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INNOVATION CLUSTERS IN THE EUROPEAN REGIONS

Abstract
This paper investigates on the presence of innovation clusters in the European regions. The analysis is based on a databank set up by CRENoS on regional patenting at the European Patent Office classified by ISIC sectors (2 digit), which considers 175 regions of 17 countries in Europe. Firstly, an analysis of the spatial distribution of innovation activities in Europe is performed. Some global and local indicators for spatial association are presented, indicating the presence of a general dependence process in the distribution of the phenomena under examination. The analysis is implemented for 23 manufacturing sectors to assess for the presence of significant differences in their spatial features. Moreover, the extent and strength of spatial externalities are evaluated for two periods: 1994-96 and 1999-01.
Secondly, this paper contributes to the analysis of the process of spatial agglomeration of innovative activities by investigating directly its determinants. Our main purpose is to identify the extent to which the degree of specialisation or diversity in a region may affect the innovative activities in a particular local industry. Other local factors are also tested such as home market effect and other agglomeration phenomena. Moreover the geographical extent of such effects is measured by means of the usual tests of spatial econometrics.

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

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1. Introduction

Technological progress is a priority for all those countries and regions which aspire to support economic development since innovation and knowledge are widely regarded as essential forces for starting and fuelling the engine of growth. Such forces crucially depend on the process of creation, accumulation and diffusion of knowledge which is often strongly localized into clusters of innovative firms, sometimes in close cooperation with public institutions such as research centers and universities.

Consequently, modern analyses of innovation processes have placed agglomeration economies and other forms of local externalities at the center of the empirical research agenda. Feldman and Audretsch (1999) provide the pioneering contribution in the search of specific determinants of the process of local innovation clustering. Two types of external economies are singled out: specialisation externalities, which operate mainly within a specific industry (Marshall, 1890) and diversity externalities which favour the creation of new ideas across sectors as originally suggested by Jacobs (1969). Following this first contribution, this approach has been applied in just a few cases: Paci and Usai (1999) for the Italian case, Massard and Riou (2002) for the French case and Greunz (2003b) for Europe.

This paper analyses the case of European regions where disparities in terms of innovative activity are higher with respect to those in terms of productivity. More specifically, the degree of spatial concentration of innovative activity across the European regions at the end of the nineties computed by means of the variation coefficient is equal to 1.5 while the corresponding value for production (proxied by employees) is equal to 0.9. The same result is found at the sectoral level where 6 out of 7 sectors show a much higher value of geographical concentration of innovative activities with respect to production activities. The presence of specialised innovation clusters is therefore a fact in the European scenario (see also Moreno *et al.* 2005b) and the aim of this paper is to investigate on the determinants of these clusters at the regional level.

Among the determinants of the spatial distribution of innovative activities we remark the influence of specialisation and diversity externalities, introducing three original features compared with the existing literature. First, the regression analysis is performed at a much disaggregated sectoral level and this allows to explore into the nature of the externalities according to the type of sector (strategic or pure manufacturing activities, among others). Second, the effect of specialisation and diversity externalities is considered both within and across regions thanks to the testing and estimation strategy of spatial econometrics. As far as we know, this is the first attempt to evaluate whether the impact of external economies is confined to the specific region in which they take place or they cross the borders of the neighbouring regions. Third, the access to data in several time periods allows us to study the dynamics of the external effects, so as to assess how the effect of diversity and specialisation has been evolving with time.

We use an original databank on regional patenting at the European Patent Office spanning from 1978 to 2001 to analyse the spatial distribution of innovative activity across 175 regions of 17 countries in Europe (the 15 members of the pre-2004 European Union plus Switzerland and Norway) in 23 manufacturing sectors. The use of this rich 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 in main industrial sectors.

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 examine the spatial mapping of innovative activity throughout the European regions. Section four discusses the empirical model to be tested whilst results are shown and discussed in section five. Final remarks conclude the analysis.

2. Literature background

Starting from Marshall (1890), there has been a long tradition of studies which relate agglomeration of economic activities 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 to knowledge spillovers, whilst the latter are due to market mediated mechanisms concerning the availability of qualified workers and specific primary and intermediate inputs.

As far as knowledge spillovers are concerned, wide evidence suggests that location and proximity are clearly important in explaining knowledge spillovers (see the recent survey by Audretsch and Feldman, 2004). Jaffe (1989) originally introduced the spatial context into the model to verify the existence of geographically mediated externalities from university research to commercial innovation. In other words, he aims to establish if knowledge produced by universities is a sort of local public good, due to its peculiar nature, its tacitness. This means that knowledge is embodied in individuals and it is virtually impossible to make it explicit and to communicate unless through personal contacts (Von Hipple, 1994). In this case agglomeration of innovation activities in a specific place is a rational response adopted by firms to facilitate knowledge sharing and learning processes. Local innovation clusters, therefore, arise since the innovation process is sensitive to geographical distance and technological spillovers, of either pecuniary or pure nature, are spatially bounded.

This concept of localised technological spillovers has been later refocused and strengthened by several empirical works mainly addressed to the US case (either at the state or at metropolitan level) such as the ones by Acs *et al.* (1994), Audrestsch and Feldman (1996), Audretsch and Stephan (1996) and Anselin *et al.* (1997). Their common feature is the attempt to find direct evidence of pure (knowledge) spillovers rather than a general sign of local externalities. The possibility that local externalities are not just pure one but also of pecuniary nature is usually a priori ruled out. 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 testing procedure has been used in the estimation of local innovation activities and agglomeration for the US case (Varga *et al.*, 2005) and for Europe (Bottazzi and Peri, 2003; Greunz, 2003a; Moreno, Paci and Usai, 2005a). Other studies at the national level are Autant-Bernard (2001) for the French departments, Andersson and Ejermo (2003) for Swedish functional regions and Fischer and Varga (2003) for Austrian political districts.

All in all, these contributions find that technological spillovers (the nature of which is not specified) may exist both within and across regions. In particular, Moreno *et al.* (2005a) find that the external spillovers decay over space, that they occur mainly across regions within a country rather than across nations and, finally, that technological together with geographical proximity may matter in defining the strength and extent of spillovers. However, the general approach of this previous research does not allow for discriminating between different sources of technological externalities (specialisation or diversity, for example) which would imply very different policy suggestions. Specialisation externalities suggest that an increased concentration of a particular industry within a specific region facilitates knowledge spillovers across firms. Geographical proximity eases the interaction between individuals sharing similar specific competences which favour the diffusion of technologies and knowledge. Contrarily, diversity externalities regard inter-industry spillovers as the most important source of new knowledge creation since the exchange of complementary knowledge leads to cross fertilisation of ideas which favour innovation.

The stream of literature that has focused on the impact of specialisation and diversity externalities on innovation was originally applied to the case of US cities and states by Feldman and Audretsch (1999) and Kelly and Hageman (1999), respectively. The most striking, and probably unexpected, result of both analyses is that there is no evidence of specialisation externalities, whilst diversity externalities are at work in the case of US metropolitan areas. In other words, in the United States innovation in a specific sector exhibits strong spatial clustering independently of the sectoral distribution of manufacturing activity in the same sector. Contrary to this result, Paci and Usai (2000) show that in the European regions there exists a positive association between the spatial distribution of technological activity and production specialisation. This result has been confirmed with a more robust econometric analysis and a larger sample of countries by Greunz (2003b). This work is based on an improved Feldman-Audretsch estimation model firstly applied to the Italian local labour systems by Paci and Usai (1999). These two contributions find that there exist spillovers arising from production specialization and from production and innovation diversity. Moreover, Paci and Usai (1999) provide some evidence that spillovers may not be constrained by administrative regional borders. Thus, this divergence of results between the European and American cases despite a very close methodology in use suggests a notable difference on the functioning of the local innovation systems in US and Europe.

These divergent results are also challenged by the outcome of the analysis by Massard and Riou (2002), who applied the analysis to French departments and do not find any evidence of either specialization or diversity externalities. This can be explained either by the peculiar features of the French system or by the fact that these authors construct their indexes based on innovation measures, that is R&D expenditures. This allows them to study the dynamic of innovation clustering within the framework of innovative activity rather than by looking at its relationship with the production system. Moreover, these results induce them to produce a set of estimation at the industrial level which proves extremely interesting given the considerable heterogeneity of results.

The present paper moves along the path traced by previous contributions. In particular we focus on European regions but with a larger sample of countries and a methodology based on a different set of indicators and measures. We directly examine the nature of technological externalities at the local level thanks to measures of specialisation and diversity externalities based on innovation. This way, we try to characterise the local structures of innovation activity which are more favourable to innovation and the emergence of knowledge externalities. In other words, we pursue to identify to which extent the organisation of innovation is either concentrated or alternatively consists of diverse but complementary innovative activities, and how this composition influences innovative output. Moreover the use of specific econometric techniques should allow analysing the nature other than the spatial scope of the diffusion of technological spillovers. The possibility to have a long database, furthermore, allows replicating the analysis for two periods in order to check the robustness of some results along the time dimension.

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. Nonetheless, the use of such indicators gives rise to some inconveniences and shortcomings (see Griliches, 1990) which ought to be kept in mind while interpreting the outcome of the analysis, both descriptive and econometric.

Patents represent the outcome of the inventive and innovative process even though inventions and innovations may never be patented, as well as patents may never be transformed into real innovations. However, with respect to the object of our research, patent statistics seem particularly suitable, due to some useful properties: firstly, they provide information on the residence of the inventor and the applicant and can thus be grouped into different territorial units identified through area codes. Secondly, they record the technological content of the invention and can thus be classified according to the industrial sectors. Thirdly, they are available as a long series of yearly records, and this allow for a dynamic analysis. Finally, our data (based on patent applications at the European Patent Office) are supposed to have a relatively homogeneous economic value since applying to EPO is difficult, time consuming and expensive.

Patents applications are classified by inventor's region in Europe instead of proponent's residence, as the latter generally corresponds to firms' headquarters. In that case, its use 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 (Paci and Usai, 2000 and Breschi 2000). Moreover, we try to deal with cases of patent with multiple inventors by assigning a proportional fraction of each patent to the different inventors' regions of residence. As for the territorial break down, 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 (15 countries of the pre-2004 European Union plus Switzerland and Norway) in 175 sub-national units (which, from now on, we will simply call *regions*) which are a combination of NUTS 0, 1 and 2 levels. Finally, despite the whole database refers to the period spanning from 1980 to 2001, we focus on just the late nineties while more detailed and extensive temporal analysis can be found in Moreno *et al.* (2005b). The empirical analysis of innovative activities is based on three-year averages to smooth out a phenomenon which can be rather sporadic and irregular across time.

Table 1 reports the innovative activity at the country level. It is clear that in absolute terms this activity is quite concentrated in a handful of big countries (that is Germany, Italy, France and United Kingdom) where almost 70% of patents in Europe are applied for. However, when we measure innovativeness in per capita terms only Germany maintains the top positions whilst the other big countries descend the rankings. The most innovative country is, in fact, Switzerland, with 19.7 and 27.8 patents per 100,000 inhabitants in the initial period (1994-96) and in the last one (1999-01) respectively. Behind Switzerland we find Germany and Sweden with around 12 patents in the middle nineties and the same two countries plus Finland in the late nineties. Finland has shown the most brilliant performance, by reaching the fourth position in the country rankings and placing its capital region, Uusimaa, among the first producers of innovation in Europe (this region was 49th at the beginning of the eighties and sixth at the end of the nineties).

Among the declining countries the most remarkable cases are the one of the United Kingdom which goes from the seventh to the eleventh position and the one of France which moves from the sixth to the tenth ranking. It should be, however, noted that the two cases are different since in the latter there are still one champion region, Ile de France, which has the 23rd rank. On the contrary the first British region in the ranking is Eastern which features in 39th position. Finally, no notable dynamics is shown by the followers, which are countries such as Italy, Norway, Spain, Portugal and Greece.

Moving from the countries to the regions one finds quite a similar picture, with mainly Swiss and German regions among the top performers. From Map 1.a we can see strong patenting activity in regions of Switzerland, West Germany, the north and east of France, the north of Italy, 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 South of Italy. Looking at the evolution of the innovative activity from 1994-96 to 1999-01 (see Map 1.b) we can suggest some remarks. First, innovation activity has increased considerably over the two periods in almost all countries. Secondly, 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. Nonetheless, after fifteen years of decline (see Moreno *et al.*, 2005b) we now observe a rather stable level of the degree of spatial concentration of innovative activity. This is not however the result of a homogenous process across the whole of Europe. In fact, if one looks at the country level in 5 out of 15 countries (two countries have no regions) internal disparities have increased, whilst they have decreased in the remaining 10 countries.

The database allows more than just a geographical analysis: in particular it may be interesting to examine the distribution of innovative activity measured by patenting across sectors. Table 2 shows that among the top innovating sectors we find Machinery and Chemicals with shares which are around twenty per cent, but both declining along time. As for the least innovative sectors we find traditional sectors such as Tobacco and Leather and footwear. The most dynamic sectors are those more involved in the information and telecommunication technologies, that is

Office and computing and Radio, television and communication equipment, the share of the former goes from 1.75 to 2.40 whilst the latter goes from 6.75 to 10.01.

In conclusion, the strong central-periphery distribution of innovation activity which characterized the eighties has weakened but this process is more recently slowing down. This whole phenomenon could be related to spatial dependence, that is, to the fact that technological activity performed in one region may be associated to the one in neighbouring regions. This possibility can be evaluated by means of the Moran's I statistic based on contiguity weight matrices. In particular, Table 3 reports the value of the Moran's I for the two periods under analysis for the first order contiguity and the highest order of contiguity for which the index of spatial autocorrelation is positive and significant. It is clear that there exist a strong positive spatial autocorrelation process often until the fourth order of contiguity, confirming the visual impression of spatial clustering given by the maps. Such a process is significant till different levels of contiguity across time and sectors. Spatial dependence is present in all sectors: in 17 sectors it extends until the 4th order of contiguity and until the 3rd in 4 more sectors and it is usually increasing both in strength and in extension. 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.

One way to investigate further on the geographical distribution of innovative activity sector by sector is to visualize it on a map. In Map 2a and 2b we show the geographical distribution of innovation specialization for just two sectors, a traditional one: Leather and shoes; and a high tech one (Office and computing). The mapping, among other interesting evidences, shows that there seem to be some clusters of common technological specialisation patterns in different parts of Europe. The same picture is found for all the other sectors. However, what these two maps suggest is that the geographical distribution, the intensity of the polarization process and the extent of the regions involved in the clusters are specific for each sector.

Thus, the analysis of technological spillovers and sectoral interdependences across regions is a promising way forward. In the following sections we try to examine the innovative process by looking at its main determinants, with special focus on those which are configured as externalities, at the local and sectoral level. Moreover, we try to assess to what extent such externalities are behind the spatial association pattern detected in the descriptive and statistical analysis above. The use of spatial econometrics techniques should allow us find some insights on the mechanisms of local interdependences of technological activity.

4. The empirical model

Our main purpose is to assess the extent to which technological activity in a local industry is affected by the degree of specialisation in the same local industry (Marshall externalities) and by the degree of industrial diversity in the local system (Jacobs externalities). Thus, we estimate a model where the dependent variable is the number of patents attributed to a specific industry in a particular region and two explanatory variables reflecting the effect of Marshallian and Jacobs externalities are included. The first type of externalities assumes that existing knowledge flows more easily between companies active in the same sector and that competition between these companies might also lead to the creation of more knowledge. The second type assumes that the exchange of ideas between firms in different sectors helps in launching new ideas and concepts within each sector and might thus increase the creation of new knowledge.

Moreover we take into account other local potential determinants of innovativeness. First of all, we include a measure of the effort in the process of creation and accumulation of knowledge, that is expenditure in Research and Development. Secondly we insert a proxy for agglomeration economies measured by the density of population. Thirdly, we try to assess the possible presence of some sort of local market effect, which is measured by the per capita gross regional product. We finally include some control variables to take into account differences which may arise due to specific features which characterise the institutional setting (national dummies) and different sectoral characteristics with respect to innovativeness and propensity to patents (sector dummies). Let us now discuss in detail the definition and the expected impact of each explanatory variable included in the model.

To measure Marshall externalities, the most commonly used index is the specialisation index (IST) based on patent data which is specific to each industry i and region j:

$$IST_{ij} = \left[P_{ij} \Big/ \sum_i P_{ij} \right] \Bigg/ \left[\sum_j P_{ij} \Big/ \sum_i \sum_j P_{ij} \right]$$

The index is normalised based on the formula (IST-1)/(IST+1). A positive and significant sign of its coefficient is interpreted as evidence of the fact that innovations are bound to arise within those sectors in which the local system is specialised with respect to other regions. The index is computed with respect to the previous period in order to allow interpreting the result in a dynamic perspective. In this light this implies that, when specialisation has a positive impact, this is deepening along time. We use this index to proxy Marshallian externalities, that is, to check whether innovations mainly arise within those industrial sectors in which the region in specialised.

To capture the crucial effects of diversity externalities a measure for the degree of variety which characterises each region is needed. To this aim, we use the Herfhindal index (DIV) based on patent data which is specific to each industry *i* (given that we compute diversity with respect to the whole economic system but the sector *i* in hand) and region *j*. As for the specialisation index, *DIV* is computed as a ratio between the regional index and the European one.

$$DIV_{ij} = \left[P_{ij} \Big/ \sum_{i^* \neq i} P_{i^* j} \right]^2 \Bigg/ \left[\sum_j P_{ij} \Big/ \sum_{i^* \neq i} \sum_j P_{i^* j} \right]^2$$

The index *DIV* allows for testing Jacobs hypothesis, according to which a higher level of diversification of the local system favours innovative activity. We interpret a positive significant sign on its coefficient as evidence of the presence of diversity externalities.

The two indexes displayed above have been constructed based on innovation measures, specifically on patents. This allows us to study the dynamic of innovation clustering within the framework of innovative activity rather than by looking at its relationship with the production system. This is interesting since as found by some authors (Kelly and Hageman, 1999), innovation clusters strongly, independently of the distribution of employment, with all sectors tending to locate their innovation in the same regions. As these authors signal, the agglomerative forces considered by Ellison and Glaeser (1999) that cause different sectors to concentrate production in different regions are different from those that affect innovation. So, tests of Marshallian or

Jacobs externalities that focus on the growth of output may miss the most important feature of these externalities which is their effect on the innovation process. Thus, we believe that the measures obtained though the use of patents will reflect more accurately the goal of our study.

We have also included a set of control variables to take into account some specific feature of the economic systems at the regional and sectoral level. First of all we insert a variable which measures the effort made at the regional level to promote research and development, measured by means of the share of gross domestic product invested in research and development activities (RD). Secondly we insert a measure of the presence of a rich market which may provide a favourable environment to pursue and test new ideas. This index is the gross domestic product per capita (GDP). Moreover we use the quota of manufacture over total production to proxy agglomeration economies (AGG) as in Moreno *et al.* (2005b). Finally, by including a set of national dummies (NAT) we control for institutional and other structural factors which may affect either the innovative activity or the propensity to appropriate its results by patenting.

As regards the temporal dimension, 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 innovation activities takes time, we assume a time lag between externalities (and the other determinants) and the innovation yield. As a result, variable *I* refers either to the period 1994-96 or to 1999-2001, whereas the independent variables refer to either 1989-91 or to 1994-96 but for the *RD* which refers to 1989-1994 and to 1997-1999, respectively.

We have thus specified a general model where the dependent variable $I_{ij,}$ (i.e. innovative activity in sector *i* and region *j* divided by population[1]) is affected by the following explanatory variables[2]:

$$I_{ji,t} = \beta_1 IST_{ij,t-q} + \beta_2 DIV_{ij,t-q} + \beta_3 AGG_{j,t-q} + \beta_4 GDP_{j,t-q} + \beta_5 RD_{j,t-s} + \sum_{c=1}^{17} \delta_c NAT_{jc} + \varepsilon_{ij,t} \qquad (1)$$

[1] Most regressions have also been run for total patents per sector and region and main results do not change.

[2] All the regressions have been estimated in the log form, too. Main results are unchanged. Tables are available on request.

Evidence on interregional spillovers 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, channeled through trade flows, external investments, imports of machinery, 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 (1) is consequently modified to reflect the fact that innovation generated in one region may spill over and help knowledge formation in other regions. Our empirical exercise, therefore, directly addresses interregional externalities in the generation of innovation through the use of spatial econometrics techniques. The use of a cross-sectional sample potentially leads to spatial autocorrelation in the regressions, 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 (1). 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 (1) would not only reveal the existence of spatial dependence in our specification, but also its possible form: a substantive or a nuisance model. The former is as follows:

$$I_{ji,t} = \beta_1 IST_{ij,t-q} + \beta_2 DIV_{ij,t-q} + \beta_3 AGG_{j,t-q} + \beta_4 GDP_{j,t-q} + \beta_5 RD_{j,t-s} + \beta_6 WI_{ji,t} + \sum_{c=1}^{17} \delta_c NAT_{jc} + \varepsilon_{ij,t} \qquad (2)$$

where *W* is a weight matrix defining linkages across regions. When W is represented by the contiguity matrix[3], the term *WI* is the spatial lag for the innovation output, that is, a weighted measure of patents in the regions with which region *i* has border contacts. We interpret an influence of this variable on the endogenous one as evidence of interregional spillovers of the knowledge located outside the region, whereas the lack of significance of $\square_6$ would indicate that the production of new knowledge is generated internally. The weight matrix W can take several forms, the most common ones are the contiguity and

[3] *W* is, therefore, a physical contiguity matrix, giving rise to a binary and symmetric matrix with elements equal to 1 in case of two regions being in contact and 0 otherwise.

the distance[4] matrix referred to geographical linkages. In this paper we also use a technological distance matrix in order to take into account the possibility of externalities crossing geographical barriers of regions due to technological similarity between regions. The hypothesis behind is that knowledge spillovers within technologies (or industries) are more important than those between technologies (industries) because each technology embodies a type of unique language and concerns a precise set of applications. Researchers are expected to benefit more form others who work in the same or related technological field, irrespective of geographical distance (Bode, 2004).

There are different ways to measure technological proximity (see the critical review by Los, 2000). One method is based on the use of some kind of input-output tables as in Verspagen (1997). 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. An alternative method which we follow, suggested by Jaffe (1986), is based on the distribution of the firms' patents over patent classes to characterize the technological position of the firm[5]. In order to obtain a measure of "technological neighbourhood", we compute a technological matrix (W_{tech}) calculated by means of patent application data disaggregated into 23 sectors for each region. To measure the proximity of regions i and l, we use the following correlation measure:

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

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

4 It should be noted that the weight matrix based on the inverse of the distance has non-zero elements for each observation pair (an observation, row, and its potential neighbour, column) that are assumed to interact.

5 This method has been already implemented in the setting of innovative activity by Autant-Bernard (2001), Greunz (2003b), and Moreno *et al.* (2005a)

This proximity measure takes a value equal to unity for regions whose technological characteristics are identical, it is zero for regions whose vector of characteristics are orthogonal, and it is bounded between 0 and 1 for all other pairs. It should be noted that, whatever the matrix used, the spatial lag model has to be estimated with Maximum Likelihood (ML) given that OLS estimators are biased and inconsistent due to the presence of an endogenous variable among regressors.

The second way to incorporate spatial autocorrelation is to specify a spatial process for the disturbance term, which is the so called nuisance model. The OLS estimators will be no longer efficient although unbiased, as a consequence of the non-spherical error covariance.[6] Following the most common specification for the spatial error term, the spatial autoregressive process, the spatial error model would be expression (1) as it stands, with an error term following the following expression:

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + \mu_{it}$$

where μ is asymptotically distributed as $N(0,\sigma^2)$, ε following a first-order Markov process and λ 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.

5. Econometric analysis

The empirical evidence in section 3 showed that there is a great deal of heterogeneity across sectors. Therefore, following the methodology outlined in the previous section, we perform the OLS estimation for each of the 23 sectors and also for the two periods 1994-1996 and 1999-2001 in order to check the robustness of the results along the time dimension. The usual set of tests for spatial autocorrelation (Moran's I, LM-ERR and LM-LAG) are computed for a spatial weight matrix based on binary contiguity. 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 the one for the LM-ERR, the estimation of the spatial lag model by ML is the preferred

[6] There are different specifications for the spatial error terms, each one presenting different implications about the extent of the spatial interaction in the model (Anselin and Moreno, 2003).

specification in most of the sectors.[7] Thus, we present the estimation correcting for the presence of spatial autocorrelation if needed, whereas the OLS estimation is the one given if spatial autocorrelation is not found.

The results are presented in Tables 4 and 5 for the two periods. As shown in the lower part of the tables, the presence of spatial autocorrelation is always rejected at the 5% level of significance.

In general terms, we observe a positive and statistically significant coefficient of specialisation. This positive sign of the relationship between specialisation and innovation remains remarkably constant across sectors, and it deepens over time. It is also interesting to note that the greatest coefficient is attributed in both periods to Chemicals followed by Electrical machinery, Communication equipment and Precision and medical instruments. The impact of innovation specialization in high-tech manufacturing sectors is thus higher than in the rest of manufactures. In other words, Marshallian externalities seem to provide more important innovative output for relatively knowledge intensive industries.

Diversity externalities, on the contrary, are never significant. This is an interesting and striking result given that it is contrary to most European previous analysis (mostly based on production data) and tells us that specialisation is the key for success in innovation. So, in contrast to the US, where diversity is always obtained to play a main role on the local production of innovation (Kelly and Hageman, 1999; Audretsch and Feldman, 1999), its effects in Europe are more uncertain.

It seems therefore that in the European case the innovation of a given industry in a given region is influenced by the degree of innovation specialization in the same industry but it is not influenced by the degree of innovation diversity of the region's innovation system. These results would indicate that increased specialisation within a region is conducive to greater innovative output and would support the Marshall-Arrow-Romer thesis. The result on specialisation confirms most of the results previously obtained for different datasets for the European case (Paci and Usai, 2000 and Greunz, 2003b) but it is in contrast to the one obtained for the US. Audretsch and Feldman (1999) reach the conclusion that specialisation affects negatively innovation activity. As

[7] This is true in all the sectors in both periods, but in the case of the sector of Wood in the second period. In such a case, the error model is the preferred one, so that the ML estimation for the error model is given.

signaled in Paci and Usai (1999) a possible explanation for this disparity in the effect of specialisation on innovation is to be found in the substantial differences in the industrial structures between the two areas. Europe is characterised by a large presence of small and medium enterprises in the traditional sectors, where innovation is more incremental in nature and it is mainly performed within the operative plants. On the contrary, in the US, the great number of multinationals and large firms performs part of their innovative activity in R&D laboratories which do not have to be located near the headquarters or the production sites.

The significance and the sign of the control variables again are very systematic. The parameter of home market effect (GDP) and the expenditure in research and development (RD) are positive and significant in almost all sectors, as expected. In relation to the magnitude of the coefficients, the high-tech manufacturing sectors (Chemicals, Machinery, Electrical Machinery, Communication equipment and Precision and medical instruments) offer again the highest values for the parameters. As for the parameter proxying agglomeration economies (AGG), it is significant and positive in 15 sectors although there is not a clear pattern according to the type of sector in relation to its knowledge usage. An interesting result which is worth noting is that although the patterns obtained are stable over time all coefficients increase appreciably from one period to the other.

In the sectors in which spatial autocorrelation is signaled and therefore corrected by means of the spatial lag model, the lag of the dependent variable is mostly significant and positive showing the presence of important interregional spillovers. Autocorrelation is almost always eliminated after the substantive or the nuisance model is estimated. Thus, there exists a spillover from innovation in a sector of a specific region to the innovative activity of the same sector in the other regions.

Finally it is worth mentioning that results are consistent across time, although, as we have signaled above, most coefficients are increasing across time. This is especially true for the specialisation variable.

Summing up, the results obtained at a sectoral level provide support that it is specialisation and not diversity that is more conducive to innovation. In addition, the evidence suggests that a greater amount of innovation effort and a greater extent of home market and agglomeration economies tend to promote innovative output. Thus, the main finding that specialisation tends to promote the agglomeration of innovative activities in the same sectors more than does the diversity holds across a broad range of manufacturing sectors.

The next step of our analysis is to check for the presence of autocorrelation due to technological proximity, rather than geographical contiguity, but the estimation results show no sign of autocorrelation in this case. Technological proximity on its own is therefore unable to create flows of externalities across regions. We therefore combine the two concepts of proximity in order to obtain a matrix which is the result of the product of the contiguity and the technological matrices. Tables 6 and 7 offer the results of the spatial autocorrelation tests as well as the estimation including the spillover effect of innovation based on this matrix. The significance and the sign of the variables as well as the differences across sectors are maintained if compared to the results obtained with the contiguity matrix alone. Most importantly the strength of the autocorrelation across regions is rather stable even though slightly increasing in some sectors. This implies that interregional spillovers can move not only in the geographical but also in the technological dimension. This second dimension however is not independent from physical distance. Moreover, results concerning the effect of specialization and diversity on innovative activity are maintained, so that the conclusions we have obtained are not sensitive to different specifications of the weight matrix.

So far, the scope of our analysis has been Europe as a whole. We have not considered the possibility that common national characteristics could play 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, enjoy a lesser flow of knowledge because of the differing national characteristics. Since the flow of ideas across regions is considered a key rationale behind the existence of interregional knowledge spillovers, and since previous literature shows that migration and trade flows are more intense between regions belonging to the same country, 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-country weight matrix. In the former case we set equal to one only the weights corresponding to regions that share a common border and belong to the same country. In the latter 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 one.

The results of the Moran's I spatial autocorrelation statistic for the estimation of each sector are summarised in Table 8. Significant positive spatial dependence is observed both in the case of the within-country and across-country matrices for 6 sectors, whereas a significant autocorrelation is only obtained with the within-country one in the case of 14 sectors. Thus, although knowledge seems to cross physical borders, some evidence shows that knowledge mainly spills over regions belonging to the same country. This result is not surprising since it corroborates previous findings (Cantwell and Iammarino, 2003) that national innovation systems, to a certain extent, still dominate over the common European one.

6. Concluding remarks

This paper investigates on the presence of innovation clusters in European regions. The descriptive analysis of the spatial distribution of innovation activities in Europe shows that spatial association across regions is present for all 23 manufacturing sectors under examination. Moreover, the extent and strength of spatial dependence increases along time.

Further, this paper contributes to the analysis of the process of spatial agglomeration of innovative activities by investigating directly its determinants. The innovation of a given industry in a certain region is influenced by the degree of innovation specialization in the same industry but it is not influenced by the degree of innovation diversity of the region's innovation system. Spatial autocorrelation is often present indicating that some externalities flow across the regional borders even though further analyses show that they do not often go across national borders. This result together with the significance of country dummies shows that institutional and geographical proximity are two reinforcing features conditioning innovative activity. In the same vein technological proximity does not prove to affect innovative activities on its own unless related to physical contiguity.

All in all our results indicate that specialized innovative clusters are present and are getting stronger both within each country and across the whole Europe. This result contrasts with the common findings of the literature for the production clusters which are continuously eroded by an ongoing delocalisation process (Combes and Overman, 2004). Our reading is that for firms' strategic activities, like innovation, the localization decisions are still greatly influenced by locally bounded interactions with similar firms. Consequently, it is clear that positive localization externalities, mostly pure technological ones, are still at work. On the other hand, in the case of production activities the balance of advantages and disadvantages of specialized agglomeration (i.e. factors costs, pecuniary externalities, congestion effects) has turned negative, making the delocalisation process more convenient. National and regional governments in Europe should take these outcomes into account when deciding their strategies to reinforce the slow but constant process of transforming the European Union in a big, if not the biggest, player in the knowledge society of the future.

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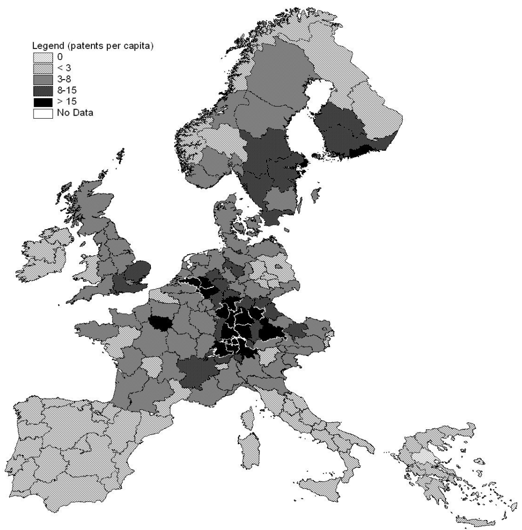
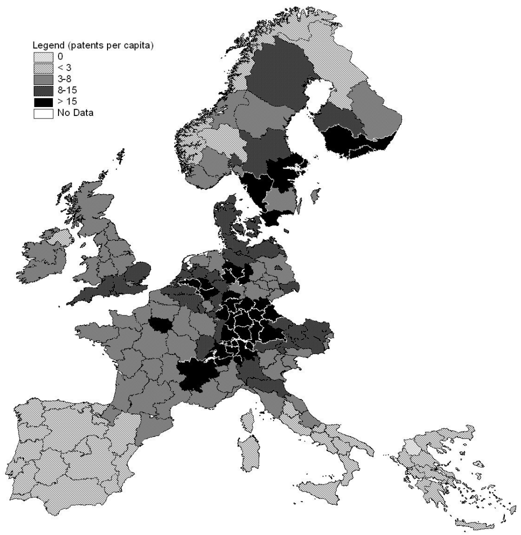
Map 1. Distribution of innovative activity in the European regions (patents per 100,000 inhabitants, annual average)

Panel a (1994-96)

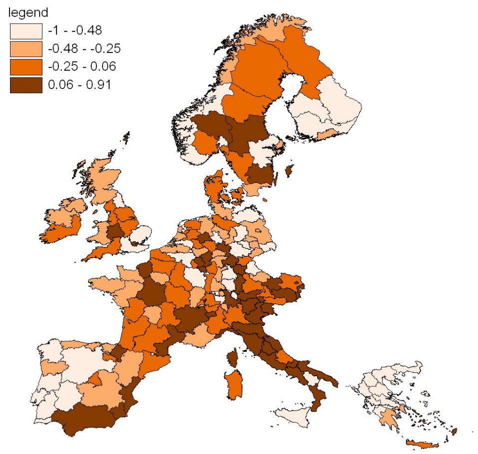


Panel b (1999-01)



Map 2. Innovation specialization index in the European regions (1999-01)

Panel a (Leather and footwear)



Panel b (Office and computing)

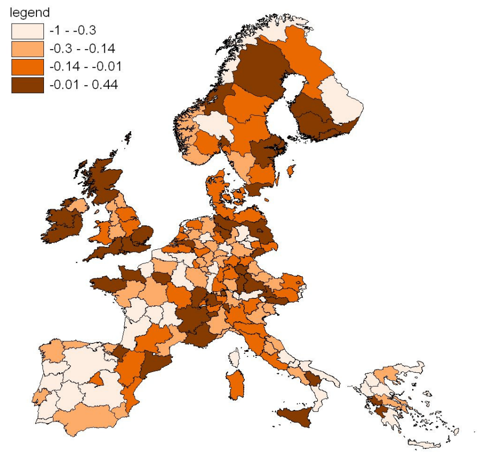


Table 1. Innovative activity across European countries
(absolute values, patents per 100.000 inhabitants, annual average)

Nation	Num. of regions	1994-96			1999-01			% variation
		Patents abs values	% values	Patents pc	Patents abs values	% values	Patents pc	Patents abs values
Austria	9	663,4	2,2%	6,8	1042,6	2,2%	10,5	57,2%
Belgium	3	773,0	2,5%	6,6	1193,6	2,5%	10,1	54,4%
Switzerland	7	1699,8	5,6%	19,7	2445,2	5,1%	27,8	43,8%
Germany	40	12076,3	39,6%	12,2	19982,7	41,5%	19,9	65,5%
Denmark	1	462,4	1,5%	7,6	807,5	1,7%	12,9	74,6%
Spain	15	361,7	1,2%	0,8	672,1	1,4%	1,5	85,8%
Finland	6	601,7	2,0%	9,6	1167,3	2,4%	18,3	94,0%
France	22	4795,3	15,7%	7,1	6716,0	13,9%	9,8	40,1%
Greece	13	22,9	0,1%	0,2	48,0	0,1%	0,4	110,0%
Ireland	2	81,9	0,3%	1,9	191,3	0,4%	4,2	133,7%
Italy	20	2401,5	7,9%	3,4	3582,2	7,4%	5,0	49,2%
Luxembourg	1	31,5	0,1%	6,4	67,7	0,1%	12,7	114,7%
Netherlands	4	1542,6	5,1%	8,3	2756,7	5,7%	14,5	78,7%
Norway	7	154,6	0,5%	3,0	274,5	0,6%	5,1	77,5%
Portugal	5	15,0	0,0%	0,1	34,9	0,1%	0,3	132,5%
Sweden	8	1287,8	4,2%	11,7	2051,4	4,3%	18,7	59,3%
United Kingdom	12	3500,2	11,5%	5,1	5151,5	10,7%	7,3	47,2%
EU	**175**	**30471,6**	**100,0%**	**6,7**	**48185,2**	**100,0%**	**10,4**	**58,1%**
CV across nations				**0,75**			**0,71**	
CV across regions				**1,05**			**1,05**	

Tab 2. Innovative activity across sectors in Europe

sector	absolute values		% composition		% variation
	94-96	**99-01**	**94-96**	**99-01**	
Food and beverages	215,6	304,1	0,71	0,63	41,1
Tobacco	20,8	20,2	0,07	0,04	-3,1
Textiles	330,1	488,0	1,08	1,01	47,8
Wearing apparel	80,7	122,7	0,26	0,25	52,1
Leather and footwear	94,0	111,0	0,31	0,23	18,1
Wood products, except furniture	245,6	339,6	0,81	0,70	38,2
Paper	301,1	392,3	0,99	0,81	30,3
Printing and publishing	89,5	135,8	0,29	0,28	51,8
Coke and refined petroleum products	377,3	455,4	1,24	0,95	20,7
Chemicals and chemical products	5844,0	8400,0	19,18	17,43	43,7
Rubber and plastic	743,1	1081,6	2,44	2,24	45,6
Non metallic mineral products	667,3	956,1	2,19	1,98	43,3
Basic metals	222,7	306,8	0,73	0,64	37,8
Fabricated metal products	2084,9	3009,4	6,84	6,25	44,3
Machinery	6683,3	9985,9	21,93	20,72	49,4
Office, computing	562,5	1155,2	1,85	2,40	105,4
Electrical machinery	3111,9	5339,1	10,21	11,08	71,6
Radio, television, communication equip.	2339,4	4823,6	7,68	10,01	106,2
Precision and medical instruments	2670,6	4751,1	8,76	9,86	77,9
Motor vehiclel, trailers and semitrailers	1275,3	2049,7	4,19	4,25	60,7
Other transport equipment	1125,2	1904,7	3,69	3,95	69,3
Furniture	1268,1	1894,5	4,16	3,93	49,4
Recycling and other	118,7	158,4	0,39	0,33	33,5
Total manufacturing	**30471,6**	**48185,2**	**100,00**	**100,00**	**58,1**

Table 3. Spatial autocorrelation in the innovative activity

(Moran's I test, normal approximation)

	94-96		99-01	
	Z	**spatial autocorrelation order***	**Z**	**spatial autocorrelation order**
Food and beverages	3,51	2	2,90	2
Tobacco	4,19	1	8,50	1
Textiles	11,61	4	11,86	4
Wearing apparel	9,72	3	11,28	4
Leather and footwear	4,21	3	4,04	3
Wood products, except furniture	11,82	4	9,91	4
Paper	9,79	3	10,72	3
Printing and publishing	9,68	3	10,02	4
Coke and refined petroleum products	4,54	3	5,88	3
Chemicals and chemical products	5,88	3	7,19	3
Rubber and plastic	10,77	4	8,38	4
Non metallic mineral products	11,91	4	11,90	4
Basic metals	10,88	4	11,23	4
Fabricated metal products	13,12	4	12,79	4
Machinery	12,94	4	12,40	4
Office, computing	9,74	3	6,95	4
Electrical machinery	10,20	3	9,63	4
Radio, television, comm. equip.	5,65	2	5,61	2
Precision and medical instruments	9,86	3	8,79	4
Motor vehicles, trailers and semitrailers	11,15	4	9,71	4
Other transport equipment	10,80	4	8,82	4
Furniture	11,66	4	12,55	4
Recycling and other	11,93	4	12,42	4

* it indicates the last order of contiguity with a significant Z at the 5% level

Table 4. Dependent variable: patents per capita, 1994-96
169 observations; national dummies included; contiguity matrix

sectors

	Food and beverages	Tobacco	Textiles	Wearing apparel	Leather and footwear	Wood products, except furniture	Paper	Printing and publishing	Coke and refined petroleum products	Chemicals and chemical products	Rubber and plastic	Non metallic mineral products
estimation method	OLS	ML	ML	ML	ML	ML	OLS	ML	ML	ML	ML	ML
W_I		31,28	33,49	9,40	37,60	34,96		14,51	17,11	25,17	20,72	37,22
		0,00	*0,00*	*0,20*	*0,00*	*0,00*		*0,07*	*0,06*	*0,00*	*0,01*	*0,00*
spatial error term												
IST_{t-q}	5,73	0,97	3,83	0,66	3,24	-0,06	2,19	1,52	16,32	252,84	8,91	4,84
	0,00	*0,00*	*0,01*	*0,08*	*0,00*	*0,95*	*0,08*	*0,00*	*0,00*	*0,00*	*0,01*	*0,09*
DIV_{t-q}	-0,01	0,00	0,04	0,01	0,02	0,01	0,02	0,00	-0,08	7,48	0,13	0,07
	0,82	*0,93*	*0,34*	*0,52*	*0,56*	*0,58*	*0,58*	*0,97*	*0,41*	*0,33*	*0,17*	*0,29*
AGG_{t-q}	-0,08	-0,02	0,21	0,01	0,10	0,11	0,10	0,04	0,09	0,41	0,49	0,19
	0,40	*0,26*	*0,00*	*0,33*	*0,04*	*0,01*	*0,09*	*0,04*	*0,51*	*0,80*	*0,00*	*0,06*
GDP_{t-q}	0,26	0,07	0,27	0,08	0,05	0,27	0,48	0,09	0,62	8,75	0,85	0,73
	0,02	*0,00*	*0,00*	*0,00*	*0,36*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*
RD_{t-s}	1,48	-0,14	3,19	1,11	0,27	1,53	1,44	0,81	2,70	52,16	5,10	5,77
	0,08	*0,29*	*0,00*	*0,00*	*0,54*	*0,00*	*0,01*	*0,00*	*0,04*	*0,00*	*0,00*	*0,00*
R2 adj	0,43	0,38	0,76	0,74	0,43	0,78	0,63	0,67	0,46	0,58	0,72	0,81
LIK	219,09	521,10	270,01	512,99	314,81	345,51	281,97	464,91	131,12	-274,64	140,43	195,08
AIC	-394,18	-996,21	-494,02	-979,98	-583,61	-645,02	-519,93	-883,83	-216,24	595,28	-234,85	-344,17
Moran's I (error)	0,36						2,27					
	0,72						*0,02*					
LM (error)	0,76						0,68					
	0,38						*0,41*					
LM (lag)	1,47						1,57					
	0,23						*0,21*					
LM (error)/(lag) for ML estim*		0,01	2,08	7,86	24,72	0,38		1,10	2,11	0,40	0,22	0,40
		0,91	*0,15*	*0,01*	*0,00*	*0,54*		*0,29*	*0,15*	*0,53*	*0,64*	*0,53*
Lik ratio (error)/(lag)		8,47	21,00	1,86	26,00	23,11		3,60	2,73	7,06	6,14	29,29
		0,00	*0,00*	*0,17*	*0,00*	*0,00*		*0,06*	*0,10*	*0,01*	*0,01*	*0,00*

	Basic metals	Fabricated metal products	Machinery	Office, computing	Electrical machinery	Radio, television, communication equip.	Precision and medical instruments	Motor vehiclel, trailers and semitrailers	Other transport equipment	Furniture	Recycling and other
estimation method	ML	ML	ML	ML	ML	OLS	ML	ML	ML	ML	ML
W_I	38,01	46,80	49,02	28,49	30,89		25,52	38,88	25,43	40,78	28,05
	0,00	*0,00*	*0,00*	*0,00*	*0,00*		*0,00*	*0,00*	*0,00*	*0,00*	*0,00*
spatial error term											
IST_{t-q}	2,58	13,35	41,52	11,75	83,61	70,48	55,58	30,64	12,67	-0,30	0,61
	0,00	*0,16*	*0,29*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,07*	*0,97*	*0,21*
DIV_{t-q}	0,03	0,17	0,28	0,07	0,62	0,40	0,38	0,24	0,11	0,04	0,01
	0,25	*0,40*	*0,39*	*0,25*	*0,08*	*0,36*	*0,19*	*0,12*	*0,38*	*0,80*	*0,42*
AGG_{t-q}	0,15	1,27	2,76	0,03	0,98	-0,04	0,16	0,58	0,26	0,91	0,07
	0,00	*0,00*	*0,00*	*0,75*	*0,08*	*0,95*	*0,72*	*0,02*	*0,14*	*0,00*	*0,00*
GDP_{t-q}	0,24	2,30	6,41	0,63	3,52	3,32	2,72	1,45	1,43	1,38	0,14
	0,00	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*
RD_{t-s}	0,99	11,11	61,62	7,59	38,12	36,48	39,89	17,26	13,46	8,90	0,38
	0,01	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,05*
R2 adj	0,72	0,84	0,86	0,77	0,76	0,57	0,79	0,78	0,79	0,77	0,74
LIK	329,88	2,95	-178,78	206,90	-99,70	-120,62	-58,11	50,81	98,37	59,05	455,45
AIC	-613,76	40,09	403,55	-367,80	245,41	285,23	162,22	-55,63	-150,73	-72,10	-864,90
Moran's I (error)						0,14					
						0,89					
LM (error)						1,19					
						0,28					
LM (lag)						0,00					
						0,97					
LM (error)/(lag) for ML estim*	0,26	0,01	1,56	0,03	0,49		1,39	1,88	0,49	0,18	0,04
	0,61	*0,94*	*0,21*	*0,87*	*0,48*		*0,24*	*0,17*	*0,48*	*0,67*	*0,84*
Lik ratio (error)/(lag)	20,77	46,74	60,19	15,65	17,49		13,18	29,19	12,60	28,02	12,61
	0,00	*0,00*	*0,00*	*0,00*	*0,00*		*0,00*	*0,00*	*0,00*	*0,00*	*0,00*

Table 5. Dependent variable: patents per capita, 1999-01
170 observations; national dummies included; contiguity matrix

sectors

	Food and beverages	Tobacco	Textiles	Wearing apparel	Leather and footwear	Wood products, except furniture	Paper	Printing and publishing	Coke and refined petroleum products	Chemicals and chemical products	Rubber and plastic	Non metallic mineral products	Basic metals	Fabricated metal products	Machinery	Office, computing	Electrical machinery	Radio, television, communicati on equip.	Precision and medical instruments	Motor vehiclel, trailers and semitrailers	Other transport equipment	Furniture	Recycling and other
estimation method	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	OLS	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML
W_I	-37,31	71,24	33,07	24,12	-9,79		22,04	17,38	25,94	22,64		33,55	24,02	44,05	43,65	18,73	32,91	16,88	23,03	33,94	21,48	39,96	28,57
	0,00	*0,00*	*0,00*	*0,00*	*0,32*		*0,00*	*0,03*	*0,00*	*0,00*		*0,00*	*0,00*	*0,00*	*0,00*	*0,02*	*0,00*	*0,04*	*0,00*	*0,00*	*0,01*	*0,00*	*0,00*
spatial error term						81,42																	
						0,00																	
IST_{t-q}	7,51	1,04	6,43	1,11	3,62	0,82	5,90	1,19	18,79	318,69	30,95	5,98	6,43	30,02	82,19	14,73	157,56	171,29	59,37	44,27	21,14	27,06	2,57
	0,00	*0,00*	*0,00*	*0,02*	*0,00*	*0,61*	*0,00*	*0,01*	*0,00*	*0,00*	*0,00*	*0,21*	*0,00*	*0,04*	*0,24*	*0,06*	*0,00*	*0,00*	*0,05*	*0,00*	*0,16*	*0,00*	*0,00*
DIV_{t-q}	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	8,40	0,01	0,00	0,00	0,01	0,02	0,01	0,04	0,04	0,02	0,01	0,01	0,01	0,00
	0,94	*0,82*	*0,36*	*0,71*	*0,54*	*0,95*	*0,38*	*0,59*	*0,76*	*0,49*	*0,15*	*0,50*	*0,49*	*0,33*	*0,34*	*0,41*	*0,12*	*0,34*	*0,38*	*0,28*	*0,40*	*0,20*	*0,16*
AGG_{t-q}	0,01	-0,01	0,31	0,07	0,15	0,19	0,16	0,05	0,13	2,79	0,93	0,64	0,30	2,32	5,31	-0,14	2,27	-0,09	0,23	1,36	0,46	1,44	0,10
	0,94	*0,48*	*0,00*	*0,00*	*0,00*	*0,02*	*0,03*	*0,04*	*0,36*	*0,14*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,61*	*0,05*	*0,96*	*0,81*	*0,01*	*0,26*	*0,00*	*0,00*
GDP_{t-q}	0,46	0,08	0,41	0,15	0,16	0,37	0,49	0,08	0,53	13,75	1,47	0,84	0,34	2,72	8,51	1,82	5,27	6,43	6,21	1,71	2,49	1,85	0,17
	0,01	*0,00*	*0,00*	*0,00*	*0,05*	*0,00*	*0,00*	*0,05*	*0,02*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,01*	*0,00*	*0,03*	*0,00*	*0,00*	*0,00*
RD_{t-s}	1,53	-0,22	5,08	1,15	0,41	0,95	2,83	1,61	4,52	76,24	10,51	8,70	1,31	20,01	108,92	17,37	73,90	82,66	70,51	36,44	26,75	14,71	0,98
	0,09	*0,12*	*0,00*	*0,00*	*0,33*	*0,06*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,02*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*
R2 adj	0,55	0,61	0,78	0,76	0,35	0,39	0,74	0,74	0,55	0,68	0,62	0,77	0,71	0,80	0,83	0,64	0,72	0,59	0,74	0,71	0,70	0,81	0,80
LIK	0,52	491,71	223,78	459,87	322,66	248,52	0,73	436,05	138,79	-286,38	54,31	109,51	264,90	-69,25	-262,52	27,83	-218,25	-274,60	-182,73	-75,23	-33,94	17,10	441,70
AIC	0,55	-937,42	-401,56	-873,74	-599,31	-453,04	0,74	-826,11	-231,59	618,77	-64,61	-173,02	-483,80	184,49	571,05	-9,67	482,49	595,21	411,46	196,47	113,89	11,81	-837,41
Moran's I (error)											3,06												
											0,00												
LM (error)											2,58												
											0,11												
LM (lag)											1,33												
											0,25												
LM (error)/(lag) for ML estim*	0,86	8,81	1,90	1,99	3,85	5,29	0,60	4,39	0,13	0,84		5,57	0,34	4,66	0,90	2,65	0,51	3,24	2,71	0,53	0,33	0,75	0,10
	0,35	*0,00*	*0,17*	*0,16*	*0,05*	*0,02*	*0,44*	*0,04*	*0,71*	*0,36*		*0,02*	*0,56*	*0,03*	*0,34*	*0,10*	*0,48*	*0,07*	*0,10*	*0,47*	*0,56*	*0,39*	*0,75*
Lik ratio (error)/(lag)	14,09	65,77	19,92	10,14	1,03	42,90	7,79	4,65	7,60	6,94		18,54	7,89	32,29	37,42	4,26	17,53	3,05	8,13	16,67	6,40	28,46	13,76
	0,00	*0,00*	*0,00*	*0,00*	*0,31*	*0,00*	*0,01*	*0,03*	*0,01*	*0,01*		*0,00*	*0,00*	*0,00*	*0,00*	*0,04*	*0,00*	*0,08*	*0,00*	*0,00*	*0,01*	*0,00*	*0,00*

* LM(error) for Spatial Lag model, LM(lag) for Spatial Error model

Table 6. Dependent variable: patents per capita, 1994-96
169 observations; national dummies included; technological contiguity matrix

	sectors																						
	Food and beverages	Tobacco	Textiles	Wearing apparel	Leather and footwear	Wood products, except furniture	Paper	Printing and publishing	Coke and refined petroleum products	Chemicals and chemical products	Rubber and plastic	Non metallic mineral products	Basic metals	Fabricated metal products	Machinery	Office, computing	Electrical machinery	Radio, television, communication equip.	Precision and medical instruments	Motor vehiclel, trailers and semitrailers	Other transport equipment	Furniture	Recycling and other
estimation method	OLS	ML	ML	ML	OLS	ML	OLS	OLS	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML
W_I		22,51	31,31	13,29		34,03			19,74	23,44	17,50	35,12	26,31	46,50	44,77	25,92	28,75		26,21	33,13	27,01	35,76	24,02
		0,01	*0,00*	*0,08*		*0,00*			*0,02*	*0,00*	*0,03*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*		*0,00*	*0,00*	*0,00*	*0,00*	*0,00*
spatial error term																		-19,72					
																		0,06					
IST_{t-q}	5,73	1,00	3,95	0,65	3,88	-0,30	2,19	1,56	16,32	248,93	8,57	5,49	2,61	14,25	53,02	11,25	80,94	70,31	48,79	31,27	12,64	-1,32	0,56
	0,00	*0,00*	*0,01*	*0,09*	*0,00*	*0,78*	*0,08*	*0,00*	*0,00*	*0,00*	*0,01*	*0,06*	*0,01*	*0,14*	*0,20*	*0,00*	*0,00*	*0,00*	*0,01*	*0,00*	*0,07*	*0,87*	*0,26*
DIV_{t-q}	-0,01	0,00	0,04	0,01	0,02	0,01	0,02	0,00	-0,08	7,74	0,12	0,07	0,03	0,15	0,26	0,06	0,57	0,41	0,32	0,23	0,10	0,02	0,01
	0,82	*0,93*	*0,36*	*0,54*	*0,54*	*0,68*	*0,58*	*0,97*	*0,40*	*0,32*	*0,19*	*0,31*	*0,30*	*0,45*	*0,45*	*0,30*	*0,11*	*0,31*	*0,27*	*0,14*	*0,42*	*0,91*	*0,49*
AGG_{t-q}	-0,08	-0,02	0,20	0,01	0,12	0,10	0,10	0,05	0,08	0,33	0,48	0,16	0,16	1,14	2,44	0,03	1,00	-0,01	0,07	0,60	0,23	0,89	0,07
	0,40	*0,22*	*0,00*	*0,46*	*0,03*	*0,02*	*0,09*	*0,02*	*0,55*	*0,84*	*0,00*	*0,11*	*0,00*	*0,00*	*0,02*	*0,74*	*0,08*	*0,98*	*0,87*	*0,02*	*0,21*	*0,00*	*0,00*
GDP_{t-q}	0,26	0,07	0,27	0,08	0,09	0,26	0,48	0,11	0,61	8,76	0,86	0,72	0,26	2,18	6,45	0,63	3,47	3,24	2,67	1,49	1,38	1,42	0,15
	0,02	*0,00*	*0,00*	*0,00*	*0,18*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*
RD_{t-s}	1,48	-0,15	3,02	1,09	0,11	1,38	1,44	0,79	2,70	51,45	4,98	5,70	0,94	10,69	56,65	7,33	36,63	38,60	38,36	16,80	12,75	8,15	0,34
	0,08	*0,26*	*0,00*	*0,00*	*0,83*	*0,00*	*0,01*	*0,00*	*0,04*	*0,00*	*0,00*	*0,00*	*0,02*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,08*
R2 adj	0,43	0,36	0,75	0,74	0,21	0,77	0,63	0,62	0,47	0,58	0,71	0,80	0,70	0,83	0,85	0,77	0,76	0,63	0,79	0,77	0,79	0,75	0,73
LIK	219,09	519,00	267,20	513,48	301,81	342,89	281,97	463,11	131,57	-275,26	139,22	191,77	323,86	-0,76	-188,17	205,00	-101,37	-119,39	-58,52	45,63	98,28	54,18	452,99
AIC	-394,18	-992,01	-488,39	-980,96	-559,62	-639,78	-519,93	-882,22	-217,15	596,52	-232,44	-337,54	-601,73	47,52	422,35	-364,00	248,74	282,78	163,04	-45,25	-150,56	-62,36	-859,98
Moran's I (error)	0,15				1,31		3,32	2,25															
	0,88				*0,19*		*0,00*	*0,02*															
LM (error)	1,49				0,03		2,55	0,42															
	0,22				*0,86*		*0,11*	*0,52*															
LM (lag)	3,13				0,09		0,46	1,88															
	0,08				*0,77*		*0,50*	*0,17*															
LM (error)/(lag) for ML estim*		2,12	0,52	6,83		1,79			0,03	0,11	0,08	0,62	1,53	0,44	1,18	1,35	3,04	5,51	5,29	0,05	5,51	0,10	0,35
		0,15	*0,47*	*0,01*		*0,18*			*0,87*	*0,73*	*0,78*	*0,43*	*0,22*	*0,50*	*0,28*	*0,24*	*0,08*	*0,02*	*0,02*	*0,82*	*0,02*	*0,75*	*0,55*
Lik ratio (error)/(lag)		4,27	15,37	2,84		17,88			3,64	5,82	3,74	22,67	8,73	39,31	41,39	11,85	14,15	2,45	12,36	18,81	12,43	18,27	7,70
		0,04	*0,00*	*0,09*		*0,00*			*0,06*	*0,02*	*0,05*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,12*	*0,00*	*0,00*	*0,00*	*0,00*	*0,01*

* LM(error) for Spatial Lag model, LM(lag) for Spatial Error model

Table 7. Dependent variable: patents per capita, 1999-01
170 observations; national dummies included; technological contiguity matrix

	Sectors																						
	Food and beverages	Tobacco	Textiles	Wearing apparel	Leather and footwear	Wood products, except furniture	Paper	Printing and publishing	Coke and refined petroleum products	Chemicals and chemical products	Rubber and plastic	Non metallic mineral products	Basic metals	Fabricated metal products	Machinery	Office, computing	Electrical machinery	Radio, television, communication equip.	Precision and medical instruments	Motor vehiclel, trailers and semitrailers	Other transport equipment	Furniture	Recycling and other
estimation method	ML	ML	ML	ML	OLS	ML	ML	ML	ML	ML	OLS	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML	ML
W_I	-38,73	71,18	32,89	23,68			22,47	17,79	28,76	25,51		33,88	23,39	43,63	43,47	20,63	34,51	19,57	25,10	33,99	23,49	39,98	28,73
	0,00	*0,00*	*0,00*	*0,00*			*0,00*	*0,02*	*0,00*	*0,00*		*0,00*	*0,00*	*0,00*	*0,00*	*0,01*	*0,00*	*0,01*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*
spatial error term						81,59																	
						0,00																	
IST_{t-q}	7,57	1,04	6,45	1,12	3,55	0,95	5,92	1,19	18,59	314,66	30,97	6,07	6,44	30,13	84,74	14,77	155,19	169,44	58,67	44,40	20,87	27,16	2,57
	0,00	*0,00*	*0,00*	*0,02*	*0,00*	*0,56*	*0,00*	*0,01*	*0,00*	*0,00*	*0,00*	*0,20*	*0,00*	*0,04*	*0,22*	*0,05*	*0,00*	*0,00*	*0,05*	*0,00*	*0,16*	*0,00*	*0,00*
DIV_{t-q}	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	8,45	0,01	0,00	0,00	0,01	0,02	0,01	0,04	0,04	0,02	0,01	0,01	0,01	0,00
	0,94	*0,83*	*0,36*	*0,70*	*0,59*	*0,93*	*0,38*	*0,59*	*0,76*	*0,48*	*0,16*	*0,50*	*0,49*	*0,33*	*0,33*	*0,41*	*0,13*	*0,34*	*0,39*	*0,28*	*0,41*	*0,20*	*0,16*
AGG_{t-q}	0,01	-0,01	0,31	0,07	0,13	0,19	0,16	0,05	0,12	2,60	0,93	0,64	0,30	2,32	5,25	-0,16	2,18	-0,23	0,14	1,35	0,42	1,43	0,10
	0,92	*0,48*	*0,00*	*0,00*	*0,01*	*0,02*	*0,03*	*0,04*	*0,39*	*0,16*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,56*	*0,06*	*0,89*	*0,89*	*0,01*	*0,30*	*0,00*	*0,00*
GDP_{t-q}	0,46	0,08	0,41	0,15	0,14	0,37	0,49	0,08	0,52	13,55	1,47	0,84	0,34	2,74	8,55	1,81	5,21	6,35	6,13	1,70	2,46	1,85	0,17
	0,01	*0,00*	*0,00*	*0,00*	*0,10*	*0,00*	*0,00*	*0,05*	*0,02*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,01*	*0,00*	*0,03*	*0,00*	*0,00*	*0,00*
RD_{t-s}	1,55	-0,21	5,06	1,15	0,40	0,91	2,82	1,61	4,49	75,90	10,50	8,64	1,31	19,98	108,73	17,27	73,45	82,27	70,14	36,39	26,60	14,65	0,98
	0,09	*0,12*	*0,00*	*0,00*	*0,37*	*0,08*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,02*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*
R2 adj	0,55	0,61	0,78	0,76	0,25	0,39	0,74	0,74	0,56	0,69	0,61	0,77	0,70	0,80	0,83	0,64	0,73	0,60	0,74	0,71	0,70	0,81	0,80
LIK	181,27	491,95	223,78	459,75	322,14	248,75	263,75	436,15	139,64	-285,52	53,54	109,67	264,68	-69,48	-262,72	28,24	-217,46	-247,10	-182,04	-75,22	-33,37	17,15	441,81
AIC	-316,53	-937,90	-401,56	-873,49	-600,28	-453,50	-481,50	-826,29	-233,27	617,04	-63,08	-173,34	-483,36	184,96	571,44	-10,48	480,92	594,20	410,09	196,45	112,73	11,69	-837,62
Moran's I (error)					-0,35						3,26												
					0,73						*0,00*												
LM (error)					2,66						2,46												
					0,10						*0,12*												
LM (lag)					1,12						2,55												
					0,29						*0,11*												
LM (error)/(lag) for ML estim*	1,75	8,24	1,99	2,11		5,31	0,51	4,23	0,24	0,98		6,06	0,30	4,73	0,99	1,83	0,30	2,84	2,09	0,57	0,10	0,79	0,19
	0,19	*0,00*	*0,16*	*0,15*		*0,02*	*0,47*	*0,04*	*0,63*	*0,32*		*0,01*	*0,59*	*0,03*	*0,32*	*0,18*	*0,59*	*0,09*	*0,15*	*0,45*	*0,75*	*0,37*	*0,66*
Lik ratio (error)/(lag)	13,75	66,25	19,92	9,90		43,36	8,14	4,83	9,29	8,67		18,86	7,45	31,82	37,03	5,08	19,10	4,06	9,51	16,68	7,56	28,57	13,97
	0,00	*0,00*	*0,00*	*0,00*		*0,00*	*0,00*	*0,03*	*0,00*	*0,00*		*0,00*	*0,01*	*0,00*	*0,00*	*0,02*	*0,00*	*0,04*	*0,00*	*0,00*	*0,01*	*0,00*	*0,00*

Table 8. Moran's I statistic for the within-country and across-country weight matrices

	1994-1996		1999-2001	
	Within matrix	**Across matrix**	**Within matrix**	**Across matrix**
Food and beverages	-0.32	-0.79	-2.35	-0.54
	0.75	*0.43*	*0.02*	*0.59*
Tobacco	2.44	-2.22	7.68	-0.12
	0.01	*0.03*	*0.00*	*0.90*
Textiles	3.58	1.45	5.13	2.37
	0.00	*0.15*	*0.00*	*0.02*
Wearing apparel	1.11	-0.07	2.53	2.46
	0.27	*0.94*	*0.01*	*0.01*
Leather and footwear	4.00	-3.39	-2.36	0.80
	0.00	*0.00*	*0.02*	*0.42*
Wood products	4.38	2.22	4.51	1.85
	0.00	*0.03*	*0.00*	*0.06*
Paper	3.27	1.31	2.02	3.51
	0.00	*0.19*	*0.04*	*0.00*
Printing and publishing	1.03	2.00	1.15	1.10
	0.30	*0.05*	*0.25*	*0.27*
Coke and refined petroleum products	2.25	0.74	3.23	1.52
	0.02	*0.46*	*0.00*	*0.13*
Chemicals	2.71	1.29	3.50	1.60
	0.01	*0.20*	*0.00*	*0.11*
Rubber and plastic	3.11	0.38	2.82	1.27
	0.00	*0.71*	*0.00*	*0.20*
Non metallic mineral products	6.04	0.49	5.86	1.28
	0.00	*0.62*	*0.00*	*0.20*
Basic metals	3.51	2.09	3.20	1.16
	0.00	*0.04*	*0.00*	*0.25*
Fabricated metal products	5.73	2.90	5.97	2.55
	0.00	*0.00*	*0.00*	*0.01*
Machinery	5.94	2.37	6.03	1.60
	0.00	*0.02*	*0.00*	*0.11*
Office, computing	3.31	0.55	1.64	1.24
	0.00	*0.58*	*0.10*	*0.21*
Electrical machinery	3.29	0.25	4.35	0.47
	0.00	*0.80*	*0.00*	*0.64*
Radio, television and communication equip.	0.23	0.11	1.62	0.73
	0.82	*0.91*	*0.11*	*0.47*
Precision and medical instruments	2.17	1.69	2.10	1.55
	0.03	*0.09*	*0.04*	*0.12*
Motor vehicle, trailers and semitrailers	4.68	0.53	4.29	-0.03
	0.00	*0.59*	*0.00*	*0.98*
Other transport equipment	2.10	0.89	3.25	0.69
	0.04	*0.37*	*0.00*	*0.49*
Furniture	3.10	1.36	4.76	2.34
	0.00	*0.17*	*0.00*	*0.02*
Recycling and other	3.13	1.10	3.42	2.91
	0.00	*0.27*	*0.00*	*0.00*