The New Operational Dynamics of Technological Diffusion: An Empirical Study of Innovation Performance

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ABSTRACT
This paper identifies and evaluates the productivity of the factors that generate new knowledge. It provides a systematic analysis of the relationship between universities and firms in Automobile, Chemical, Electro-technology and Manufacturing industries which generates economically useful new technological knowledge. An applied spatial econometric framework is employed since this approach is particularly useful in the study of the spatial patterns of patents' productivity, at the lowest possible levels of spatial aggregation.

INTRODUCTION

Economic history is full of examples which suggest that technological creativity has been one of the most important sources of long-term economic growth. However, like other 'gifts', this talent has not been equally distributed among people, firms, industries or regions. What is more this kind of inequality often not even balances out on the level of states or regions. Obviously some nations have done better than others in bringing forth particular industries dominating international markets by their comparatively superior capability to innovate. That is why, measured by economic standards, some countries have been forging ahead while others have been falling behind (European Commission 2000, 2001). Nevertheless, it would be wrong to conclude from these empirical observations that we have to accept such an uneven development in the future too. Instead socioeconomic framework of those nations lagging behind may be able to improve the technological creativity in their particular home market by changing the attributes of the legal, cultural and economic environment.

Entrepreneurship and innovation became synonymous when Schumpeter made them central to his model of economic development. Through the impact of 'creative destruction' he saw them lying at the very heart of the competitive process (Schumpeter 1942; Westhead and Wright 2000). Schumpeter has had a massive impact on business history, on the history of innovation, on the shaping of ideas relating to strategic response, and on the analysis of economic decline (Elbaum and Lazonick 1996). Similarly, whilst there has been extensive work by business historians on innovation, it has been set either in the context of technology or Research and Development (R &D) with the result that there has been little analysis of how the innovation process worked as an integral part of a competitive strategy. Most significantly , whilst 'innovation' may be an acknowledged entrepreneurial trait, business historians have tended not to explore the relationship between universities and the production of new technology by firms. Moreover, where it ha been discussed, the emphasis has tended to be on sectoral industrial behavior, rather than on systematic network among the universities and industries.

Economists often assume that a firm needing new equipment will purchase outright the most advanced technology available at the time (Paci and Usai, 2000). The frictionless acquisition of new technologies is a common modeling assumption. But, in fact, firms do have an alternative: they can produce new technology. In particular, when a technology is expected to improve over time and when the firm's investment in technology is at least partially irreversible, the option value of creating new equipment may be significant. Expectations about future productivity growth and related price changes may substantially alter the decision to invest (Krugman, 1991). A firm considering investment in new technology must wrestle with a difficult tradeoff of whether to buy it or to create it (assuming that it has the capability). Real options methods now provide managers a better means to make technology adoption decisions, to gauge conditions for the acceptance of new technology more accurately, and to understand which market segments might be most likely to adopt (Zucker et al, 1998). This paper explores the creation of new, improving technologies using an econometric model which accounts for spatial dependence. These methods are applied to a case of technological advancement in a particular geographical area (Soete and Weel, 1999). Economic models tend to view technological change either as a discrete switch of technologies or as a steady stream of incremental improvements without considering the case of spatial clustering effects (Acs et al, 2002). In the first case, technological change is treated as a sudden "technology shock," to which economic variables slowly adjust; in the latter case, it is treated as continuous change often at a fixed rate of productivity growth (Feldman, 1994). Yet in reality, both sorts of change may occur concurrently. Discrete new technology shifts are typically accompanied by changes in the rate of incremental improvement. Firms contemplating the adoption of a new technology are, of course, aware of this pattern of sequential improvement. They consider not only the current productivity level of the new technology, but also expectations of future productivity. Two sorts of expectations may affect their investment decisions. First, firms expect alternative sources (i.e., universities) of the new technology to be more productive (Fischer and Varga, 2001). Second, to the extent that entry into the market is unrestricted and that the technology is available to other prospective entrants, firms expect future vintages to be accompanied by lower entry thresholds and hence lower prices.

The focus of this paper is on productivity measurement of new technology. More precisely, technological growth for any industrial sector follows a Cobb-Douglas production function framework and is called the index number approach. The basic research question behind this paper is to identify and evaluate the productivity of the factors that generate new knowledge. It examines the issue of knowledge spillovers from an explicit spatial econometric perspective, yielding more precise insights into the range of spatial correlation between productivity of patents, R&D expenditure and employment, across European Union (13 countries). In the remainder of the paper, we briefly describe the data, followed by an outline of a spatial econometric framework. The forth section presents the models of study and analytical results are shown in the fifth section. A summary concludes the paper.

DATA AND VARIABLES

The data used for this analysis contains territorial units identified by Eurostat (official statistical bureau of European Union) in each European country, called NUTS (Nomenclature Units Territory Statistics). In contrast to any related studies, we carry out an analysis at the lowest possible of European Union[1] (EU) sub-country level (i.e., NUTS 2 level) of spatial aggregation. These regions are rather homogeneous within them and are administrative units, which have some degree of independence. As a measure of innovative output of a region we use the number of patents in each region filed with the European Patent Office, as it is generally done in this literature (Jaffe et al, 1993). Thus, patents can be viewed as a satisfactory indication of knowledge spillovers, which one would like to have for exploring theories on innovation or R&D policies.

Furthermore, there is a number of explanatory variables that are employed in our

[1] Austria and Greece were excluded due to data limitations.

analysis. The R&D expenditures of firms in four industries [Automobile (RD_A), Chemical (RD_C), Electro-technology (RD_E) and Manufacturing (RD_M)], and universities (RD_U) refer to the expenditures made by those institutions for research and development purposes. Moreover, employment at firms (L_F , with F = A, C, E, M) and universities (L_U) denotes the number of employees (Head Count) at each region. Moreover, we use Gross Domestic Product (GDP) and employment at the R&D sector of the european governments (L_G) in order to capture local economic characteristics.

The are two sources of knowledge, we include in the regression model, universities and firms in the described industries. Our data refers to 13 European Countries and all the variables are measured according to the suggestions of Eurostat. A major target of this study is two-fold. Firstly, to clarify whether productivity of patents in European Union presents any spatial dependence or characteristics, and secondly to examine the separate role of industries and universities in the productivity of patents.

METHODOLOGY

We use a spatial econometric framework (Anselin 1988, 2002; Anselin and Bera, 1998) since this approach[2] is particularly useful in the study of the spatial patterns of patents' productivity. When models are estimated for cross-sectional data on neighboring spatial units the presence of spatial dependence may cause serious problems of model misspecification. The methodology of spatial econometrics consists of examining and testing for the potential presence of such misspecifications and of providing a more appropriate modeling that incorporates the spatial dependence (Anselin et al, 1997; Varga, 1998). There are two forms that are most relevant in applied empirical work (Varga, 2000). Firstly, we have the model for dependence in the form of a spatially lagged dependent variable and secondly, we have the model for dependence in the regression error form. Therefore, the Spatial Lag Model for Knowledge Production Function can be expressed in matrix notation:

$$Y = \rho WY + Z\alpha + \phi \tag{1}$$

where Y is a vector of observations on the patent variable, W is the weights matrix, which is typically constructed from information on the contiguity between two spatial units. The resulting spatial lag WY can be considered a spatial weighted average of the observations at "neighboring" location (Anselin, 1988). We have to mention that by ignoring a spatially lagged dependent variable yields inconsistent and biased estimates for the coefficients of the model. Also, ϕ is a vector of normally distributed random error terms, and ρ is the spatial autoregressive parameter. Therefore, the spatial lag term has to be treated as an endogenous variable and proper estimation procedures have to account for endogeneity.

The second way to incorporate spatial autocorrelation into the regression model for knowledge production is to specify a spatial process for the disturbance terms. It goes without saying that unbiased and efficient estimators are obtained by specifying the error covariance implied by the spatial process (Anselin and Bera, 1998). Thus, the Spatial Error Model for Knowledge Production Function, in matrix notation, is given by:

$$Y = Z\alpha + \phi \tag{2}$$

with,

$$\phi = \lambda W\varphi + v \tag{3}$$

where ϕ is the error vector, λ is the spatial autoregressive coefficient and v is considered to be a white noise error. Finally, the errors ϕ are assumed to follow a spatial autoregressive process with autoregressive coefficients.

[2] From the recent literature, see for example Acs et al. (2002) and Quevedo (2002).

As evidence in a large Monte Carlo simulation experiments in Anselin and Rey (1991), the joint use of the Langrage Multiplier (LM) tests for spatial lag[3] and spatial error[4] dependence, suggested by Anselin (1988), provides the best guidance for model specification. When both tests have high values indicating significant spatial dependence in the data, the one with the highest value (lowest probability) will indicate the proper specification. Moreover, a widely used diagnostic test for spatial error dependence is an extension of Moran's I to the regression context[5].

Then, we define the log likelihood function for spatial lag model (5.1), which is:

$$L(\sigma^2,\lambda,\beta) = \sum \ln(1-\rho\omega_i) - (N/2)\ln(2\pi) - (N/2)\ln(\sigma^2) - \{(y-\rho Wy - X\beta)'(y-\rho Wy - X\beta)\}/(2\sigma^2) \quad (4)$$

The first conditions for the ML estimators yield nonlinear (in parameters) equations and need to be solved by numerical methods. For a ML estimate for ρ it is obtained from a numerical optimization of the concentrated log-likelihood function.

The maximum likelihood estimation for the spatial error model employs the error covariance term into log-likelihood function as follows:

$$L(\sigma^2,\lambda,\beta) = -(1/2)\ln|\Omega(\lambda)| - (N/2)\ln(2\pi) - (N/2)\ln(\sigma^2) - \{(y-X\beta)'\Omega(\lambda)^{-1}(y-X\beta)\}/(2\sigma^2) \quad (5)$$

As in spatial lag model, the ML estimate can be solved numerically and the estimate of is obtained from the optimization of a concentrated log-likelihood function.

It has to be mentioned that $\log|I-\lambda W| = \sum_{i=1}^{n}\log(1-\lambda\omega_i)$, where ω_i are the eigenvalues of W (Anselin, 1988). In addition, we have the ML estimators $\hat{\sigma}^2 = n^{-1}y'\mathrm{M}'My$. The estimates for the □$_t$ are obtained as the solution to T nonlinear equations for each t, of the form,

$$tr W(I-\lambda_t W)^{-1} = \sum_n \sigma^{tn}[\varepsilon_t' W'(I-\lambda_t W)\ \varepsilon_n] \quad (6)$$

where □^{tn} is the tth element in the inverse matrix. Based on the framework outlined in Heijmans and Magnus (1986), it can be shown (e.g., Anselin and Bera, 1988) that the resulting estimates have the usual asymptotic properties, including consistency, normality, and asymptotic efficiency (e.g., Silverman, 1986). The asymptotic variance matrix follows as the inverse of the information matrix. So,

Asy Var[□,□,,□^{2}]=

$$= \begin{bmatrix} tr(Q)^2 + tr(Q'Q) + \frac{[QX\beta]'[QX\beta]}{\sigma^2} & \frac{(X'QX\beta)'}{\sigma^2} & \frac{tr(Q)}{\sigma^2} \\ \frac{X'QX\beta}{\sigma^2} & \frac{X'X}{\sigma^2} & 0 \\ \frac{tr(Q)}{\sigma^2} & 0 & \frac{N}{2\sigma^4} \end{bmatrix} \quad (7)$$

where Q=W(I-□W)$^{-1}$. It has to be mentioned that the covariance between □ and the error

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[3] The LM-LAG statistic has the following form: $LM-LAG = \frac{(e'Wy/s^2)^2}{RJ_{\rho-\alpha}}$ where, e is a vector of OLS residuals, y is the dependent variable and $RJ_{\rho-\alpha} = [T + (WZa)' M (WZa)/s^2]$, where $T = tr(W'W + W^2)$ with tr as the matrix trace operator and $M = I - Z(Z'Z)^{-1}Z'$ is the projection matrix. The statistic is distributed as χ^2 with one degree of freedom.

[4] The LM-ERR test for spatial error dependence is suggested by Burridge (1980) and has the following form: $LM-ERR = \frac{(e'We/s^2)}{T}$. The statistic is distributed as χ^2 with one degree of freedom.

[5] The test statistic is I = e'We/e'e , where e is an N by 1 vector of regression residuals from the OLS estimation on a sample with N observations, and W is a (typically row-standardized) N by N weights matrix. Inference is based on the normal distribution.

variance is different than zero. In other words, we lack block diagonality in the information matrix for the spatial lag model.

MODEL SPECIFICATION

We employ a standard Cobb-Douglas production function (Jaffe, 1989) to represent the relationship among productivity of patents, R&D expenditure, employment and a number of explanatory variables, which capture the local characteristics of each spatial unit:

$$P_i = A(RD_{ui})^a (RD_{fi})^b L_{ui}^c L_{fi}^d X_i^j \tag{8}$$

where subscript i=1,…,157 refers to cross-sectional spatial units, P_i is the number of patents at area i, RD_u is the research and development expenditure for universities, RD_f is the research and development expenditure for each industrial sector, L_u is the employment at universities, L_f is the employment at each industrial sector and X is a vector of explanatory variables which includes Gross Domestic Product (GDP), and employment at R&D sector of the government (L_G).

By dividing both sides by [(RD).L], the left-hand side of equation coincides with the official Total Factor Productivity (TFP) measure used by OECD (1999). We know that OECD defines factor productivity using:

$$TFP = \frac{Y}{K^v L^g} \tag{9}$$

where Y is the total output, K is the corresponding value of the capital stock and L is the labor input. Furthermore, parameters v and g are, respectively, 0.3 and 0.7, as suggested in OECD (1999). We have to mention that the proposed capital and labor shares are derived from all the sectors of the economy. Following a similar intuition we define Total Patent Productivity (TPP) for firms in different industries. We slightly manipulate the OECD formula in order to adjust it to our case. After, using the proper notation we get

$$TPP_f = P_i \frac{(RD_{ki})^v L_{ki}^g}{(RD_{ui})^v L_{ui}^g + (RD_{fi})^v L_{fi}^g} = P_f \tag{10}$$

where f represents firms of each industry and, i refers to the spatial unit of study and P_i is the total number of patents per region i. Thus, the equations for patent productivity of firms in different industrial sectors is defined as

$$P_f = A(RD_{ui})^a L_{ui}^c (RD_{fi})^b L_{fi}^d X_i^j \tag{11}$$

After taking natural logarithms and using equations (8) to (11) we have the following model:

$$P_f = \ln A_u + a\ln(RD_{ui}) + c\ln L_{ui} + b\ln(RD_{fi}) + \\ + d\ln L_{fi} + n\ln GDP_i + q\ln L_{Gi} \tag{12}$$

We will use the following diagnostic and specification tests in order to formulate our empirical model:

1. Test for Spatial Autocorrelation----Moran's I test.
2. Test against Spatial AR/MA Error----LM Test/Rao Score (RS) Test
3. Test against Spatial Lag----LM Test for spatial lag.

The empirical form of the model for each industry is established according to the results of the described tests. Therefore, estimation of models that incorporate spatial dependence is achieved by maximum likelihood estimation, which is known to achieve the properties of consistency, asymptotic efficiency, and asymptotic normality. As an alternative to maximum likelihood approach, instrumental variables (IV) estimation is employed under the condition that asymptotic normality is violated (Anselin and Bera, 1988).

RESULTS AND DISCUSSION

The empirical evidence suggests that the productivity of patents by firms in different industries, in a particular geographical area, is affected by the presence and activities of the universities. In light of the above result, we can conclude that R&D and employment indeed affect the productivity of patents by firms in a relatively different degree. Moreover, productivity seems to respond to changes in R&D and employment at a considerable spatial degree. We studied spatially lagged error terms for certain specification of contiguity matrix (W) and in several cases they are significant at conventional levels.

Our findings suggest that the productivity of patents is highly related with the spatial dimension of R&D and employment. In other words, it seems that there is a significant interaction among the spatial units under study (NUTS 2 level), implying that the effect of R&D and employment on those units innovative activities spill over from outside the units at NUTS 2 level. To the extent to which patent counts are reliable measure of innovative activity, we would expect to see similar results when the patent measure is substituted for the number of innovations in the regression models. However, when patents are applied to measure innovation in the regression context some caution is suggested while interpreting the results.

Tables I, II, III and IV estimate model (12) for each industry. White test reveals that there is a specification problem if we follow the standard OLS approach. Thus, we use a spatial error equation which incorporates heteroskedasticity (since Breusch-Pagan test fails to accept the null hypothesis). Therefore, we estimate the model using a common specification of heteroskedasticity which is called additive heteroskedasticity[6]. Under such type of heteroskedasticity the error variance is expressed as a linear function of a set of explanatory variables. Estimation of the model (12) is followed Amemiya's three-step FGLS method (Amemiya, 1985).

Our results (Table I to Table IV) indicate that the estimated coefficients of R&D for Chemical and Electro-technology industries are greater than one but the corresponding coefficients for Manufacturing and Automobile industries are smaller than one. In other words, an investment in R&D sector of firms in Chemical and Electro-technology industries returns a higher number of patents than in Manufacturing and Automobile industries. Moreover, the elasticity of employment differs significantly across the described industries. In contrast, the elasticity of employment in universities affects any industrial sector almost at the same rate. Furthermore, GDP per region has an important impact on the production of patents per industry. Thus, the financial welfare of any geographical area is directly related to the ability of firms to produce new technology. Finally, employment at R&D sector of governmental research institutions plays a minor role for the creation of new technology.

According to the diagnostic tests all the industrial sectors follow a spatial error model formulation (since LM-Error statistic is greater than LM-Lag statistic) which means that the neighboring firms (spatial lag dependent variable) in the same industry do not have a severe participation in the production process of new technology at a particular geographical area. In other words, the productivity of new knowledge from firms in a given industry presents spatial dependence on factors which are not related directly to the productivity of technology of nearby competitive firms.

CONCLUDING REMARKS

The empirical evidence suggests that the productivity of patents by firms in Automotive, Chemical, Electro-technology and Manufacturing Industries is affected, by the presence and activities of the universities, at a significant way. In light of the above result, we can conclude that R&D and employment in any of the above industries have an important role but it's not unique. Moreover, productivity seems to respond to changes in R&D and

[6] For more details see Amemiya, 1985.

employment at neighboring locations for certain specification of contiguity matrix (W).

Our findings suggest that the productivity of patents in European Union is highly related with the spatial dimension of R&D and employment. In other words, it seems that there is a significant interaction among the spatial units under study (NUTS 2 level), implying that the effect of R&D and employment on those units innovative activities spill over from outside the units at NUTS 2 level. To the extent to which patent counts are reliable measure of innovative activity, we would expect to see similar results when the patent measure is substituted for the number of innovations in the regression models.

The results of this study may be particularly useful for the formulation of any regional development plan. Too often successful projects[7] did not produce marketable results, either because they have been isolated from market and social considerations despite their technical excellence, or because the means by which they were to be exploited were not specified or even thought about at the earliest stages of work. On the other hand they have helped to keep Europe in the technological race. But the most important effect is that those programs have gradually become the driving force behind the formation of dynamic networks beyond formal collaboration, since they bring together researchers from the best laboratories in European firms and give private firms the opportunity to benefit from a larger pool of resources than is available in a single nation. They have unquestionably fostered the emergence of closer linkages and the creation of a critical mass through networking. In addition, they provide stable financial support; they lead to a reduction of competition among researchers and between researchers and industry and of course provide access to complementary skills, means and tools. Such projects may be considered or formulated under the results of our approach.

In the light of the above discussion, we may understand the 'spatial' dimension of the relationship among industries and universities. For instance, any change in the number of neighboring universities' researchers has a direct impact on the productivity of patents by the industries at a particular area. In sum, we have found in this paper that the productivity of patents by industries in European Union presents a substantive spatial dependence and that there is a well established connection among those institutions across the European Union.

[7] The term 'project' refers to the stage of creation of a new invention where the objective is to generate a new idea. Ideas that show preliminary signs of creating valuable inventions are retained for further consideration and become development 'programs'.

Table I
Spatial Regression for Chemical Industry (Depended Variable: Patents)

	OLS	**Spatial-Error ML**	**FGLS**	**FGLS (Augmented)**
Constant	-1.71 (0.55)	-1.57 (0.56)	-1.72 (0.53)	-4.59 (2.34)
RD_C	1.12 (0.12)	1.14 (0.12)	1.19 (0.11)	1.17 (0.12)
RD_U	-0.34 (0.14)	-0.42 (0.14)	-0.35 (0.13)	-0.51 (0.18)
L_C	0.42 (0.16)	0.50 (0.15)	0.35 (0.15)	0.31 (0.15)
L_U	-0.45 (0.08)	-0.50 (0.09)	-0.49 (0.08)	-0.52 (0.09)
Lambda		0.41 (0.11)		
GDP				0.32 (0.09)
L_G				0.06 (0.01)
Diagnostics				
R^2-adj	0.74			
Jarque-Bera Test	9.12			
Breusch-Pagan Test	55.21	45.35		
White Test	47.96			
Moran's I (error)	2.28			
LM-Error				
W_{41}	5.85	2.45		
W_6	6.81	3.52	0.28	1.34
W_{12}	1.64	0.98		
LM-Lag				
W_{41}	5.37	2.11		
W_6	3.71	1.12		
W_{12}	0.80	0.12		

Notes: Regression results for Chemical Industry at the NUTS 2 level of European Union. Estimated standard errors are in parentheses; critical value for the White test-statistic with 5 degrees of freedom is 11.07 (P=0.05); critical value for LM-Error and LM-Lag is 3.84 (P=0.05); spatial weights are row-standardized: W_{41} is distance-based contiguity for 41 Km; W_6 is a contiguity matrix based on the 6 nearest neighbors; and W_{12} is a contiguity matrix based on the 12 nearest neighbors Reported estimates are significant at P=0.05.

Table II
Spatial Regression
for Manufacturing Industry (Depended Variable: Patents)

	OLS	Spatial-Error ML	FGLS	FGLS (Augmented)
Constant	-3.29 (0.53)	-3.36 (0.53)	-2.65 (0.51)	-6.88 (1.98)
RD_M	0.85 (0.12)	0.82 (0.11)	0.88 (0.11)	0.85 (0.12)
RD_U	-0.03 (0.14)	-0.02 (0.13)	-0.11 (0.03)	-0.38 (0.17)
L_M	0.41 (0.16)	0.43 (0.16)	0.32 (0.15)	0.24 (0.05)
L_U	-0.23 (0.08)	-0.34 (0.08)	-0.37 (0.07)	-0.41 (0.09)
Lambda		0.24 (0.13)		
GDP				0.52 (0.27)
L_G				0.08 (0.01)
Diagnostics				
R^2-adj	0.58			
Jarque-Bera Test	52.26			
Konker-Bassett Test	85.31			
Breusch-Pagan Test		203.11		
White Test	92.36			
Moran's I (error)	1.63			
LM-Error				
W_{41}	5.15	2.34		
W_6	6.85	2.58	3.05	2.43
W_{12}	1.64	0.67		
LM-Lag				
W_{41}	2.66	1.96		
W_6	5.37	2.11		
W_{12}	0.81	0.34		

Notes: Regression results for Chemical Industry at the NUTS 2 level of European Union. Estimated standard errors are in parentheses; critical value for the White test-statistic with 5 degrees of freedom is 11.07 (P=0.05); critical value for LM-Error and LM-Lag is 3.84 (P=0.05); spatial weights are row-standardized: W_{41} is distance-based contiguity for 41 Km; W_6 is a contiguity matrix based on the 6 nearest neighbors; and W_{12} is a contiguity matrix based on the 12 nearest neighbors Reported estimates are significant at P=0.05.

Table III
Spatial Regression for Electro-Technology Industry (Depended Variable: Patents)

	OLS	**Spatial-Error ML**	**FGLS**	**FGLS (Augmented)**
Constant	-1.53 (0.51)	-1.54 (0.52)	-1.53 (0.51)	-5.79 (2.26)
RD_E	1.18 (0.11)	1.16 (0.11)	1.17 (0.11)	1.14 (0.12)
RD_U	-0.48 (0.14)	-0.48 (0.14)	-0.48 (0.14)	-0.71 (0.18)
L_E	0.48 (0.15)	0.51 (0.15)	0.49 (0.15)	0.41 (0.15)
L_U	-0.31 (0.08)	-0.44 (0.08)	-0.43 (0.07)	-0.44 (0.09)
Lambda		0.23 (0.13		
GDP				0.52 (0.28)
L_G				0.03 (0.01)
Diagnostics				
R^2-adj	0.74			
Jarque-Bera Test	14.92			
Konker-Bassett Test	41.77			
Breusch-Pagan Test		61.82		
White Test	44.62			
Moran's I (error)	2.07			
LM-Error				
W_{41}	2.32	1.08		
W_6	5.16	3.02	2.75	3.05
W_{12}	0.07	0.01		
LM-Lag				
W_{41}	2.57	1.67		
W_6	3.64	2.23		
W_{12}	0.03	0.02		

Notes: Regression results for Chemical Industry at the NUTS 2 level of European Union. Estimated standard errors are in parentheses; critical value for the White test-statistic with 5 degrees of freedom is 11.07 (P=0.05); critical value for LM-Error and LM-Lag is 3.84 (P=0.05); spatial weights are row-standardized: W_{41} is distance-based contiguity for 41 Km; W_6 is a contiguity matrix based on the 6 nearest neighbors; and W_{12} is a contiguity matrix based on the 12 nearest neighbors Reported estimates are significant at P=0.05.

Table IV

Spatial Regression for Automotive Industry (Depended Variable: Patents)

	OLS	**Spatial-Error ML**	**FGLS**	**FGLS (Augmented)**
Constant	-2.56 (0.56)	-2.61 (0.56)	-2.51 (0.55)	-8.87 (2.06)
RD_A	1.01 (0.13)	1.00 (0.13)	1.06 (0.12)	0.98 (0.13)
RD_U	0.06 (0.13)	0.04 (0.13)	-0.35 (0.13)	-0.39 (0.18)
L_A	0.03 (0.15)	0.08 (0.15)	0.24 (0.11)	0.18 (0.09)
L_U	-0.54 (0.09)	-0.55 (0.09)	-0.51 (0.08)	-0.53 (0.11)
Lambda		0.21 (0.11)		
GDP				0.78 (0.26)
L_G				0.09 (0.02)
Diagnostics				
R^2-adj	0.55			
Jarque-Bera Test	6.76			
Breusch-Pagan Test	80.89	76.21		
White Test	62.74			
Moran's I (error)	1.34			
LM-Error				
W_{41}	3.81	0.98		
W_6	4.39	1.99	0.83	0.44
W_{12}	0.52	0.02		
LM-Lag				
W_{41}	2.02	0.55		
W_6	3.49	1.09		
W_{12}	0.75	0.23		

Notes: Regression results for Chemical Industry at the NUTS 2 level of European Union. Estimated standard errors are in parentheses; critical value for the White test-statistic with 5 degrees of freedom is 11.07 (P=0.05); critical value for LM-Error and LM-Lag is 3.84 (P=0.05); spatial weights are row-standardized: W_{41} is distance-based contiguity for 41 Km; W_6 is a contiguity matrix based on the 6 nearest neighbors; and W_{12} is a contiguity matrix based on the 12 nearest neighbors Reported estimates are significant at P=0.05.

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