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 across 138 regions of 17 countries in Europe (the 15 members of the European Union plus Switzerland and Norway). The analysis is based on an original statistical databank set up by CRENoS on regional patenting at the European Patent Office spanning from 1978 to 1997 and classified by ISIC sectors (3 digit).
In a first step, a deep exploratory spatial data analysis of the dissemination of innovative activity in Europe is performed. Some global and local indicators for spatial association are presented, summarising the presence of a dependence process in the distribution of innovative activity for different periods and sectors.
Secondly, we attempt to model the behaviour of innovative activity at the regional level on the basis of a knowledge production function. Econometric results points to the relevance of internal factors (R&D expenditure, economic performance, agglomeration economies). Moreover, the production of knowledge by European regions seems to be also affected by spatial spillovers due to innovative activity performed in other regions.

Keywords: Innovative activity, Spatial analysis, European regions, Knowledge production function.

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1. Introduction

Knowledge and technological progress are basically the main engines of economic dynamics in most endogenous growth models (Romer, 1986, 1990). In the spatial context this implies that local growth depends on the amount of technological activity which is carried out locally and on the ability to exploit external technological achievements through information spillovers (Martin and Ottaviano, 2001, Grossman and Helpman, 1991, Coe and Helpman, 1995). Such spillovers may follow particular patterns depending on economic, technological and geographical distances among firms and regions. In this sense, Glaeser *et al.* (1992) and Henderson (1997), among many others, outline the importance of proximity for sharing innovations.

The most important empirical approach to analyse the process of innovation creation is the knowledge production function, originally formalized by Griliches (1979) and Pakes and Griliches (1984) and re-focused by Jaffe (1989) to study the geographic scope of knowledge spillovers.[1] Empirical estimations of the model of the knowledge production function have been carried out for different levels of aggregation with a common result on a positive and significant effect of research spillovers on innovation activity. However, most of these studies are applied to the US case, such as the ones by Acs *et al*. (1994) Jaffe (1989); Jaffe *et al.* (1993); Audrestsch and Feldman (1996), Anselin *et al.* (1997). At the European level previous attempts are those by Maurseth and Verspagen (1999) and by Bottazzi and Peri (2003). Among the studies applied to other geographical areas we find the ones by Autant-Bernard (2003) for the French departments, Fischer and Varga (2003) for Austrian political districts, Andersson and Ejermo (2003) for Sweden.

In the present paper we follow the objective of analysing the importance of proximity and technological similarity in the diffusion of knowledge at the European regional case. With this aim we first check the necessity of introducing knowledge spillovers in a regression based on the framework given by the knowledge production function. Once this necessity is tested, the statistically correct specification of the knowledge function is searched by the use of the methodology of spatial econometrics. In such specification we will study the geographical scope of knowledge spillovers, so that the possible existence of a spatial decay effect in these spillovers is analysed. Additionally, we explore whether the similarity of the technological composition between two certain regions is an advantage in the diffusion of knowledge.

[1] For a comprehensive and updated review on knowledge production and spillovers within the geographical space, see Audretsch and Feldman (2003).

Here an original statistical databank on regional patenting at the European Patent Office spanning from 1978 to 1997 and classified by ISIC sectors (up to 3 digit) is used for the first time allowing the analysis of the spatial distribution of innovative activity across 138 regions of 17 countries in Europe (the 15 members of the European Union plus Switzerland and Norway). Therefore, the use of this rich dataset presents an advantage if compared with the previous studies for the European case. Plus, it allows us to explore the evolution of technological activity across both regions and sectors. In order to exploit the potential of this dataset, we start it with a mapping of innovative activity in European regions by means of a deep exploratory spatial analysis based on several global and local indicators of spatial dependence. The analysis is carried out for different time periods starting from the early eighties up to the middle nineties and it is implemented for different sectors in order to evaluate differences and similarities.

The paper is organised as follows. In the following section we deal with some measurement issues by describing the database in use. In the third section we analyse the spatial mapping of innovative activity as well as the spatial properties of innovation throughout European regions along the eighties and nineties and across sectors. In the fourth section we turn to the question regarding the main determinants of the local process of innovative activity in which knowledge spillovers play a central role. This framework is dealt with by means of a spatial econometric analysis. Empirical results with a distinction among the proximity relevance of regions both in the space and in technological terms are given in section fifth. Final remarks conclude.

2. Some measurement issues

Several economists (for instance, Pavitt, 1982 and Griliches, 1990) have been debating about the issue of measuring innovative activity and technological progress, but no universal solution has been found. Starting from the concept of knowledge production function two types of indicators are usually identified: technology input measures (such as R&D expenditure and employees) and technology output measures (such as patents and new product announcements).

The main drawback of the former indicators is that they embrace firms' efforts for invention and innovation together with imitation activities. Moreover, they do not take into account for informal technological activity and, as a consequence, tend to underestimate the amount of innovative activity of medium and small firms. On the contrary, patent and product announcement represent the outcome of the inventive and innovative process. The fact that there are inventions that are never patented and many patents are never developed into innovations marks the shortcomings of this measure. However, the patenting procedures require that innovations have novelty and usability features and imply relevant costs for the proponent. Therefore innovations which are patented, especially those extended in foreign countries, are expected to have economic value, although highly heterogeneous.

With respect to the object of our research, patent statistics seem particularly suitable, given that they are the only available indicator with useful properties with respect to R&D data: (a) they provide information on the residence of the inventor and proponent and can thus be grouped regionally (potentially at different territorial units starting from zip areas), whereas R&D statistics are available just for some regions or at the national level; (b) they record the technological content of the invention and can, thus, be classified according to the industrial sectors whilst R&D data is usually aggregated, especially at the regional level; (c) they are available year by year for a long time span and this allow for a dynamic analysis, on the contrary regional R&D data is available only for recent years and discontinuously.

Our proxy for innovative activity refers to patents applications at the European Patent Office over the period 1978-97 classified by the inventor's region in Europe. Applications at EPO should provide a measure of sufficiently homogenous quality, due to the fact that applying to EPO is difficult, time consuming and expensive. This indicator, in other words, should prove particularly effective in order to take into account potentially highly remunerative innovations which for this reason are patented abroad. The use of the inventor's residence, rather than the proponent's residence, is preferred in order to attribute the spatial localisation of each innovation (Paci and Usai, 2000, Breschi 2000). Indeed, the latter generally corresponds to firms' headquarters and therefore 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.[2] Moreover, differently from previous research (Bottazzi and Peri, 2003) we do not assign patents just to the first investor, given that this may bias our result as inventors are usually listed in alphabetical order. For the case of patents with more than one inventors, therefore, a proportional fraction of each patent is assigned to the different inventors' regions of residence.

As for the territorial break up we have only partially followed the classification provided by EUROSTAT through NUTS (*Nomenclature des Unités Territoriales*

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[2] For instance, the headquarter of Enichem, the Italian petroleum and chemical multinational, is located in Milan (Lombardia) but the innovative activity (as indicated by the residence of the inventors) is much more dispersed due to the presence of several plants in other regions (e.g. Veneto, Sicilia, Liguria and Sardegna).

Statistiques)[3]. For some countries, this classification turns out to be artificial, based mainly on statistical concerns while failing to identify uniform regional areas in terms of economic, administrative and social elements. In fact we have tried to select, for each country, a geographical unit with a certain degree of administrative and economic control.[4] The result is a division of Europe (15 countries of the European Union plus Switzerland and Norway) in 138 sub-national units (which, from now on, we will simply call, *regions*) which are a combination of NUTS 0, 1 and 2 levels[5] (see Appendix for details).

As far as the sectoral classification is concerned, it should be noted that patent data are still of minimal use for economic analysis due to their mode of classification. Patents are recorded for administrative purposes using the International Patent Classification (IPC) system, which categorizes inventions by product or process. Instead, most economic data and analyses are interested in the particular sectors of the economy responsible for the invention or its subsequent use. For this reason patent data, originally classified by means of the IPC, have been converted to the industry of manufacture thanks to the Yale Technology Concordance[6] [see in Evenson (1993) and Evenson and Johnson (1997)]. Such a concordance uses the probability distribution of each IPC or product code across industries of manufacture in order to attribute each patent proportionally to the different sectors where the innovation may have originated.

3. The spatial distribution of innovation activity in European regions

3.1 The geography of innovative activity

At the beginning of the period under consideration (early eighties) a strong central-periphery distribution of innovation activity is observed in Map 1.[7] Innovation activity is concentrated in regions in Switzerland, West Germany, North and East of France, North of

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[3] Eurostat classification list four categories of territorial units: 15 NUTS 0 nations; 77 NUTS 1 regions, 206 NUTS 2 regions and 1031NUTS 3 regions.

[4] The perfect territorial unit is difficult to be found since administrative units not necessarily reflect economic phenomena. Better territorial units used in the empirical literature are the functional urban region just for main urban centres at the European level (Cheshire, 1990 and Cheshire and Magrini 2000), the local labour system in Italy (Paci and Usai, 1999), the *basin d'emploi* in France (Combes, 2000).

[5] In future applications we will attempt to disaggregate some nations which are currently at the NUTS0 level (Finland, Denmark and Norway in particular). Moreover, the option of disaggregating further German regions going from the 16 NUTS1 regions to the 26 NUTS2 regions is under study.

[6] The original YTC was conceived by Evenson, Kortum and Putnam. Updates to the YTC have been programmed by Daniel Johnson who provide downloadable conversion tables and detailed explanations on the procedures at the Internet address: http://www.wellesley.edu/Economics/johnson/jeps.html.

[7] Although the analysis of the innovative activity as well as the spatial dependence is given only for patents, the same pattern and conclusions are obtained when R&D expenses are considered.

Italy, United Kingdom, Denmark, the Netherlands and Sweden. None or modest technological activity is documented in most regions of the South of Europe: Spain, Greece, Portugal and South of Italy.

This picture is confirmed looking at the innovative activity at the country level (Table 1) and among the twenty most innovative regions (Table 2). At the beginning of the eighties the most innovative country is Switzerland, followed by Luxembourg and Germany. A similar picture appears at the regional level, where, among the top performers, we find six Swiss regions, six German regions plus the capital regions of other countries (London, Paris, Stockholm and Brussels).

Looking at the evolution of innovative activity over time, it is possible to remark some important elements. First, the intensity to innovate has increased considerably over the two decades in all countries.[8] More importantly, the innovations have been spreading to some more regions in the South of Europe (especially in Spain and Southern Italy) in the mid-nineties (see Map 2). The spatial diffusion of technological activity is also confirmed for the case of some regions in central Europe (France and East Germany). However, the most brilliant performance is shown by Finland, which in the nineties manages to reach the second position in the ranking (Table 1).

The database on patenting allows one to investigate the geographical distribution of innovative activity also sector by sector. One way to look at such a distribution is reported in Map 3 where the highest revealed technological advantage index is used to define the specialisation in European regions in the mid nineties. The mapping, among other interesting evidences, shows that there seem to be some clusters of common technological specialisation patterns: textiles and clothing in Italy, fuels, chemicals and rubber in Germany, food and beverages in Northern Europe. This suggests that a promising way forward in our research programme is the analysis of technological spillovers and sectoral interdependences across regions.

The level of inequality in the spatial distribution of the innovative activity is very high: the ratio between the most innovative country (Switzerland) and the least (Portugal) is equal to 245. In general, the coefficient of variation (CV) in the patenting activity among the 138 regions for the manufacturing and the energy sector is around 2.6 in 1980 but descends gradually to 2.1 at the end of the period (see the top-left panel in figure 1). Such a regular decline in the geographical concentration of innovative activity is a common feature of some macro-sectors, such as electronics and fuels, chemical and rubber. In some other sectors, such as food, beverages and tobacco, textiles and clothing and mining and energy supply, there appear a sharp decline at the beginning and an almost unvarying evolution in the following years. The only sector with a clear increasing polarisation in innovative activity along the years is the transport equipment sector while other manufacturing and building show a rather constant pattern throughout the period.

3.2. Spatial dependence of innovative activity

As for the study of spatial dependence, the degree of spatial association can be analysed by means of the Moran's I statistic, which is defined as:

$$I = \frac{N}{S_0} \frac{\sum_i^N \sum_j^N w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

where x_i and x_j are the observations for region *i* and *j* of the variable under analysis, patents in our case; $\bar{x}$ is the average of the variable in the sample of regions; and w_{ij} is the *i-j* element of the row-standardised *W* matrix of weights. $S_0 = \sum_i \sum_j w_{ij}$ is a standardisation factor that corresponds to the sum of the weights. As it equals the number of observations, *N*, in case of a row-standardised *W* matrix, N/S_0 is equal to 1 in our analysis.

The use of the Moran index for the entire economy (see first rows in Table 3) shows a clear rejection of the null hypothesis with a positive value of the statistic: there appears a strong positive spatial autocorrelation, confirming the visual impression of spatial clustering given by the maps. If one also considers the spatial correlogram, this rejection is observed till the third order of contiguity, reported in Table 3. Nonetheless, there also appears a pattern of decreasing autocorrelation with increasing orders of contiguity typical of many spatial autoregressive processes.[9]

We have computed the Moran's I for different distance matrices and for different bandwidth. With respect to the latter case, results show that the Moran's I is significant till a band of 725 km, which is quite a wide length. This outcome suggests that regions are not

[8] This phenomenon is partly due to a shift of patent applications by European firms from National patenting offices to the European one.

[9] The correlogram also shows a strong spatial autocorrelation for the fourth order at the end of the period, which would tend to indicate that spatial dependence across regions has widened with time. This result needs to be

always the proper unit of analysis. An interesting and promising result is that the distance rises with time, which implies that diffusion effects of innovative activity are spatially enlarging with time. Among the probable causes of this outcome we can perceive the development and diffusion of the ICT and, in general, of the New Economy which are producing the phenomenon known as "death of distance". Of course, more research is required on this respect.

We have also constructed the scatter maps in order to assess the sign of the spatial association in the different areas. The scatter maps show that there is a clear association of high-high values in the centre, and low-low values in the south (see Map 4 for the period 1995-97). This positive association remains true throughout the period, with few exceptions: some regions in the North of Italy presented initially high value of patents surrounded by low values whilst in the nineties became a cluster of high values. Additionally, Finland has performed remarkably well along this period, presenting low values at the beginning surrounded by low values, but changing to high values. However when the LISA statistics is computed only one significant cluster results, basically consisting of some regions in West Germany. In other words, this only cluster presents similar values of patents (high magnitudes), without observing any region with a dissimilar behaviour with respect to their neighbours. These are also the regions that contribute the most to the value of the global test of Moran's I. This pattern shows almost no difference along time.[10]

In Table 3 we have also reported the Moran tests for spatial autocorrelation in the innovative activity for seven macro-sectors. The sectoral results confirm the presence of spatial association up to the third contiguity order for all sectors considered. This means that patenting activity in a certain sector tends to be correlated to innovation performed in the same sector in contiguous areas, determining the creation of specialised clustering of innovative regions in different sectors.

4. The determinants of innovative activity

4.1 Modelling the determinants of innovation activity

Among the questions and issues brought about in the previous sections one appear to stand out as the most intriguing one: which are the main determinants of the local process of

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taken with caution since, in fact, the territorial unit chosen may prove too wide to reflect the real technological process causing the diffusion of technology.

[10] Scatter and LISA maps for other periods not reported in the paper are available on request.

innovative activity? To assess the importance of different factors in the determination of the output of the innovation we assume that there exist a relationship between the R&D investment made within a region and its production of useful new knowledge. Although it is difficult to observe new knowledge we trace some of its consequences such as the generation of patent applications. This way, the basic model we take up relates the innovative output in region *i*, measured through patent applications, to research and development inputs in the same region through a knowledge production function as introduced by Griliches (1979) and developed by Pakes and Griliches (1984). We slightly modify this production function so that the increment of the innovative output depends upon a number of further factors related to the economic and institutional environment within which the process of innovation takes place, so that the general form of our basic knowledge production function is given as

$$I_i = RD_i^{\partial_1} \; Z_{1i}^{\partial_2} \; e_i \tag{1}$$

where *I* is innovative output, *RD* the research and development expenditures, Z_1 is a vector of variables that reflects these additional influences, *e* represents a stochastic error term, and *i* indexes the unit of observation (regions, in this case).

Among the additional factors that influence the innovation process we may think of the usual production factors (labour, capital) as well as externalities internal to the region related to human capital, social and public capital, network externalities, agglomeration economies, etc. Most of all, considering innovative activity and its knowledge intensive nature, one is inclined to think that the tacit component of knowledge which cannot be codified has a major role. A role which is due to the fact that knowledge diffusion based on face to face encounters is obviously facilitated at the local level.

However, theoretical and empirical literature[11] seems to suggest that the production of knowledge in a region not only depends on its own research efforts but also on the knowledge stock available in the whole economy. The factors external to the region that can act as a determinant of technological activity are many and can be channelled by trade across regions, foreign R&D investments, imports of machinery and instruments, common markets for skilled labour and final goods. Also, pecuniary externalities may lead to the concentration of firms in macro-areas, thereby translating externalities at the firm level to higher territorial levels. As a result, we may think of some agglomeration economies operating at a supra-regional level, giving rise to an external regional effect. Our general framework given in (1) is consequently modified in order to introduce an additional vector Z_2 of external factors that reflects the fact that knowledge generated in one region may spills over while helping knowledge formation in other regions:

$$\mathrm{I_i} = \mathrm{RD_i^{\partial_1}}\ \mathrm{Z_{1i}^{\partial_2}}\ \mathrm{Z_{2i}^{\partial_3}}\ \mathrm{e_i} \tag{2}$$

Instead of estimating simply the model as given in (2), we will firstly estimate a knowledge production function as in (1), where the output of innovation activity, that is patents per capita, is explained by the innovation activity input, R&D expenditure, while a set of controls tries to take into account other potential internal determinants. Based on these results, a thorough spatial econometric analysis will let us conclude whether external effects are necessary in the knowledge production function, as in (2), through the use of the concept of spatial dependence in a regression model. This being the case, we will consider different ways of including knowledge externalities across regions. In this setting, it will be possible to take advantage of the geographical dimension of the data in the fashion of Bottazzi and Peri (2003), with respect to whom we can fully exploit a larger and more disaggregated database[12]. Several measures of geographical distances, i.e. different types of distance matrices, can be tested, to assess also the geographical reach of external spillovers, if any.

4.2. Empirical specification and econometric issues

We begin by assuming that the new knowledge produced by a region in a period is related to its R&D efforts in the previous period and a vector of internal factors, $\mathrm{Z_1^{'}}$ = (GDP, MAN, NAT) according to a modified Cobb-Douglas technology as follows:

$$\log I_{i,t} = \beta_1 \log RD_{i,t-1} + \beta_2 \log GDP_{i,t-1} + \beta_3 \log MAN_{i,t} + \sum_{c=1}^{17} \delta_c NAT_{ic} + \varepsilon_{i,t} \tag{3}$$

[11] The literature is the one starting from Coe and Helpman (1995) and going to Keller (2002) at the international level (even though their main focus is on the effect of spillovers on economic growth) and from Jaffe *et al* (1993) and Audretsch and Feldman (1996) at the regional level for innovative activity.

[12] It should be remembered that 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 sectoral representativeness is an important issue.

The dependent variable, *I* is proxied by the average number of patents per capita in one region. As for the independent variables, the input of innovative activities, *RD*, is measured by the share of gross domestic product invested in research and development activities. Among the other potentially relevant internal forces, we introduce a mix of factors connected with the economic structure of the region, such as an index of economic wealth and an indicator of agglomeration economies. The former is proxied by the gross domestic product per capita, *GDP*, whilst the latter is measured by *MAN*, the quota of manufacturing employment[13]. Moreover, we attempt to control for institutional and other structural factors which may affect either the innovative activity or the propensity to appropriate it results by patenting, through the use of a set of national dummies, *NAT*.

Since we estimate a cross section, each variable is an average of three years' data, to smooth out possible transient effects (particularly for patents counts and for R&D expenses) and approximate long-run values. Additionally, because the production of knowledge takes time, we assume a time lag between the action of investment on R&D and the yield in terms of innovation. This way, the variable I is measured as an average of the value of the correspondent variable in the period going from 1995 to 1997, whereas *RD* is measured as an average of the value in the period going from 1989 to 1993[14]. In the case of *GDP* and *MAN*, we consider an average of the value in the period 1988 to 1990 in order to avoid endogeneity problems[15].

To date, most empirical analyses have not devoted special attention to an econometric method capable of robustly testing and estimating externalities in the case of the knowledge production function. Our empirical exercise directly addresses this issue. Specifically, we will use techniques from spatial econometrics for the empirical consideration of the externalities across regions that may appear in the process of generating innovation. In case of erroneously omitting the external effects, the estimation of expression (3) would suffer from spatial dependence, affecting the standard estimation and inference. In such a case, spatial econometrics provides the necessary tools to deal with this problem (Anselin, 1988).

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[13] Another proxy for agglomeration economies is the density of population (see Ciccone, 2002). The inclusion of such indicator in the regression has been tested and main results are robust.

[14] As for the case of Switzerland and Sweden, the lack of regional data for R&D has forced us to estimate them. In the former case national data has been assigned to each region according to investment quotas, whilst in the latter case we were able to use R&D employment quotas in 1997.

[15] A robustness check of the main econometric results with respect to different lag structures has been done.

Our suggestion is therefore checking for spatial dependence in models such as the one given in (1). If the null hypothesis of non spatial dependence is rejected through both the Moran's I and Lagrange Multiplier tests for spatial autocorrelation, our proposal would be to correct such misspecification by considering measures for spillover effects across the units of observation, as in model (2). This way, the introduction of an external effect will not be ad-hoc but based on the results of a battery of tests which should provide directions to the best specification of the externalities.

Specifically, the spatial statistics applied to estimation of equation (3) will not only point to the existence of remaining spatial dependence in our specification, but also to the estimation of the various forms of spatial dependence, either a substantive or a nuisance process (see Florax and Folmer, 1992, and Anselin and Florax, 1995). The substantive model for the case of our knowledge production function will stand as

$$\log I_{i,t} = \beta_1 \log RD_{i,t-1} + \beta_2 \log GDP_{i,t-1} + \beta_3 \log MAN_{i,t} + \beta_4 W \log I_{i,t} + \sum_{c=1}^{17} \delta_c NAT_{ic} + \varepsilon_{i,t} \tag{4}$$

where W is a weight matrix defining across-region linkages. The spillover variable gathered by the term $W\log I_{i,t}$ is therefore the spatial lag for the innovation output, in other words, a weighted measure of patents in the regions with which region i has contacts. Model (4) has to be estimated by Maximum Likelihood (ML) procedures given that the OLS estimators are not appropriate when a lagged value of the dependent variable is inserted among the explanatory variables.

In model (4) we assume that the production of knowledge of a region depends not only on its own research efforts and internal factors but also on the knowledge available in other regions. This knowledge available in other regions is proxied by the innovation output in neighbouring regions measured through their patents. However, some authors such as Bottazzi and Peri (2003) have considered the research effort made in those other regions as the one generating spillovers. We also consider this idea through the model:

$$\log I_{i,t} = \beta_1 \log RD_{i,t-1} + \beta_2 \log GDP_{i,t-1} + \beta_3 \log; MAN_{i,t} + \beta_4 W \log RD_{i,t-1} + \sum_{c=1}^{17} \delta_c NAT_{ic} + \varepsilon_{i,t} \tag{5}$$

where the term $WlogRD_{i,t-1}$ is the spatial lag for the innovation input. After estimating equation (5), we implement the standard check-up for spatial dependence and look for solutions until this is eliminated.

5. Empirical results

5.1. Testing the existence of knowledge spillovers and evaluating their magnitude

Econometric results are summarised in Table 4[16]. The knowledge production function for innovative output holds in the European regions. The elasticity of patents with respect to R&D expenditures when the OLS estimation (see first column) is carried out for equation (3) is 0.43 being clearly significant.[17] This result is in line with the ones obtained in the previous literature. Additionally, economic performance and agglomeration economies are positive (and significant) determinants of innovative activity with elasticity of 1.62 and 0.37 respectively. As for the institutional factors related to national differences, dummies are all significant. The higher coefficients are shown for Switzerland, Finland, Sweden and Austria, in sum, those countries which have shown high levels of innovative activity. On the contrary, the lowest fixed effects are those of Portugal, Greece and Spain which are apparently lagging behind in the innovation competition, after controlling for economic performance and R&D expenditure.

In order to check whether it is necessary to introduce the innovation spillover effect the spatial autocorrelation tests are computed as shown in the lower section of Table 4.

For the construction of the weight matrix we have used two different definitions. The first one (W_{bin}) is a physical contiguity matrix, giving rise to a binary and symmetric matrix where its elements would be 1 in case of two regions being in contact and 0 otherwise. The second one will be the inverse of the square of the distance (W_{dist}). Both rely on the idea that only geographical proximity matters in the interaction across regions. However in section 5.4 we show that also the technological composition of the regions is important in determining the magnitude of the innovation spillovers.

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[16] Note that regressions are carried out for a sample of 123 regions. Eight regions are eliminated because they show a zero value for the dependent variable (8 Portuguese regions and one Greek region). Two regions (Luxemburg and Corse in France) are removed because no data for R&D expenditure is provided, whilst five former East German regions are not considered because R&D and GDP data are not available for the period before reunification and post-reunification data does not still appear reliable.

[17] We have also tried to include separately private and public R&D, but only the first component turns out to be significant.

The LM-LAG test clearly rejects the null hypothesis, so that some kind of externalities takes place in the explanation of the innovative output. Following the "classical" specification search approach adopted in the spatial econometric literature, and given that the LM-LAG test is significant whereas the LM-ERR is no, we estimate the spatial lag model as presented in (4) by Maximum Likelihood (ML). When estimated by ML, the spatial lag of the endogenous variable is significant and the LR test points to a statistical adequacy of the estimation of the spatial lag model. This result remarks the important role played by the innovative activity performed in the neighbouring regions in the knowledge production function. The elasticity of patents with respect to internal R&D expenditures gives a robust value of 0.47 for the two weight matrices, whereas the elasticity of patents in one region with respect to patents in the neighbouring regions ranges between 0.17, with W_{bin}, and 0.25, with W_{dist}[18]. The results on the effect of the economic performance and agglomeration economies lead to similar conclusions as before.

We finally estimate the model given in (5) whose results are shown in the first column of Table 5. The method of estimation is OLS and the weight matrix considered is the binary one based on the connectivity criteria. The results concerning R&D, economic performance and agglomeration economies are in line with the ones obtained before. The elasticity of patenting activity with respect to R&D expenditures in the neighbouring regions is significantly positive with a value of 0.33. In this specification there is no remaining sign of spatial dependence as given by the LM tests on spatial dependence, so that the results are both economically and econometrically compelling.

Thus, irrespective of the way of considering the spatial innovative spillovers, they present a positive and significant sign implying that there are positive effects on output innovation coming from the innovative activity in neighbouring regions both represented by input and output indicators.

5.2. Analysing the spatial scope of knowledge spillovers

Results obtained so far lead us to conclude that knowledge spillovers are important both when the neighbouring regions are the only ones from which the spillovers arise and when all the regions in the sample are considered with a smaller weight as distance increases. However, it is interesting to check for the potential effect of a cut-off in the distance, so that after a given distance interaction would be insignificant.

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[18] The higher elasticity when the distance matrix is used is due to the fact that this is a full matrix which

A first way to check the existence of a decay effect in the influence of innovation spillover is through the use of lags of the variable R&D of an order higher than the first one[19]. Based on equation (5) we have considered a second and third-order lags of the variable R&D expenditures. The results, in column two and three in Table 5, show that the spillover is significant till a second-order neighbourhood, that is, innovation made in one region spills over not only the first-order neighbouring regions but also the regions sharing a border with these first-order neighbours. Spillovers stop at this level given that the third order contiguity R&D is negative and not significant.

In a second attempt to be more specific in the analysis of the distance decay effect of the knowledge spillovers, we define different weight matrices based on different values for the cut-off distance. A first matrix considers a region to be a neighbour if it is in a range of 250 km ($W_{0\text{-}250}$), the second one considers the range between 250 and 500 km ($W_{250\text{-}500}$) and in the third one a region is considered to be a neighbour if it is located in a range between 500 and 750 km ($W_{500\text{-}750}$). Columns 4-6 in Table 5 shows the results of the analysis considering the 250 km intervals. The coefficients of the spillover that are statistically significant are those in the range between 0 and 500 km, whereas the coefficient on the R&D spillover in the 500-750 km range is positive but no longer significant. These results point out the existence of a limit in the geographical space for the relevance of spillovers.

5.3. Analysing the national or transnational scope of knowledge spillovers

So far, the scope of our analysis has been the European Union as a whole without considering that national characteristics common to all the regions within a country could be important in the transmission of knowledge. On the contrary, regions belonging to different countries even if sharing a common border could experiment that different national characteristics[20] would be an impediment for the flow of knowledge.

In order to check the potential barriers to externalities across regions due to national borders, we construct a within-country and across countries weigh matrices. In the former case, only the weights corresponding to regions that share a common border and belong to the same country are set equal to one. In the second matrix the weights for regions sharing a

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considers the whole range of spillovers arising from all other regions.

[19] The use of different lags of the dependent variable is not an easy task due to the current features of the econometric software Spacestat. Their insertion is expected in the future.

[20] An ample description of European regional systems of innovations may be found in Cantwell and Iammarino (2003).

border and being within the same country are set equal to zero and only the weights for regions sharing a border but belonging to different countries are set equal one.

The results are summarised in Table 6. In the estimation of equation 3, a significant positive spatial dependence is observed when the within-country matrix is used, whereas none of the autocorrelation tests are significant when the across-countries interactions are considered.

The significance of the LM-LAG test in the case of the within-country regions points to the estimation of the spatial lag model by ML. Results are shown in the second column of Table 6. The spatial lag of the endogenous variable is significant and the LR test indicates the statistical adequacy of this estimation. The values for the elasticity of patents with respect to internal R&D expenditures and the parameters for the economic performance and agglomeration economies lead to very similar conclusions as before. The elasticity of patents in one region with respect to patents in the neighbouring regions that belong to the same country present a value of 0.12, a slightly smaller value than in the case of not confining to the national scope. In order to be robust with the strategy followed so far, in the last column, the results of the estimation of equation (5) are given, so that the spillovers proxied by R&D expenditures are taken into account. The results confirm the previous ones: only the spatial lag of the R&D carried out in the neighbouring regions within the same country is significant, with no-remaining spatial autocorrelation in the estimation of this model.

Summing up, evidence shows that knowledge essentially spill over regions belonging to the same country, so that the national innovation systems seem to dominate the European one.

5.4. Analysing the importance of technological proximity in the diffusion of knowledge

Although so far we have only considered the possibility of externalities crossing geographical barriers of regions due to their proximity in the space, we may also think of the possibility of the existence of externalities across regions due to their technological proximity. The assumption underlying this idea goes to the literature at the firm level, in which it is showed that the capacity to absorb another firms' knowledge depends on their technological similarity. The paper by Jaffe (1986) is one of the seminar ones in the study of technological proximity spillovers. Using firm patent data to compute the similarities between firms, he finds that technological spillovers are an important explanatory factor of productivity. The R&D productivity is increased by the R&D of "technological neighbours". Further evidence is provided by Keller (1998, 2002). He estimates the elasticity of total factor productivity with respect to own-industry R+D investments and other industries' investments. Among his results it is shown how elasticity for investments in other industries is strongly significant, representing between a fifth and a half of the elasticity to own R+D investments. As a consequence, if R+D investments adequately proxy for the improvement in technology levels, it is worthwhile considering externalities across industries. And since a region is composed of a set of firms belonging to different industries, one would expect that spillovers across regions would be higher as the technological similarity between the regions increases.

There are different ways to measure technological proximity. One method is based on the use of some kind of input-output tables as in Bartelsman et al (1994), Verspagen (1997), Wolff (1997) and Moreno et al (2004). Under this conception, we may think of externalities via technology diffusion through purchases of intermediates (supplier-driven externalities) or through sales to other industries (customer-driven externalities). This way, industries using similar inputs would use similar technologies. The second method would follow the idea of Jaffe (1986) of using the distribution of the firms' patents over patent classes to characterize the technological position of the firm. There is probably some relationship between industries and patent classes in the sense that firms in a certain industry will patent more in some classes than in others.

In this paper we follow the approach suggested by Jaffe. It is assumed 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 distance, "technological neighbourhood", we compute a technological matrix (W_{Tech}) calculated by means of patent application data (1978-97) disaggregated into 101 sectors (energy and manufacturing, 3-digit Ateco91) for each region. To measure the proximity of regions i and j, we use the following correlation measure:

$$P_{ij} = \frac{\sum_{k=1}^{K} f_{ik} f_{jk}}{\left(\sum_{k=1}^{K} f_{iK}^2 \sum_{k=1}^{K} f_{jk}^2 \right)^{1/2}}$$

where f_{ik} is the share of a particular patent class k in the total of patents of region i.

This proximity measure takes a value equal to unity for regions whose technological characteristics are identical, it is zero for firms whose vector of characteristics are orthogonal, and it is bounded between 0 and 1 for all other pairs. The closer to unity the greater the degree of similarity of the two regions' technological structure is. This way, the spatial lag of patents constructed with this weigh matrix, $W_{tech} * I$, would imply a weighted sum of other regions' patents with weights proportional to the proximity of the firms in technological space.

Additionally, we will also take into account both similarities used so far, geographical and technological, in a unique measure. With this aim we construct two new weight matrices in which the technological similarity is weighted by the geographical proximity. In a first case, we consider that only regions that are geographical neighbours play a role in the diffusion of knowledge, and in this case, the weight is the technological distance ($W_{tech\text{-}contiguity}$). In a second case, we divide the technological distance between two regions by the inverse of the squared of the distance ($W_{tech\text{-}dist}$).

Results are summarised in Table 7. When we first estimate equation 3 and compute the spatial dependence statistics for the weight matrix of technological distance (see column one), we do not observe a significant spatial autocorrelation process. This would indicate that for the European case technological distance is not as important as geography in the diffusion of knowledge. However, when we test the existence of spatial dependence with the two weight matrices that consider both types of similarities, a significant spatial dependence is observed. In such cases, the values of the spatial autocorrelation statistics (the one being significant, LM-LAG) is higher than the values of the statistics obtained for the binary contiguity and the inverse of the distance showed in the first two columns of table 4. This would imply that the spatial dependence process obtained when considering both geographical and technological proximity is higher than when considering any of them separately. Thus, knowledge spillovers in the EU are very important in the case of physical neighbours but do not seem to be significant in the case of technological neighbours. However, once geographical proximity is taken into account, the more similar in their technological specialisation two regions are, the more knowledge diffuses between them.

Once again, following the spatial specification search approach, the significance of the LM-LAG test in the case of the weight matrices gathering geographical as well as technological similarity points to the estimation of the spatial lag model by ML. Results are also shown in Table 7 based on the maximum likelihood estimation of the spatial lag model. The spatial lag of the endogenous variable is significant and the LR test points to the statistical adequacy of this estimation. The values for the elasticity of patents with respect to internal R&D expenditures as well as the parameters for the economic performance and agglomeration economies point to analogous results to the ones obtained so far, whereas the elasticity of patents in one region with respect to patents in its neighbours (both geographically and technologically speaking) present values of 0.17 and 0.68, respectively, slightly higher values than in the case of just considering geographical proximity.

6. Conclusions

In this paper we attempt to provide original empirical evidence on the process of spatial creation and dissemination of knowledge in Europe.

We have started from a mapping of innovative activity in European regions by means of a deep exploratory spatial analysis based on several global and local indicators of spatial dependence. The analysis has been carried out for different time periods and sectors in order to evaluate differences and similarities. Two main outcomes are worth remarking. First, the presence of a strong central-periphery distribution of innovation activity at the beginning of the period. Innovation activity is concentrated in regions in North and centre Europe, while none or modest technological activity is performed in most Southern European regions. Secondly, this concentration tends to decrease over time and the innovations have been spreading to some more regions in Scandinavia and in the South of Europe.

The analysis of global indicator of spatial association confirms the presence of a strong and positive spatial autocorrelation process in the innovative activity. This means that patenting activity in a certain region tends to be correlated to innovation performed in contiguous areas. Moreover the local indicators show the existence of a significant local cluster of highly innovative regions in West Germany. Spatial association is also found at the sectoral level determining the formation of specialised clustering of innovative regions in different sectors.

The econometric analysis appears particularly revealing. Findings confirm the importance of internal R&D expenditure in affecting innovative activity and also the role played by other internal factors such as the economic performance, the agglomeration economies and the national institutions. Moreover we find that also external effects, or innovative spillovers, may count. 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 show that there appears to exist a decay process of knowledge diffusion among European regions. More specifically, not only the own R&D expenditures have an important impact on the output of the innovative process but also the geographical neighbours' R&D expenditures are concerned, with a strong impact of the 1st and 2nd order neighbours, which translated into distance would imply a distance between 250 and 500 kilometres.

Additional results have shown that externalities across regions are mostly constrained by national borders and this suggests that the national innovation systems seem to dominate the European one. Finally, in order to improve our understanding of the inner mechanics of knowledge diffusion, we have associated the technological composition of each region with the geographical distance. Results are worthy of note: spatial proximity effects are enhanced when regions are technologically homogeneous.

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Appendix *Table A.1 European Regions in CRENoS database*

(ID-CRENoS; ID-NUTS; Region; Nuts level)

1	AT11	BURGENLAND	2
2	AT12	NIEDEROSTERREICH	2
3	AT13	WIEN	2
4	AT21	KARNTEN	2
5	AT22	STEIERMARK	2
6	AT31	OBEROSTERREICH	2
7	AT32	SALZBURG	2
8	AT33	TIROL	2
9	AT34	VORARLBERG	2
10	BE1	BRUXELLES_BRUSSEL	1
11	BE2	VLAAMS GEWEST	1
12	BE3	REGION WALLONNE	1
13	CH01	REGION IEMANIQUE	2
14	CH02	ESPACE MITTELLAND	2
15	CH03	NORDWESTSCHWEIZ	2
16	CH04	ZÜRICH	2
17	CH05	OSTSSCHWEIZ	2
18	CH06	ZENTRALSCHWEIZ	2
19	CH07	TICINO	2
20	DE1	BADEN_WURTTEMBERG	1
21	DE2	BAYERN	1
22	DE3	BERLIN (WEST)	1
23	DE4	BRANDENBURG	1
24	DE5	BREMEN	1
25	DE6	HAMBURG	1
26	DE7	HESSEN	1
27	DE8	MECKLENBURG VORPOMMERN	1
28	DE9	NIEDERSACHSEN	1
29	DEA	NORDRHEIN_WESTFALEN	1
30	DEB	RHEINLAND_PFALZ	1
31	DEC	SAARLAND	1
32	DED	SACHSEN	1
33	DEE	SACHSEN ANHALT	1
34	DEF	SCHLESWIG_HOLSTEIN	1

35	DEG	THUERINGEN	1
36	DK	DENMARK	0
37	ES11	GALICIA	2
38	ES12	PRINCIPADO ASTURIAS	2
39	ES13	CANTABRIA	2
40	ES21	PAIS VASCO	2
41	ES22	NAVARRA	2
42	ES23	RIOJA	2
43	ES24	ARAGON	2
44	ES3	COMUNIDAD DE MADRID	2
45	ES41	CASTILLA _ LEON	2
46	ES42	CASTILLA _ LA MANCHA	2
47	ES43	EXTREMADURA	2
48	ES51	CATALUNA	2
49	ES52	COMUNIDAD VALENCIANA	2
50	ES61	ANDALUCIA	2
51	ES62	REGION DE MURCIA	2
52	FI	FINLAND	0
53	FR1	ILE DE FRANCE	2
54	FR21	CHAMPAGNE_ARDENNE	2
55	FR22	PICARDIE	2
56	FR23	HAUTE_NORMANDIE	2
57	FR24	CENTRE	2
58	FR25	BASSE_NORMANDIE	2
59	FR26	BOURGOGNE	2
60	FR3	NORD _ PAS_DE_CALAIS	2
61	FR41	LORRAINE	2
62	FR42	ALSACE	2
63	FR43	FRANCHE_COMTE	2
64	FR51	PAYS DE LA LOIRE	2
65	FR52	BRETAGNE	2
66	FR53	POITOU_CHARENTES	2
67	FR61	AQUITAINE	2
68	FR62	MIDI_PYRENEES	2
69	FR63	LIMOUSIN	2

70	FR71	RHONE_ALPES	2
71	FR72	AUVERGNE	2
72	FR81	LANGUEDOC_ROUSSILLON	2
73	FR82	PROVENCE_ALPES_COTE_ D'AZUR	2
74	FR83	CORSE	2
75	GR11	ANATOLIKI MAKEDONIA, THRAKI	2
76	GR12	KENTRIKI MAKEDONIA	2
77	GR13	DYTIKI MAKEDONIA	2
78	GR14	THESSALIA	2
79	GR21	IPEIROS	2
80	GR22	IONIA NISIA	2
81	GR23	DYTIKI ELLADA	2
82	GR24	STEREA ELLADA	2
83	GR25	PELOPONNISOS	2
84	GR3	ATTIKI	2
85	GR41	VOREIO AIGAIO	2
86	GR42	NOTIO AIGAIO	2
87	GR43	KRITI	2
88	IE	IRELAND	0
89	IT11	PIEMONTE	2
90	IT12	VALLE D'AOSTA	2
91	IT13	LIGURIA	2
92	IT2	LOMBARDIA	2
93	IT31	TRENTINO_ALTO ADIGE	2
94	IT32	VENETO	2
95	IT33	FRIULI_VENEZIA GIULIA	2
96	IT4	EMILIA_ROMAGNA	2
97	IT51	TOSCANA	2
98	IT52	UMBRIA	2
99	IT53	MARCHE	2
100	IT6	LAZIO	2
101	IT71	ABRUZZI	2
102	IT72	MOLISE	2
103	IT8	CAMPANIA	2
104	IT91	PUGLIA	2
105	IT92	BASILICATA	2
106	IT93	CALABRIA	2
107	ITA	SICILIA	2
108	ITB	SARDEGNA	2
109	LU	LUXEMBOURG	0
110	NL1	NOORD_NEDERLAND	1
111	NL2	OOST_NEDERLAND	1
112	NL3	WEST_NEDERLAND	1
113	NL4	ZUID_NEDERLAND	1
114	NO	NORWAY	0
115	PT11	NORTE	2
116	PT12	CENTRO	2
117	PT13	LISBOA E VALE DO TEJO	2
118	PT14	ALENTEJO	2
119	PT15	ALGARVE	2
120	SE01	STOCKHOLM	2
121	SE02	OSTRA MELLANSVERIGE	2
122	SE04	SYDSVERIGE	2
123	SE06	NORRA MELLANSVERIGE	2
124	SE07	MELLERSTA NORRLAND	2
125	SE08	OVRE NORRLAND	2
126	SE09	SMALAND MED OARNA	2
127	SE0A	VASTSVERIGE	2
128	UKC	NORTH EAST	1
129	UKD	NORTH WEST	1
130	UKE	YORKSHIRE, THE HUMBER	1
131	UKF	EAST MIDLANDS	1
132	UKG	WEST MIDLANDS	1
133	UKH	EASTERN	1
134	UKJ+ UKI	SOUTH EAST+LONDON	1
135	UKK	SOUTH WEST	1
136	UKL	WALES	1
137	UKM	SCOTLAND	1
138	UKN	NORTHERN IRELAND	1

Tab 1. Innovation activity in the European countries
(patents per 100.000 inhabitants, annual average)

Nation	Num. of regions	1981-83		1988-90		1995-97	
		value	*ranking*	*value*	*ranking*	*value*	*ranking*
1 - Austria	9	3.7	*8*	8.0	*6*	8.1	*8*
2 - Belgium	3	4.4	*6*	8.7	*5*	9.2	*5*
3 - Switzerland	7	17.1	*1*	26.4	*1*	23.8	*1*
4 - Germany	17	7.9	*3*	14.2	*2*	10.4	*4*
5 - Denmark	1	3.0	*10*	5.7	*11*	7.9	*9*
6 - Spain	15	0.1	*16*	0.4	*15*	0.8	*15*
7 - Finland	1	1.9	*11*	6.7	*8*	11.5	*2*
8 - France	22	3.2	*9*	6.0	*10*	6.1	*10*
9 - Greece	13	0.0	*16*	0.1	*17*	0.1	*17*
10 - Ireland	1	0.6	*14*	1.7	*14*	2.4	*14*
11 - Italy	20	1.1	*13*	2.9	*13*	3.4	*13*
12 - Luxembourg	1	9.4	*2*	7.0	*7*	8.4	*7*
13 - Netherlands	5	4.7	*5*	9.2	*4*	9.2	*6*
14 - Portugal	5	0.0	*17*	0.1	*16*	0.1	*16*
15 - Norway	1	1.6	*12*	3.5	*12*	3.9	*12*
16 - Sweden	8	7.2	*4*	9.4	*3*	11.0	*3*
17 - United Kingdom	11	3.9	*7*	6.2	*9*	5.4	*11*
EU	**138**	**3.7**		**6.4**		**6.3**	
CV across nations		*1.06*		*0.93*		*0.80*	

Tab 2. Innovation activity in the top twenty regions
(patents per 100.000 inhabitants, annual average)

Region	Nation	Period 1981-83 value	1981-83 ranking	1988-90 value	1988-90 ranking	1995-97 value	1995-97 ranking
Nordwestschweiz	CH	36.3	*1*	44.3	*1*	39.6	*1*
Zürich	CH	22.1	*2*	33.4	*2*	30.2	*2*
Hessen	DE	15.3	*3*	24.6	*5*	23.3	*5*
Ostsschweiz	CH	15.3	*4*	30.9	*3*	23.5	*4*
Region Iemanique	CH	14.9	*5*	17.5	*14*	17.4	*15*
South East+London	UK	14.6	*6*	22.2	*9*	17.5	*14*
Ile De France	FR	13.8	*7*	20.0	*11*	18.9	*11*
Baden_Wurttemberg	DE	13.6	*8*	28.0	*4*	28.8	*3*
Stockholm	SE	13.4	*9*	16.9	*16*	23.1	*6*
Bayern	DE	13.0	*10*	23.5	*8*	22.9	*8*
Rheinland_Pfalz	DE	13.0	*11*	20.4	*10*	21.1	*10*
Zentralschweiz	CH	11.7	*12*	24.5	*6*	22.9	*7*
Espace Mittelland	CH	11.5	*13*	17.6	*13*	18.5	*12*
Sydsverige	SE	11.4	*14*	11.9	*22*	12.9	*22*
Zuid_Nederland	NL	11.1	*15*	23.6	*7*	22.5	*9*
Nordrhein_Westfalen	DE	10.6	*16*	18.1	*12*	15.8	*16*
Luxembourg	LU	9.4	*17*	7.0	*38*	8.4	*32*
Bruxelles_Brussel	BE	9.0	*18*	17.5	*15*	14.8	*18*
Vastsverige	SE	8.9	*19*	10.4	*24*	12.2	*23*
Berlin (West)	DE	8.2	*20*	12.0	*21*	8.9	*29*

Tab 3. Spatial autocorrelation in the innovation activity (Moran's I test, normal approximation)

Period		1981-83		1988-90		1995-97	
Sector	contiguity	Z-value	Prob	Z-value	Prob	Z-value	Prob
Total manufacturing	1	8.083	0.00	9.734	0.00	10.022	0.00
	2	6.410	0.00	7.637	0.00	8.195	0.00
	3	2.876	0.00	3.847	0.00	4.727	0.00
Mining and energy	1	4.144	0.00	5.686	0.00	5.333	0.00
	2	7.100	0.00	6.510	0.00	5.970	0.00
	3	8.465	0.00	4.403	0.00	2.930	0.00
Food	1	3.028	0.00	4.103	0.00	2.748	0.01
	2	2.851	0.00	3.605	0.00	2.086	0.04
	3	0.237	0.81	1.603	0.11	0.624	0.53
Textile and clothing	1	7.971	0.00	7.718	0.00	8.184	0.00
	2	6.166	0.00	6.351	0.00	8.308	0.00
	3	1.785	0.07	2.652	0.01	4.450	0.00
Chemicals and plastic	1	3.254	0.00	5.126	0.00	6.159	0.00
	2	3.273	0.00	4.792	0.00	5.683	0.00
	3	0.747	0.46	2.291	0.02	3.540	0.00
Electronics	1	6.066	0.00	6.351	0.00	6.596	0.00
	2	3.662	0.00	4.034	0.00	4.215	0.00
	3	1.998	0.05	2.317	0.02	3.118	0.00
Transport equipment	1	7.388	0.00	7.750	0.00	7.965	0.00
	2	4.801	0.00	6.013	0.00	5.951	0.00
	3	3.267	0.00	3.693	0.00	2.948	0.00
Other manufacturing	1	9.748	0.00	11.292	0.00	11.299	0.00
	2	7.775	0.00	8.410	0.00	9.201	0.00
	3	4.549	0.00	4.630	0.00	5.269	0.00

Table 4. Estimation of innovative activity.
Dependent variable: Log (I).

	OLS estimation (equation 3)		**ML estimation (equation 4)**	
Variables	Wbin	Wdist^2	Wbin	Wdist^2
Log (RD)	0.429		0.476	0.471
	(0.000)		(0.000)	(0.000)
Log (GDP)	1.617		1.322	1.312
	(0.000)		(0.000)	(0.000)
Log (MAN)	0.367		0.368	0.224
	(0.035)		(0.014)	(0.176)
W Log (I)			0.169	0.246
			(0.000)	(0.034)
NAT dummies	Yes		Yes	Yes
R^2-adj	0.899		0.908	0.902
AIC	11.079		0.734	9.207
LM-ERR	0.058	1.763		
	(0.810)	(0.184)		
LM-LAG	11.962	3.610		
	(0.001)	(0.057)		
LR Test			12.345	6.728
			(0.000)	(0.049)

Notes: 123 observations. p-values are in parentheses.
Wbin is a first order contiguity matrix, Wdist^2 is an inverse square distance matrix.

Table 5. Estimation of innovative activity with distance decay effect
Dependent variable: Log (I).

	OLS estimation (equation 5)					
Log (RD)	0.485	0.528	0.530	0.485	0.551	0.550
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (GDP)	1.223	1.140	1.129	1.285	0.898	0.873
	(0.000)	(0.001)	(0.001)	(0.000)	(0.007)	(0.011)
Log (MAN)	0.319	0.217	0.205	0.303	0.052	0.044
	(0.057)	(0.191)	(0.221)	(0.072)	(0.761)	(0.801)
W_1 Log (RD)	0.330	0.261	0.255			
	(0.002)	(0.016)	(0.019)			
W_2 Log (RD)		0.302	0.274			
		(0.007)	(0.021)			
W_3 Log (RD)			0.100			
			(0.471)			
$W_{0\text{-}250}$ Log (RD)				0.293	0.205	0.202
				(0.003)	(0.032)	(0.037)
$W_{250\text{-}500}$ Log (RD)					0.544	0.548
					(0.000)	(0.000)
$W_{500\text{-}750}$ Log (RD)						0.045
						(0.777)
NAT dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2-adj	0.908	0.914	0.915	0.909	0.918	0.918
AIC	2.061	-4.632	-3.267	2.586	-10.500	-8.598
LM-ERR	0.954	0.000	0.027	0.532	0.215	0.204
	(0.329)	(0.998)	(0.870)	(0.465)	(0.642)	(0.651)
LM-LAG	1.963	0.536	0.363	2.668	1.057	1.017
	(0.161)	(0.464)	(0.547)	(0.102)	(0.304)	(0.313)

Notes: 123 observations. p-values are in parentheses.
W_1, W_2 and W_3 are 1st, 2nd and 3rd order contiguity matrices, respectively. $W_{0\text{-}250}$ $W_{250\text{-}500}$ $W_{500\text{-}750}$ are weight matrices with neighbours in 0-250 km, 250-500 km, 500-750 km rings, respectively.

Table 6. Estimation of innovative activity within and across countries
Dependent variable: Log (I).

	OLS estimation		ML estimation	OLS estimation
Variables	Wwithin	Wacross	Wwithin	
Log (RD)	0.429		0.465	0.492
	(0.000)		(0.000)	(0.000)
Log (GDP)	1.617		1.461	1.403
	(0.000)		(0.000)	(0.000)
Log (MAN)	0.367		0.386	0.397
	(0.035)		(0.012))	(0.023)
W – Log (I)			0.117	
			(0.013)	
W_{within} Log (RD)				0.329
				(0.006)
W_{across} Log (RD)				-0.099
				(0.321)
R^2-adj	0.899		0.897	0.907
AIC	11.079		7.20	5.214
LM-ERR	0.003	0.063		0.593
	(0.957)	(0.801)		(0.441)
LM-LAG	5.854	1.707		0.231
	(0.016)	(0.191)		(0.631)
LR Test			5.878	
			(0.015)	

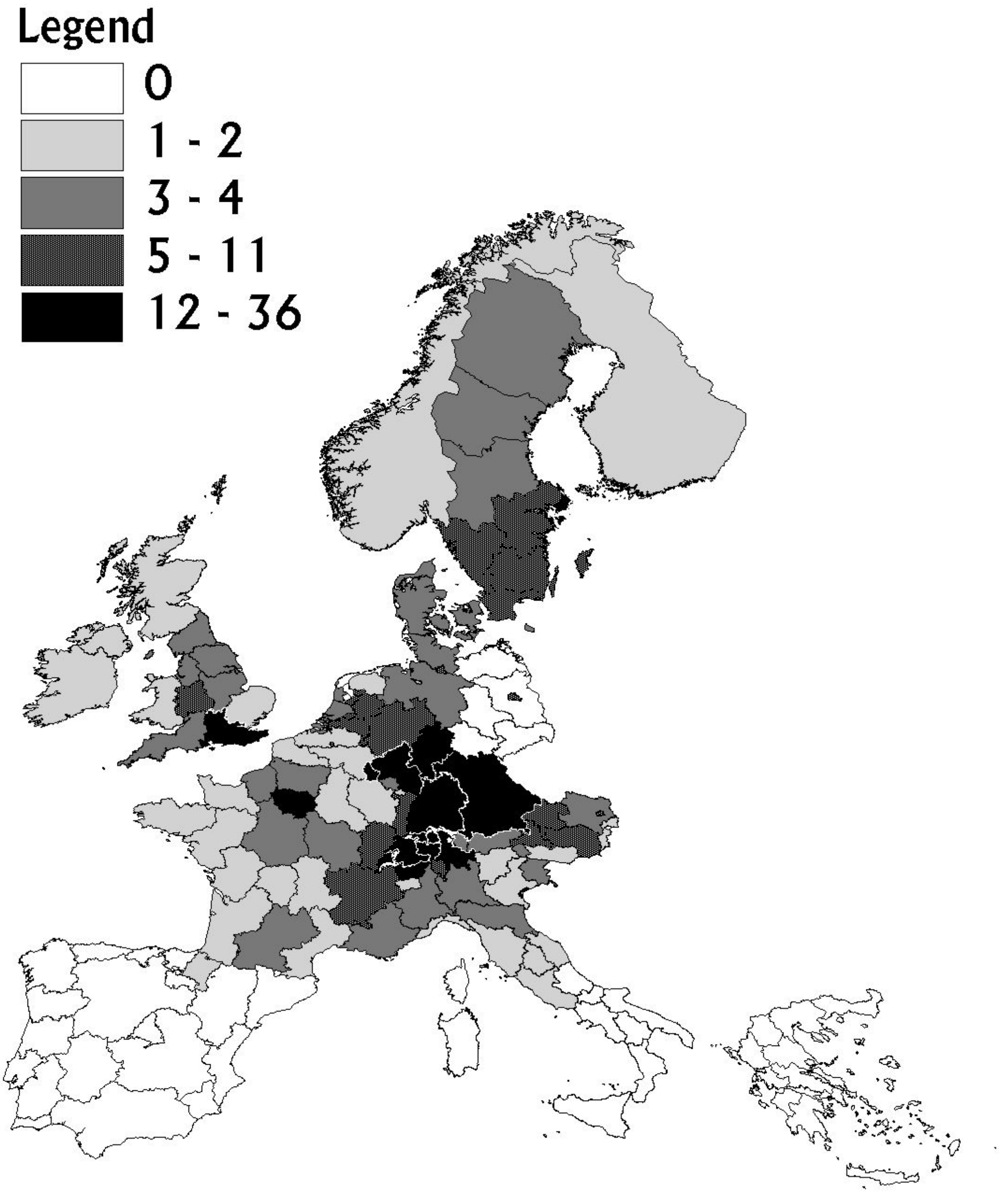
Notes: 123 observations. p-values are in parentheses.
Wwithin is a contiguity matrix for regions within the same country, Wacross is a contiguity matrix for regions belonging to different countries.

Table 7. Estimation of innovative activity with tech-distance matrices
Dependent variable: Log (I).

	OLS estimation			ML estimation	
Variables	W_{tech}	$W_{tech\text{-}contiguity}$	$W_{tech\text{-}distance}$		
Log (RD)		0.429		0.474	0.467
		(0.000)		(0.000)	(0.000)
$W_{tech\text{-}contiguity}$ Log (I)				0.172	
				(0.000)	
$W_{tech\text{-}distance}$ Log (I)					0.683
					(0.000)
Controls					
Log(GDP)		1.617		1.321	1.278
		(0.000)		(0.000)	(0.000)
Log(MAN)		0.367		0.369	0.199
		(0.035)		(0.014)	(0.207)
NAT dummies		Yes		Yes	Yes Yes
R^2-adj		0.899		0.908	0.902
AIC		11.079		0.294	6.654
LM-ERR	0.420	2.534	0.299		
	(0.517)	(0.111)	(0.585)		
LM-LAG	0.573	14.783	6.225		
	(0.449)	(0.000)	(0.013)		
LR Test				12.785	6.424
				(0.000)	(0.011)

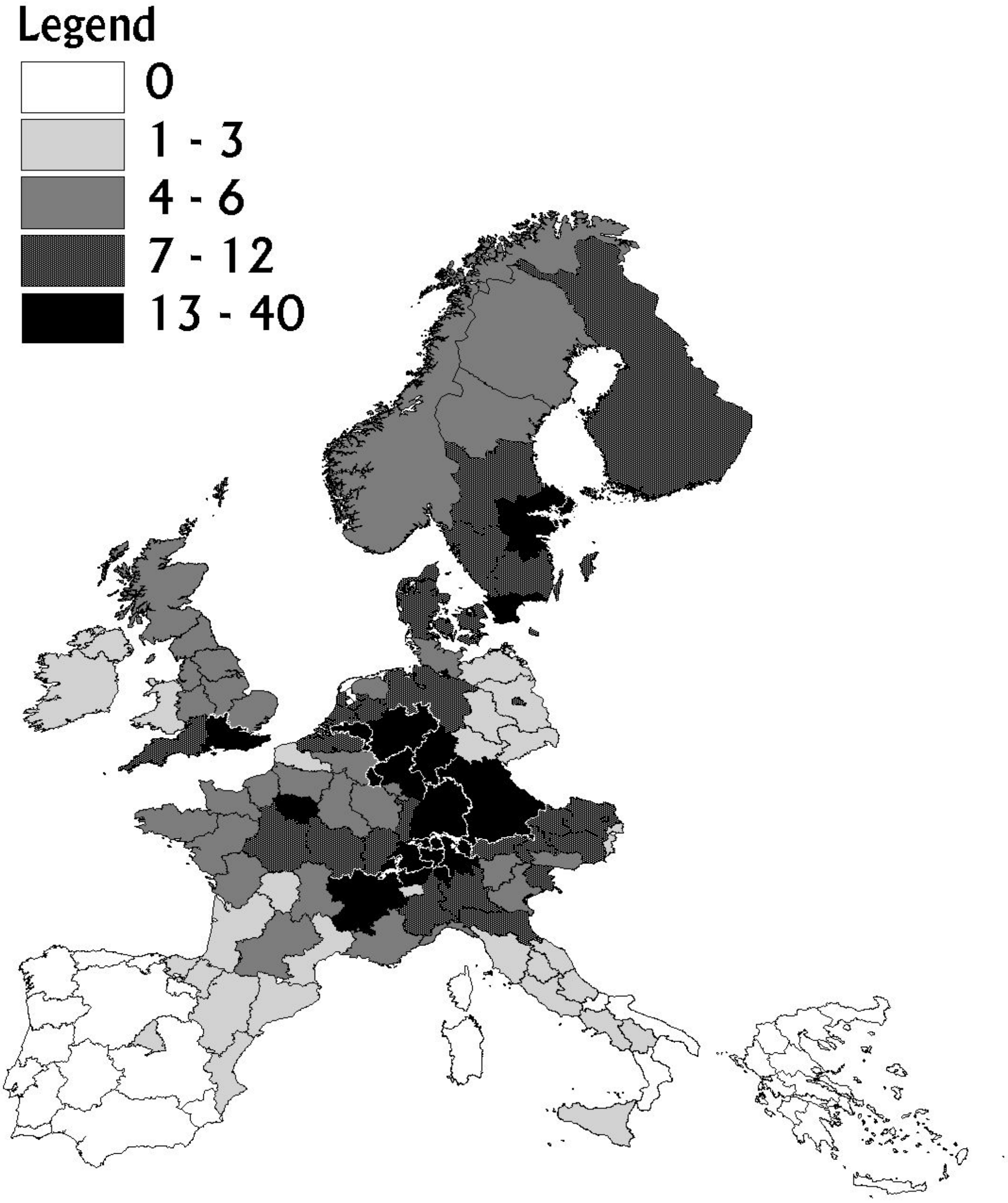
Notes: 123 observations. p-values are in parentheses.
W_{tech} is a technological distance matrix (see text for details), $W_{tech\text{-}contiguity}$ is a contiguity matrix weighted by the technological distance matrix and $W_{tech\text{-}distance}$ is a distance matrix weighted by the technological distance matrix.

Map 1. Distribution of innovative activity in the European regions, 1981-1983
(patents per capita, annual average)



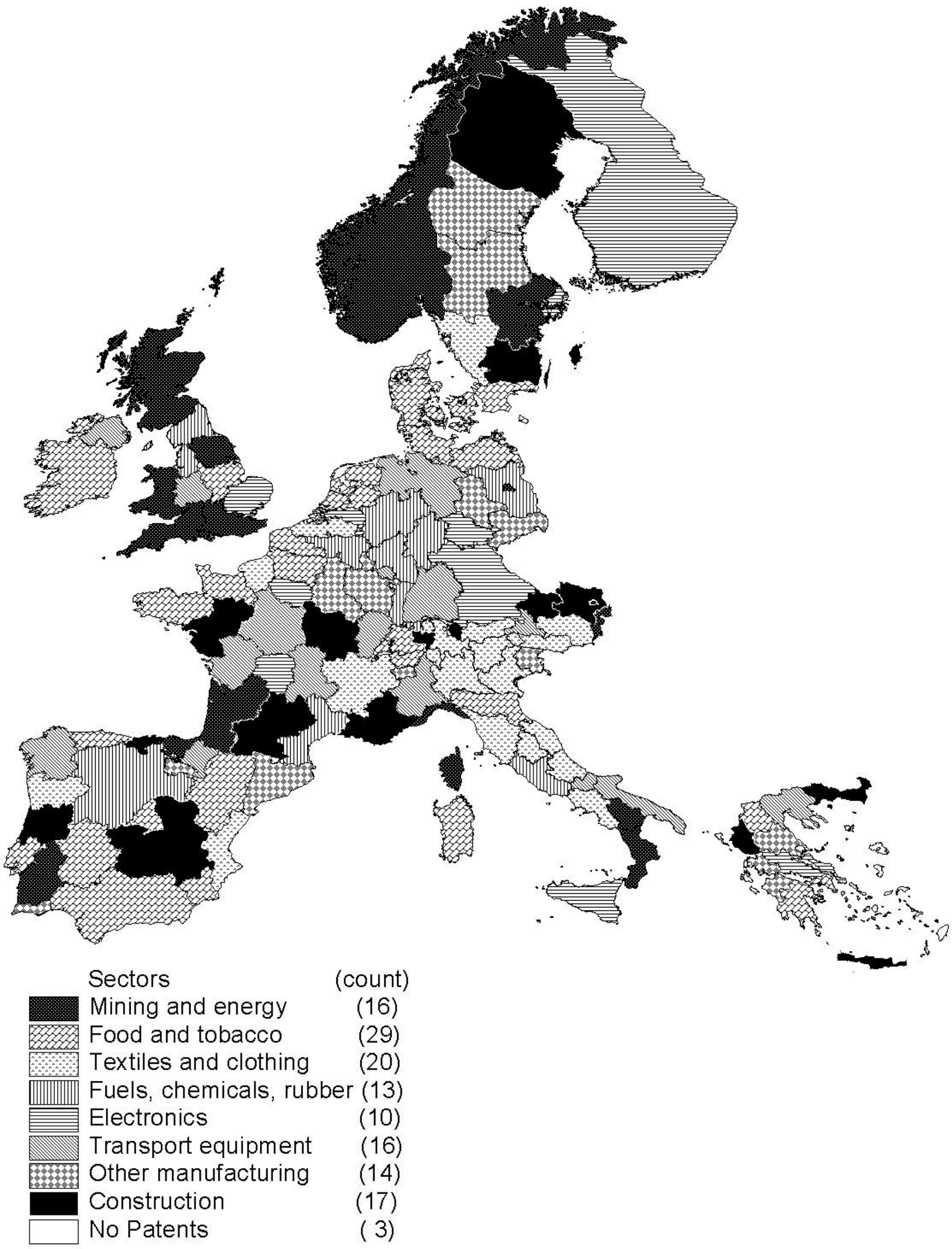
Map 2. Distribution of innovative activity in the European regions, 1995-1997

(patents per capita, annual average)



Map 3. Sector specialisation in innovative activity in European regions, 1995-1997

(Based on Revelead Technological Advantage index)



Map 4. Scatter for innovative activity in the European regions, 1995-1997

(patents per capita, annual average; number of regions in parenthesis)

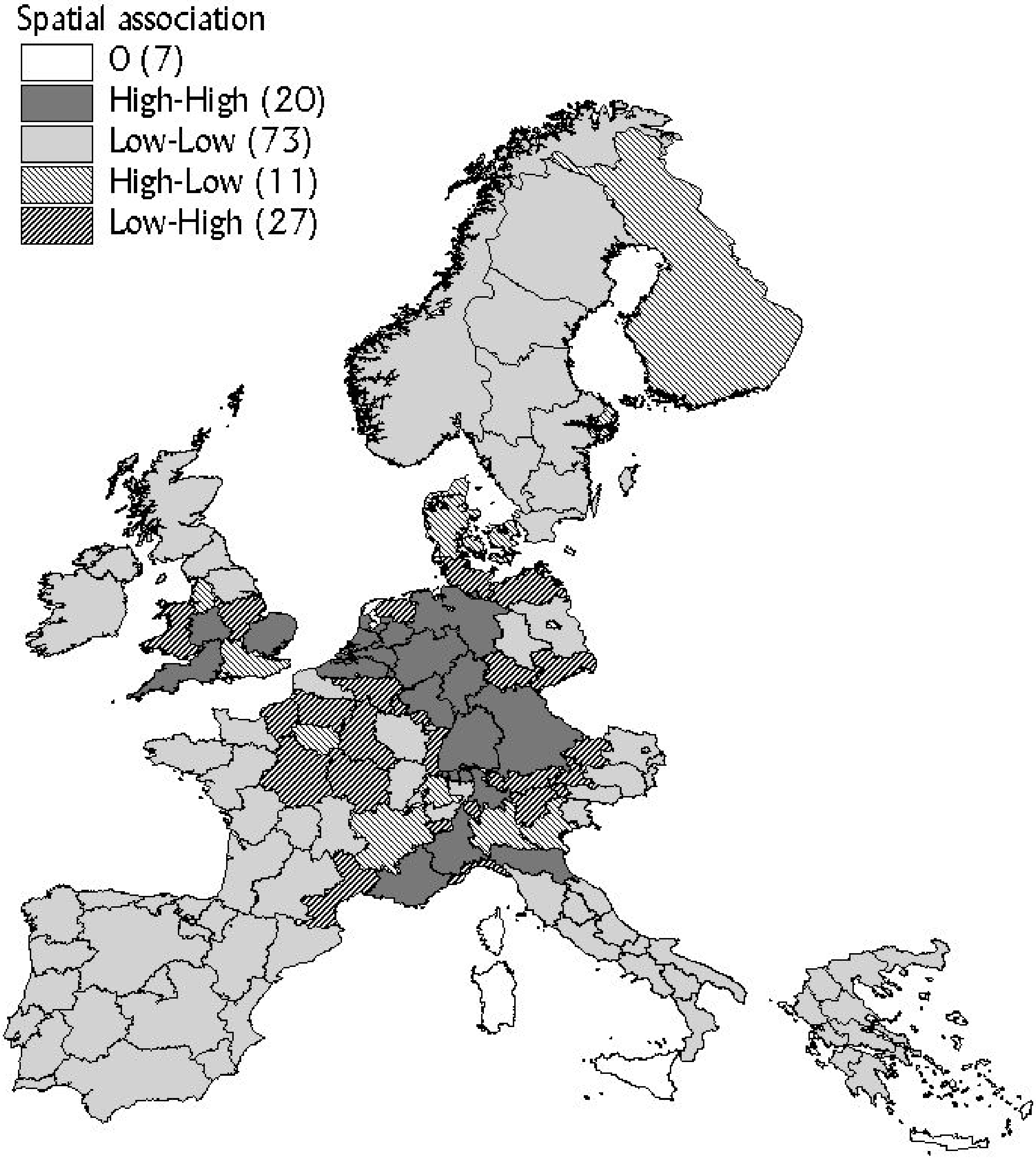


Figure 1. Coefficient of variation for innovative activity in manufacturing sectors. 1978-1997.