University of Piraeus

SPOUDAI
Journal of Economics and Business
Σπουδαί
http://spoudai.unipi.gr

ΣΠΟΥΔΑΙ / SPOUDAI

Identifying and Exploring Sources of Knowledge Spillovers in European Union: Evidence from Patenting Data

By

Sotiris Karkalakos
University of Piraeus, Dept. of Economics,
80, M. Karaoli & A. Dimitriou Street, 18534, Piraeus, Greece, sotkar@unipi.gr

Abstract

Although the process of innovation is a crucial aspect of economic growth, there is less clarity about the measurement of economically useful ideas. Determining the extent to which different types of institutions contribute to the creation of new knowledge is essential for a deeper understanding of the dynamics involved. Using a spatial econometric framework, this article examines the productivity of knowledge and notes that the changes in productivity appear to correlate to the spatial distribution of new knowledge creation. The channels and the relationships through which knowledge can flow between different sources are identified and estimated.

JEL Classifications: O31, H41, O40, D24.

Keywords: Knowledge Spillovers, Spatial effects, Regional policy.

1. Introduction

The role of geographically mediated knowledge spillovers in regional innovation systems has become a major issue in research policy. The European Research Council (ERC) funds scientific projects that enable Europe's brightest minds to tackle research challenges such as climate change, health and ageing and economic governance. Many of these projects can lead to scientific and technological discoveries, and even open up new possibilities for industries, markets and the broader society. Measures of technological change have typically involved one of the three major aspects of the innovative process (Acs *et al.,* 2002): (1) a measure of the inputs into the innovation process, such as R&D expenditures; (2) an intermediate output, such as the number of patents; (3) a direct measure of innovative output. Localized R&D spillovers exist if the productivity of R&D in a region is affected by the amount of R&D resources used in other regions in spatial proximity. Research and Development (R&D) is widely recognized as an important source of technological change and productivity growth. The latter definition is derived as the reduced form of a model in which new ideas are generated using R&D resources and existing ideas as inputs (Romer, 1990 and Jones, 1995). According to Acs *et al.* (2002), an innovative system includes not only networks of innovative companies with research organizations, suppliers and customers, but also several institutional factors, such as the way publicly financed research is organized in a given country, or the nation's system of schooling, training and financial institutions.

Advances in the state of knowledge have been responsible for much of the economic growth. Economically useful new knowledge that leads to innovation plays an important role in economic development. Our understanding of the role of knowledge in economic activity has traditionally been guided by the state of measurement of knowledge. Given that R&D indeed contributes to economic growth, the next obvious question is, how the different types of institutions affect the productivity of innovations or patents. Sterlacchini (1989) criticizes the literature for ignoring the lag structure in analyzing the effects on Total Factor Productivity (TFP). It is widely emphasized in the national innovation systems literature (e.g. Nelson, 1993; Patel and Pavitt, 1994; Edquist, 1997) that technological advance in industry is significantly influenced by several external and internal factors resulting in specific innovation systems. Universities and firms are among the most important factors for technological and economic development. Production of economically useful new technological knowledge results from direct and indirect linkages of the different factors. There are many channels through which knowledge can flow between different factors of the system, including personnel mobility within and between different sectors, or, technical collaboration among different units, such as firms. Those channels depend on the regulatory frameworks or a series of rules and conventions.

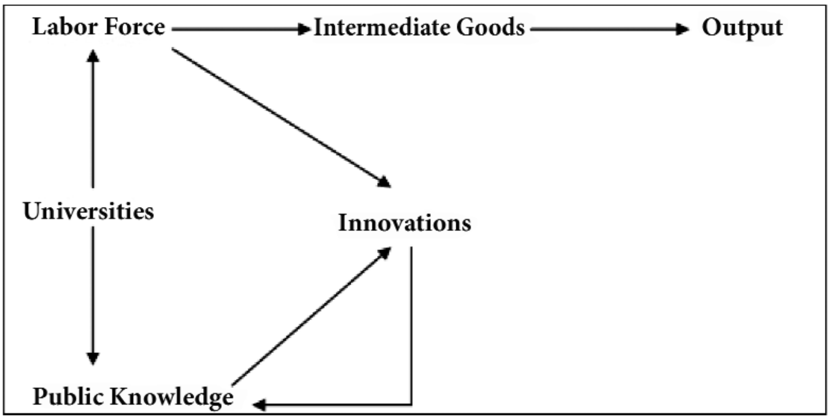
Figure 1 provides a basic schematic representation of economic activities (Aghion and Howitt, 1998). This figure illustrates that a firm can possibly split its labor force in a research department and a manufacturing division. In the research department workers are supposed to invent new product or technology standards, while workers in the manufacturing division produce intermediate goods, that are used to create the final output of the particular firm. On the other hand, public knowledge is enhanced by research performed at universities and research institutions. Their output in the form of knowledge is often published in scientific journals or transmitted by channels such as conferences. This improves the overall knowledge stock in the economy and induces innovative activities. Moreover, universities educate individuals who may once enter the labor force. By means of education the labor force becomes more productive because individuals obtain a higher skill level. These skills can be applied in any department of the firm. The latter results to higher levels of innovative activities in the research department on the one hand and higher levels of production in the manufacturing division on the other. Furthermore, the market position of innovating firms is improved and creative accumulation leads to higher degrees of concentration.

A peculiar feature of R&D is that a firm or a university investing in it is often unable to exclude others from freely obtaining some of the benefits. Accounting for these spillovers should contribute to the explanatory power of our model. It has been suggested, however, that these spillovers are merely a specification error (Basu *et al.,* 1995).

A powerful approach to empirically model the characteristics of localized knowledge flows as well as to examine the contribution of each factor to the creation of new knowledge is the Knowledge Production Function (KPF) framework initiated by Griliches (1979). This framework has been widely applied in empirical studies of regional innovation in the US (Jaffe, 1989; Anselin *et al.,* 1997, 2000; Varga 2000) and in Europe (Audretsch and Vivarelli, 1994; Fisher and Varga, 2001; Fritsch, 2001). One of the most crucial issues in such an analysis is the measurement of economically useful new knowledge.

FIGURE 1

A schematic presentation of economic activities



Source: Aghion and Howitt, 1998.

The basic research question behind this paper is twofold. First, it is the identification and the evaluation the productivity of the factors that generate new knowledge. Second, the examination of the relationship among the productivity of patents by universities and the productivity of patents by firms. The current study represents the first attempt in the literature to provide a systematic analysis of the relationship between productivity of patents and the factors that generate economically useful new technological 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 (14 countries). The current work is mainly motivated by a critical assessment from Breschi and Lissoni (2001) of the recent fortunes met by the debate on the spatial boundaries of the spillovers from both private and academic institutions. Their survey set a tight research agenda for those who want to understand the role of geography in firms' and universities' innovative activities. According to them, it remains to be examined more carefully the impact of local academic or private research institutions on innovative activity.

The remainder of the paper consists of four sections and a conclusion. Section 2 discusses the set up of our model and section 3 develops the theoretical framework of our analysis. Section 4 provides some information about the data and presents some diagnostic results for spatial dependence. Section 5 includes a presentation and an explanation of the results. Finally, section 6 summarizes our findings.

2. The Model

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

$$P_i = A.(R\,\&\,D)^{a}_{ui}.(R\,\&\,D)^{b}_{fi}.X^{j}_{i} \tag{1}$$

where subscript i=1,...,157 refers to cross-sectional spatial units, P_i is the number of patents at area I (TPP), $R\&D_u$ is the research and development expenditure for universities, $R\&D_f$ is the research and development expenditure for firms, and X is a vector of explanatory variables which refers to Gross Domestic Product (GDP), Knowledge Intensive Services (KIS), and employment at firms with High-Technology (EMPHT). Equation (1) is used for the identification and the evaluation of the productivity of the factors that generate new knowledge which is the first task of this paper.

By dividing both sides with (R&D), the left-hand side of equation coincides, with the official[1]. Total Factor Productivity (TFP) measure used by OECD (1999). Following a similar intuition we define Total Patent Productivity (TPP) for universities and firms. Thus, the equations for Total Patent Productivity of

Firms (TPPF) and Total Patent Productivity of Universities (TPPU) are defined as following:

$$TPPU = \frac{P_i}{(R\&D)_{ui}^{a}} = A.(R\&D)_{fi}^{b}.X_i^{j} \tag{2}$$

$$TPPF = \frac{P_i}{(R\&D)_{fi}^{b}.} = A.(R\&D)_{ui}^{a}.X_i^{j} \tag{3}$$

We know that OECD (1999) defines factor productivity using the following expression:

$$TPF = \frac{Y}{K^{v}.L^{g}} \tag{4}$$

where Y is the total output, K is the corresponding value of the capital stock and L is the labor. We manipulate the OECD formula in order to adjust it to our problem.

After, using the proper notation we get

$$TPPF_k = \frac{P_i}{(R\&D)_{ki}} \tag{5}$$

where k represents firms (f) or universities (u). In addition, i refers to the spatial unit of study. After taking natural logarithms and using equations (1) to (5) we have that

$$\ln TPPU = \ln A_u + b\ln(R\&D)_{fi} + m\ln GDP_i + n\ln KIS_i + q\ln EMPHT_i \tag{6}$$

and

$$\ln TPPF = \ln A_f + a\ln(R\&D)_{ui} + m\ln GDP_i + n\ln KIS_i + q\ln EMPHT_i \tag{7}$$

Equations (6) and (7) refer to the second task of this paper which is the examination of the relationship among the productivity of patents by universities and the productivity of patents by firms.

Since we are particularly interested in the geographical scope of knowledge externalities and the productivity of new patents, we constructed new spatially lagged explanatory variables that are called "ring variables" (Anselin *et al.,* 1997). These variables are designed to capture the effects of R&D expenditure of firms and universities, and also of the employment, surrounding the spatial units of study within a given distance band from the geographic center of the spatial units. Based on information of commuting patterns, three distance bands were considered: 16 kilometers[2], the four nearest neighbor units and a band considering the squared inverse distance between any units. Specifically, the lagged variables RDU16, RDUinv, RDUneig and RDF16, RDFinv, RDFneig, are the sums of surrounding universities' and firms' expenditures. The effect that local characteristics have on patents is measured by the use of three variables. Gross Domestic Product (GDP), Knowledge Intensive Services (KIS), and employment at firms with High-Technology (EMPHT) include important characteristics of each spatial unit of the European Union. Moreover, they allow us to examine their statistical significance under different types of model specification.

3. The Methodology

The theoretical analysis in section 3 has generated knowledge production functions of the form in (6) and (7). For empirical purposes, however, this specification raises a number of issues. The first relates to whether any spatial relationship of the variables is merely random or responds to a pattern of spatial dependence. Clearly, if it is the latter, then one should integrate spatial autocorrelation into the knowledge production functions. Two types of spatial correlation can be modeled within regression models. The first type is represented by equation

$$Y = \rho WY + Z\alpha + \phi \tag{8}$$

where Y is the M-vector of patents, W is the MxM spatial weight matrices, ϱ is the estimated autoregressive coefficients associated with matrix W, Z is the MxV matrix of exogenous variables, α is the V-vector of parameters to be estimated, and φ is the M-vector of error terms, with $E(\varphi \mid Z)=0_{Mx1}$. Equation (8) gives a causal relationship of the dependent variables of other observations on each focal observation (the main spatial unit) that in the present context are the neighboring provinces of each particular province. The second type of spatial correlation is given by

$$Y = Z\alpha + \phi \tag{9}$$

with

$$\phi = \lambda W \varphi + \nu \tag{10}$$

where φ is the estimated autoregressive coefficients associated with the matrix W --- with W being the MxM spatial weight matrix, ν is the M-vector of identically and independently distributed spherical-error terms that represents a correlation of the error terms of other observations on each focal observation.

Notice that the model in (8) is analogous to the temporal autoregressive model, whereas the model in (9 and 10) is analogous to the autoregressive error model used in temporal time series. Several diagnostic tests have been developed in the literature to find the appropriate model specification. Widely used diagnostic tests for spatial error dependence is an extension of Moran's I to the regression context. The LM-LAG and LM-ERROR tests define the proper model specification.

We assess those types of specification by using three different spatial weights matrices that reflect different a priori notions on the spatial structure of dependence:

1. Distance[5] based matrices for 16 km [W_{16}] between the spatial units.
2. Distance[5] based matrices to 4 nearest neighbors [W_{neig}].
3. The inverse[3] distance squared weights matrix [W_{id}].

These weights consist of exogenously specified elements w_{ij} that capture the neighbor relations of observations i and j that is, the extent to which provincial patents are correlated causally or via the error terms. In this case two such matrices are of particular interest. The first one, specifies the spatial lag of the dependent variable whereas the second, specifies the spatial lag of the error term. We make use of three approaches to define the value of each element w_{ij} within these two matrices: the distance-based approach, the contiguity-based (k-neighbors), and the inverse distance-based. The distance-based approach assumes a mileage threshold within which all provinces j are competitors of province i and outside of which they are not. The second approach is based on the number of neighboring provinces that exist for any particular observation. Finally, the third approach focuses on the distance decay effect. It emphasizes the rate at which the spatial effects are minimized as one moves away from the geographical observation of interest. One major advantage of the use of contiguity or inverse distance-based approach to assess neighbor relations is that the boundaries naturally take into account heterogeneity in population density in a way that the distance threshold does not. The inverse distance-based weights are specified as a decaying function of the distance between observation i and all other observations and takes the form $W_i = f(\theta, d_i)$, where the vector d_i contains distances between observation i and all other observations in the sample and the parameter θ plays the role of generating a decay of influence with distance. Changing the distance-decay parameter θ results in a different weighting profile, which in turn produces estimates that vary more or less rapidly over space.

Spatial effects are a major econometric issue. More specifically, two different spatial effects are considered: spatial autocorrelation and spatial heterogeneity. Spatial autocorrelation refers to the coincidence of attribute similarity and locational similarity, (Anselin and Bera, 1998). In the present context spatial autocorrelation implies that patents of European regions tend to be geographically clustered and so economic activity is unevenly distributed. Spatial heterogeneity means that economic behaviors are not stable over space.

4. The Data

We choose as regions for our analysis the territorial units identified by Eurostat in each country, called NUTS (Nomenclature Units Territory Statistics). In contrast to any related studies, we carry out an analysis at the lowest possible European Union (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 satisfactory proxies for economically useful new knowledge, which one would like to have for exploring theories on innovation or R&D policies.

Furthermore, there are a number of explanatory variables that are employed in our analysis. The R&D expenditures of firms (RDF) and universities (RDU) refer to the expenditures made by those institutions for research and development purposes. Moreover, Gross Domestic Product (GDP) (*Anselin et al.,* 1997), Knowledge Intensive Services (KIS, employees at firms with a substantial academic education; i.e., graduate studies, Audretsch and Vivarelli, 1994), and employees at firms with High-Technology services or products, (EMPHT) (Acs *et al.,* 2002) measure the effect that local economies have on the productivity of patents.

Several theoretical explanations and approaches have been proposed in the literature to account for the definition and the measurement of productivity. Essentially, a typical measure of Total Factor Productivity (TFP) is computed as the difference output and the factor cost share weighted average of input[5]. The latter definition follows the Cobb-Douglas production function framework and is called the index number approach.

Table 1 provides some descriptive statistics of the main variables used for estimation. The are two sources of knowledge, we include in the regression model, universities and firms. Our data refers to 14 European Countries[1] and all the variables are measured according to the suggestions of Eurostat.

TABLE 1

Descriptive Statistics

	Mean	S.D	Minimum	Maximum
TPP	122.04	47.05	0	3397.4
TPPF	43.51	88.04	0.77	829.18
TPPU	77.66	95.11	0.34	3361.93
RDF	39.38	75.99	0.21	890.24
RDU	21.26	27.91	0.80	179.99
EMPHT	16.38	24.28	1	138.17
GDP	7806.08	11071.21	540.66	81621.25
KIS	172.91	243.25	10.18	1854.37

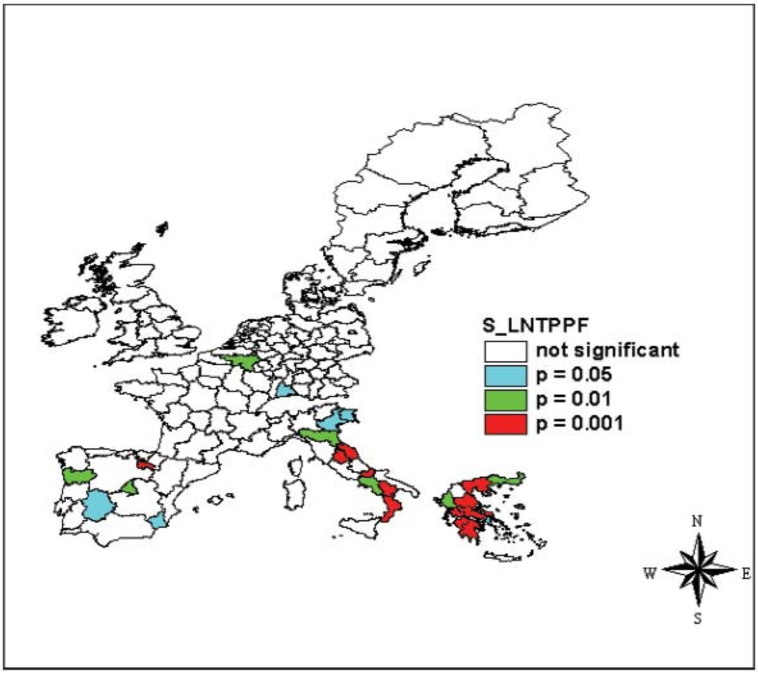
Source: Eurostat database, 2002.

A major target of this study is two-fold. At first hand, to clarify whether productivity of patents in European Union presents any spatial dependence or characteristics, and at second hand to examine the role of firms or universities in the productivity of patents. As part of a pre-modeling stage of research, we explore the tendencies of productivity of patents by firms and universities. Thus, we use Local Indicators of Spatial Association (LISA) to exhibit significant spatial clustering for each location (Anselin, 1995). Figures 2 and 3 present the significant local outliers for European Union. It is obvious that the central and south European areas are the one that indicate spatial concentration. In order to test for it, local measures of spatial association are computed. Significance of local clusters are measured by the local Moran statistics and represented by LISA maps (Anselin, 1995).

A LISA map (Local Indicators of Spatial Association) exhibits significant spatial clustering for each location. A LISA map distinguishes between the four types of local association (high-high, low-low, low-high, high-low). A LISA map is a good device to help easily recognize outliers and leverage points (Varga, 2000). Locations that are extreme to the central tendency are outliers (i.e., high observation value and low average value). Leverage points are observations that have a large influence on the central tendency (i.e., high observation value and low average value). The number of patents per region (Figures 2, 3) suggests the existence of a "cluster". According to LISA maps, central Europe presents a significant number of patents per region, shedding light on the spatial pattern of universities and firms.

FIGURE 2

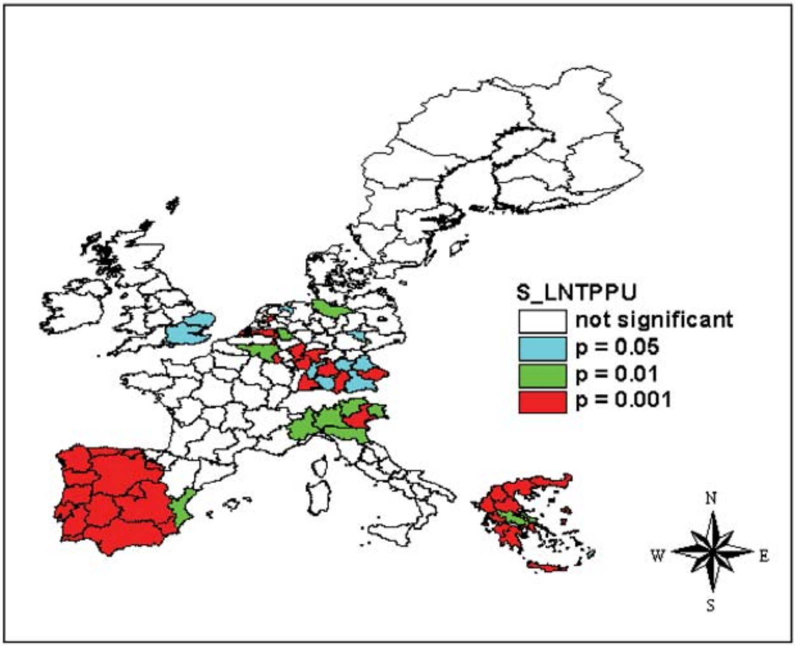
The spatial clusters[a] of productivity of patents by firms



a) S_LNTPPF represents the significant clustering values of the productivity of patents by firms.

FIGURE 3

The spatial clusters[a] of productivity of patents by universities



a) S_LNTPPU represents the significant clustering values of the productivity of patents by universities.

4. Estimation Results

The regression results are reported in Tables 2 and 3 for the logarithm specifications of Total Patent Productivity (TPP); aggregate indicator of productivity of patents, and Total Patent Productivity for firms (TPPF) and Total Patent Productivity for universities (TPPU). Table 2 presents the case for European Union of 15 countries (EU15) and European Union of 27 countries (EU27). Three different specifications were estimated: the models (6) and (7) with only the expenditure [$(R\&D)_k$] variables included in the right hand side [Base model], a spatial model which is the base model extended with the spatial lags for the expenditure [$(R\&D)_k$] variables (only the most significant are reported), and finally an augmented spatial model that includes a vector of local characteristics which refers to Gross Domestic Product (GDP), employment at firms with Knowledge Intensive Services (KIS), and employment at firms with High-Technology (EMPHT). The base model in both tables confirms the strong significance of both expenditure and employment variables. There is a clear dominance of the coefficient of private expenditure (RDF), in equation (6), over university expenditure (RDU), in equation (7), showing an elasticity that is higher. Typical examples are the case of clustering activities in southern UK regions, western German regions or northern Italian regions. In all the above regions the RD is a critical component that affects employment. Furthermore, in both tables base models present a strong evidence of misspecification (at $p<0.05$).

The significant LM-Lag and LM-Error statistics in both models suggest that the extent of knowledge flows go well beyond the spatial units at NUTS 2 level in European Union. To explicitly account for this effect ring variables were introduced to the models (6) and (7). As a result, adjusted R^2 improves slightly with no spatial dependence remaining. The augmented spatial models verify the importance of local characteristics in any type of specification. For model (6) concerning TPPU, since no heteroskedasticity problems were discovered, the final model is estimated with OLS under the regular space lag specification (Table 3, column 5). Model (7) incorporates heteroskedasticity (according to Wald test) in the form of a random coefficients model that is estimated by means of maximum likelihood[6] (Table 3, column 5). In the followings, we provide a comparative perspective on the behavior of the aggregate model (TPP) and the two models of measure of productivity (TPPF, TPPU).

1. Total Productivity of Patents (TPP) is affected by both the universities and firms. According to Table 2, research and development expenditures from firms increase at a higher rate the regional productivity of patents than the research and development expenditures from universities. Moreover, local characteristics are significant factors for the regional productivity of patents. The model follows a lag specification since LM Lag statistic (9.98) is higher than LM Error statistic (9.41). Therefore, regional patents are affected by the productivity of patents at neighboring locations both for EU15 and EU27.

2. All the variables that refer to the local characteristics of the spatial units are highly significant in both models. Furthermore, the economic variables exhibit the expected sign. For TPPU model (Table 3), positive for firms with knowledge intensive services (KIS), for gross domestic product (GDP) and for employment at High-Technology firms. In other words, the presence of firms which require the employment of highly educated employees tends to increases the amount of patents produce by universities. Also, for TPPF model, all the variables related to local characteristics exhibit positive signs. The presence of firms with knowledge intensive services (GDP) or with high-technology (EMPHT), has a positive effect on the productivity of patents by firms.

TABLE 2: Total Patents Productivity (TPP)

	Base, ln(TPP)	Spatial, ln(TPP)	Augmented Spatial, ln(TPP) for EU15	Augmented Spatial Lag Model, ln(TPP)	Augmented Spatial, ln(TPP) for EU27
W_{inv}TPP				0.21 (0.04)	
Constant	1.25 (0.25)	-0.61 (0.07)	-7.92 (1.12)	-8.16 (1.08)	-2.14 (1.82)
lnRDF	0.79 (0.14)	0.51 (0.14)	0.43 (0.02)	0.44 (0.01)	0.52 (0.09)
lnRDF16					
lnRDFinv		1.33 (0.37)	0.91 (0.31)		0.96 (0.17)
lnRDFneig			0.92 (0.14)		0.64 (0.29)
lnRDU	0.32 (0.08)	0.31 (0.11)	0.19 (0.09)	0.14 (0.05)	0.25 (0.08)
lnRDU16		0.54 (0.12)	0.14 (0.01)		0.19 (0.02)
lnRDUinv			0.11 (0.04)		0.15 (0.07)
lnRDUneig			0.17 (0.06)		0.11 (0.08)
lnKIS			-0.18 (0.02)	-0.15 (0.01)	-0.12 (0.04)
lnGDP			0.78 (0.09)	0.81 (0.09)	0.86 (0.07)
lnEMPHT			0.11 (0.01)	0.09 (0.00)	0.05 (0.02)
R^2-adj	0.51	0.62	0.71	0.72	0.68
Log-likelihood		-187.82	-104.21	-90.02	-148.37
Wald Test			11.18		16.15
White Test	79.91	30.15	41.94	50.66	37.11
LM-Error					
W_{16}	4.88	3.56	3.71		4.03
W_{inv}	6.41	2.81	2.64		1.89
W_{neig}	5.64	2.01	2.81		2.53
LM-Lag					
W_{16}	4.75	3.08	2.77		2.73
W_{inv}	7.07	2.14	2.99		2.22
W_{neig}	3.51	1.32	1.41		2.38

Notes: Regression results for lnTPPU model at the NUTS 2 level of European Union. Estimated standard errors are in parentheses; critical values for the White test-statistic with respectively 5 and 44 degrees of freedom are 11.07 and 62.77 (P=0.05); critical value for Wald test-statistic with 8 degrees of freedom is 15.51; critical value for LM-Error and LM-Lag is 3.84 (P=0.05); spatial weights are row-standardized: W16 is distance-based contiguity for 16 Km; Winv is inverse distance squared; and Wneig is a contiguity matrix based on the 4 nearest neighbors.

TABLE 3

Total Patents Productivity of Firms (TPPF) and Universities (TTPU)

Total Patents Productivity of Firms (TPPF)				
	Base, ln(TPPF)	**Spatial, ln(TPPF)**	**Augmented Spatial, ln(TPPF)**	**Augmented Spatial ML-Lag Model, ln(TPPF)**
W_{inv}TPPF				0.27 (0.06)
Constant	2.22 (0.61)	2.61 (0.28)	3.09 (0.93)	2.37 (0.09)
lnRDU	0.37 (0.08)	0.44 (0.08)	0.32 (0.11)	0.24 (0.07)
lnRDU16		0.23 (0.06)	0.14 (0.21)	
lnRDUinv			0.23 (0.05)	
lnRDUneig			0.17 (0.06)	
lnKIS			0.42 (0.11)	0.36 (0.09)
lnGDP			0.21 (0.09)	0.15 (0.14)
lnEMPHT			0.05 (0.01)	0.04 (0.01)
R^2-adj	0.51	0.63	0.67	0.71
Log-likelihood		-214.16	-198.76	-116.23
Wald Test			24.23	12.97
White Test	38.92	26.75	107.56	58.89
LM-Error				
W_{16}	4.23	2.11	0.98	
W_{inv}	9.41	3.56	2.59	
W_{neig}	7.33	3.89	2.01	
LM-Lag				
W_{16}	3.75	1.72	1.99	
W_{inv}	9.98	2.12	2.01	
W_{neig}	2.54	1.62	1.48	
Total Patents Productivity of Universities (TPPU)				
	Base, ln(TPPU)	**Spatial, ln(TPPU)**	**Augmented Spatial, ln(TPPU)**	**Augmented Spatial Lag Model, ln(TPPU)**
W_{inv}TPPU				0.17 (0.05)
Constant	1.75 (0.62)	3.44 (0.17)	2.59 (0.07)	1.67 (0.00)
lnRDF	0.44 (0.08)	0.49 (0.06)	0.51 (0.19)	0.48 (0.15)
lnRDF16		0.24 (0.11)	0.14 (0.01)	
lnRDFinv			0.27 (0.09)	
lnRDFneig			0.04 (0.06)	
lnKIS			0.03 (0.01)	0.56 (0.09)
lnGDP			0.11 (0.19)	0.85 (0.14)

(to be continued)

lnEMPHT			0.03 (0.01)	0.18 (0.08)
R^2-adj	0.49	0.51	0.57	0.62
Log-likelihood		-222.15	-175.71	-106.29
Wald Test			25.23	14.92
White Test	38.92	26.75	107.56	58.89
LM-Error				
W_{16}	4.23	2.24	2.09	
W_{inv}	6.77	3.51	1.88	
W_{neig}	3.64	0.89	0.91	
LM-Lag				
W_{16}	5.05	3.78	2.06	
W_{inv}	7.62	3.42	1.31	
W_{neig}	3.54	1.26	1.48	

Notes: Regression results for lnTPPF model at the NUTS 2 level of European Union. Estimated standard errors are in parentheses; critical values for the White test-statistic with respectively 5 and 44 degrees of freedom are 11.07 and 62.77 (P=0.05); critical value for Wald test-statistic with 8 degrees of freedom is 15.51; critical value for LM-Error and LM-Lag is 3.84 (P=0.05); spatial weights are row-standardized: W16 is distance-based contiguity for 16 Km; Winv is inverse distance squared; and Wneig is a contiguity matrix based on the 4 nearest neighbors.

3. There are several important characteristics such as the explanatory power of regression equations, the significance of the spatial statistics and the elasticities where the two models behave in a similar manner. Regression fits of the two final models, in both Tables, follow the same pattern, with adjusted R^2 of 0.62 for TPPU model and 0.71 for TPPF model. According to Table (3), both models follow a structure since LM-Error statistic is lower than LM-Lag statistic when contiguity matrix is defined according to the inverse criteria. Finally, the sign of R&D expenditure is both positive and significant for any specification for both definitions of EU (with 15 countries and with 27 countries).

5. Conclusion

This paper has offered an alternative approach to the existed literature emphasizing the *spatial distribution* of patents in a federation. The novel element of this paper has been that patent productivity is examined in two dimensions. The influence of R&D expenditures of firms on the productivity of patents by universities and vice versa. Within this framework the analysis of the paper has confirmed the existence of spatial externalities in the setting of patents whose magnitudes vary asymmetrically across European regions. The use of spatial econometrics has also added a new perspective to the issue under investigation.

The empirical evidence suggests that the productivity of patents by universities is affected, by the presence and activities of the firms, at a higher degree than the productivity of patents by firms, which are influenced by the presence and activities of the universities. Moreover, productivity seems to respond to changes in R&D at a considerable spatial lag (ring variables). We include spatially lagged variables, under different types of specification of contiguity matrix (W); in most 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 of local characteristics. 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 on those units innovative activities spills over from outside the units at NUTS 2 level. Our analysis indicates that the estimated coefficient for firms R&D variable is higher than the respective coefficient for university R&D variable (Table 3, column 5). This relatively higher weight of firms R&D variable can be related to the fact that in the later stages of innovation the need for applied research collaboration (e.g. conducting tests by university researchers) is more pronounced than in the earlier stages. Later stages of research require the existence of personnel (i.e., academic researchers) and appropriate facilities (i.e., laboratories). Therefore, patenting is defined (according to Eurostat) as the part of innovation process which is attributed to the initial (early) part of innovation process. Since patenting reflects more the earlier stages of innovation, the relatively higher weight of firms R&D in the productivity of patents by universities could reflect the different spatial patterns in research collaboration. The later result is also supported by Acs *et al.* (2002) who discuss it from a different perspective. They conclude that the local universities research (RDU) have a low weight in patenting. In sum, we have found in this paper that the productivity of patents by firms or universities in European Union presents a substantive spatial dependence and that there is a well established relationship among universities and firms.

The findings in this paper have three important economic impacts for regional policy. Firstly, the role of agglomeration for both universities and firms is considered. Empirical results would suggest that strengthening universities and firms in order to advance local economies can be a serious option. Secondly, another economic impact is related to the distance decay pattern of knowledge transfers. Although firms (coefficient of growth rate of R&D) have a considerably larger impact on the productivity of patents by universities than the vice versa, spillover effects of those institutions within a commuting distance (16 kilometers) could be notable as well, since 'ring' variables are statistically significant. Thirdly, the productivity of patents in the regions of the European Union is affected by the changes of output (patents) in neighboring locations, since results are robust to any specification of contiguity matrices. Therefore, any financial project which aims to support technology diffusion should allocate funds in both universities and firms but according to their spatial distribution.

A final topic for policy makers to consider is the possible interaction between R&D spending targets and other social or policy objectives. At a more nuanced level, the objective of boosting levels of R&D funding can create incentives that must be balanced against other policies and priorities. Within the realm of R&D policy, for example, efforts to boost R&D funding can distract attention from policies and programmes that attempt to boost the *efficiency* of existing R&D funds without necessarily raising their level. Efforts to encouraging greater networking and co-operation among firms or strengthening industry-science linkages—which might go a long way toward boosting levels of innovation and economic growth, as R&D targets are established to do—might receive lower priority. Similarly, specific strategies for achieving higher R&D intensities, such as by attracting R&D investment from foreign multi-nationals, or developing high-technology industries, can come into conflict with other social objectives, such as reducing unemployment, supporting development of local SMEs, or expanding local industries.

Notes

1. The study was conducted when European Union had 15 members. However, Austria was excluded due to data limitations. Table 2 includes also an extension of our base dataset for 27 European countries (EU27).

2. For more details see Good *et al.,* 1996.

3. The two parameters in the denominator of the dependent variable are defined as discussed in OECD (1999).

4. It is the minimum required distance for achieving at least one neighbor for any spatial unit.

5. See Anselin, 1988.

6. Estimation of the model is followed Amemiya's three-step FGLS method (Amemiya, 1985).

References

Acs, Z., Anselin, L. and A. Varga. "Patents and Innovation Counts as Measures of Regional Production of New Knowledge". *Research policy* 31, 2002, 1069-1085.

Aghion, P. and P. Howitt. *Endogenous Growth Theory*, Cambridge MA, MIT Press, 1998.

Amemiya, T. *Advanced Econometrics*, Cambridge, MA, Harvard University Press, 1985.

Anselin, L. *Spatial Econometrics: Methods and Models*, Boston, Kluwer Press, 1988.

Anselin, L. "Local Indicators of Spatial Association – LISA", *Geographical Analysis* 27 (2), 1995, 93-115.

Anselin, L. and A. Bera. "Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics", in *Handbook of Applied Economic Statistics*, edited by Marcel Dekker. New York, 1998, 237-289.

Anselin L. and R. Florax. *Small sample properties of tests for spatial dependence in regression models: some further results.* In New Directions in Spatial Econometrics, 1995, 21-74.

Anselin, L. and S. Rey. "Properties of Tests for Spatial Dependence in Linear Regression Models". *Geographical Analysis* 23, 1991, 112-131.

Anselin, L., Varga, A. and Z. Acs. "Local Geographic Spillovers between university research and high technology innovations". *Journal of Urban Economics* 42, 1997, 422-448.

Anselin, L., Varga, A. and Z. Acs. "Geographic spillovers and university research: A spatial econometric perspective". *Growth and Change* 31, 2000, 501-516.

Audretsch, D. and M. Vivarelli. "Small-firms and R&D spillovers: Evidence from Italy". *Discussion Paper* 953, Center for Economic Policy, University of Bocconi, Italy, 1994.

Basu, M., Sand J. and A. Fernald. "Are Apparent Productive Spillovers a Figment of Specification Error?" *NBER Working Paper* 5073, National Bureau of Economic Research, Cambridge, Massachusetts, 1995.

Breschi, S. and F. Lissoni. "Knowledge Spillovers and Local Innovation Systems: A Critical Survey". *Liuc Papers* n. 84, Serie Economia e Impresa 27, 2001, 55-85.

Burridge, P. "On the Cliff-Ord test for spatial correlation". *Journal of Royal Statistic* B 42, 1980, 107-108.

Durlauf, S. and P. Johnson. *Multiple regimes and cross-country growth behavior*, Journal of Applied Econometrics 10, 1995, 365-384.

Edquist, C. *Systems of Innovation*, London, Cassel, 1997.

Fisher, M. and A. Varga. "Production of knowledge and geographically mediated spillovers from universities", in *Proceedings of the 41st Congress of the European Regional Science Association meetings*, Zagreb, August 29-September 1, 2001.

Fritsch, M. "Measuring the quality of regional innovation systems – A knowledge production function approach". *International Regional Science Review* 25 (1), 2003, in press.

Good, D., Nadiri, N. and R. Sickles. "Index Number and Factor Demand Approaches to the Estimation of Productivity", *NBER Working Paper* 5790, National Bureau of Economic Research, Cambridge, Massachusetts, 1996.

Griliches, Z. "Issues in assesing the contribution of R&D to productivity growth". *Bell Journal of Economics* 10, 1979, 92-116.

Jaffe, A. “Real effects of academic research”. *American Economic Review* 79, 1989, 957-970.

Jaffe, A., Trajtenberg, M. and R. Henderson. “Geographic localization of knowledge spillovers as evidence by patent citations”. *Quarterly Journal of Economics* 2, 1993, 577-598.

Jones, C. “R&D based Models of Economic Growth”. *Journal of Political Economy* 103, 1995, 739-784.

Nelson, R. *National Innovation Systems: A Comparative Study*, New York, Oxford University Press, 1993.

OECD. *ISDB 98: International Sectoral Database*, Paris, Organization for Economic Co-operation and Development, 1999.

Patel, P. and K. Pavitt. “The Nature and Economic Importance of National Innovation Systems”, *STI Review* 14, Paris, OECD, 1994.

Sterlacchini, A. “R&D, Innovations, and Total Factor Productivity Growth in British Manufacturing”. *Applied Economics* 21, 1989, 195-202.

Romer, P.M. “Endogenous Technological Change”. *Journal of Political Economy* 98(5), 1990, 71-102.

Varga, A. “Local academic knowledge spillovers and the concentration of economic activity”. *Journal of Regional Science* 40, 2000, 289-309.