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Factors affecting the levels of technology in the EU27 regions: A spatial model

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Abstract

A spatial and a non-spatial model are developed in an attempt to elucidate the factors that affect the variation in regional levels of technology. Both models encompass the same set of factors, viz. technology adoption, technology creation, and the overall conditions prevailing in a region. Both models are tested successfully in the context of the EU27 NUTS2 regions (during the 1995-2003 period using EUROSTAT data); although the spatial one performs better. Besides the apparent beneficial effects of spatial-interaction, the test results also suggest that the aforementioned factors, and adoption in particular rather than creation and/or conditions, are of critical importance in explaining the variation in regional levels of technology. Recommendations are thus made for technology adoption-enhancing policies.

Key words: Technology Creation Adoption, European Regions, Spatial Econometrics
JEL: O3; R1

I. Introduction

Contemporary approaches to regional development in Europe and elsewhere have placed increasing attention to the role of clusters, institutions, knowledge/learning, and innovation as key growth factors (BORRÁS and TSAGDIS, 2008). Ideas such as that regional development takes place in locations of technological innovation, that it is usually accompanied by new economic activities, market expansion, technological adaptation, and that it requires an appropriate environment (e.g. of proximity and collective learning) are as old as MARSHALL's (1890) writings; if not older.

There is thus a plethora of empirical studies dealing with technology creation and adoption. Nonetheless, an approach that explicitly combines these two elements in the ambit of a single model has remained, to our knowledge, an unexplored area in regional economics. To remedy this, an empirical model is developed in this paper to study the interaction between these two separate, but interrelated elements. Moreover, there seems to be little doubt that these two elements affect the level of technology in a region. What is less clear, however, is their relative impact. That is, which element is more powerful in enhancing the 'stock' of technology in a region? The nature of this issue appears to be an empirical one. Consequently, the approach adopted in this paper is also empirical. The rest of this paper is structured in the following manner. Section II is devoted to the development of the theoretical framework underpinning the empirical analysis. The empirical specification and econometric results are discussed in sections III and IV respectively. The paper concludes with policy recommendations in section V.

II. Determining the Level of Regional Technology

MASKELL and MALMBERG (1999, p. 174), among others (see MOULAER and SERIA, 2003 for a review), suggested that a region should not be ‘seen merely as a ‘container’, in which attractive location factors may (or may not) happen to exist, but rather as a milieu for collective learning through intense interaction between a broadly composed set of actors.’ A milieu is a created space that is both a result of and a precondition for learning and becomes, as COFFEY and BAILLY (1996) adduced an active resource rather than a passive surface. Indeed, as BOSCHMA (2005) stated ‘[…] an absorptive capacity that is open to new ideas is essential for interactive learning’ (p. 64). Regions should not just be seen as homogenous units across geographical space, but rather as “competitive geographical units that try to obtain an economic advantage through developing or adopting technologically advanced products or processes” (BUTTON and PENTECOST, 1999, p. 57).

It follows, therefore, that the level of technology in a region is the outcome of two sources. The first is a process of intentional creation of technology; a process that takes place exclusively within the ‘borders’ of a region. This is, however, only one facet of the available ‘stock’ of technology in a region. As regions are, by definition, open economies their stock of technology is also affected by technological improvements that take place in other regions. This constitutes the second source that adds to the existing stock of technology in a region. It is possible to express this process of regional ‘technogenesis’ in terms of an identity of ‘technology creation’:

$$A_{i,t} = C_{i,t} + E_{i,t} \tag{1}$$

where the subscripts i and t denote a particular region and a point in time, respectively.

In equation (1) $A_{i,t}$ is the total stock of technology available in a region, $C_{i,t}$ denotes the part of technology that is created intentionally within the region while $E_{i,t}$ accounts for the additions in the level of technology induced by the adoption of technology from other regions. Alternatively, this term includes the part of technology that is generated from interaction between spatial units. Essentially, equation (1) can be seen as a ‘snapshot’ of the level of technology prevailing in a region at any point in time. Furthermore, this equation by separating out the two distinct elements of technology provides a way to examine the contribution of each element to the stock of technology in a region.

To better grasp the above it is necessary to examine each technological component separately. Technology-creation in current time (t) improves the technology already established, i.e. the technological level in time $t-1$. Thus,

$$C_{i,t} = \bar{c}_{i,t} + \gamma_i A_{i,t-1} \ , \quad \text{with } 0 < \gamma < 1 \tag{2}$$

where $\bar{c}$ denotes the autonomous part of technology-creation. In this context the “autonomous” part can be conceived as those technological discoveries that do not necessarily improve the existing technologies in a region (e.g. not yet assimilated in production), but which nevertheless, enhance the ‘technological stock’ available in a region. Of particular importance is the parameter γ, which measures the rate at which the technology of past periods is improved, due to current research.

Using equation (2), equation (1) can be written as follows:

$$A_{i,t} = \bar{c}_{i,t} + \gamma_i A_{i,t-1} + E_{i,t} \tag{3}$$

Assuming, for the moment, that $E_{i,t} = 0$, then equation (3) can be written as follows:

$$A_{i,t} - \gamma_i A_{i,t-1} = \bar{c}_{i,t} \tag{4}$$

Equation (4) is a first order difference equation with the following solution:

$$A_{i,t} = A_{i,0}\gamma_i^t + \left(1 + \gamma_i^t\right)\frac{\bar{c}_{i,t}}{1-\gamma_i} \tag{5}$$

According to equation (5), differences in the levels of technology between regions can arise due to variations in both the autonomous and the induced part of technology creation, with the latter caused by differences in the values of γ across regions. Thus, the higher the values of γ and $\bar{c}_{i,t}$, the higher the level of technology and vice versa.

Even in the case where regions create new technological innovations at the same rate, differences in the technological stocks may arise due to differences in the ways regions improve their existing technology-related practices. Stated in alternative terms, even if $A_{i,t-1} - A_{j,t-1} = 0$ and $\bar{c}_{i,t} - \bar{c}_{i,t} = 0$, then $A_{i,t} - A_{j,t} \neq 0$ provided that $\gamma_i - \gamma_j \neq 0$.

This can be shown using an example with two regions ($i = 1, 2$). Assuming that $A_{1,t-1} - A_{2,t-1} > 0$, $\bar{c}_{1,t} - \bar{c}_{2,t} > 0$ and $\gamma_1 - \gamma_2 > 0$ then $A_{1,t} - A_{2,t} > 0$, then the initial technological differences between the two regions are perpetuated if $(\Delta\gamma_{1,2})_t \to \infty$ as $t \to \infty$, i.e. $(\Delta A_{1,2})_t \to \infty$. Of course, the 'technological gap' is exaggerated if $(\Delta\bar{c}_{1,2})_t \to \infty$. It seems thus legitimate to ask, if there is a way for Region 2, the 'technologically poor' region to catch up with the 'technologically rich' Region 1? Two possibilities can be identified. Under the assumptions of the model a technological catch up is feasible only if it increases the lagging region's rate of improving existing technologies, i.e. if $(\Delta\gamma_{1,2})_t \to 0$ as $t \to \infty$. However, this might prove to be quite difficult. A relatively low initial stock of technology might be considered as an indication that a 'technologically poor' region implements 'inferior' or obsolete technologies, compared to other regions. A relatively high initial level of technology provides an initial advantage. This, if it is sustained for some time, will allow for further additions to its level of technology. A relatively low initial level of technology, on the other hand, constrains any possible additions, a situation that may be difficult to change. There is, of course, the possibility that technologically poor regions can create new technological breakthroughs, i.e. to increase the value of $\bar{c}_{i,t}$ through time.

As introduced above the process of intentional technological creation is not the only way of enhancing a region's stock of technology. Adoption of technological improvements developed in other regions can also lead to increases in the 'stock of technology' in a region. This process of technology adoption can be incorporated in equation (1) as follows:

$$A_{i,t} = \bar{c}_{i,t} + \gamma_i A_{i,t-1} + \bar{d}_{i,t} + \varepsilon_i A_{j,t-n}, \text{ with } n > 1 \tag{6}$$

where $\bar{d}$ is the autonomous part of technology adoption and ε measures the degree of adopting technological improvements developed in an other region, j.

Equation (6) also indicates that the process of technology adoption occurs with a time-lag. A region, for example, at time $t-1$ adopts technological improvements developed in another region at time $t-2$. This process, however, will add to the level of technology in that region at time t. Therefore, equation (6) is written as follows:

$$A_{i,t} = \bar{c}_{i,t} + \gamma_i A_{i,t-1} + \bar{d}_{i,t} + \varepsilon_i A_{i,t-1} \tag{7}$$

Equation (7) can be written as follows:

$$A_{i,t} + \left(\gamma_{i,t} + \varepsilon_i\right)A_{i,t-1} = \bar{c}_{i,t} + \bar{d}_{i,t} \tag{8}$$

Equation (8) indicates that differences in the technological levels across regions arise not only due to initial technological differences but also in differences in their ability to create and adopt technological improvements.

It is possible to extent this model by assuming that technology adoption depends, firstly, upon the sources devoted to sectors implementing the latest technological improvements ($\varepsilon_{s,i}$) and, secondly the general environment of a region ($\varepsilon_{u,i}$). Once this knowledge is introduced, equation (8) is written as follows:

$$A_{i,t} = \bar{c}_{i,t} + \gamma_i A_{i,t-1} + \bar{d}_{i,t} + \left(\varepsilon_{s,i} + \varepsilon_{u,i}\right)A_{i,t-1} \tag{9}$$

Equation (9) is a first order differential equation with the following solution:

$$A_{i,t} = A_{i,0}\rho_i^{\ t} + \left(1 - \rho_i^{\ t}\right)\frac{\varphi_i}{1 - \rho_i} \tag{10}$$

where $\varphi_i = \bar{c}_{i,t} + \bar{d}_{i,t}$ and $\rho_i = \left(\gamma_i + \varepsilon_{s,i} + \varepsilon_{u,i}\right)$

The expression in equation (10) has an important implication. According to equation (10) differences in technological stocks will arise if the terms φ_i and ρ_i vary across regions. From the above the paper’s key research question arises, viz. which factor is the most powerful in shaping the level of technology in a region and in particular is it the endogenous intentional creation of technology or the adoption of exogenous technological innovations? The answer to this question is to be determined empirically in the context of the EU27 NUTS2 regions. This extensive regional context is introduced in the following section so to provide the background of the subsequent empirical analysis.

III. Empirical Specification

The model developed in the previous section emphasises certain factors that seem to play a crucial role in determining technological variations across regions. Its main argument can be summarized in terms of the following general function:

$$T_{i,t} = f\left(D_{i,t_0}, I_{i,t_0}, A_{i,t_0}\right) \tag{11}$$

Equation (11) encapsulates the argument that the level of technology available ($T_{i,t}$) in a region i over a given point in time t depends on the degree of technology adoption (D_{i,t_0}) that has taken took place in that particular region during a past period of time, the degree of intentional creation of technology (I_{i,t_0}) that occurred during a past time and the general environment of that region (A_{i,t_0}).

In order to apply empirically this model, the function in equation (11) can be written in a linear form to produce the following regression equation:

$$T_{i,t} = a + b_1 D_{i,t_0} + b_2 I_{i,t_0} + b_3 A_{i,t_0} + e_i \qquad (12)$$

where e_i is the error term of the regression.

Based on the model developed in the previous section it is expected that the relation between the levels of technology and all the explanatory variables would be positive. To be more specific, in a cross-section context, regions with relatively high (low) initial degree of technology adoption or creation, for example, will also exhibit high (low) levels of technology. A similar argument can be raised for the variable approximating the overall environment in a region. A ‘favourable’ environment, reflected by a relatively high value of A_{i,t_0}, is expected to have a positive impact on the level of technology. By the same token, a relatively low value of A_{i,t_0} reflects ‘unfavourable’ conditions in a region. Such conditions would not have any substantial impact on the level of technology and in certain cases can prevent a region to enhance its level of technology.

As it stands, this approach neglects spatial factors. Equation (12) treats regions as closed-economies. It is possible to overcome this, clearly unrealistic, assumption by introducing in equation (12) the effects of spatial interaction. Indeed, in the light of the reviewed literature[1] it could be argued that any econometric model tested in a regional context is miss-specified if the spatial dimension is ignored, the presumption being that the extent of regional interaction, such as technology spillovers, are significantly dependent upon the location of regions relative to each other.

Introducing spatial interaction, the general form of the model can be extended as follows:

$$T_{i,t} = f\left(D_{i,t_0}, I_{i,t_0}, A_{i,t_0}, S_{ij}\right) \qquad (13)$$

where S_{ij} captures the effects from interactions between regions.

In econometric terms, the potential for spatial interaction can be incorporated by means of the spatial-error model. In this model, the key feature is that spatial interaction occurs through the error term of equation (12):

$$e_i = \zeta \mathbf{W} e_i + u_i = \left(\mathbf{I} - \zeta \mathbf{W}\right)^{-1} u_i \tag{14}$$

where ζ is the spatial error coefficient and u_i is a $n \times 1$ vector for the new independent error-term with $u \sim N\left(0, \sigma^2 \mathbf{I}\right)$. Inter-regional spatial dependence is generated by means of the $n \times n$ spatial-weights matrix ($\mathbf{W}$) the elements of which (w) may be devised in various ways. For example, a common practice is to allow these weights to take the value of 1 if a region is contiguous to another and 0 otherwise (a first order continuity matrix). Alternatively, the spatial weights may be continuous variables (CLIFF and ORD, 1981), constructed so as to produce declining weights as distance between regions increases. Thus:

$$w_{ij} = \frac{1/d_{ij}}{\sum_j 1/d_{ij}} \tag{15}$$

where d_{ij} denotes the distance between two regions i and j, as measured by the distance between the major urban centres where the majority of economic activities are located. The denominator is the sum of the (inverse) distances from all regions surrounding region i. This approach is used in the empirical analysis in the subsequent section.

Thus, taking into account the effects of spatial interaction, equation (12) is transformed as follows:

$$T_{i,t} = a + b_1 D_{i,t_0} + b_2 I_{i,t_0} + b_3 A_{i,t_0} + \left(\mathbf{I} - \zeta \mathbf{W}\right)^{-1} u_i \tag{16}$$

At this stage, however, it is important to comment on the estimation methods for these spatial econometric models. Estimation of the spatial error model is carried out by the maximum likelihood method, as OLS may result in problems of bias. To be more specific, the presence of spatial interaction in the error term leads to the following non-spherical covariance matrix (REY and MONTOURI, 1999, p. 149):

$$E\left[\varepsilon_t \varepsilon_t'\right] = (\mathbf{I} - \zeta\mathbf{W})^{-1} \sigma^2 \mathbf{I} (\mathbf{I} - \zeta\mathbf{W})^{-1'} \tag{17}$$

The presence of non-spherical errors results in unbiased OLS estimators but biased estimations of a parameter’s variance. BERNAT (1996) noted that the presence of spatial autocorrelation invalidates the standard tests in OLS regressions in a way similar to heteroscedasticity. Thus, all inferences based on that model are invalid. Hence, the recommended estimation method is through maximum likelihood.

Having established the specification of the model its testing, in the context of the EU27 NUTS2 regions, follows in the next section.

IV. Empirical Application

A key feature of the model discussed in section II is that technical change originates either from within the region or from other regions. The literature (FAGERBERG *et al.* (1996), JAFFE *et al.* (1993), GUERRERO and SERÓ (1997), PIERGIOVANNI and SANTARELLI (2001) among others) uses various proxies of technology; e.g. related to R&D expenditure, patent applications and citations. SOETE (1981) however, drew a distinction between two alternative measures of technology, viz. input and output ones. R&D expenditures and labour employed in R&D activities would fall under the input category, whereas patents (citations, applications, etc.) would fall under the output category. Given that the dependent variable in equation (12) and (16) refers to the output of the technological activities, this is expressed in terms of patents per inhabitant as those are reported by the patent applications to the European Patent Office (EPO) by priority year at the regional level. The relevant data, as for all explanatory variables, were obtained from EUROSTAT and cover the 1995-2003 period.

The geographical distribution of patent applications in 1995, the initial year of the analysis, is provided in Figure 1. A high number of patents per-capita (over 200) is detected in the capital regions of France, Germany, Belgium, and the UK. An overall impression from Figure 1 is that the number of patents per-capita reduces as the distance from these regions increases. Figure 1 suggests that the EU27 peripheral regions exhibit rather low levels of ‘technological stocks’; a situation that characterises the vast majority of Mediterranean and Eastern European regions.

Regarding the explanatory variables, these are approximated as follows. A region’s level of technological development and adoption capacity is measured as the percentage of total employment in technologically advanced sectors. A similar approach is used for measuring the intentional creation of technology; viz. by the number of workers employed in the science and technology sectors of each region.

A common way of approximating the overall environment of a region is by considering external or agglomeration effects, defined as “all economic advantages accruing to firms from concentrated location close to other firms” (CAPELLO, 2007, p. 18), usually measured[2] by population density (inhabitants per square mile) of a region. This approximation is used for the measurement of the A_{i,t_0} variable.

Finally, it should be noted that the time dimension of variables describing technology should refer to the initial point in time for the period of study (viz. 1995). From an econometric point of view, inclusion of technological variables measured at the initial time helps to avoid the problem of endogeneity. Moreover, PIGLIARU (2003) claimed that models which include measures of technology require data on total factor productivity. In the absence of such data, econometric estimation requires that the variables related to technology ought to be included in initial values.

The estimation results of the non-spatial version of the model are reported in Table 1. Estimation of equation (12) yields significant results for all the explanatory variables. This implies that the intentional creation and adoption of technology undertaken over an initial time, in conjunction with the overall conditions prevailing in a region make a contribution in determining its level of technology. As the estimated coefficients are positive, it could be further argued that the aforementioned factors have a positive effect upon the level of technology. The obtained value of the adjusted R^2, however, is low. This suggests that additional variables should be included so to capture the additional factors that determine a region’s level of technology. An obvious shortcoming of the regression so far is the omission of spatial interaction. Table 2 sets out the results from estimating the spatial version of the model, i.e. equation (16).

As previously, all explanatory variables are statistically significant, as indicated by the obtained t-ratios.[3] In a spatial context, a frequent problem is the presence of heteroscedasticity. Based on the Breusch-Pagan and Koenker tests, the hypothesis of heteroscedasticity is accepted in the case of the non-spatial version. Those tests, however, accept the alternative hypothesis of homoscedasticity for the spatial version, since the associated values are less than the critical χ^2 values, at 95% level of probability. The Lagrange-Multiplier and the Robust Lagrange-Multiplier tests accept the hypothesis of spatial dependence and confirm the superiority of the spatial over the non-spatial version of the model. This argument is further enhanced according to the Akaike (AIC) and the Schwartz-Bayesian (SBC) information criteria.[4]

The spatial version of the model is clearly preferred based on the LIK statistic.[5] As shown in Table 2, the spatial version scores the highest value of the LIK statistic, suggesting that this particular model provides a better explanation of the determinants of technology across the European regions.

A potential problem with this model is related with the presence of multicollinearity, which can be detected by calculating the variance inflation factors (VIF). More specifically, for any regression equation with k independent variables, it is possible to calculate a VIF for every dependent variable running an OLS regression for each variable as a function of all the other explanatory variables. Then a VIF is calculated for each $\hat{\beta}_i$ using the following formula:

$$VIF(\hat{\beta}_i) = \frac{1}{1-R_i^2}, \quad \forall\, i = 1, \ldots, k \tag{14}$$

where R_i^2 is the multiple correlation coefficient.

As a rule of thumb, if $VIF(\hat{\beta}_i) > 5$, then multicollinearity is high. The obtained VIF values associated with the independent variables of the model are set out in Table 3. High multicollinearity is not detected for any of the explanatory variables. The average VIF value is about 1.2, which may be taken as an indication that multicollinearity in the model is not very high.

In quantitative terms, the impact of the variable approximating the process of technology adoption is such that a 1% change is associated with an impact on a region’s technological level about 11% on average, as suggested by the obtained results using the spatial version. This impact is slightly greater than that implied by the non-spatial version. This increase might attribute to the fact that the model is adjusted for the effects of spatial interaction. A factor which indubitably enhances the degree of technology adoption, especially in the case of regions located in close distance. Attention should also be drawn to the fact that the estimated value of the adoptive factor is higher than those obtained for the other two factors. According to the estimated coefficients the overall conditions and the intentional creation of technology imply each, a 2% impact on the level of technology.

This difference in the relative impacts suggests that technology adoption might be the best ‘vehicle’ for lagging regions to enhance their technological levels. Nevertheless, this might be difficult for technologically lagging regions, especially during their early stages of development when conditions are least supportive. The message, therefore, from the empirical application of the model developed in this paper should be clear. The adoption of technology to set the technologically lagging EU regions in a process of technological enhancement requires developing such conditions that will allow them to adopt and assimilate technological innovations.

VI. Conclusions

It is of little doubt that a region's ability to act as a 'hub of innovation' is related to the efficient use of its resources, rendering activities related to technological innovation as the key to regional development. Such activities are obviously related to investments in R&D and innovative sectors. These however, do not automatically translate to increases in the 'technological stock' of a region. Technological progress also requires an appropriate environment. Such an environment can be considered as a 'collective learning process' within which many individuals interact and exchange ideas and information. Thereby developing a 'knowledge-rich' environment that determines technical progress across space; bringing to the forefront in turn, issues of space, and in particular spatial proximity and interaction.

This paper has offered a theoretical model that takes explicitly into consideration the aforementioned considerations. The model was empirically tested using data for the EU27 NUTS2 regions during the 1995-2003 period. It is clear from the econometric results that the regional levels of technological stock are positively related with all three factors of the tested model; viz. the level of intentional technology creation, adoption, and the overall environment of a region. A further indication that the econometric analysis offers is that adoption of technological innovations appears to increase the technological stock to a greater extent, compared to the two other factors. A policy implication, therefore, is that efforts to enhance regional levels of technology (at the face of scarce policy-resources) are better off concentrating on improving adoption capacity through appropriate: education and training policies, incentives (e.g. tax breaks for technology adoption), the development/engagement of knowledge-breaking institutions (e.g. HEIs, technology transfer centers), knowledge propagation networks, etc.

Obviously the evidence reported here are indicative at best, and thus further research is also recommended as additional data become available, through additional explanatory variables, and more detailed case studies of actual policies and instruments that may have yielded the sought improvements.

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Table 1. *Determinants of Technological levels across the EU27 Regions, non-spatial model*

$T_{i,t} = a + b_1 D_{i,t_0} + b_2 I_{i,t_0} + b_3 A_{i,t_0} + e_i$, OLS, n=267 $t = 2003$, $t_0 = 2003$

	Estimated Coefficient	Standard Error	t-ratio [prob]	F (3, 263) [prob]
a	0.0341396	0.0347482	0.982 [0.327]	51.51 [0.000]
b_1	0.1050242	0.0128425	8.178 [0.000]	
b_2	0.0202499	0.0065060	3.112 [0.002]	
b_3	0.0206837	0.0068681	3.012 [0.003]	
Adjusted R^2	LIK	AIC	SBC	
0.3629	176.912	-345.8240	-331.4750	
Breusch-Pagan Test	Koenker Test	LM	Robust LM	
7.95423 [0.0469]	4.79554 [0.18739]	15.6759 [0.0739]	12.5139 [0.0514]	

Note: Column F gives the F-Statistic and the probability [prob] for the overall significance of the regression. AIC, SBC and LIK denote the *Akaike*, the *Schwartz-Bayesian* information criteria and Log-Likelihood, respectively. LM denotes the Lagrange Multiplier.

Table 2. *Determinants of Technological levels across the EU27 Regions, spatial model*

$T_{i,t} = a + b_1 D_{i,t_0} + b_2 I_{i,t_0} + b_3 A_{i,t_0} + (\mathbf{I} - \zeta \mathbf{W})^{-1} u_i$, Maximum Likelihood, n=267 $t = 2003$, $t_0 = 2003$

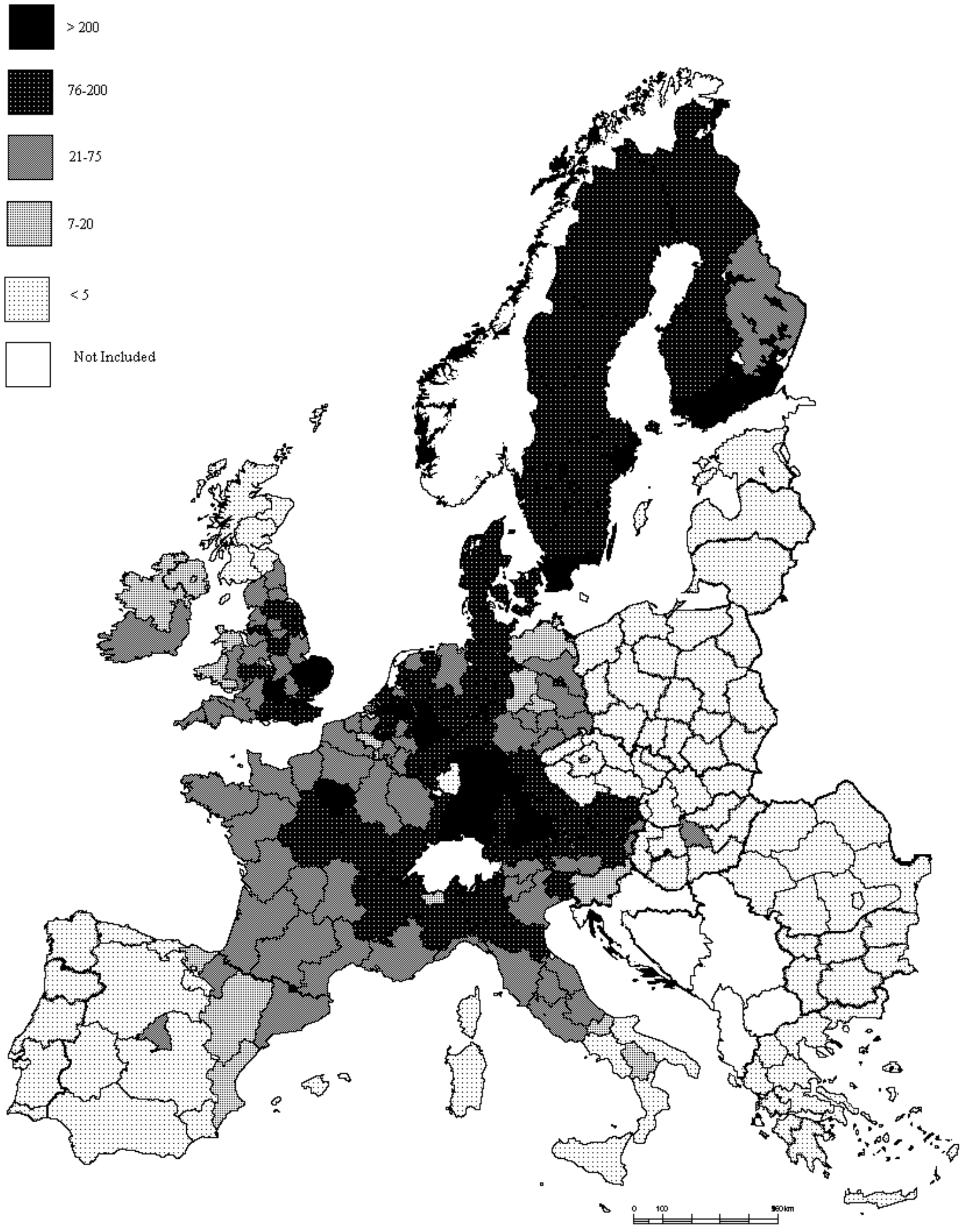
	Estimated Coefficient	Standard Error	t-ratio [prob]	F (4, 262) [prob]
a	0.074828	0.020967	3.569 [0.000]	223.52 [0.000]
b_1	0.110732	0.009457	11.708 [0.000]	
b_2	0.021377	0.003910	5.467 [0.000]	
b_3	0.018374	0.004128	4.450 [0.000]	
ζ	0.233071	0.047392	2.601 [0.000]	
LIK	AIC	SBC		
313.3850	-616.7700	-548.8338		
Breusch-Pagan	Koenker	LM	Robust LM	
7.21257 [0.005]	2.2661 [0.003]	23.9199 [0.002]	15.301 [0.005]	

Notes: Column F gives the F-Statistic and the probability [prob] for the overall significance of the regression. AIC, SBC and LIK denote the *Akaike*, the *Schwartz-Bayesian* information criteria and Log-Likelihood, respectively. LM denotes the Lagrange Multiplier

Table 3. *Variance Inflation Factors*

Variable	VIF
D_{i,t_0}	1.25266
I_{i,t_0}	1.22309
A_{i,t_0}	1.10926

Fig. 1. *Patents per-capita, EU27 NUTS-2 Regions, 1995*



NOTES

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[1] See for example ANSELIN (1988), ANSELIN *et al*. (1996), ANSELIN and FLORAX (1995a) among others.

[2] See for example SVEIKAUSKAS (1975), SVEIKAUSKAS *et al*., (1988), MION (2004), BRAUNERHJELM and BORGMAN (2004) among others.

[3] The presence of spatial autocorrelation makes the R^2 an unreliable measure of the goodness of fit and so is not reported.

[4] As a rule of thumb, the best fitting model is the one that yields the minimum values for the AIC or the SBC criterion, calculated as $AIC = -2L + 2K$ and $SBC = -2L + K \ln(T)$, where L is the value of the log likelihood function, T is the number of observations and K stands for the number of parameters estimated. SBC is superior to the AIC which is biased towards an over-parameterized model.

[5] The Log-Likelihood is extensively used in spatial econometrics, such that the best fitted model is the one that yields the greatest value for this criterion (ANSELIN, 1988; ANSELIN *et al*., 1996).