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Spatial spillovers and innovation activity in European regions

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Abstract. This paper explores the spatial distribution of innovative activity and the role of technological spillovers in the process of knowledge creation and diffusion across 175 regions of seventeen countries in Europe (the fifteen members of the pre-2004 European Union plus Switzerland and Norway). The analysis is based on a databank set up by CRENoS on regional patenting at the European Patent Office, spanning 1978 – 2001 and classified by ISIC sectors. The first step is an exploratory spatial data analysis of the dissemination of innovative activity in Europe. The goal of the rest of the paper is to analyse to what extent externalities that cross regional boundaries can explain the spatial association process detected in the distribution of innovative activity in the European regions. The framework given by the knowledge-production function together with the use of spatial econometrics techniques allow us to look for insights on the mechanics of knowledge interdependences across regions, which are shown to exist. Empirical results point to the relevance of internal regional factors (R&D expenditure and agglomeration economies). Moreover, the production of knowledge appears also to be affected by spatial spillovers due to innovative activity (both patenting and R&D) performed in other regions. Additional results show that spillovers are mostly constrained by national borders within less than 250 km, and that technological similarity between regions also matters.

1 Introduction

Knowledge and technological progress are the main engines of economic dynamics in most endogenous growth models (Romer, 1986). In the spatial context this suggests that local growth depends on the amount of technological activity which is carried out locally, and possibly appropriated, and on the ability to take advantage of external technological achievements (Coe and Helpman, 1995; Martin and Ottaviano, 2001). These two phenomena—localised knowledge and absorptive capacity—are intertwined and, according to Audretsch and Feldman (2004), have to be jointly analysed because they are key factors in explaining the determinants of local technological change and, indirectly, of local economic growth. The analysis of such factors has traditionally been accomplished through the estimation of a knowledge production function (KPF) across regions rather than firms (as in the original setting by Griliches, 1979). The shift in the analytical framework of the KPF is credited to Jaffe (1989) who was the first to show that local externalities in the process of creation and diffusion of knowledge may operate outside the firm but, nonetheless, within the local space of regions.

In the present paper we proceed in the tradition of Jaffe's seminal contribution, with the aim of assessing the role of localised knowledge and absorptive capacity in enhancing the technological capability of European regions. In particular, we try to assess if the pattern, extent, and pace of the absorptive capacity depend not only on geographical proximity but also on technological, economic, and institutional similarities. This aim is pursued with a specific econometric strategy, which allows for rigorous testing procedures in the search for the best specification. First, we check the need to introduce external spillovers in the estimation of a regional KPF. Once this need has been assessed, the statistically correct specification of the KPF is searched by means of the usual testing strategy of spatial econometrics. In the process, we study the geographical scope of spillovers, in order to evaluate and measure the possible existence of a spatial decay effect. Additionally, we explore whether the similarity of the technological structure among regions is an advantage in the diffusion of knowledge and test the relevance of sharing a common institutional background in facilitating spillovers across regions.

We use an original databank on regional patenting at the European Patent Office (EPO) spanning 1978 to 2001 to analyse the spatial distribution of innovative activity across 175 regions of seventeen countries in Europe (the fifteen members of the pre-2004 European Union plus Switzerland and Norway). The use of this rich longitudinal panel dataset is an advantage with respect to previous studies on Europe for investigating how technological agglomerations are forming and evolving through space and time.

The paper is organised as follows. The next section provides a short summary of the background literature and a critical discussion of the interpretation of some recurring findings from the abundant empirical production. In the third section we deal with some measurement issues by describing the pros and cons of the database in use, and we examine the spatial mapping of innovative activity throughout the European regions. In the fourth section we use spatial econometrics analysis to explore the question of the relevance of externalities in the process of spatial creation and dissemination of knowledge which may cross the boundaries of regions. Section 5 is a discussion of the empirical results for the basic model together with some extensions to explore how national and technological proximity influences technological spillovers. Final remarks conclude the analysis.

2 Literature background

The traditional starting point of the analysis of the determinants of innovative activity by means of a so-called KPF is the seminal contribution by Griliches (1979). This early contribution found that the model in hand was more appropriate to describe the functional relationship between technological progress and innovative inputs at the industry or the country level, rather than at the firm or the plant level. This is interpreted, by Audretsch and Feldman (2004), as evidence of spillovers or externalities generated by innovative activity performed by single economic agents. Starting from Marshall (1920), there has been a long tradition of studies which relate externalities to geographical space. A tradition recently revived by the new economic geography (see Henderson and Thisse, 2004), according to which local increasing returns may play a crucial role in explaining the existence of core – periphery settings among regions. Such increasing returns are usually classified in two categories: pure technological and pecuniary externalities (Krugman, 1991). Going back to Marshall's classical taxonomy, one can see that the former are clearly associated with knowledge spillovers, whereas the latter are the result of market-mediated mechanisms concerning the availability of qualified workers and specific primary and intermediate inputs.

The spatial context was originally introduced into the KPF model by Jaffe (1989), whose aim was to analyse externalities created by universities. In other words, he aimed to establish if knowledge produced by universities is a sort of local public good, because of its peculiar nature, its tacitness, which makes it transmissible only through personal contacts (von Hipple, 1994).

This concept of localised knowledge spillovers was later refocused and strengthened by several empirical works addressed mainly to the US case (either at the state or at the metropolitan level) such as those by Acs et al (1994), Anselin et al (1997), and Audrestsch and Feldman (1996). Their common feature is that the estimation of a KPF is seen only as a practical device to find direct evidence of knowledge spillovers.

The possibility that local spillovers are caused by other mechanisms, such as pecuniary externalities, is only marginally taken into account. Breschi and Lissoni (2001) provide an excellent critical review of the risks related to this biased approach which treats knowledge spillovers as homogeneous. In this light, a more general line of research has attempted to investigate the main mechanisms and determinants of the process of creation and diffusion of innovative knowledge in terms of temporal dynamics and geographical scope, using a full set of spatial econometrics techniques. Such a testing procedure has become standard in the estimation of regional KPFs for the US case, as in Varga et al (2005). At the European level, previous attempts were made by Bottazzi and Peri (2003) and Greunz (2003), who indeed addressed the problem of spatial dependence, but never with proper measures to assess its relevance. Similar comments apply to the studies of Autant-Bernard (2001) for the French departments and of Andersson and Ejermo (2003) for Swedish functional regions. By contrast, spatial econometrics techniques were applied to their full potential in Fischer and Varga (2003) for Austrian political districts.

3 The spatial distribution of innovation activity in the European regions

The contributions surveyed in the previous section make extensive use of patent statistics in order to analyse the determinants of innovation activity. But the use of such indicators gives rise to some inconveniences and shortcomings (see Griliches, 1990)—both descriptive and econometric—which ought to be kept in mind while interpreting the outcome of the analysis. Starting from the concept of KPF, two types of indicators are usually identified: technology-input data (such as R&D expenditure and employees) and technology-output data (such as patents and new product announcements).

The main drawback of the former is that they include firms' efforts both for innovation and for imitation activities. Moreover, they do not take into account informal technological activity and, as a consequence, tend to underestimate the amount of innovative activity of medium and small firms. Technology-output data represent the outcome of the inventive and innovative process even though there may be inventions which are never patented, as well as patents which are never developed into innovations. However, the patenting procedures require innovations to have novelty and usability features and imply relevant costs for the proponent. This in turn implies that patented innovations, especially those extended to foreign countries, are expected to have economic, although highly heterogeneous, value. With respect to the object of our research, patent statistics seem particularly suitable, thanks to some useful properties with respect to R&D data: first, they provide information on the residence of the inventor and proponent and can thus be grouped into different territorial units identified through area codes, whereas R&D statistics are available at the national or regional level. Second, they record the technological content of the invention and can thus be classified according to the industrial sectors, whereas R&D data are usually aggregated, especially at the regional level. Third, they are available as a long series of yearly records, and this allows for a dynamic analysis; in contrast regional R&D data are available only for recent years and discontinuously.

Our proxy for innovative activity refers to patent applications at the EPO over the period 1978–2001, classified by inventor's region in Europe. Applications at the EPO should provide a measure of sufficiently homogeneous quality, because applying to the EPO is difficult, time consuming, and expensive. This indicator, in other words, should prove particularly effective at taking into account innovations that are potentially highly remunerative. The use of the inventor's rather than the proponent's residence is preferred in order to attribute the spatial localisation of each innovation (Breschi, 2000; Paci and Usai, 2000). Indeed, as the latter generally corresponds to firms' headquarters, it might lead to an underestimation of peripheral regions' innovative activity whenever the invention has been developed in a firm's subsidiary located in another area. Moreover, unlike previous research (Bottazzi and Peri, 2003), we deal with multiple inventors by assigning a proportional fraction of each patent to the different inventors' regions of residence.

As for the territorial breakdown, we have tried to select, for each country, a geographical unit with a certain degree of administrative and economic control. The result is a division of Europe (fifteen countries of the pre-2004 European Union plus Switzerland and Norway) in 175 subnational units (which, from now on, we will simply call *regions*) which are a combination of NUTS 0, 1, and 2 levels (see table 1 for details).

Table 1. Innovative activity in the European countries (patents per 100 000 inhabitants, annual average).

Nation	Number of regions	NUTS level	1981 – 83		1988 – 90		1994 – 96		1999 – 2001	
			value	rank	value	rank	value	rank	value	rank
Switzerland	7	2	14.5	1	20.9	1	19.7	1	27.8	1
Germany	40	2	8.3	2	14.7	2	12.2	2	19.9	2
Sweden	8	2	6.5	4	8.3	4	11.7	3	18.7	3
Finland	6	2	1.4	11	4.7	10	9.6	4	18.3	4
The Netherlands	4	1	4.1	5	8.3	3	8.3	5	14.5	5
Denmark	1	0	2.5	9	4.8	9	7.6	6	12.9	6
Luxembourg	1	0	7.2	3	5.0	8	6.4	10	12.7	7
Austria	9	2	3.3	8	6.8	6	6.8	8	10.5	8
Belgium	3	1	2.2	10	4.5	11	6.6	9	10.1	9
France	22	2	3.9	6	6.8	5	7.1	7	9.8	10
United Kingdom	12	1	3.4	7	5.4	7	5.1	11	7.3	11
Norway	7	2	0.9	13	2.1	13	3.0	13	5.1	12
Italy	20	2	1.1	12	3.0	12	3.4	12	5.0	13
Ireland	2	1	0.5	14	1.3	14	1.9	14	4.2	14
Spain	15	2	0.1	15	0.5	15	0.8	15	1.5	15
Greece	13	2	0.1	16	0.1	16	0.2	16	0.4	16
Portugal	5	2	0.0	17	0.1	17	0.1	17	0.3	17
European Union	175		3.6		6.5		6.7		10.4	
Coefficient of variation										
across nations			1.05		0.91		0.75		0.71	
across regions			1.42		1.17		1.05		1.05	

We now concentrate on the spatial distribution of innovative activity in Europe and its changes over two decades by using patents per 100 000 inhabitants as a measure of innovative intensity. Table 1 reports the innovative activity at country level. At the beginning of the period under consideration (1981 – 83), the most innovative country by far is Switzerland, with 14.5 patents per 100 000 inhabitants, followed by Germany (8.3) and Luxembourg (7.2). The regional level exhibits a similar picture, with mainly Swiss and German regions among the top performers. From figure 1(a) (over) we can see strong patenting activity in regions of Switzerland, West Germany, the north and east of France, the north of Italy, the United Kingdom, Denmark, the Netherlands, and Sweden. Little or no technological activity is documented in most regions of the south of Europe: Spain, Greece, Portugal, and the south of Italy.

Looking at the evolution of the innovative activity from 1981–83 to 1999–01, we can make some important remarks. First, innovation activity has increased considerably over the two decades in all countries: the average innovative output was 3.6 patents per 100 000 inhabitants in the early 1980s and almost three times higher (10.4) at the end of the 1990s. This is partly caused by a shift of patent applications by firms from national patenting offices to the EPO. Most importantly, innovations have been spreading to more regions in the south of Europe (especially in Spain and the south of Italy) and in the Scandinavian countries [see figure 1(b)]. Accordingly, we observe a decrease in the degree of spatial concentration of innovative activity as shown by the coefficient of variation (CV) for countries and regions, reported in the last rows of table 1. More specifically, the CV across nations decreases from 1.05 at the beginning of the 1980s to 0.71 twenty years later. Similarly, the CV computed at the regional level shows a sharp decrease from 1.42 to 1.05.

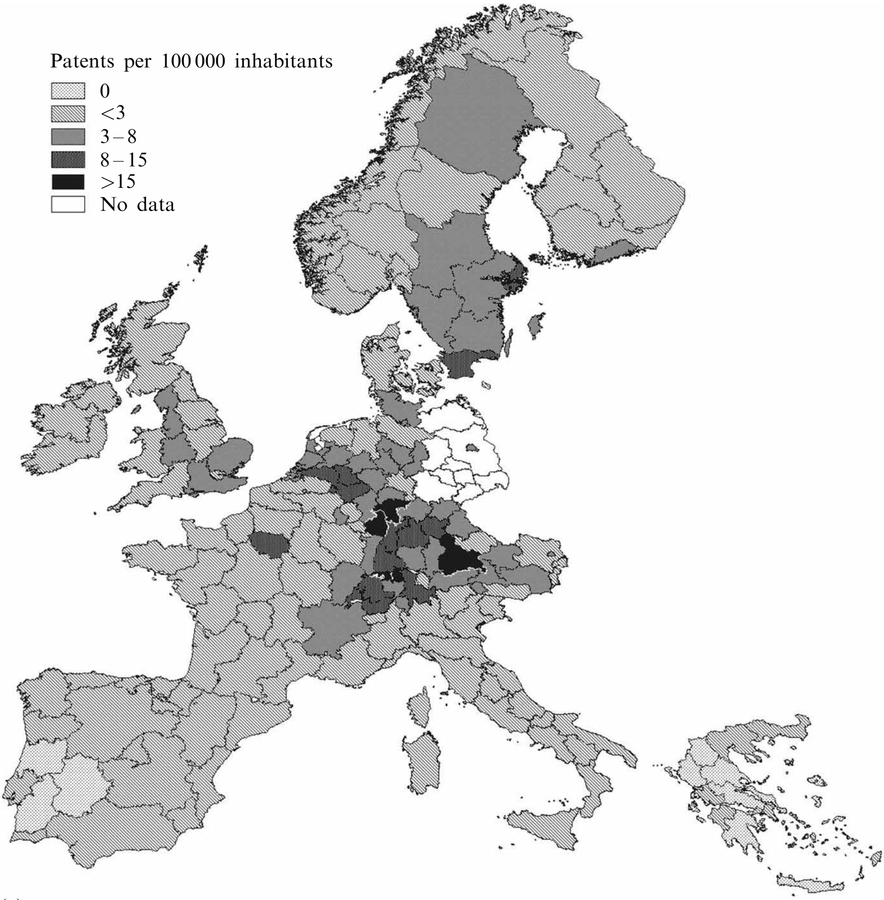
The process of spatial diffusion of technological activity characterizes some regions of central Europe (France and East Germany), where there is evidence of an expansion in spatial clustering. However, the most brilliant performance is shown by the Scandinavian countries, particularly by Finland, which in the 1990s managed to reach fourth position in the country rankings and place its capital region, Uusimaa, among the first producers of innovation in Europe. This region was 49th at the beginning of the 1980s and 6th at the end of the 1990s: undoubtedly one of the most remarkable catching-up performances in Europe in the last twenty years.

Interestingly, fifteen of regions which are in the top twenty in the last period were already there in the early 1980s. Here, there are some interesting stories to highlight: Stuttgart and Zuid Nederland, for example, were in the 13th and 18th position and are now 2nd and 4th. The Austrian region of Voralberg (the most westerly Austrian region, lying between Switzerland and Germany) was 64th and it is now 14th. Conversely, among the most remarkable cases of decline are Luxembourg, which goes from 20th to 44th place, and Île de France, which moves from 9th to 23rd. Two Swiss regions (Région Lémanique and Espace Mittelland) and one German (Düsseldorf) have also lost their places among the top innovators in the two decades considered.

In conclusion, the strong centre–periphery distribution of innovation activity which characterized the 1980s has now weakened; more regions in northern and southern Europe participate in technological activity. The process described above could be related to spatial dependence, that is, to the fact that technological activity performed in one region may be associated with the technological activity in neighbouring regions. This possibility can be evaluated by means of the Moran's I-statistic based on contiguity weight matrices. The most general specification for the matrix is one of physical contiguity, where unity represents the case of two regions sharing a boundary, and zero the case where they do not.

The Moran index for the entire economy (table 2, over) shows the existence of a strong positive spatial autocorrelation process, confirming the visual impression of spatial clustering given by the maps. If one also considers the spatial correlogram, this rejection is observed until the third order of contiguity—first, second, and third-order neighbours—as reported in table 2. Nonetheless, we observe a typical pattern of decreasing autocorrelation with increasing orders of contiguity.

Scatter maps enable us to assess the sign of spatial association of innovative activity in the different areas. The scatter map shows that there is a clear association



(a)

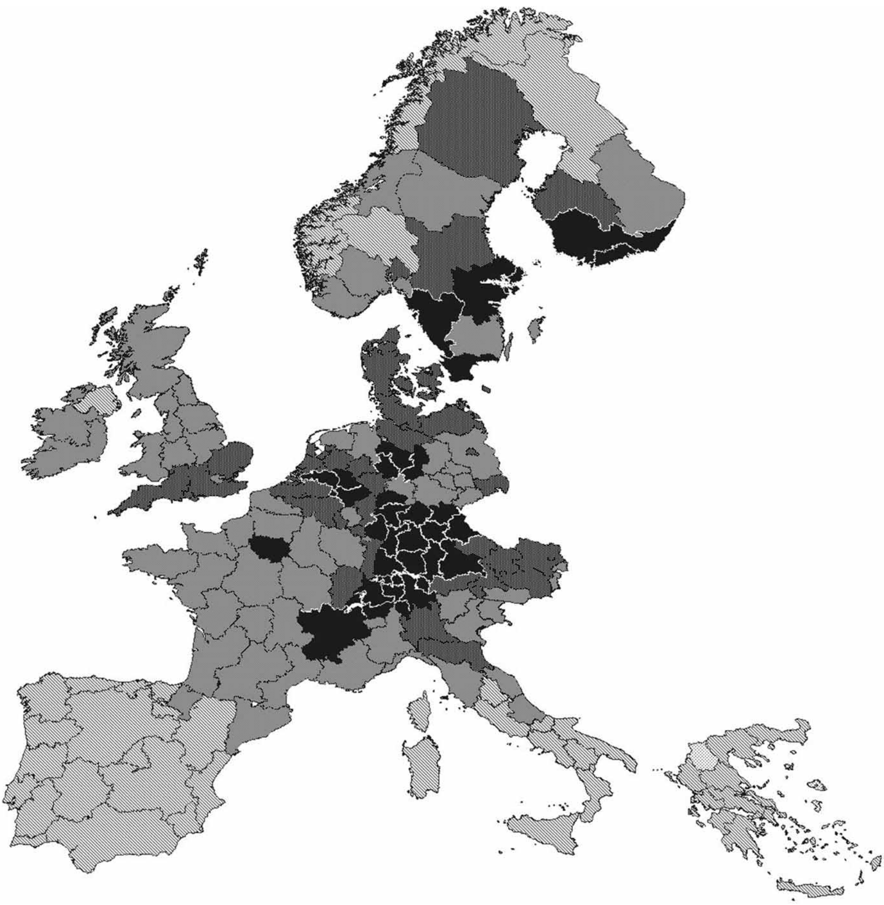
Figure 1. Distribution of innovative activity in the European regions (patents per 100 000 inhabitants): (a) 1981 – 83, (b) 1999 – 2001.

Table 2. Spatial autocorrelation in the innovative activity, total manufacturing (Moran's I test, normal approximation).

Contiguity	1981 – 83		1988 – 90		1994 – 96		1999 – 2001	
	Z-value	prob.	Z-value	prob.	Z-value	prob.	Z-value	prob.
1st-order	3.4	0.0	4.1	0.0	4.3	0.0	4.5	0.0
2nd-order	2.8	0.0	3.6	0.0	4.2	0.0	4.3	0.0
3rd-order	3.4	0.0	3.4	0.0	3.7	0.0	3.5	0.0

prob. probability.

of high – high values in the centre, and low – low values in the south [see figure 2 (over) for the annual average in the period 1999 – 2001]. This picture remains almost unchanged if we look throughout the period considered, with only few exceptions: some regions in the north of Italy initially presented isolated high values of patents, surrounded by low values, whereas in the 1990s they became a cluster of high values. Finland has performed remarkably well during the entire period, presenting low values surrounded by low values at the beginning, but changing to high values later.



(b)

Figure 1 (continued).

In the following sections we analyse to what extent externalities that cross regional boundaries are behind the spatial association pattern detected in the descriptive and statistical analysis above. The use of spatial econometrics techniques in conjunction with the KPF framework should allow us to obtain some insights into the mechanisms of local interdependences of knowledge.

4 The KPF model

In this section we describe the econometric model used to investigate the mechanisms and determinants of the process of creation and diffusion of innovative knowledge using spatial econometrics techniques.

The basic KPF relates the innovative output in region i to R&D inputs in the same region. We depart slightly from this specification by introducing a number of further factors related to the economic and institutional environment, so that the general form of our basic KPF is given as

$$I_i = R_i^{\partial_1} Z_{1i}^{\partial_2} e_i \,, \qquad (1)$$

where I is a proxy for innnovative output, R indicates R&D expenditures, $\boldsymbol{Z}_1$ is a vector of variables that reflects the economic and institutional additional determinants and e represents a random independent and identically distributed error term capturing

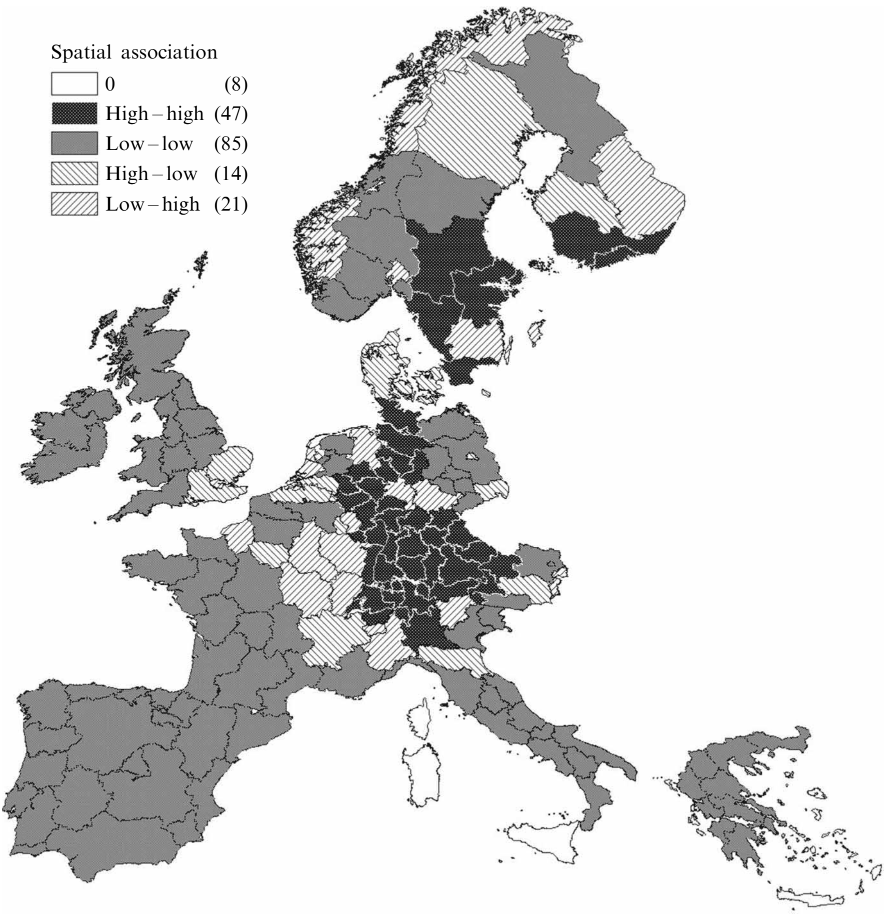


Figure 2. Scatter for innovative activity in the European regions, 1999–2001 (patents per 100 000 inhabitants, annual average; number of regions in parenthesis).

other unobservable determinants of innovative output. These additional factors are included in the model to control for systematic effects that may be present in the innovation process but are neglected by the original KPF. We consider the institutional environment within which the resources are deployed, as well as externalities internal to the region and associated with human, social, and public capital, and agglomeration economies. This latter component, in the form of either Marshall–Arrow–Romer externalities (that is, localisation economies) or Jacobs externalities (that is, urbanisation economies), can be considered the basis of benefits for individual firms in certain geographic areas. It can be argued that the same R&D expenditure results in a higher level of innovative activity in large metropolitan areas than in smaller cities because of agglomeration economies (Audretsch and Stephan, 1996). In particular, considering the knowledge-intensive nature of innovative activity, it is likely that the tacit component of knowledge has a major role. In this respect, the concentration of skilled workers in one place is a mechanism through which knowledge externalities may materialise, as direct communication enables flows of information and knowledge (Feldman and Florida, 1994).

The theoretical and empirical literature surveyed in section 2 suggests that the production of knowledge in a region depends not only on its own research efforts, but also on the knowledge stock available in the whole economy. In other words, knowledge may spill over from other regions. Many factors, external to the region, can act as determinants of technological activity, channelled through trade flows, external investments, imports of machinery, and common markets for skilled labour and final goods. Moreover, pecuniary externalities may be at work, thereby shifting externalities at the firm level to higher territorial levels. Our general framework given in equation (1) is consequently modified to introduce an additional vector of external factors $\boldsymbol{Z}_2$, reflecting the fact that innovation generated in one region may spill over and help knowledge formation in other regions:

$$I_i = R_i^{\partial_1} Z_{1i}^{\partial_2} Z_{2i}^{\partial_3} e_i \,. \tag{2}$$

This extended model can provide an explanation for spatial dependence at the level of innovation output and, because the distribution of innovation output has been shown to be spatially correlated, we should expect the estimates of the coefficients of $\boldsymbol{Z}_2$ to be significant.

However, instead of estimating model (2) directly, we start with model (1) and by means of spatial econometric techniques we assess whether external effects are to be included in the KPF, as in model (2). Therefore we begin by assuming that any new knowledge produced by a region in a given period is related to its R&D efforts in previous periods and to a vector of internal factors $\boldsymbol{Z}_1 = (D, M, N)$ according to a Cobb–Douglas technology which can be written in logarithmic form as follows:

$$\ln I_{i,t} = \beta_1 \ln R_{i,t-q} + \beta_2 \ln D_{i,t-s} + \beta_3 \ln M_{i,t-s} + \sum_{c=1}^{17} \delta_c N_{ic} + \varepsilon_{i,t} \,, \tag{3}$$

where β_1, β_2, and β_3 are interpreted as the elasticities of the increment of economically valuable technological knowledge, I, owing to changes in the respective variables. The dependent variable is proxied by the number of patents per capita in one region. As for the independent variables, the input of innovative activities, R, is measured by the share of gross domestic product invested in research and development activities. Among the other potentially relevant internal forces, we introduce density of population, D, and the quota of manufacturing employment, M. Following general practice in the literature, the rationale behind the introduction of these variables into the basic KPF is to capture agglomeration economies. Different variables have been used in the related literature to proxy agglomeration economies, such as employment in the business sector and high-technology employment (Anselin et al, 1997), the relative importance of large firms in the geographical area (Varga, 2000), or the density of population (Ciccone, 2002). In our opinion, the inclusion of the quota of manufacturing employment presents the advantage of proxying not only agglomeration economies, but also the differences in the propensity to patent across regions. The propensity to patent is usually higher in manufacturing than in service industries, and therefore including this variable should prevent the output elasticity of R&D from being biased (Bode, 2004). Finally, by including a set of national dummies, N, we control for institutional and other structural factors, which may affect either the innovative activity or the propensity to appropriate its results by patenting.

Because we are estimating a cross-section, each variable is an average of three years' data, to smooth out possible transient effects and approximate long-run values. Additionally, because the production of knowledge takes time, we assume a time lag between R&D expenditure and the innovation yield. As a result, variable I refers to the period 1999–2001, whereas R refers to 1989–96, and D and M to 1997–99. We also performed a robustness check of the main econometric results with respect to different lag structures.

To date, most empirical analyses have not devoted special attention to an econometric method capable of robustly testing and estimating externalities within a KPF. The only important exceptions are the works by Anselin et al (1997; 2000) focused on the US case, and Fischer and Varga (2003) for Austrian regions, although in both cases the emphasis is on the effect of academic knowledge spillovers on private R&D. Our empirical exercise, instead, directly addresses interregional externalities in the generation of innovation through the use of spatial econometrics techhniques. The use of a cross-sectional sample potentially leads to spatial autocorrelation in the regression equations which is assessed by means of a set of Lagrange multiplier tests. They are used to assess the extent to which remaining unspecified spatial spillovers may be present in the estimation of expression (3). If this is the case, spatial econometrics provides the necessary tools to deal with this problem.

Specifically, spatial statistics applied to the estimation of equation (3) would reveal not only the existence of spatial dependence in our specification, but also its possible form: a substantive or a nuisance model. The former is as follows:

$$\ln I_{i,t} = \beta_1 \ln R_{i,t-q} + \beta_2 \ln D_{i,t-s} + \beta_3 \ln M_{i,t-s} + \beta_4 W_i \ln I_i + \sum_{c=1}^{17} \delta_c N_{ic} + \varepsilon_{i,t} , \tag{4}$$

where $\mathbf{W}$ is a weight matrix defining linkages across regions. The variable represented by the term $\mathbf{W} \ln \mathbf{I}$ is therefore the spatial lag for the innovation output; in other words, it is a weighted measure of patents in the regions with which region i has contacts. We interpret an influence of this variable on the endogenous variable as evidence of interregional spillovers of the knowledge located outside the region, whereas the lack of significance of β_4 would indicate that the production of new knowledge is generated internally. This spatial lag term has to be treated as an endogenous variable and maximum likelihood (ML) has to be used because ordinary least squares (OLS) estimators are biased and inconsistent.

The nuisance model represents a second way to incorporate spatial autocorrelation into the knowledge-production function by specifying a spatial process for the disturbance term. Although unbiased, the OLS estimators will no longer be efficient, as a consequence of the nonspherical error covariance [for different specifications of the spatial error terms see Anselin and Moreno (2003)]. The spatial error model for the regional KPF would be expression (3) as it stands, with the error term denoted as:

$$\boldsymbol{\varepsilon}_i = \lambda \mathbf{W} \boldsymbol{\varepsilon}_i + \boldsymbol{\mu}_i , \tag{5}$$

where $\boldsymbol{\mu}$ is asymptotically distributed as $\mathrm{N}(0, \sigma^2)$, ε follows a first-order Markov process, and λ is the spatial autoregressive coefficient for the error lag. In the case of spatial error autocorrelation, OLS parameter estimates are inefficient, whereas in the presence of spatial lag dependence parameters become not only biased, but also inconsistent (Anselin, 1988; Anselin and Florax, 1995).

5 Econometric results

5.1 Evidence on interregional technological spillovers

Econometric results are summarised in table 3. The KPF holds in the European regional case: the elasticity of patents with respect to R&D expenditure when the OLS estimation (see first column[(1)]) is carried out for equation (3) presents a significant value of

[(1)] Following a referee's suggestion we have also tested the robustness of our results with respect to the estimation methodology by using Poisson and negative binomial models applied to the dependent variable transformed into an integer. The main results of table 3 (column 1) are maintained. However, coefficients are not perfectly comparable given that in order to use negative binomials

Table 3. Estimation of innovative activity, dependent variable: $\ln I$.

Variable	OLS estimation equation (3)		ML estimation equation (4)	
	$\mathbf{W}_{\text{bin}}$	$\mathbf{W}_{\text{dist}}$	$\mathbf{W}_{\text{bin}}$	$\mathbf{W}_{\text{dist}}$
$\ln R$	0.244 (0.000)		0.225 (0.000)	0.257 (0.000)
$\ln D$	0.286 (0.000)		0.319 (0.000)	0.265 (0.000)
$\ln M$	0.741 (0.000)		0.455 (0.007)	0.434 (0.010)
$\mathbf{W} \ln \mathbf{I}$			0.051 (0.000)	0.086 (0.000)
N (dummies)	yes		yes	yes
R^2—adjusted	0.853		0.883	0.885
AIC	376.9		357.3	354.3
LM-ERR	10.733 (0.001)	5.473 (0.019)		
LM-LAG	23.522 (0.000)	26.238 (0.000)		
Likelihood ratio test			21.639 (0.000)	24.549 (0.000)

Notes: OLS—ordinary least squares; ML—maximum likelihood. $N = 175$. p-values are given in parentheses.
$\mathbf{W}_{\text{bin}}$ is a first-order contiguity matrix, $\mathbf{W}_{\text{dist}}$ is an inverse distance matrix. $\mathbf{W} \ln \mathbf{I}$ is the spatially lagged dependent variable where $\mathbf{W}$ stands for the weight matrix corresponding to the column.

around 0.24. This result confirms the consensus found in the literature, although it is in the lower limit of the range of values obtained in previous works. The elasticity goes from 0.2 to 0.9 in the USA (Acs et al, 1994; Anselin et al, 1997; Jaffe, 1989), and from 0.4 to 0.8 in the European case (see Bottazzi and Peri, 2003; Greunz, 2003). It should be noted that with respect to these two previous contributions we exploit a more disaggregated and updated database. In particular, contrary to Bottazzi and Peri (2003), we use the whole set of information available from the EPO office rather than a random subsample. This difference is supposed to be particularly relevant for the analysis of peripheral regions, whose innovative activity is rather sporadic, and for the analysis of the complex set of industrial interdependences for which sector representativeness may prove an important issue. We have also estimated the KPF without considering the vector $\boldsymbol{Z}_1$, to check the robustness of this result: the elasticity is still significant with a much greater value of 0.87. However, when these additional factors are included, the explanatory power of the regressions is substantially and significantly increased. The added variables increase regression fit from an adjusted R^2 of 0.57 to 0.85, and the Akaike information criterion (AIC) decreases from 549 to 377.

The local agglomeration factors exhibit a positive and significant effect on innovative activity, with elasticities of 0.29 for density and 0.74 for the quota of the manufacturing sector. As for the institutional factors related to national differences, all dummies are significant. They can be interpreted as a reflection of the general

[1] (continued)
and Poisson we have to estimate a semilog function instead of a double-log. Furthermore, it should be stressed that estimating the whole set of regressions with Poisson and negative binomial models including spatial autocorrelation is not straightforward and the derivation of these estimation methods would go beyond the scope of this paper.

efficiency of research influenced by countrywide institutional settings as well as the productivity effects of the knowledge diffused throughout the country. Higher coefficients are shown for Sweden, Finland, Switzerland, Denmark, and Luxembourg, that is, for those countries which have shown high levels of innovative activity. In contrast, the lowest fixed effects are those of Portugal, Greece, and Spain, which appear to be lagging behind in the innovative competition, after we have controlled for R&D expenditure and agglomeration economies.

We have also analysed the sensibility of the results to the inclusion of different variables proxying agglomeration externalities and economic performance, such as an urban dummy variable and GDP per capita. The idea behind the urban dummy is that equal R&D expenditures result in a higher level of innovative activity in large metropolitan areas than in smaller cities, because of agglomeration economies, whereas GDP per capita is a general index of economic wealth. Overall, main results are preserved. Moreover, several tests have been carried out to assess the adequacy of the regression. Multicollinearity is not a problem (with a condition number equalling 16) but the distribution of error terms is nonnormal as indicated by the Jarque–Bera normality test. This is critical because the spatial autocorrelation tests as well as the appropriate estimation methods for the spatial models are based on this assumption. However, the analysis of the distribution of the errors shows that the nonnormality is a result of the existence of some extreme values corresponding to the Greek regions plus two German, a Spanish, and a Portuguese region. Once these observations have been discarded, the distribution of the error terms is normal and neither the size of the estimated parameters nor their significance changed at all. Therefore, we have decided to keep all the observations in order to maintain the whole sample of European regions.

As for spatial autocorrelation, its presence is clearly shown in the lower section of table 3. The tests for spatial autocorrelation (LM-ERR, Lagrange multiplier test for error dependence, and LM-LAG, Lagrange multiplier test for a missing spatially lagged dependent variable) were computed for two different spatial weight matrices, reflecting different assumptions on the spatial structure of dependence. The former ($\mathbf{W}_{\text{bin}}$) is a physical contiguity matrix, giving rise to a binary and symmetric matrix with elements equal to 1 in the case of two neighbouring regions and 0 otherwise. The latter is the inverse of the distance ($\mathbf{W}_{\text{dist}}$). Thus, the weight matrices have nonzero elements for each observation pair that is assumed to interact. The inverse exponential distance implies that knowledge spills over with a spatial transaction cost: the shorter the distance between any two regions, the higher the intensity of spillovers. However, both matrices rely on the idea that only geographical proximity matters in the interaction across regions, a notion which has been largely supported by recent literature (see Karlsson and Manduchi, 2001). In section 5.4 we relax this assumption and consider the technological composition of the regions as important determinants for externalities.

The tests clearly reject absence of spatial autocorrelation at the 1% level of significance for both weight matrices, indicating misspecification of the model and potentially some kind of externalities across regions. Following the 'classical' specification search approach adopted in the spatial econometrics literature, and given that the value of the LM-LAG test is higher than that for the LM-ERR, the estimation of the spatial lag model by ML is the preferred specification. The model estimated by ML provides an increased explanatory power (AIC equal to 357 and 354) and the significant value of the likelihood ratio tests implies the statistical adequacy of the spatial lag models. The elasticity of patents with respect to internal R&D is significant, ranging from 0.22 to 0.26 for the two weight matrices, and all control variables keep their expected positive sign. The elasticity of patents in one region with respect to patents in the neighbouring regions ranges between 0.05 for the binary contiguity criteria and 0.09 when the distance is accounted for. The higher elasticity obtained with the distance matrix is a result of the fact that this is a full matrix which considers the whole range of spillovers arising from all regions. This positive and significant effect of the knowledge externality, proxied by the spatial lag of patents, highlights the role played by interregional spillovers in innovative activity in European regions. The contribution of knowledge from outside the region is, however, of limited magnitude.

In model (4) we assume that the production of knowledge in a region depends not only on its own research efforts and internal factors, but also on the knowledge available in other regions. The knowledge available in the neighbouring regions is proxied by their innovation output measured through their patents. However, following an idea given in Bottazzi and Peri (2003), we have considered spillovers generated by the research effort, which will allow us to analyse the sensibility of our previous results to other proxies for interregional knowledge spillovers as follows:

$$\ln I_{i,t} = \beta_1 \ln R_{i,t-q} + \beta_2 \ln D_{i,t-s} + \beta_3 \ln M_{i,t-s} + \beta_4 W_{i,t-q} \ln R_{i,t-q} + \sum_{c=1}^{17} \delta_c N_{ic} + \varepsilon_{i,t}, \tag{6}$$

where the term $\mathbf{W} \ln \mathbf{R}$ is a spatial lag for the innovation input. The results obtained from the estimation of model (6) are shown in the first column of table 4. The method of estimation is OLS, because there are no endogeneity problems, and the weight matrix considered is the contiguity one. The results concerning R&D expenses and

Table 4. Estimation of innovative activity with distance-decay effect, dependent variable: $\ln I$.

	Ordinary least squares estimation, equation (6)				
$\ln R$	0.2779	0.294	0.287	0.253	0.260
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln D$	0.242	0.239	0.240	0.279	0.277
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln M$	0.660	0.641	0.639	0.707	0.699
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\mathbf{W}_1 \ln \mathbf{R}$	0.056	0.051	0.0498		
	(0.005)	(0.011)	(0.013)		
$\mathbf{W}_2 \ln \mathbf{R}$		0.032	0.031		
		(0.047)	(0.056)		
$\mathbf{W}_3 \ln \mathbf{R}$			−0.011		
			(0.0489)		
$\mathbf{W}_{0-250} \ln \mathbf{R}$				0.049	0.053
				(0.000)	(0.000)
$\mathbf{W}_{250-500} \ln \mathbf{R}$					0.007
					(0.516)
N (dummies)	yes	yes	yes	yes	yes
R^2—adjusted	0.876	0.879	0.862	0.863	0.863
AIC	369.9	367.4	368.9	365.6	367.1
LM-ERR	0.035	0.574	0.281	0.641	0.505
	(0.852)	(0.448)	(0.596)	(0.423)	(0.477)
LM-LAG	10.566	7.446	8.765	8.918	8.551
	(0.001)	(0.006)	(0.003)	(0.002)	(0.003)

Notes: $N = 175$. p-values are given in parentheses. $\mathbf{W}_1$, $\mathbf{W}_2$, and $\mathbf{W}_3$ are 1st, 2nd, and 3rd-order contiguity matrices, respectively. $\mathbf{W}_{0-250}$ and $\mathbf{W}_{250-500}$ are weight matrices with neighbours in 0–250 km and 250–500 km rings, respectively.

agglomeration economies are in line with previous findings. The elasticity of patenting activity with respect to R&D expenditure in the neighbouring regions presents a significant value of 0.06, very close to the one obtained above. Therefore, irrespective of the measures of spatial innovative spillovers, the parameter for interregional knowledge externalities is significant and positive, indicating that regions benefit from being situated in close spatial proximity to other highly innovative regions.

5.2 Analysing the spatial scope of spillovers

Results obtained so far lead us to conclude that localised spillovers are important when contiguous neighbours are considered as well as when all the regions are considered—although with a lower weight as distance increases. This leads us to question whether there is a cutoff point, after which interaction among regions becomes insignificant.

One way to check the existence of a decay effect in the influence of innovation spillovers is through the use of higher order lags of the variable R&D. Using equation (6), we have considered second-order and third-order lags of the variable R. The results, in columns 2 and 3 of table 4, show that the spillovers are significant until a second-order neighbourhood. In other words, innovation made in one region spills over not only to the physical neighbouring regions, but also to the regions sharing a border with these first-order neighbours, although with a lower impact. Spillovers stop at this level, because the third-order contiguity lag in R is not significant.

In a second exercise, we define different weight matrices based on increasing values for the cutoff level of distance. Specifically, for any region i, the spatial lag $\mathbf{W}_{0-250} \ln \mathbf{R}$ is the sum of the R&D expenses in those surrounding regions within a radius of 250 km. We also computed similar measures for a 500 km range ($\mathbf{W}_{250-500} \ln \mathbf{R}$). Columns 4 and 5 in table 4 show the results of this cutoff distance analysis. The statistically significant coefficient of the technological spillover is within the range of 250 km, whereas the coefficient in the range of 250–500 km is positive but not significant. The highly significant spatial lag for R within the first radius value suggests that innovative activity in a region is positively related to the level of innovative activity in regions located within 250 km, but no further. In conclusion, the spatial range of interaction between R&D and patents reaches beyond the regions where the R&D is actually carried out, but within a limited distance.

5.3 Analysing the national or transnational scope of spillovers

So far, the scope of our analysis has been Europe as a whole. We have not considered the possibility that common national characteristics could have a crucial role in the transmission of knowledge within the regions of a given country. And, conversely, that regions belonging to different countries, even if sharing a common border, have a lesser flow of knowledge because of the differing national characteristics. Because the flow of ideas across regions is considered a key rationale behind the existence of interregional knowledge spillovers, and because previous literature shows that migration and trade flows are more intense between regions belonging to the same country (Helliwell and McKitrick, 1998), the same border effect could apply to innovation spillovers.

In order to check the potential barriers to interregional externalities posed by national borders, we construct a within-country and an across-countries weight matrix. In the first case we set equal to one only the weights corresponding to regions which share a common border and which belong to the same country. In the second version, the weights for regions sharing a border and being within the same country are set equal to zero and those for regions sharing a border but belonging to different countries are set equal to one.

The results are summarised in table 5. In the estimation of equation (3), significant positive spatial dependence is observed both in the within-country and in the across-countries matrices, a result that goes against the rationale of the existence of spillovers only between regions belonging to the same country. The significance of the LM-ERR test when using the within-country matrix points to the estimation of the spatial error model in equation (5) as the preferred specification. In contrast, the significance of the LM-LAG test points to the estimation of the spatial lag model when the across-countries weight matrix is considered. The results of the two ML estimations are shown in the second and third columns of table 5. They imply that, when externalities across regions within the same country are taken into account, the spatial error coefficient (λ) is significant and positive. Additionally, if spillovers across regions of different countries are analysed, the spatial lag of the endogenous variable is significantly positive.

To remain coherent with the strategy followed so far, the results of the estimation of equation (6) are given in the last column, so that the spillovers referred to R&D expenditure are also considered by using the two matrices. The spatial lag of R within the same country is significant, with no remaining spatial autocorrelation in the estimation, whereas spillover across countries is not. Thus, although knowledge seems to cross physical borders, some evidence shows that knowledge spills mainly over regions belonging to the same country. This result is not surprising because it corroborates previous findings (Cantwell and Iammarino, 2003) that national innovation systems, to a certain extent, still dominate the common European one.

Table 5. Estimation of innovative activity within and across countries, dependent varible: $\ln I$.

Variable	OLS estimation		ML estimation		OLS estimation
	$\mathbf{W}_{\text{within}}$	$\mathbf{W}_{\text{across}}$	$\mathbf{W}_{\text{within}}$	$\mathbf{W}_{\text{across}}$	
$\ln R$	0.244 (0.000)		0.246 (0.000)	0.240 (0.000)	0.277 (0.000)
$\ln D$	0.286 (0.000)		0.271 (0.000)	0.299 (0.000)	0.243 (0.000)
$\ln M$	0.741 (0.000)		0.486 (0.000)	0.668 (0.000)	0.677 (0.000)
$\mathbf{W} \ln \mathbf{I}$				0.043 (0.007)	
Spatial error term (λ)			0.107 (0.000)		
$\mathbf{W}_{\text{within}} \ln \mathbf{R}$					0.056 (0.021)
$\mathbf{W}_{\text{across}} \ln \mathbf{R}$					0.049 (0.240)
N (dummies)	yes		yes	yes	yes
R^2—adjusted	0.853		0.839	0.874	0.859
AIC	376.9		363.1	372.1	372.4
LM-ERR	5.098 (0.024)	0.043 (0.835)			1.385 (0.239)
LM-LAG	2.559 (0.109)	6.921 (0.008)			1.736 (0.187)
Likelihood ratio test			13.745 (0.000)	6.855 (0.009)	

Notes: OLS—ordinary least squares; ML—maximum likelihood. $N = 175$. p-values are given in parentheses. $\mathbf{W}_{\text{within}}$ is a contiguity matrix for regions within the same country, $\mathbf{W}_{\text{across}}$ is a contiguity matrix for regions belonging to different countries.

5.4 Analysing the importance of technological proximity in the diffusion of innovation

So far we have proved the existence of externalities across geographical boundaries. However, interregional spillovers may also take place thanks to technological contiguity across regions. The rationale underlying this idea comes from economic literature at the firm level, where firms' capacity to absorb other firms' knowledge depends on technological similarity between firms. In other words, spillovers within the same industry can be more substantial than those across industries, because each technology embodies a unique type of language and concerns a precise set of applications. Researchers are expected to benefit more from others who work in the same or related technological field, irrespective of geographical distance (Bode, 2004).

The paper by Jaffe (1986) has resulted in several others about the effect of technological proximity on knowledge spillovers. Using firms' patent data to compute similarities between firms, he finds that technological spillovers are an important explanatory factor of productivity. There are different ways to measure technological proximity (Los, 2000). One method is based on the use of input–output tables (Moreno et al, 2004; Verspagen, 1997) in which externalities via technology diffusion occur either through purchases of intermediate goods (supplier-driven externalities) or through sales to other industries (customer-driven externalities). An alternative method would follow Jaffe's idea of using the distribution of firms' patenting activity across sectors to characterise the technological structure of a firm or a region. This is our choice, as already done in the setting of KPF by Autant-Bernard (2001) and Greunz (2003). We assume that the existence of technological spillovers implies that a region's R&D success is affected by the research activity of its neighbouring regions in technological space. In order to obtain a measure of 'technological neighbourhood', we compute a technological matrix ($\mathbf{W}_{\text{tech}}$) calculated by means of patent application data (1981–2001) disaggregated into 101 sectors (three-digit ISIC) for each region. To measure the proximity of regions we follow Jaffe (1986) in whose work the proximity measure takes a value equal to unity for technologically identical regions, and zero otherwise. The closer to unity, the greater the degree of similarity of the two regions' technological structure. Consequently, the spatial lag of patents constructed with this matrix, $\mathbf{W}_{\text{tech}} \ln \mathbf{I}$, implies a weighted sum of other regions' patents, with weights proportional to the proximity of the firms in technological space. Furthermore, we contemplate both concepts of proximity, geographical and technological, in a unique measure. Basically, we construct two new weight matrices in which the technological similarity is weighted by the geographical proximity in terms of either contiguity ($\mathbf{W}_{\text{tech-contiguity}}$) or the inverse of the distance ($\mathbf{W}_{\text{tech-distance}}$).

The results are summarised in table 6. With the estimation of equation (3), the spatial dependence statistic LM-LAG for the pure technological weight matrix (see column 1) rejects the null hypothesis of absence of spatial dependence. The value of this statistic is lower than the values of the statistics obtained for the binary contiguity and the inverse of the distance shown in the first two columns of table 3. The spatial dependence process with respect to geographical proximity is stronger than that referring only to technological similarity. Nonetheless, when spatial dependence is tested with respect to the two weight matrices that consider both types of similarities simultaneously, a significant autocorrelation is also observed. In such cases, the values of the spatial autocorrelation statistic (LM-LAG) are also lower than the values obtained for the binary contiguity and the inverse of the distance, but are still higher than those obtained when one considers pure technological proximity. In other words, physical vicinity proves more important than technological proximity.

Once again, following the usual search approach, the significance of the LM-LAG tests points to the estimation of the spatial lag model in all the cases. Results are also

Table 6. Estimation of innovative activity with tech – distance matrices, dependent variable: $\ln I$.

Variable	OLS estimation			ML estimation		
	$\mathbf{W}_{\text{tech}}$	$\mathbf{W}_{\text{tech-contiguity}}$	$\mathbf{W}_{\text{tech-distance}}$	$\mathbf{W}_{\text{tech}}$	$\mathbf{W}_{\text{tech-contiguity}}$	$\mathbf{W}_{\text{tech-distance}}$
$\ln R$		0.244		0.222	0.222	0.234
		(0.000)		(0.000)	(0.000)	(0.000)
$\mathbf{W}_{\text{tech}}$				0.053		
				(0.000)		
$\mathbf{W}_{\text{tech-contiguity}} \ln I$					0.028	
					(0.000)	
$\mathbf{W}_{\text{tech-distance}} \ln I$						0.041
						(0.000)
Controls						
$\ln D$		0.286		0.321	0.322	0.303
		(0.000)		(0.000)	(0.000)	(0.000)
$\ln M$		0.741		0.525	0.474	0.430
		(0.000)		(0.000)	(0.005)	(0.011)
N (dummies)		yes		yes	yes	yes
R^2—adjusted		0.854		0.881	0.883	0.886
AIC		376.9		361.1	357.9	353.4
LM-ERR	1.972	1.547	1.776			
	(0.162)	(0.214)	(0.183)			
LM-LAG	10.871	13.365	19.235			
	(0.001)	(0.000)	(0.000)			
Likelihood ratio test				17.777	20.975	25.474
				(0.000)	(0.000)	(0.000)

Notes: OLS—ordinary least squares; ML—maximum likelihood. $N = 175$. p-values are given in parentheses. $\mathbf{W}_{\text{tech}}$ is a technological distance matrix (see text for details), $\mathbf{W}_{\text{tech-contiguity}}$ is a contiguity matrix weighted by the technological distance matrix, and $\mathbf{W}_{\text{tech-distance}}$ is an inverse distance matrix weighted by the technological distance matrix.

shown in table 6. The spatial lag of the endogenous variable is significant in the three cases and the LR tests indicate that autocorrelation has disappeared. The elasticities of patents with respect to internal R&D expenditures as well as the parameters for agglomeration economies are analogous to previous results, whereas the elasticity of patents in one region with respect to patenting in its technological neighbours presents a value of 0.05, quite similar to those obtained in the case of geographical proximity. As far as the technological spillovers generated within the geographical and technological space are concerned, we find a slightly lower but still significant elasticity, with a value of 0.03 and 0.04 for the $\mathbf{W}_{\text{tech-contiguity}}$ and $\mathbf{W}_{\text{tech-distance}}$, respectively.

In sum, interregional spillovers exist between close regions, both from a geographical and a technological point of view, although the geographical factors seem to dominate the technological factors to a certain extent.

6 Conclusions

In this paper we sought to provide original empirical evidence on the process of spatial creation and dissemination of knowledge in Europe, with a special focus on the relevance of interregional technological spillovers. We provide an answer to the question of whether regional geographical and technological proximity matters in explaining innovation activity.

We started mapping innovative activity in European regions with two main outcomes. First, there was a strong centre – periphery distribution of innovation activity at the beginning of the period. Innovation activity is concentrated in regions in the north and centre of Europe, and little or no technological activity is performed in most Southern European regions. Second, this concentration has tended to decrease over time, and innovations have spread to regions in Scandinavia and in the south of Europe. The analysis of global indicators of spatial association confirms the presence of a strong and positive spatial autocorrelation process in innovative activity. This means that patenting activity in a certain region tends to be correlated to innovation performed in contiguous areas.

Furthermore, we investigated to what extent knowledge externalities that cross the boundaries of the regions can be behind the spatial association process detected in the distribution of innovation. Using the KPF framework in conjunction with spatial econometric techniques we can look for some insights into the mechanisms of interregional interdependencies in knowledge. Spatial econometrics turns out to be a very powerful analytical tool in empirically modelling spillovers when cross-sectional data are applied, as it generates the statistics to test for potential misspecifications in the form of spatial autocorrelation as well as indicating different modelling strategies and measures for interregional spillovers.

The econometric analysis appears particularly revealing. Findings confirm the importance of internal R&D expenditure on patenting activity, with a highly significant and stable effect. It also confirms the important role played by other internal factors reflecting agglomeration economies and national institutions. Moreover, we find that external effects or innovative spillovers also matter. They arise both through the patenting activity and the R&D efforts performed in other regions. Estimation results on the spatial extent of such spillovers suggest the existence of a clear decay process in knowledge diffusion. Additional results show that spillovers occur mainly across regions within a country. In other words, interregional external effects in innovation are mostly constrained by national borders and this in turn suggests that national innovation systems, rather than the European one, are predominant. Finally, in order to improve our understanding of the inner mechanics of knowledge diffusion, we have associated diffusion with proximity in the technological structure of regions. Results are worthy of note: technological proximity matters with an effect of a comparable magnitude to that obtained with geographical proximity.

In sum, the results highlight the relevance of an accurate consideration of the spatial range of interaction in the analysis of spatial externalities. Once the KPF has been remodelled after testing the empirical necessity of including explicitly spatial effects, it produces the important conclusion that the spatial dimension of spillovers cannot be ignored. However, we are aware that the KPF approach does not allow for discrimination between different sources of R&D externalities (pure technological externalities or pecuniary externalities) which would imply very different policy suggestions.

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