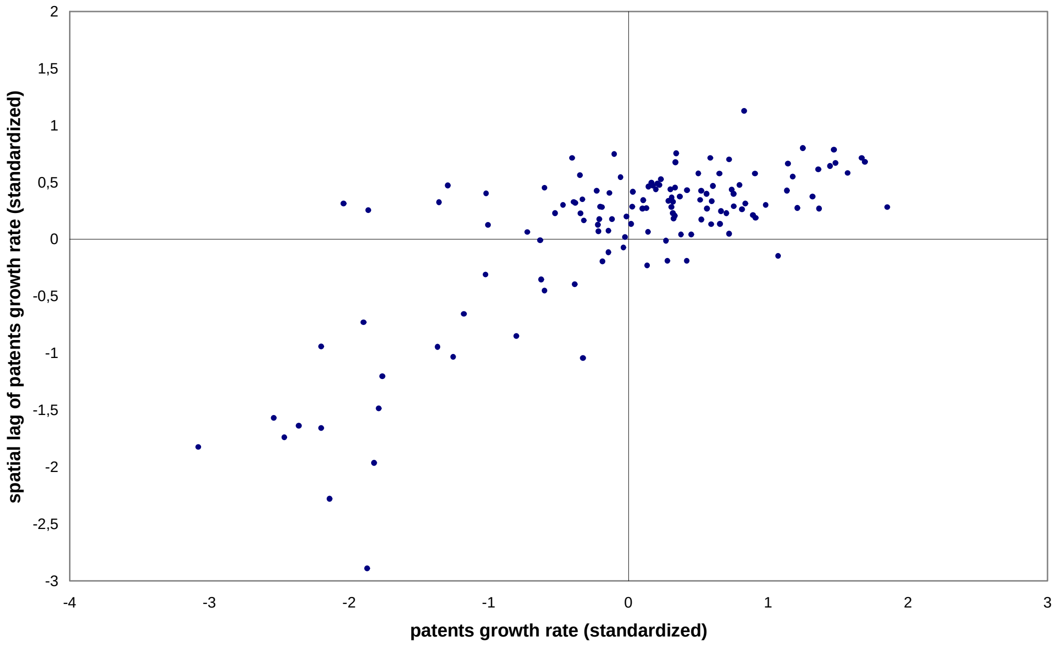
Table 2: Distribution of regions into Moran Scatterplots

	HH	**LL**	**HL**	**LH**
1981	$51,15\%$	$22,14\%$	$6,87\%$	$19,85\%$
2001	$47,33\%$	$29,77\%$	$7,63\%$	$15,27\%$
Growth rate	$21,37\%$	$45,80\%$	$17,56\%$	$15,27\%$

After visualization of Moran scatterplots, some regions which belonged to the HH (LL) quadrant of Moran scatterplot of the patent applications in 1981 belong to the LL (HH) quadrant when we consider the average growth rate over the period 1981-2001 (cf. table of appendix 3). More exactly, 58 % of the regions which were in a certain quadrant in 1981 are in the opposite quadrant for their growth rate. All the Spanish regions and the majority of the least efficient Italian regions which belonged to a clustering of LL type en 1981 have a growth rate superior to the average and belong to a clustering of HH type. This finfing underlines the good performances in innovation of these regions over the period 1981-2001. Conversely, the majority of the very successful regions, which were surrounded with regions so successful (configuration of HH type), are characterized by a configuration of LL type for the growth rates. These results suggest the idea of a catching up phenomenon of the least successful regions in innovation. The LISA statistics indicate some significant spatial clustering which strengthens this idea (cf. table of appendix 3). However, this convergence process should be considered with caution because of persistence of spatial disparities revealed in time.

Although the ESDA is a very powerful tool to explain the performances of each region in connection with its geographical environment, we do not wish to give here more explanations about the individual performances, but we attempt to highlight some spatial effects (spatial autocorrelation and heterogeneity) with the aim at including them into our econometric analysis

Figure 2: Moran scatterplot of patent applications in 1981



of the convergence.

4 Absolute convergence and spatial effects

In this section, we investigate the idea of convergence by testing a model of absolute β convergence similar to that proposed by Barro and Sala-I-Martin (1991, 1992, 1995). As suggested by Fingleton (1999) and Le Gallo and Dall'erba (2005), including spatial autocorrelation in a absolute convergence model drives to a minimal specification of conditional convergence insofar as spatial autocorrelation catches all the effects of the omitted variables.

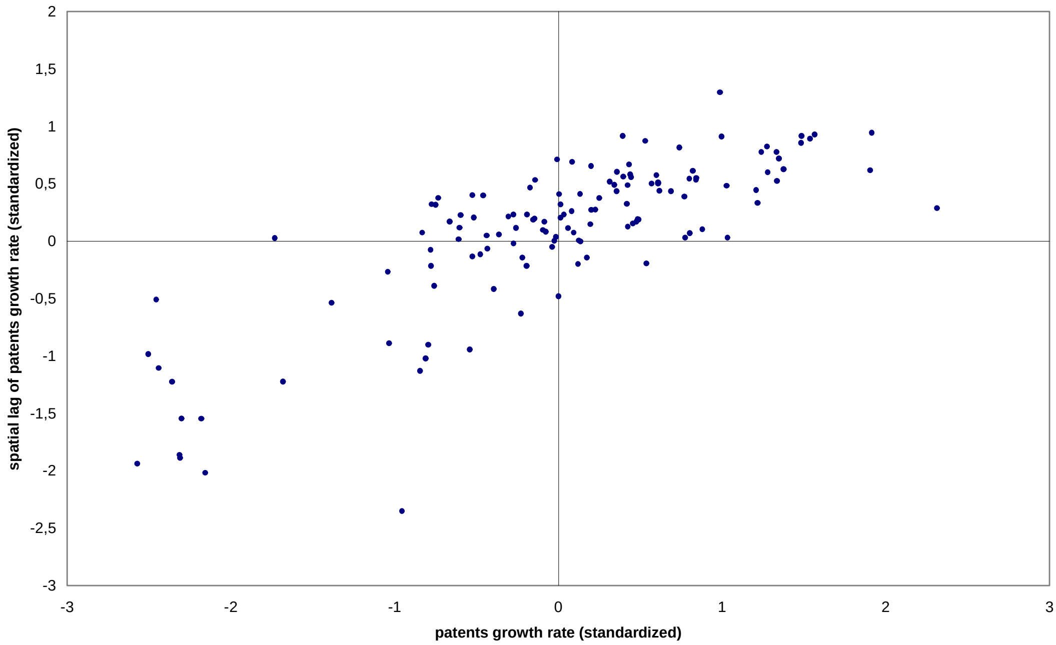
4.1 Beta convergence analysis over 1981-2001 period

First, we estimate the following simple model of absolute convergence:

$$\text{Model 1: } gpat = \alpha + \beta pat81 + \varepsilon \text{ with } \varepsilon \sim N(0, \sigma^2 I) \tag{5}$$

Where *gpat* is the average growth rate of patent applications over the 1981-2001 period and *pat81* is the logarithm of patent applications in 1981. The convergence process is characterized by a speed of convergence, $\upsilon = -\ln(1 + \hat{\beta}T)T$ and a half-life $\tau = -\ln(2)/\ln(1 + \hat{\beta})$, i.e. the time necessary for an economy to reach half of the distance from its steady.

Figure 3: Moran scatterplot of patent applications in 2001



The Ordinary Least Squares (OLS) estimation results of model 1 are displayed in the first two columns of table 3. The coefficient associated with patent applications is negative and significant: $\hat{\beta} = -0.0203$, which drives us to accept the hypothesis of absolute β convergence between European regions. Over the period 1981-2001, the regions which deposit few patent applications in 1981 have a higher growth rate than the most successful regions, which lead to a catch up of the least successful regions. The speed of convergence is estimated at 2.65 percent and the half-life is 34 years. Since the AEDS revealed a positive spatial autocorrelation, it is necessary to realize a serie of tests to detect and identify the most appropriate form of spatial effects which will be afterward included in a new econometric specification. The Koenker-Bassett (1982) test, robust to the non-normality, rejects the hypothesis of homoskedasticity (p-value= 0.006). The Moran test adapted to the residus of a regression by Cliff and Ord (1981) gives a significant value indicating that there is a positive spatial dependence between the observations, similar to that observed with the ESDA. Two forms of spatial autocorrelation are possible: spatial errors autocorrelation or spatial lag[6]. Anselin and Florax (1995) suggested tests based on Lagrange Multiplier which allow discrimination between these two forms of spatial dependence: the LM (ERROR) and LM (LAG) statistics. The LM (ERROR) test has the null hypothesis of spatial errors autocorrelation whereas the LM (LAG) test has the null hypothesis of spatially lagged endogenous variable. Following the decision rule proposed by Anselin and Florax (1995), we notice that only the LM (ERROR) statistic is significant[7]. Therefore, model 1 appears to be

[6] See Le Gallo J. (2002) for a presentation of the procedures of estimation in the presence of autocorrelation.
[7] In the hypothesis where LM (LAG) and LM (ERROR) statistics are both significant, it is necessary to consider

misspecified because of the omission of the residual spatial autocorrelation. We have to estimate a second model taking into account this spatial dependence[8] :

$$\text{Model 2: } gpat = \alpha + \beta pat81 + \varepsilon \text{ with } \varepsilon = \lambda W\varepsilon + \mu \text{ and } \mu \sim N(0, \sigma^2 I) \tag{6}$$

Where λ is the parameter representing the intensity of the spatial autoccorelation between residuals of regression. This model is estimated using the Maximum Likelihood (ML) method[9] and the results displayed in table 3 show that the convergence hypothesis is also accepted. The speed of convergence is 3.87 percent, superior to that of the initial model and the half-life is not more than 26 years. It also appears a strong positive and significant spatial errors autocorrelation ($\hat{\lambda} = 0.80$).

Table 3: Estimation and tests of models 1 & 2

MODEL 1		MODEL 2	
OLS estimation	Coefficient (p-value)	ML estimation	Coefficient (p-value)
$\hat{\alpha}$	0,1418 (0,00)	$\hat{\alpha}$	0,1544 (0,00)
$\hat{\beta}$	-0,0203 (0,00)	$\hat{\beta}$	-0,02649 (0,00)
		$\hat{\lambda}$	0,8015 (0,00)
speed of convergence	2,65%	speed of convergence	3,87%
half-life	34	half-life	26
TESTS		TESTS	
Moran's I	6,0017 (0,00)		
LM (ERROR)	29,0432 (0,00)		
LM (LAG)	1,5122 (0,2187)	LM* (LAG)	0,5001 (0,4794)
Koenker-Bassett	7,3636 (0,0066)	Spatial Breusch-Pagan	11,5338 (0,0006)
AIC	-567,392	AIC	-599,213
SC	-561,642	SC	-593,463

The additional LM*(lag) test indicates that no supplementary endogenous variable is necessary. Finally, Akaike (1974) and Schwarz (1978) criteria of information suggest that the second model is better than the first one.

All these results confirm the intuition of convergence formulated previously. The estimation of the model with residual autocorrelation is accompanied by a speed of convergence higher than the one in the initial model. The spatial effects put in forward imply geographic spillovers that contribute positively to the convergence process. However, according to the Breuch-Pagan (1979) spatially adjusted test for heteroskedasticity, there is a certain spatial heterogeneity

the robust versions of these two tests.

[8] Because the presence of heteroskedasticity revealed by the Koenker-Bassett test can be due to the presence of autocorrelation (Anselin, 1988), we first consider the problem of autocorrelation.

[9] In presence of spatial dependance, OLS estimations are no longer efficients (Anselin, 1988).

which could be due to structural instability (Le Gallo, 2004). In other words, it is possible that coefficients of the convergence equation may not be stable over space. Moreover, the findings of the ESDA strengthens this idea of heterogeneity. Therefore, it seems relevant to suppose that the convergence process may not be identical for all European regions. We determine these clubs or groups of regions having each its own regime of convergence by using a purely statistical method.

4.2 Differents spatial regimes

The method of critical level of localization proposed by Jean-Pierre (1997) aims at determining in an endogenous way clubs of convergence, i.e. groups of countries or regions whose initial conditions are near enough to converge toward the same long-term steady state. This method is based on the works of Thong and Lim (1980) and Thong (1983), taken back afterward by Tsay in 1989. It consists in making recursive regressions on reclassified data to identify thresholds of break which let suppose the existence of various regimes of convergence. Several stages are necessary: first, the patent applications in 1981 are reclassified by increasing order. Next, the stability of the coefficients of the convergence equation of model 1 is tested from a Fischer test[10]. If the hypothesis of no stability is rejected, one or several thresholds separating the various groups of regions must be located. For that, a first regression is made on the n first observations allow inferring from the β coefficient the Student's t. Then, we proceed to recursive estimations until the whole sample is used. The last stage is the location of thresholds with a graphic representation of recursive Student's t according to the threshold variable chosen (the initial level of patent applications in 1981). The graphic interpretation is the following one. Any change in the direction line of Student's t may reveal the presence of a new regime. This graphic analysis is sometimes completed by the graphic representation of other indicators, such as standardized residuals recursive. In that case, an analysis in term of change of shape of the scatterplot is more appropriated.

This methodology applied to our convergence equation (model 1) leads us to reject the null hypothesis of stability of the equation coefficients. The figure of appendix 4 displaying recursive Student's t shows a change of regime for a logarithm of patent applications (pat81) around 1.98, which correspond to approximately 7 patents per million inhabitants[11]. Up to this threshold, the series *pat81* grows slightly and beyond, it changes brutally tendency and decreases in an exponential way. The graph of recursive residuals (appendix 5) confirms this hypothesis of change of regime for the same threshold. So, two groups of regions with different regimes appea.

[10] To carry out this test, recursive estimations of the model 1 are made to obtain a series of standardized residuals which will allow us to estimate the following equation: $\hat{e} = \alpha + \beta pat + \mu$

The statistics of the test of Fisher is: $F = \frac{(\sum \hat{e}^2 - \sum \hat{\mu}^2)}{\sum \hat{\mu}^2} \frac{q}{p}$ with p the number of coefficients to be estimated and q the number of observations less p.

[11] The Bai and Perron (2003) test for multiple structural changes confirms this threshold.

The group 1 consists of 24 regions belonging to a "peripheral" zone of Europe: Spain, South of Italy (Provincia Autonoma Trento, Umbria, Marche, Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna), Ireland, East Germany (Oberfranken, Mittelfranken, Braunschweig, Thüringen), Austria (Kärnten), the United Kingdom (South West).

The group 2 consists of 107 regions belonging to the "central" zone of Europe: Austria (except Kärnten), Belgium, Germany (except Oberfranken, Mittelfranken, Braunschweig, Thüringen), France, North of Italy (Piemonte, Valle d' Aosta, Liguria, Lombardia, Provincia Autonoma Bolzano-Bozen, Veneto, Friuli-Venezia Giulia, Emilia-Romagna, Toscana, Lazio), Luxelbourg, Netherlands, Sweden, the United Kingdom (except South West). (The table in appendix 3 gives the distribution of regions for each group.)

We modelize the spatial heterogeneity linked to structural instability by a specification including these two spatial regimes and we proceed to new estimations (models 3 and 4). Unlike model 3, model 4 incorporates some spatial autocorrelation.

$$\text{Model 3: } gpat = \alpha_1 G_1 + \beta_1 pat81 G_1 + \alpha_2 G_2 + \beta_2 pat81 G_2 + \varepsilon \text{ with } \varepsilon \sim N(0, \sigma^2 I) \tag{7}$$

$$\text{Model 4: } gpat = \alpha_1 G_1 + \beta_1 pat81 G_1 + \alpha_2 G_2 + \beta_2 pat81 G_2 + \varepsilon \tag{8}$$
$$\text{with } \varepsilon = \lambda W \varepsilon + \mu \text{ and } \mu \sim N(0, \sigma^2 I)$$

$G1$ and $G2$ represent dummy variables corresponding to each identified groups. The interest of this new specification is double: on one hand, it allows possible different regimes of convergence and on the other hand, the same matrix of spatial interaction is used which allows the regions of both groups to exercise an influence each others. Nevertheless, it drives to consider that spatial autocorrelation is identical between both groups.

According to the results report in the table 4, the model 3 is misspecified because of the presence of spatial errors autocorrelation in the regression. Indeed, the Moran's I statistic and the LM (ERROR) test are both significant. The model 4 including this autocorrelation is therefore the most appropriate. Moreover, results highlight a significant convergence only for regions belonging in the centre of Europe (group 2) because the β_2 is the alone negative and significant coefficient. The speed of convergence is 2.86 % and the half-life of 32 years. Finally, the Breuch-Pagan test leads to accept the null hypothesis of homoscedasticity (p-value=0.24). Thus, it seems that spatial instability was totally taken into account by the specification of model 4. This later model is also better than the previous ones if we consider the criteria of information.

Table 4: Estimations and tests of models 3 & 4

MODEL 3		MODEL 4	
OLS estimation	Coefficient (p-value)	ML estimation	Coefficient (p-value)
$\hat{\alpha}_1$	0,1410 (0,00)	$\hat{\alpha}_1$	0,1560 (0,00)
$\hat{\beta}_1$	0,0017 (0,774)	$\hat{\beta}_1$	-0,0081 (0,152)
$\hat{\alpha}_2$	0,1171 (0,00)	$\hat{\alpha}_2$	0,1329 (0,00)
$\hat{\beta}_2$	-0,0141 (0,00)	$\hat{\beta}_2$	-0,0214 (0,00)
		$\hat{\lambda}$	0.08237(0,00)
speed of convergence	1,68%	speed of convergence	2,86%
half-life	49	half-life	32
TESTS		TESTS	
Moran's I	6,5376 (0,00)		
LM (ERROR)	32,6046 (0,00)		
LM (LAG)	0,8176 (0,365)	LM*(LAG)	2,0558 (0,1516)
Koenker-Bassett	10,2749 (0,0360)	Spatial Breusch-Pagan	5,4699 (0,242)
AIC	-585,965	AIC	-621,394
SC	-574,464	SC	-609,893

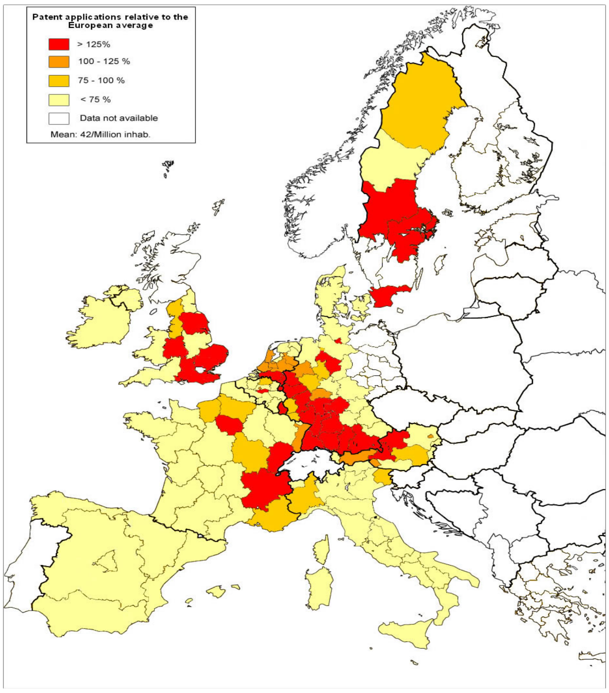
The whole results underlines clearly that the global regional process of convergence is hiding disparities between European regions. A single process of convergence exists and concerns only regions located in the centre of Europe. These last findings support the idea that innovation diffusion is not an instantaneous and costless process. With their very low innovative performances, peripheral regions seem to belong to a kind of "less-growth technological trap" that prevent them from starting a convergence process.

5 Conclusion

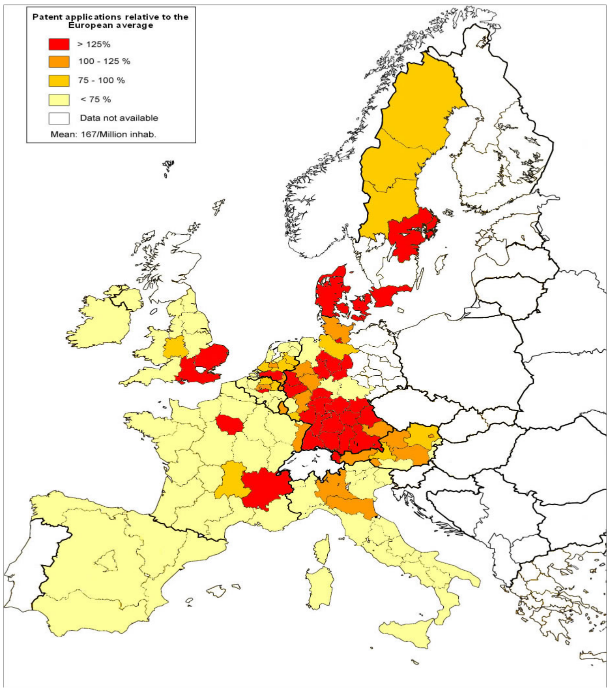
The purpose of this paper has been to analyse the convergence of innovation activities for European regions from 1981 to 2001. Spatial data analysis and spatial econometrics methodologies are applied in order to investigate the role of geography both in regional performances and in the patent catch-up process. A first analysis revealed a geographical clustering of innovative activities in European space. In particular, a core-periphery spatial pattern was identified, the regions of the centre of Europe being most innovative ones. Besides, we have shown that a region's propensity to innovate was correlated with that of neighbouring regions. These findings imply that spillovers of technological knowledge exist and tend to be spatially bounded. This contrasts with the neoclassical assumption that knowledge would be a public good, free available by everybody and elsewhere.

Althought the technological gap across regions remains in time, some lagging regions have shown a higher dynamism in term of growth rate than regions initially more successful. This last result led us to test for a possible patent catch-up process. Our econometric analysis gives evidences of a global convergence of regions and also shows a positive impact of spatial spillovers on the speed of convergence. Some lagging regions succeed to reduce a part of their technological gap by benefiting from their neighbours' performances. Another analysis including two spatial regimes was carried out in order to take into account the structural instability detected in the convergence equation. Finally, a single process of convergence for regions belonging to the centre of Europe appears. The results highlight the lack of absorptive capacity of the backward regions, i.e. firms with a low patent activity do not seem to be able to assimilate and exploit knowledge from their environments (Cohen and Levintal, 1989). A minimum level of research activities seems to be necessary to benefit from external information and therefore to reduce the gap. However, the efficiency of a policy aiming at increasing R&D subsidizing is not so obvious. Our study suggests, in line with Fagerberg, Verspagen and Caniëls (1997), that R&D activities should be undertaken in an adequate context, since socioeconomic conditions such as economic structure, employment or educational achievement may have an effect on the capacity of a region to transform R&D investments into innovation and economic growth. Futhermore, a possible interesting development of this research would be to analyse the effects of such factors on the patent catch-up process and also the economic growth.

Appendix 1: Spatial distribution of regional patent applications relative to the European average in 1981



Appendix 2: Spatial distribution of regional patent applications relative to the European average in 2001



Appendix 3: Local spatial pattern

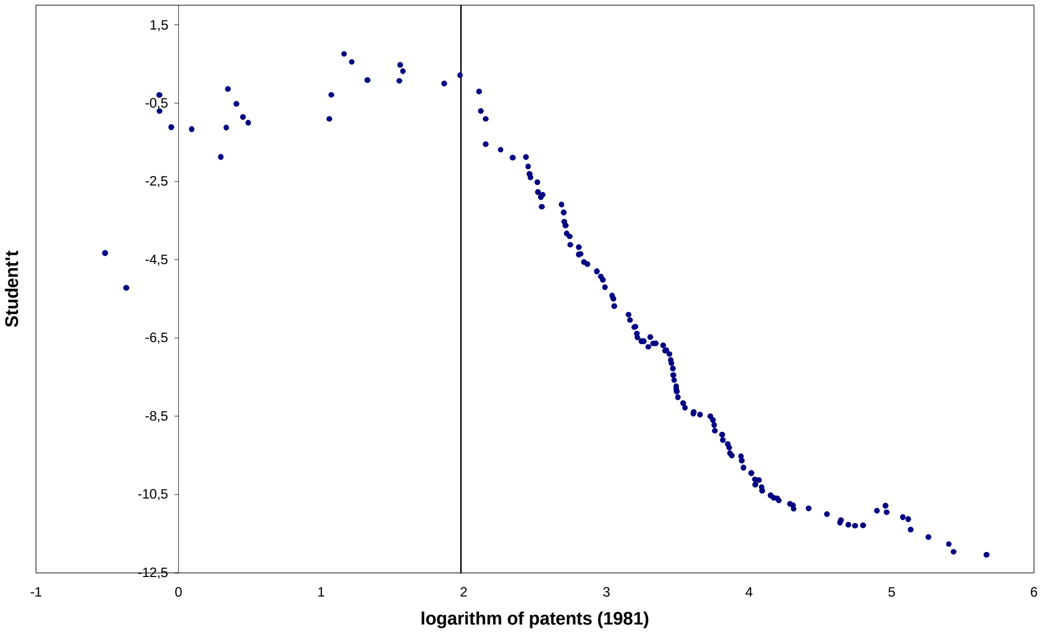
Group	Nuts Code	Region	1981	2001	81-01
2	at11	Burgenland	BH	BH	HB
2	at12	Niederösterreich	HH	HH	BB
2	at13	Wien	HH	HH	BB
1	at21	Kärnten	BH	HH	HB*
2	at22	Steiermark	HB	HH	BH
2	at31	Oberösterreich	HH	HH	BH
2	at32	Salzburg	HH	HH	BH
2	at33	Tirol	HH	HH	BH
2	at34	Vorarlberg	HH	HH*	HB
2	be10	Région de Bruxelles-Capitale	HH	HH	BH
2	be21	Prov. Antwerpen	HH	HH	BB
2	be22	Prov. Limburg (B)	BH	BH	HB
2	be23	Prov. Oost-Vlaanderen	BH	HH	HB
2	be24	Prov. Vlaams Brabant	HH	HH	HB
2	be25	Prov. West-Vlaanderen	BH	BB	HB
2	be31	Prov. Brabant Wallon	HH	HH	BB
2	be32	Prov. Hainaut	BH	BH	BB
2	be33	Prov. Liège	HH	HH	BB
2	be34	Prov. Luxembourg (B)	HH	BH	BB
2	be35	Prov. Namur	BH	BH	BB
2	de11	Stuttgart	HH*	HH*	BH
2	de12	Karlsruhe	HH*	HH*	BB
2	de13	Freiburg	HH*	HH*	BB
2	de14	Tübingen	HH*	HH*	BB
2	de21	Oberbayern	HH*	HH*	BH
2	de22	Niederbayern	HH	HH*	HH
2	de23	Oberpfalz	BH	HH*	HH*
1	de24	Oberfranken	BB	HH*	HH*
1	de25	Mittelfranken	BH*	HH*	HH*
2	de26	Unterfranken	HH	HH*	HH
2	de27	Schwaben	HH*	HH*	BH
2	de50	Bremen	HH	HH	BH
2	de60	Hamburg	HB	HH	BH
2	de71	Darmstadt	HH*	HH*	BB
2	de72	Gießen	HH	HH*	BB
2	de73	Kassel	HH	HH	BH
1	de91	Braunschweig	BH	HH	HH
2	de92	Hannover	HH	HH*	BH
2	de93	Lüneburg	BH	HH	HB
2	de94	Weser-Ems	BH	HH	HB
2	dea1	Düsseldorf	HH*	HH*	BB
2	dea2	Köln	HH*	HH*	BB*
2	dea3	Münster	HH	HH	BB
2	dea4	Detmold	HH	HH	HB
2	dea5	Arnsberg	HH	HH*	BB
2	deb1	Koblenz	HH*	HH	BB*

Group	Nuts Code	Region	1981	2001	81-01
2	deb2	Trier	HH	BH	BB*
2	deb3	Rheinhessen-Pfalz	HH*	HH*	BB*
2	dec0	Saarland	HH	HH	BB
2	def0	Schleswig-Holstein	BH	HH	HB
1	deg0	Thüringen	BH*	BH	HH*
2	dk00	Danemark	HH	HH	HB
1	es1	Noroeste	BB*	BB*	HH*
1	es2	Noreste	BB*	BB*	HH*
1	es3	Comunidad de Madrid	BB*	BB*	HH*
1	es4	Centro	BB*	BB*	HH*
1	es5	Este	BB*	BB*	HH*
1	es6	Sur	BB*	BB*	HH*
2	fr10	Île de France	HH	HB	BB*
2	fr21	Champagne-Ardenne	HH	BH	BB*
2	fr22	Picardie	HH	BH	BB*
2	fr23	Haute-Normandie	HH	BB	BB
2	fr24	Centre	HH	BH	BB
2	fr25	Basse-Normandie	BH	BB	HB
2	fr26	Bourgogne	HH	BH	BB*
2	fr30	Nord – Pas-de-Calais	BH	BB	BB
2	fr41	Lorraine	BH	BH	BB
2	fr42	Alsace	HH*	HH	BB
2	fr43	Franche-Comté	HH*	HH	BB*
2	fr51	Pays de la Loire	BH	BB	BB
2	fr52	Bretagne	BB	HB	HB
2	fr53	Poitou-Charentes	BB	BB	BB
2	fr61	Aquitaine	BB	BB	BB
2	fr62	Midi-Pyrénées	HB	HB	BB
2	fr63	Limousin	HH	BB	BB
2	fr71	Rhône-Alpes	HH	HB	BB
2	fr72	Auvergne	HH	HB	HB
2	fr81	Languedoc-Roussillon	BB	BB	BB
2	fr82	Provence-Alpes-Côte d'Azur	HH	BB	BB
2	fr83	Corse	BB	BB*	BH
1	ie0	Irlande	BB	BB	HB
2	itc1	Piemonte	HB	HB	BH
2	itc2	Valle d'Aosta	BH	BH	HB
2	itc3	Liguria	BB	BB	HH
2	itc4	Lombardia	HB	HH	HH
2	itd1	Provincia Autonoma Bolzano-Bozen	BH	BH	BH
1	itd2	Provincia Autonoma Trento	BH	BH	HH
2	itd3	Veneto	BB	HB	HH
2	itd4	Friuli-Venezia Giulia	HB	BH	BH
2	itd5	Emilia-Romagna	HB	HB	HH
2	ite1	Toscana	BB	BB	HH
1	ite2	Umbria	BB	BB	HH
1	ite3	Marche	BB	BB	HH
2	ite4	Lazio	BB	BB*	BH

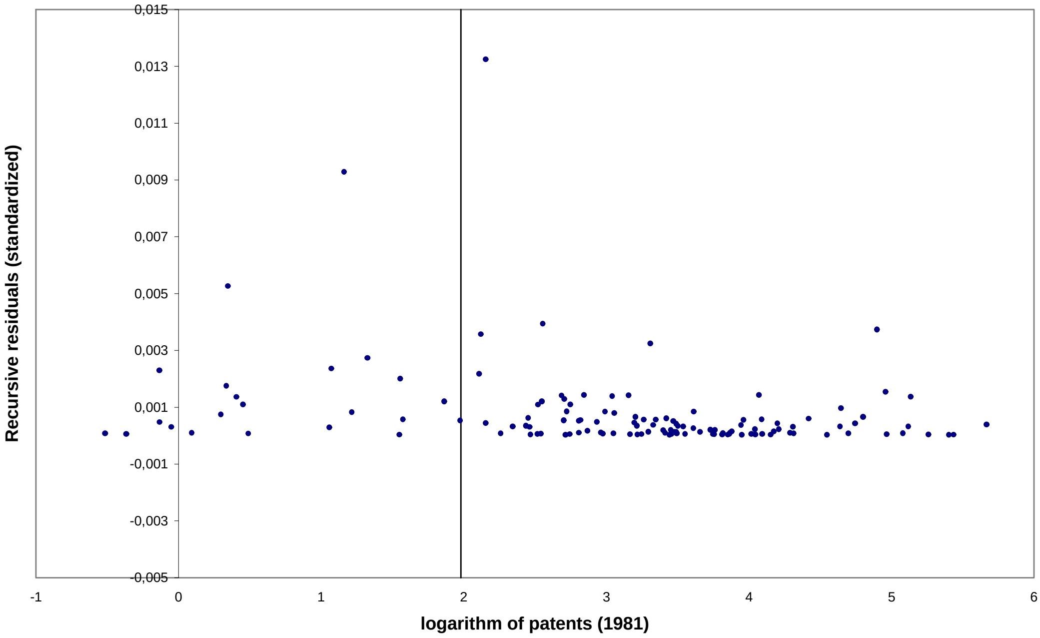
Group	Nuts Code	Region	1981	2001	81-01
1	itf1	Abruzzo	BB*	BB*	HH
1	itf2	Molise	BB*	BB*	HH
1	itf3	Campania	BB*	BB*	HH
1	itf4	Puglia	BB*	BB*	HH
1	itf5	Basilicata	BB*	BB*	HH
1	itf6	Calabria	BB*	BB*	HH
1	itg1	Sicilia	BB*	BB*	HH
1	itg2	Sardegna	BB*	BB*	HB
2	lu00	Luxembourg	HH	HH	BB*
2	nl11	Groningen	BH	BB	HB
2	nl12	Friesland	BH	BH	BB
2	nl13	Drenthe	HB	BB	BB
2	nl21	Overijssel	HH	HH	BB
2	nl22	Gelderland	HH	HH	BB
2	nl23	Flevoland	BH	BH	HB
2	nl31	Utrecht	HH	HH	BB
2	nl32	Noord-Holland	HH	HH	BB
2	nl33	Zuid-Holland	HH	HH	BB
2	nl34	Zeeland	HH	BH	BB
2	nl41	Noord-Brabant	HH*	HH*	HB
2	nl42	Limburg	HH	HH	BB
2	se01	Stockholm	HH	HH	BB
2	se02	Östra Mellansverige	HH	HH	BB
2	se04	Sydsverige	HH	HH*	BH
2	se06	Norra Mellansverige	HH	HH	BB
2	se07	Mellersta Norrland	BH	HH	HB
2	se08	Övre Norrland	HH	HH	BH
2	ukc	North East	HH	BB	BB
2	ukd	North West	HH	BB	BB
2	uke	Yorkshire and The Humber	HH	BB	BB*
2	ukf	East Midlands	HH	BH	BB
2	ukg	West Midlands	HB	HB	BB
2	ukh	Eastern	HH	HH	BB
2	ukj	South East	HH	HB	BB
1	ukk	South West	BB	BB	BB
2	ukl	Wales	BH*	BB	HB*
2	ukn	Northern Ireland	BB	BB	BH

*Note: * indicates that LISA statistics is significant.*

Appendix 4: Recursive Student's t



Appendix 5: Standardized recursive residuals



References

[1] Acs Z., Anselin L. and Varga V. (2002), "Patents and innovation counts as measures of regional production of new knowledge", Research Policy, 31, pp. 1069-1085.

[2] Akaike H. (1974), "A new look at the Statistical Model Identification", IEEE Transactions on Automatic Control, AC-19, pp. 716-723.

[3] Anselin L. (1988), Spatial Econometrics: Methods and Models, Kluwer Academic Publishers, Boston, Dortrecht.

[4] Anselin L. (1995a), "Local indicators of spatial association-LISA ", Geographical Analysis, 27 (2), pp. 93-115

[5] Anselin L. (1995b), SpaceStat, A Software Program for the Analysis of Spatial Data, Version 1.80. Regional Research Institute, West Virginia University, Morgantown, WV.

[6] Anselin L. (1996), "The Moran scatterplot as an ESDA tool to assess local instability in spatial association", in: Fischer M., Scholten M., Unwin D. (eds.), Spatial analytical perspectives on GIS, London, Taylor & Francis.

[7] Anselin L. and Bera A. (1998), "Spatial Dependance in Linear regression Models with an Introduction to Spatial Econometrics", in: Ullah A. and Giles DEA (Eds.), Handbook of Applied Economic Statistics, Berlin, Springer-Verglag.

[8] Anselin L. and Florax R. (1995), "Small Sample Properties of Tests for Spatial Dependance in Regression Models", in: Anselin L., Florax, R. (eds), New Directions in Spatial Econometrics, Berlin, Springer-Verglag.

[9] Anselin L., Varga A. and Acs Z. (1997), "Local Geographic Spillovers between University Research and High Technology Innovations", Journal of Urban Economics, 42, 422-448.

[10] Arrow K. (1962), "Economic Welfare and the Allocation of Resources for Invention", in: Nelson R. (eds), the Rate and Direction of Inventive Activity, Princeton University Press.

[11] Audretsch D. and Feldman M. (1996), "R&D Spillovers and the Geography of Innovation and Production", The American Economic Review, 86 (3), pp. 631-640.

[12] Basberg B. (1987), "Patents and the Measurement of Technological Change: A Survey of the Literature", Research Policy, 16, pp. 131-141.

[13] Barro R. and Sala-i-Martin X. (1991), "Convergence Across States and Regions", Brookings Papers on Economic Activity, 1991 (1), pp. 107-182.

[14] Barro R. and Sala-i-Martin X. (1992), "Convergence", Journal of Political Economy, 100 (2), pp. 223-251.

[15] Barro R. and Sala-i-Martin X. (1995), Economic Growth. New York, McGraw Hill.

[16] Breusch T. and Pagan A. (1979), "A Simple Test for heteroskedasticity and Random Coefficient Variation", Econometrica, 47, pp. 1287-1294.

[17] Coe D. and Helpman E. (1995), "International R&D spillovers". European Economic Review, 39, pp. 859-887.

[18] Cohen W. and Levinthal D. (1989), "Innovation and Learning: The Two Faces of R & D", The Economic Journal, 99 (397), pp. 569-596.

[19] Cliff A. and Ord J. (1981), Spatial Processes: Models and Applications, London, Pion.

[20] Dall'erba S. and Le Gallo J. (2005), "Dynamique du processus de convergence régionale en Europe", Région et Développement, 21, pp. 119-138.

[21] Dettori B., Paci R. and Usai S. (2005), "Technological Avtivity in the European Regions", Working Paper CRENoS, 2005/13.

[22] Fagerberg J., Verspagen B. and Caniëls M. (1997), "Technology, Growth and Unemployement across European Regions", Regional Studies, 31 (5), pp. 457-466.

[23] Fingleton B. (1999), "Estimates of Time to Economic Convergence: An Analysis of Regions of the European Union", International Regional Science Review, 22, pp. 5-34.

[24] Fischer M. and Varga A. (2003), "Spatial Knowledge Spillovers and University Research: Evidence from Austria", Annals of Regional Science, 37 (2), pp. 303-322.

[25] Griliches Z. (1979), "Issues in Assessing the Contribution of Research and Development to Productivity Growth", The Bell Journal of Economics, 10 (1), pp. 92-116.

[26] Griliches Z. (1990), "Patent Statistics as Economic Indicators: A Survey", Journal of Economic Literature, 28, pp. 1661-1707.

[27] Grossman G. and Helpman E. (1991), Innovation and Growth in the Global Economy, Cambridge MA, MIT Press.

[28] Jaffe A.B. (1986), "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits and Market Value," American Economic Review, 76 (5), pp. 984-1001.

[29] Jaffe A.B. (1989), "Real Effects of Academic Research," American Economic Review, 79 (5), pp. 957-970.

[30] Jaffe A.B, Trajtenberg M. and Henderson R. (1993), "Geographic Localization of Knowledge Spillovers as Evidence by Patent Citations", The Quaterly Journal of Economics, 63 (3), pp. 577-598.

[31] Jean-Pierre P. (1997), "Sélection et tests de seuils de convergence", Revue économique, 48 (3), pp. 429-440.

[32] Le Gallo J. (2002), "Econométie spatiale : l'autocorrélation spatiale dans les modèles de régression linéaire", Economie et Prévision, 155 (4), pp. 139-158.

[33] Le Gallo J. (2004), "Hétérogénéité spatiale, principes et méthodes", Economie et Prévision, 162, pp.

[34] Le Gallo J. and Dall'erba S. (2005), "Dynamique du processus de convergence régional en Europe", Région et Développement, 21, pp.119-138.

[35] Le Gallo J. and Ertur C. (2003), "Exploratory Spatial Data Analysis of the Distribution of Regional per Capita GDP in Europe, 1980-1995", Papers in Regional Science, 82, pp. 175-201.

[36] Moreno-Serrano R., Paci R. and Usai S. (2003), "Spatial Distribution of Innovation Activity. The case of European Regions", Working Paper CRENoS, 10/2003.

[37] Romer P. (1990), "Endogenous Technological Change", Journal of Political Economy, 98, pp. 71-102.

[38] Schwarz G. (1978), "Estimating the Dimension of a model", The Annals of Statistics, 6, pp. 461-464.

[39] Tobler W. (1979), "Cellular Geography", in: GaleS., Olsson G. (eds.), Philosophy in Geography, Dordrecht, Reidel Publishing Company, pp. 379-386.

[40] Tong H. and Lim K.S. (1980), "Threshold Autoreression Cycles and Cyclical Data", Journal of the Statistical Society, 42, pp. 245-292.

[41] Tong H. (1983), "Threshold Models in Non Linear Time Series Analysis", Lecture Notes in Statistics, 21, New-York, Springer Verglag.

[42] Tsay R.S. (1989), "Testing and Modelling Threshold Autoregressive Process", Journal of American Statistical Association, 84 (405), pp. 231-240.

Documents de Recherche parus en 2007[1]

DR n°2007 - 01 : María Noel PI ALPERIN, Michel TERRAZA
« Test d'inférence statistique de l'indice multidimensionnel flou de pauvreté appliqué à l'Argentine »

DR n°2007 - 02 : Romina BOARINI, Christine LE CLAINCHE
« Social Preferences on Public Intervention : an empirical investigation based on French Data »

DR n°2007 - 03 : Jean-Pascal GUIRONNET, Magali JAOUL-GRAMMARE
« Educational Mismatches, Wages and Economic Growth : A Causal Analysis for the French Case since 1980»

DR n°2007 - 04 : Aurélie BONEIN, Daniel SERRA
« Another experimental look at reciprocal behaviour : indirect reciprocity »

DR n°2007 - 05 : Charles FIGUIERES, Fabien PRIEUR, Mabel TIDBALL
« Public Infrastrucuture, Strategic Interactions and Endogenous Growth»

DR n°2007 - 06 : Dimitri DUBOIS, Marc WILLINGER
« The role of players' identification in the population on the trusting and the trustworthy behavior: an experimental investigation »

DR n°2007 - 07 : Sandra SAÏD, Sophie THOYER
« Agri-environmental auctions with synergies »

DR n°2007 - 08 : David MASCLET, Marc WILLINGER, Charles FIGUIERES
« The economics of the telethon:leadership, reciprocity and moral motivation»

DR n°2007 - 09 : Emmanuel SOL, Sylvie THORON, Marc WILLINGER
« Do binding agreements solve the social dilemma?»

DR n°2007 - 10 : Philippe JOURDON
« L'étude des cycles de KONDRATIEFF nous permet-elle d'en savoir plus sur la nature sociale de la monnaie ? »

[1] La liste intégrale des Documents de Travail du LAMETA parus depuis 1997 est disponible sur le site internet : http://www.lameta.univ-montp1.fr

.

Contact :

Stéphane MUSSARD : mussard@lameta.univ-montp1.fr