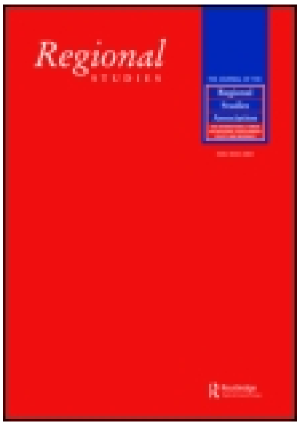

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The Geography of Inventive Activity in OECD Regions

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The Geography of Inventive Activity in OECD Regions

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USAI S. The geography of inventive activity in OECD regions, *Regional Studies*. This work is among the first systematic attempts to analyse comparatively the distribution of inventive activity across regions in OECD (Organisation for Economic Co-operation and Development) economies with a set of homogenous measures to measure the process of knowledge production and dissemination. The descriptive analysis shows that inventive performance is concentrated in some regions in Continental Europe, North America and Japan. Highly inventive regions tend to cluster together. This spatial dependence is found to have increased over time. The inventive performance of regions is directly influenced by the availability of human capital and research and development expenditure. Local agglomeration factors are also found to have a significant impact, while some negative effects appear when regions are mainly rural or when they are mainly service-oriented.

Innovative activity Spatial analysis Organisation for Economic Co-operation and Development (OECD) regions Knowledge production function

USAI S. 经合组织区域内发明创造活动的地理学特征，区域研究。一批系统性的研究试图通过一系列同质指标评估知识生产及扩散的过程，并以此对经济合作与发展组织（OECD）经济区内创造性活动的分布进行比较性分析。本研究即是此类研究中的一项。描述性分析表明，创造性活动集中在欧洲大陆、北美以及日本的某些区域。高创造力的地区往往呈聚集状。研究发现这种对于空间的依赖性随时间推移而有所增加。某一区域的创新力直接受人力资本与研发支出的影响。地方聚集因素也被认为是具有重大影响，而当（上述集聚）主要存在于农村地区或者主要以服务为导向的时候，会产生某些负面效应。

创新活动 空间分析 经济合作与发展组织（经合组织）区域 知识生产函数

USAI S. La géographie de l'activité innovatrice dans les régions de l'OCDE, *Regional Studies*. Cette étude représente l'une des premières tentatives systématiques d'analyser comparativement la distribution de l'activité innovatrice à travers les régions des économies de l'Organisation de coopération et de développement économique (OCDE) à partir d'un ensemble de mesures homogènes afin d'évaluer le processus de production et de diffusion de la connaissance. L'analyse descriptive montre que l'esprit d'innovation se concentre dans certaines régions situées en Europe continentale, en Amérique du Nord et au Japon. Les régions à forte intensité d'innovation ont tendance à s'agglomérer. Il s'avère que cette dépendance géographique a augmenté dans le temps. L'esprit d'innovation des régions est en corrélation étroite avec la disponibilité du capital humain et des dépenses en faveur de la recherche et du développement. Il s'avère aussi que les facteurs d'agglomération ont un impact non-négligeable, tandis que certains effets négatifs sont évidents lorsque les régions sont situées principalement en milieu rural ou quand elles sont orientées plutôt vers les services.

Activité innovatrice Analyse géographique Organisation de coopération et de développement économqiue (OECD) Fonction de production de la connaissance

USAI S. Geografie der Erfindungsaktivität in OECD-Regionen, *Regional Studies*. Dieser Beitrag ist einer der ersten systematischen Versuche einer vergleichenden Analyse der Verteilung der Erfindungsaktivität in den verschiedenen Regionen der Wirtschaftsräume der Organisation für wirtschaftliche Zusammenarbeit und Entwicklung (OECD) mit Hilfe einer Reihe von homogenen Maßstäben zur Messung des Prozesses der Wissenserzeugung und -verbreitung. Aus der beschreibenden Analyse geht hervor, dass sich die Erfindungsleistung auf bestimmte Regionen von Kontinentaleuropa, Nordamerika und Japan konzentriert. Hochgradig erfinderische Regionen bilden in der Regel Cluster. Diese räumliche Abhängigkeit hat sich im Laufe der Zeit verstärkt. Die Erfindungsleistung von Regionen wird unmittelbar durch die Verfügbarkeit von Humankapital und durch die Ausgaben für Forschung und Entwicklung beeinflusst. Auch lokale Agglomerationsfaktoren haben eine signifikante Auswirkung, während einige negative Effekte auftreten, wenn die Regionen überwiegend ländlich oder dienstleistungsorientiert geartet sind.

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Innovative Aktivität Raumanalyse Regionen der Organisation für wirtschaftliche Zusammenarbeit und Entwicklung (OECD) Wissensproduktionsfunktion

Usai S. La geografía de la actividad inventiva en las regiones de la OCDE, *Regional Studies*. Este trabajo es uno de los primeros intentos sistemáticos de analizar comparativamente la distribución de la actividad inventiva en las regiones de las economías de la Organización para la Cooperación y el Desarrollo Económico (OCDE) con ayuda de una serie de medidas homogéneas para medir el proceso de la producción y difusión del conocimiento. En el análisis descriptivo se demuestra que el desempeño inventivo se concentra en algunas regiones en Europa continental, Norteamérica y Japón. Las regiones altamente inventivas tienden a aglomerarse. Se observa que esta dependencia espacial ha aumentado con el tiempo. El desempeño inventivo de las regiones está directamente influido por la disponibilidad de capital humano y los gastos para investigación y desarrollo. Asimismo se observa que los factores de aglomeración locales tienen un impacto significativo mientras que algunos efectos negativos aparecen cuando las regiones son principalmente rurales o cuando están sobre todo orientadas en los servicios.

Actividad innovadora Análisis espacial Regiones de la Organización para la Cooperación y el Desarrollo Económico (OCDE) Función de la producción de conocimiento

JEL classifications: O33, O34, R11

INTRODUCTION

This line of research originates from the belief that technological activity is the main engine of growth and that its functioning has an important geographical component. The localization of inventive activity may, in fact, depend on some factors and externalities which are local in nature since one of the main ingredients of innovation – knowledge – can be transmitted more easily through interpersonal contacts.

This paper is the first systematic attempt to analyse the processes of knowledge creation and diffusion comparatively across regions in OECD (Organisation for Economic Co-operation and Development) countries by using a set of homogenous measures for both input and output in the process of knowledge production and diffusion. The main objective is to describe the patterns of invention across regions in some OECD countries in order to determine the main factors behind the process of localization of such activities.

A new database concerning social, economic, and inventive phenomena in OECD regions was set up by the OECD and further extended by the Centro Ricerche Economiche Nord Sud (CRENoS – Centre for North–South Economic Research) to achieve these objectives. In addition, a knowledge production function (KPF) at the regional level is estimated for OECD regions.

The descriptive analysis shows that there are important differences in the inventive performance of regions in OECD countries. Such performance is clustered around some areas in Continental Europe, in North America, and, to a lesser extent, in Japan. Spatial dependence across regions is quite stable with time in almost all OECD countries, but for the dispersed macro-region of Asia and Oceania. Even though several regularities characterize the three macro-areas of Europe, North America, Asia, and Oceania, important differences across countries are found that probably indicate how critical national innovation systems can be for regional performance.

The estimation of a model that links inventive output to its main inputs shows that this process is at work across regions in OECD countries. Some particular results are worth noting: research and development (R&D) is a crucial determinant, as are human capital and agglomeration economies. The performance of neighbouring regions is also an important determinant of inventive performance. Institutional factors, which vary from country to country, are relevant too. The effect of R&D is not monotonous, but it decreases as the country becomes richer. These results are differentiated with respect to the two macro-areas of Europe and North America. All in all, the KPF model seems to be able to explain inventive performance both in Europe and in North America, even though some interesting differences emerge.

This paper is structured as follows. The next section presents a review of the main theoretical and empirical underpinnings on which the analysis of the distribution of invention is based. The third section deals with the main issues concerning the data and the measurement of inventive activity. The fourth section is the core of the empirical analysis, where maps, tables, and figures are used to illustrate the main characteristics of the geographical distribution of invention across regions in OECD countries. The fifth section presents the KPF model, the estimation strategy, and the main results. Such results are then tested with respect to a number of robustness checks. The sixth section concludes the work.

LITERATURE BACKGROUND

The last three decades have witnessed a resurgence of interest in the localization of inventive activity. This resurgence has occurred within the context of a more general attention to the issue of the spatial distribution of economic activity, following the contribution of KRUGMAN (1991) on economic geography.[1] It is by now undisputed that economic activity is not randomly distributed in space, even after controlling for spatial characteristics. Rather, activities tend to agglomerate spatially (ELLISON and GLAESER, 1997). This phenomenon also occurs for innovation activities. AUDRETSCH and FELDMAN (1996) further argue that:

> the propensity for innovative activity to cluster is more attributable to the role of knowledge spillovers and not merely to the geographic concentration in production.
>
> (pp. 638–639)

From a theoretical point of view, the traditional reasons behind agglomeration, beyond the case of innovation, can be traced back to the work of MARSHALL (1890) more than a century ago. Theoretical work helps in understanding how innovation activities are strongly clustered spatially, given the importance of knowledge spillovers. Of course, the extent of such spillovers and the rate at which they decay with distance are open to empirical investigation. Some of the most important contributions to the field have been concerned precisely with investigating this question, which is fraught with difficulties. The first important issue is how to measure inventive output, which is dealt with in the next section. Many different indicators have been used in the literature, but given an interest in patents, the text that follows will focus mainly on papers using patents as the indicator of inventive output, and in particular on those studies which use the KPF to measure the intensity and spatial extent of knowledge spillovers.

The KPF approach was introduced by GRILICHES (1979) to study the functional relationship between knowledge inputs and outputs. Griliches applied it at the firm level; the subsequent literature has both generalized the unit of analysis (an area, a sector, etc.) and expanded the set of inputs that might enter the production of innovation (R&D employee/expense, university or firm-based R&D, the spatial extent of such indicators, urban density and diversity, etc.). This approach is very flexible and has been extensively used to analyse how the surrounding economic activity enters a unit's KPF, using spatial econometric techniques to assess the rate of spatial decay of knowledge spillovers.

Most studies, particularly in the early literature, are based on US data. JAFFE (1989) explores the existence of geographically mediated spillovers from university research to commercial innovation. University research appears to have an indirect effect on local invention by inducing industrial R&D spending; on the contrary, the econometric test shows no evidence to support the hypothesis that private R&D has any sort of effect on university research. These results are broadly confirmed by ACS *et al.* (1992) using innovation counts rather than patents (which are considered a better proxy of innovation output) as a measure of innovative output.

AUDRETSCH and FELDMAN (1996) examine the extent to which industrial activity clusters spatially and they link this geographic concentration to the existence of knowledge externalities. According to their results, the propensity for inventive activity to cluster will tend to be higher in industries where new economic knowledge is predominant – that is, where industry R&D, university research, and skilled labour are most important. ANSELIN *et al.* (1997) test the role of universities and the spatial extent of its geographic effects in the stimulation of technological innovation. The introduction of a spatial model improves the model fit: private R&D effect falls outside state borders, while university research influence remains positive and significant. ACS *et al.* (2002) perform a similar exercise using patent data as a measure of output to test their reliability as a proxy for regional inventive activity and they conclude that patents provide a reliable, albeit imperfect, measure of inventive activity.

The common feature of most of the studies reviewed above is the focus on pure (knowledge) spillovers rather than local externalities as a whole. The possibility that local externalities may also have a pecuniary nature is usually ruled out a priori, despite such an option being thoroughly discussed in the literature (for example, GRILICHES, 1992). BRESCHI and LISSONI (2001) provide a critical review of the risks of such an approach, which treats knowledge spillovers as homogeneous entities. The latest studies have attempted to investigate the main general mechanisms of the process of creation and diffusion of inventive knowledge rather than just looking for localized knowledge spillovers. Such studies have been applied to the US case (VARGA *et al.*, 2005; CARLINO *et al.*, 2007) as well as that of Europe (BOTTAZZI and PERI, 2003; GREUNZ, 2003; MORENO *et al.*, 2005; RODRIGUEZ-POSE and CRESCENZI, 2008; TAPPEINER *et al.*, 2008; ACOSTA *et al.*, 2009). All in all, these contributions find that technological spillovers (both pure and pecuniary) may exist both within and across regions.

In particular, BOTTAZZI and PERI (2003) estimate the effect of R&D externalities in generating innovation for eighty-six European Regions in the 1977–1995 period. Their findings show that spillovers are localized and take effect within a 180-minute travel radius. GREUNZ (2003) investigates inter-regional knowledge spillovers across European sub-national regions and tries to assess if geographical and technological proximity influences the creation of new knowledge within European regions. Results show that:

> interregional knowledge spillovers exist between geographically close regions and between regions displaying similar technological profiles.
>
> (p. 657)

MORENO *et al.* (2005) find that the external spillovers decay over space, for seventeen European countries (the EU-15 plus Norway and Switzerland), and that they occur mainly across regions within a country rather than across nations. This indicates that geographical distance is not the only dimension to be investigated and that knowledge spillovers may be also affected by cognitive, social, organizational, and institutional distance, as suggested by TORRE and RALLETT (2005) and BOSCHMA (2005). RODRIGUEZ-POSE and CRESCENZI (2008) use a model, for the first time referring to the EU-25 regions, that combines R&D, spillovers, and innovation system approaches, discriminating 'between the influence of internal factors and external knowledge and institutional flows on regional economic growth' (p. 51). Results highlight the importance of proximity (spillovers show a strong distance decay) and interaction between local and external research in maximizing innovation capacity.

Other studies at the national level in the same line of research are by AUTANT-BERNARD (2001) for the French *departments*, by ANDERSSON and EJERMO (2004) for Swedish functional regions, by FISCHER and VARGA (2003) for Austrian political districts, by BUESA *et al.* (2006) for the Spanish regions, and by GONÇALVES and ALMEIDA (2009) for Brazilian micro-regions.

The only paper to analyse different continents at the regional level is by CRESCENZI *et al.* (2007). They study to what extent the innovation gap between the United States and Europe can be attributed to differences in the spatial organization of inventive activities (as opposed to differences in the levels of inputs). They find that the United States seems to take better advantage of the localized character of innovation activities, due to the greater mobility of capital, labour force, and knowledge, in turn related to a higher degree of economic integration. It is worth noting that the model of Crescenzi *et al.*, unlike the present model, is based on the use of a different dependent variable for each of the two macro-areas: European Patent Office (EPO) patents for Europe and United States Patent Office (USPTO) patents for the United States. Moreover, they focus on the dynamics of patent activities rather than on differences in their level, making it problematic to compare their results with others in the literature.

The last strand of the literature reflects on which characteristics of the local structure influence inventive activity. Following the previous Marshallian citation, the literature has been debating the relative importance of concentration, of having 'innovators' in the same field of activity clustered together (specialization economies), or of having a sort of diversification in production (urbanization economies). The debate on the effects of concentration and diversity on innovation is still open (BEAUDRY and SCHIFFAUEROVA, 2009). FELDMAN and AUDRETSCH (1999) test the role of specialization (Marshallian externalities) versus diversity (Jakobian externalities) on the creation of inventive activity measured at the sector level. The most striking, and probably unexpected, result is that there is no evidence of specialization externalities, whilst diversity externalities are at work in the case of US metropolitan areas. These results have been somewhat disputed by several analyses based on European data (for example, PACI and USAI, 1999, 2000; MASSARD and RIOU, 2002; GREUNZ, 2003; and MORENO *et al.*, 2006), suggesting a notable difference in the functioning of the local innovation systems in the United States and Europe.

In this vein, the latest contribution of CARLINO and HUNT (2007) examines the effects of local economic characteristics on the rate of innovation (as measured by patents) in over a dozen industries. Crucially, these authors confirm the difference between the United States and the European Union, since they find that specialization within manufacturing industries is not particularly helpful. Nevertheless, they find the opposite for specialization in the service industries. Finally, CARLINO *et al.* (2007) support the view that more competitive local market structures are more conducive to innovation.

SOME METHODOLOGICAL AND DATA ISSUES

The use of patents as indicators of inventive activity may entail some inconveniences and shortcomings which ought to be kept in mind when interpreting the outcome of both descriptive and econometric analysis. Since the extensive review by GRILICHES (1990), economists have debated the issue of measuring inventive activity and technological progress, even though no universal solution has been proposed. Based on 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).

Patents represent the outcome of the inventive process which has some novelty and usability features. Moreover, since patenting implies relevant costs for the proponent, it is reasonable to assume that patented invention have an expected value higher than those costs. This in turn implies that patented inventions, especially those extended to foreign countries, are expected to have economic value, however heterogeneous. Nevertheless, certain inventions are not patented, whereas certain patented inventions are not implemented into real products and processes.

With respect to the object of the present research,[2] that is, the study of inventive activity across regions, sectors, and time, patent statistics seem particularly suitable, although imperfect.[3] First of all, patents directly reflect inventions, defined as the creation of new ideas or knowledge with an industrial application in view. Compared with R&D data, they also exhibit some useful properties, which are summarized below:

- They provide information on the residence of the inventor and proponent and can thus be grouped regionally (potentially at different territorial levels, starting from zip codes), whilst R&D statistics are available only for some regions or at the national level.

- They record the technological content of the invention and can, thanks to a conversion, be classified according to the industrial sectors, whilst R&D data are usually aggregated, especially at the regional level.
- They are available year by year for a long time span, thus allowing for dynamic analysis. On the contrary, regional R&D data are available only for recent years and, for some countries, discontinuously.

This paper provides an analysis of the performance of regions in OECD member countries where invention is measured by patent production. The analysis is based on the latest available international comparable data on patents made available by the OECD (2008). The main indicator for invention activity is identified as the number of patent applications filed through the Patent Cooperation Treaty (PCT),[4] instead of the traditional indexes based on the EPO or the USPTO, or the Japanese Patent Office (JPTO). The latter data are, as a matter of fact, fairly problematic when applied to international comparison outside their respective macro-areas. Since patents at the EPO, USPTO, and JPTO protect inventions within their respective geographical area, they are preferred by domestic firms, and thus their quota overestimates their inventive capability with respect to foreign firms. The PCT data, on the contrary, are based on an international procedure which allows inventors to file pre-applications to many offices worldwide at a relatively low cost (WORLD INTELLECTUAL PROPERTY ORGANIZATION (WIPO), 2007). In other words, by providing a unified procedure to protect inventions in each of its 139 contracting countries, the PCT database consists of international patent applications.[5] Its procedure is an intermediate step between the priority application and filing for patent protection abroad and it is increasingly used to file international patent applications. Given the present author's perspective and purposes, such data are interesting because they do not suffer from the usual home bias effect of the EPO, USPTO, and JPTO data, and, most importantly, the data can be easily regionalized thanks to the information on inventors' and applicants' addresses. At the same time, the fact should not be ignored that since patent applications via PCT filter the potentially most valuable inventions, such data are bound to underestimate the overall inventive process.

REGIONAL DESCRIPTIVE ANALYSIS

The following maps, figures, and tables refer mainly to one indicator for inventive performance: the value of PCT per capita (or better, per million population). This allows one to take into account the high heterogeneity of regions with respect to population size. Data refer, mostly, to two- or three-year periods in order to smooth out yearly peaks (1998–2000 and 2002–2004). An analysis is presented of the short-term dynamics between these two periods. The choice of territorial unit is territorial level 2 (TL2)[6] whenever possible, that is, for twenty-three out of thirty nations. For the remaining cases (Denmark, Iceland, Ireland, Luxembourg, Mexico, New Zealand, and Turkey), the availability of information restricts analysis to the country level. Some macro-areas (Europe, North America, Asia, and Oceania) are selected in order to perform a deeper investigation and to make a few comparisons across continents.

Table 1 provides a summary of the statistics concerning the main indicator for inventive performance and its regional counterpart. The first few columns provide some general information concerning the regions in each country. Columns 2 and 3, for instance, report the number of regions and the level of variable disaggregation in each country. As mentioned above, seven countries' data are reported at the national level. Columns 4 and 5 describe the average region within each country in terms of surface area and population size. These two dimensions are quite important when interpreting correctly both the geographic and the econometric analyses. The sample of regions is extremely heterogeneous, as regions may range from an average size of almost 1 million km^2 in Australia to an extension of just 6000 km^2 in Switzerland. The regions exhibit a similarly wide range, even though less marked, in demographics: the most populous regions, the Japanese prefectures, have almost 12 million inhabitants on average, whilst the smallest ones, in Norway, have just around 600 000 people.

The subsequent columns focus on PCT values. At the OECD level, the aggregate flow of PCT in 2002–2004 was of 308 163 patents, with an increase of around 27% from the 1998–2000 level (around 242 000). Such growth regards PCT per capita too, which increases of about 24%, from 71.98 to 89.15.

The country with the highest number of PCT in the two periods is the United States, whilst Portugal lies at the other extreme with the lowest amount. In terms of per-capita patents, it is worth noting the high performance of some small high-technology nations such as Sweden, Finland, the Netherlands, and Switzerland. There are some interesting trends to point out, which imply some convergence in inventive performance at least at the national level. Firstly, there is a remarkable growth of PCT production (per capita and in absolute terms) in Japan and Korea (+102.8 and +151.4, respectively). Secondly, most countries that registered low values in the first period (Mexico, Poland, Turkey, and the Slovak Republic) also show consistent PCT growth. On the contrary, some countries that performed very well in the first period experienced a relative worsening of their invention rate, especially

Table 1. Organisation for Economic Co-operation and Development (OECD): nations and regions – Patent Cooperation Treaty (PCT) and PCT per million population

OECD nation	Number of regions	Territorial level	Average size of the region (km^2)	Average population in the region, 2002–2004	PCT 1998–2000	PCT 2002–2004	PCT Growth rate (%)	PCT per million population 1998–2000	PCT per million population 2002–2004	PCT per million population Growth rate (%)
Australia	8	TL2	962 919	2 484 040	4466	5618	25.8	78.65	94.23	19.8
Austria	9	TL2	9319	902 893	1856	2589	39.5	77.40	106.20	37.2
Belgium	3	TL2	10 173	3 458 922	2210	2332	5.5	72.06	74.91	4.0
Canada	12	TL2	766 934	2 639 336	5579	6992	25.3	61.14	73.59	20.4
Czech Republic	8	TL2	9859	1 276 004	216	215	−0.5	7.00	7.02	0.3
Denmark	*1*	*TL0*	*43 098*	*5 389 733*	*2396*	*2975*	*24.2*	*150.12*	*183.99*	*22.6*
Finland	5	TL2	67 629	1 042 780	3959	3571	−9.8	255.50	228.30	−10.6
France	22	TL2	24 726	2 735 994	12 069	14 800	22.6	68.56	81.96	19.5
Germany	41	TL2	8708	2 012 461	35 355	42 702	20.8	143.54	172.51	20.2
Greece	4	TL2	32 907	2 756 083	136	122	−10.3	4.17	3.69	−11.5
Hungary	7	TL2	13 290	1 447 386	442	459	3.8	14.54	15.10	3.8
Iceland	*1*	*TL0*	*102 696*	*290 661*	*87*	*124*	*42.5*	*103.96*	*142.20*	*36.8*
Ireland	*1*	*TL0*	*69 797*	*3 993 767*	*576*	*794*	*37.8*	*51.26*	*66.27*	*29.3*
Italy	21	TL2	14 349	2 745 044	4421	5998	35.7	25.89	34.68	34.0
Japan	10	TL2	37 758	12 758 000	23 658	49 560	109.5	62.25	129.49	108.0
Korea	7	TL2	14 209	6 835 549	3844	9914	157.9	27.47	69.06	151.4
Luxembourg	*1*	*TL2*	*2586*	*449 733*	*145*	*95*	*−34.5*	*112.27*	*70.41*	*−37.3*
Mexico	*1*	*TL0*	*1 959 248*	*101 970 271*	*245*	*404*	*64.9*	*0.84*	*1.32*	*57.0*
Netherlands	4	TL2	8471	4 054 683	7528	7788	3.5	158.67	160.06	0.9
New Zealand	*1*	*TL0*	*277 039*	*4 002 267*	*784*	*1019*	*30.0*	*68.14*	*84.87*	*24.6*
Norway	7	TL2	43 928	650 180	1482	1341	−9.5	111.08	98.21	−11.6
Poland	16	TL2	19 543	2 387 900	189	239	26.5	1.64	2.09	27.5
Portugal	7	TL2	13 135	1 491 029	71	50	−29.6	2.33	1.60	−31.3
Slovak Republic	4	TL2	12 259	1 345 067	79	86	8.9	4.88	5.33	9.2
Spain	19	TL2	26 631	2 210 705	1623	2118	30.5	13.54	16.81	24.2
Sweden	8	TL2	55 168	1 119 863	7584	5506	−27.4	285.32	204.86	−28.2
Switzerland	7	TL2	5898	1 052 053	3760	5148	36.9	174.95	233.01	33.2
Turkey	*1*	*TL0*	*769 603*	*70 228 333*	*196*	*400*	*104.1*	*0.98*	*1.90*	*92.7*
United Kingdom	37	TL2	6573	1 610 381	12 233	12 041	−1.6	68.96	67.36	−2.3
United States	51	TL2	119 774	5 702 560	104 803	123 161	17.5	125.20	141.16	12.7
Total	324		94 757	3 556 366	241 992	308 163	27.3	71.98	89.15	23.8

Note: Values shown in italics denote national values.
Source: OECD Regional Database.

the Scandinavian countries and Luxembourg in Central Europe. Most of Continental Europe improved its inventive production capacity, as well as some Mediterranean countries (with the exception of Greece).

Figs 1–4, which represent the quantile distribution of PCT per capita of the four OECD macro-areas (Europe, North America, Asia, and Oceania) for the two periods across 2000, provide a first insight on the cluster distribution of invention, and they help to develop a preliminary idea of the correlation structure across regions and countries. The maps show the geography of invention in OECD regions, highlighting some clusters centred in Continental and Scandinavian Europe, Western and Eastern North American states, and central Japan. The analysis of these maps is made clearer by Table 2, which provides some further concise information for the same macro-areas.

Examining Table 2 and the maps together, the focus is first on European countries and regions. In the European area, the increase of PCT per capita is similar to the OECD average. PCT per capita in Europe show a large high-performance cluster, which starts from Rhône-

Table 2. Macro-areas– Patent Cooperation Treaty (PCT) and PCT per million population

Macro-area	Number of regions	PCT 1998–2000	PCT 2002–2004	PCT Growth rate (%)	PCT per million population 1998–2000	PCT per million population 2002–2004	PCT per million population Growth rate (%)
Europe	234	98 613	111 495	13.06	63.46	70.32	10.81
North America	64	110 628	130 557	18.02	90.7	102.53	13.04
Asia	17	27 502	59 474	116.25	52.89	113.01	113.66
Oceania	9	5250	6637	26.42	76.32	92.66	21.42

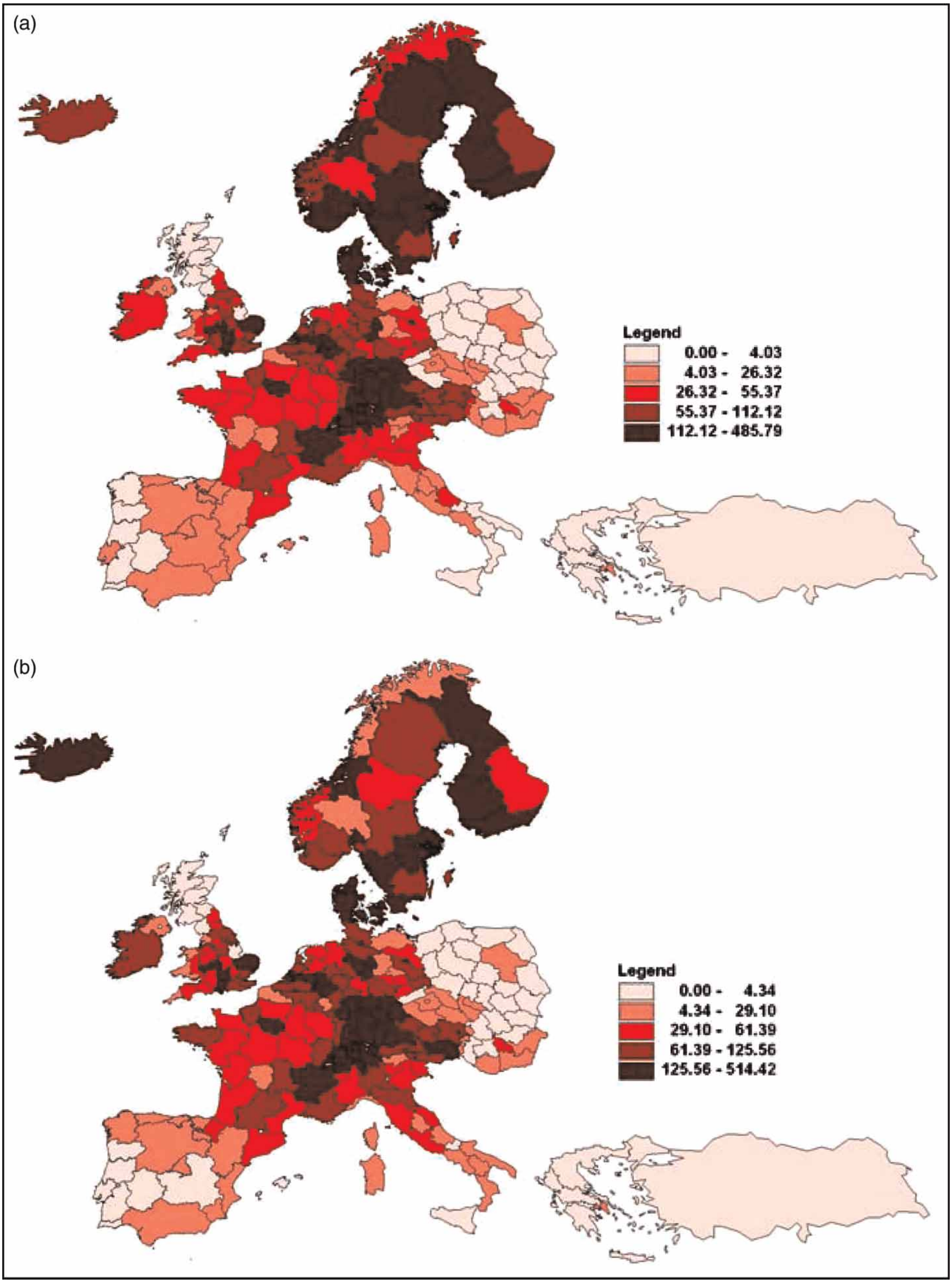

Fig. 1. *Europe: Patent Cooperation Treaty (PCT) per million population: (a) 1998–2000; and (b) 2002–2004*
Source: Organisation for Economic Co-operation and Development (OECD) Regional Database

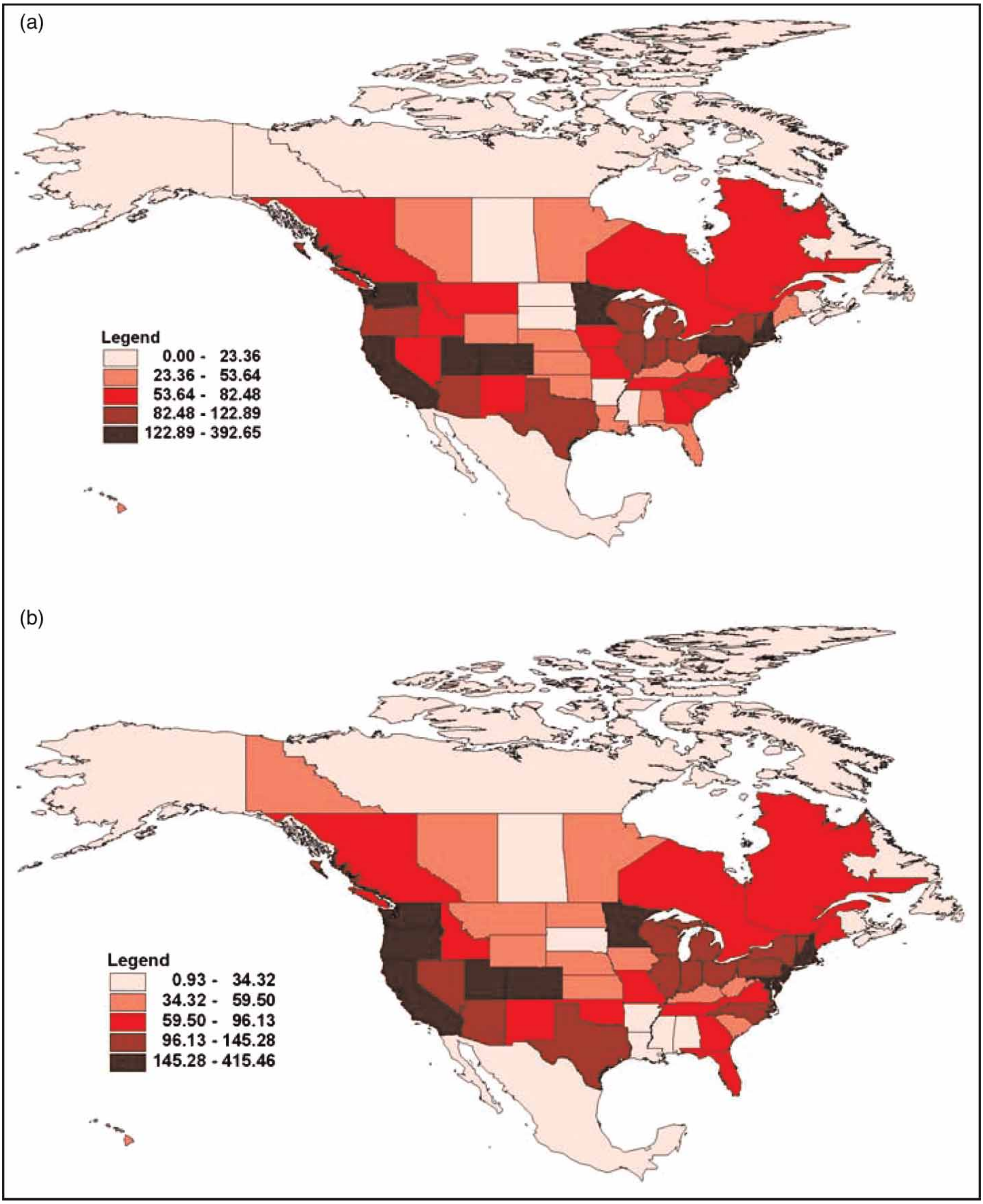

Fig. 2. North America: Patent Cooperation Treaty (PCT) per million population: (a) 1998–2000; and (b) 2002–2004
Source: Organisation for Economic Co-operation and Development (OECD) Regional Database

Alpes (in France), passes through all Swiss regions and the Vorarlberg region in North Austria, and ends in the south-central part of Germany. This wider agglomeration is named the Continental Europe cluster. Sweden, Norway (but for the regions of Nord-Norge, Hedmark og Oppland, and Vestlandet), Finland, and Denmark show top high-invention performance, suggesting the presence of a sort of Scandinavian cluster. Great Britain also shows an English cluster located mainly in the South East. On the contrary, the low-performance

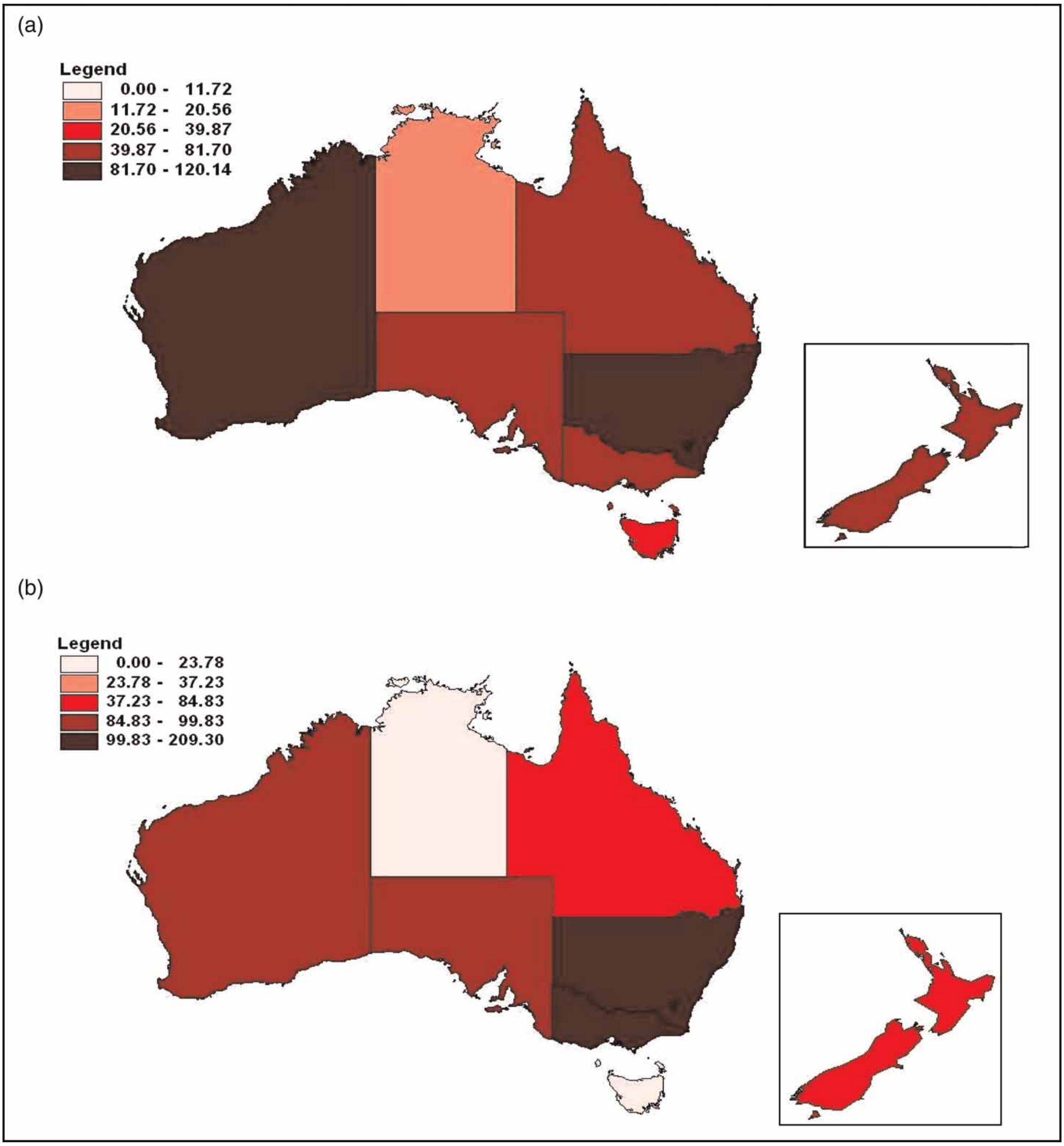

Fig. 3. Oceania: Patent Cooperation Treaty (PCT) per million population: (a) 1998–2000; and (b) 2002–2004
Source: Organisation for Economic Co-operation and Development (OECD) Regional Database

regions are situated mainly at the European borders, to the west (Spain and Portugal), to the south (South-Central Italy, Greece, and Turkey), to the east (Poland, the Czech Republic, Hungary, and the Slovak Republic), and finally to the north (Scotland).

In the second period, 2002–2004, some interesting trends appear. First of all, most of Italy shows a growth of PCT per capita, especially the Centre-North, which appears to extend the Continental cluster to the South. Secondly, the border states of Iceland and Ireland improve their position in the quantile distribution of the regions, showing high-performance values. Thirdly, there is a light increase of PCT per capita in the eastern European regions which are closer to the Continental cluster. Finally, a general worsening of the inventive activity emerges in the Scandinavian cluster.

As far as the North American macro-area is concerned, the strongest increase is recorded in Mexico, although its top values are still very low compared with Canada and the United States. Canada shows a significant increase both in absolute and per-capita terms, especially in the provinces of Prince Edward Islands and

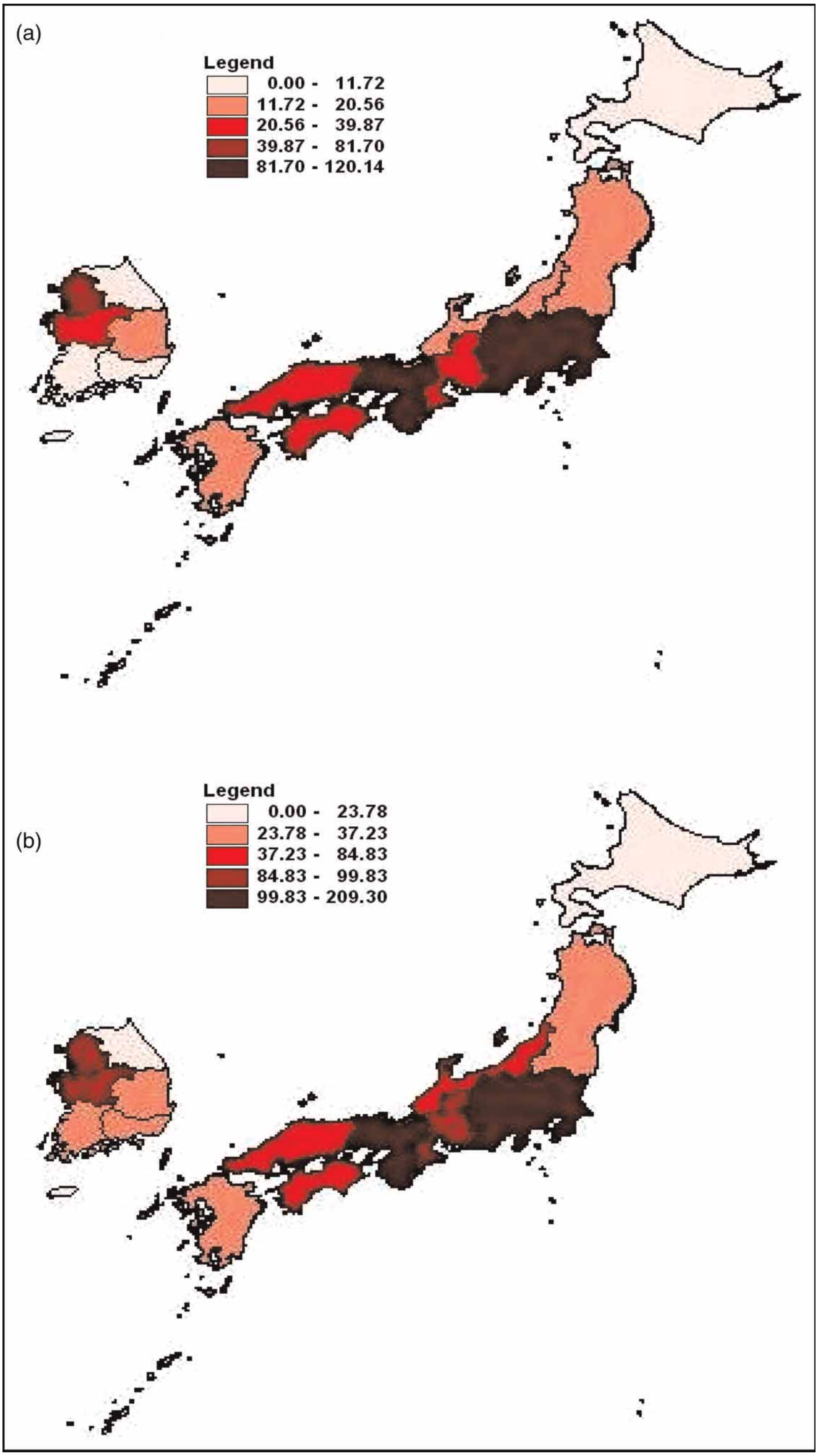

Fig. 4. *Asia: Patent Cooperation Treaty (PCT) per million population: (a) 1998–2000; and (b) 2002–2004*
Source: Organisation for Economic Co-operation and Development (OECD) Regional Database

Nova Scotia, whereas the highest increases in the United States are recorded in Florida, Nevada, Oregon, and North Dakota.

In the first period, a cluster of top performance states materializes in the Eastern US regions, surrounded by high-invention performance states: this wider geographical zone, which includes Eastern Canadian states, could be considered as a unified belt. In the West, the top-performance states are surrounded by more high-performance states, generating a Western invention belt. As before, this belt travels from the United States (Texas) to Canada (British Columbia). Within these two belts, there are states which record a medium-to-low performance of PCT per capita. Nevertheless, it seems that the American belts (especially the Western one) tend to extend their influence to the central states along time.

Finally, in the Asian macro-area, which comprises just Japan and Korea, there is a significant cluster centred in the region of Tokyo, which seems to consolidate in the second period. As for the Oceania macro-area, the low number of regions does not allow any particular inference.

The analysis so far has shown that the phenomenon under examination is uneven at both the international and the interregional levels. Both levels are more closely investigated in Fig. 5, where the Box plot illustrates the variability of PCT per capita across and within national borders for the period 2002–2004. If one focuses on the right-hand side of Table 5, one can envisage very different national settings among the most innovative countries. On the one hand, some very diversified and asymmetric countries, such as the Netherlands and Germany, are found. There are also countries that are rather homogenous, but with a very asymmetric distribution, such as Switzerland and Korea, or countries, such as the United Kingdom or the United States, which show a very high variability but a fairly symmetric distribution. On the other hand, there are countries that are both symmetric and homogenous, such as Finland and Sweden.

Finally, the analysis which has so far suggested the presence of some cluster, can be somewhat corroborated through spatial dependence analysis. This assesses the spatial similarity or dissimilarity of neighbouring regions in order to measure the geographical extent of innovative activity. The most widely used index to measure spatial dependence, and to test the hypothesis of no clustering for spatially distributed variables, is Moran's *I* index.[7] Table 3 presents the results for contiguity weight matrices based on adjacency (for first, second, and third order of contiguity) and for the distance matrix. The choice of different orders of contiguity together with distances is not just a technicality, since it complies with the need to consider space as a continuum. The set of indices based on contiguity is computed for both the whole of the OECD and for the two biggest macro-areas, that is, Europe and North America. The two other macro-areas are excluded due to their low numbers of regions. Further, the index based on

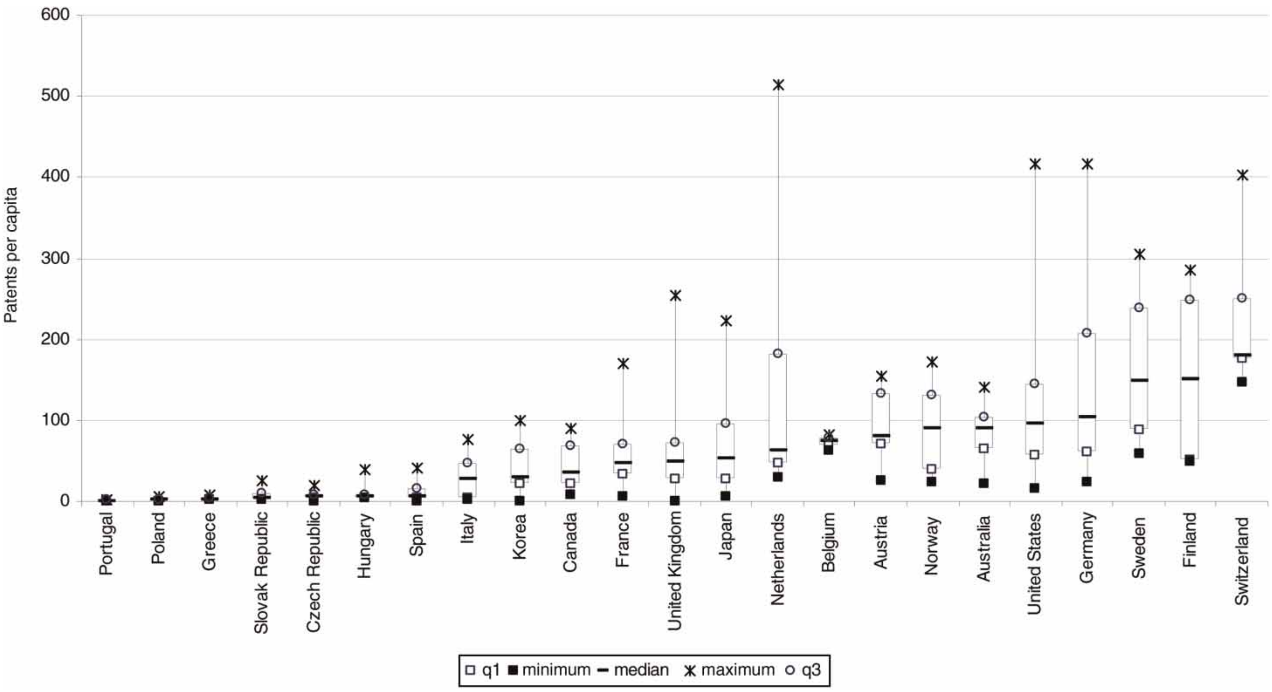

Fig. 5. Organisation for Economic Co-operation and Development (OECD) regions: Patent Cooperation Treaty (PCT) per million population variability, 2002–2004
Source: OECD Regional Database (ORDB)

Table 3. Patent Cooperation Treaty (PCT) per capita – Moran's index for spatial dependence

		1998–2000			2002–2004		
	Matrix	Moran's *I*	*z*-value	*p*-value	Moran's *I*	*z*-value	*p*-value
OECD	First contiguity	0.52	11.96	0.00	0.52	12.00	0.00
	Second contiguity	0.42	11.18	0.00	0.38	10.10	0.00
	Third contiguity	0.31	8.29	0.00	0.24	6.47	0.00
Europe	First contiguity	0.56	11.15	0.00	0.56	11.16	0.00
	Second contiguity	0.47	11.30	0.00	0.42	10.01	0.00
	Third contiguity	0.31	7.70	0.00	0.23	5.79	0.00
	Distance	0.11	11.62	0.00	0.15	15.84	0.00
North America	First contiguity	0.32	3.55	0.00	0.37	4.09	0.00
	Second contiguity	0.20	2.83	0.00	0.22	2.99	0.00
	Third contiguity	0.22	3.05	0.00	0.21	2.90	0.00
	Distance	0.19	6.01	0.00	0.19	5.78	0.00

Note: OECD, Organisation for Economic Co-operation and Development.

distances is computed only for the two aforementioned macro-areas since one cannot appropriately discriminate between distances which are taken across land and those which are taken across sea for the whole of OECD.[8]

Table 3 shows that European and North American regions have a strong positive spatial association for the three orders of contiguity for both periods, indicating a geographic clustering for high and low values. In other words, high/low values for one location are more similar to the high/low values of its neighbours than would be the case under spatial randomness. This spatial pattern is confirmed by results for the distance-based statistics which suggest reiterating the use of such a matrix in the econometric analysis, too. It might also be noticed that the value of the statistics is much higher for Europe than for North America. This result may be due to structural differences, but it can be also attributed to the differences in size for regions in the two macro-areas: regions are quite small in Europe, whilst they are very large (at the state level) in North America (Table 1).

Econometric estimation

The second section presented the KPF as an ordinary tool to investigate the capacity of a firm or a region to produce inventions. Though an imperfect tool, the KPF's almost universal application makes its implementation useful to compare results in different countries and time periods. Most importantly, its application at the territorial level (instead of firms) allows this tool to be used to evaluate the presence of local externalities of different forms. Although one cannot discriminate perfectly among such different externalities (in particular, between pecuniary and knowledge ones), an attempt is made to attribute them to some general categories such as technology inputs, external spillovers, institutional factors, and agglomeration effects.

The basic KPF relates the inventive output in region *i* to R&D input in the same region. This specification is refined by introducing a set of further factors related to the economic and institutional environment, so that the general form of the basic KPF is given by:

$$I_i = RD_i^{\partial_1} IF_i^{\partial_2} e_i \tag{1}$$

where *I* is a proxy for inventive output; *RD* is the primary input, that is, investment in R&D; *IF* (internal factors) is a vector of variables that reflects the economic and institutional additional determinants; and *e* is a random independent and identically distributed (i.i.d.) error term capturing other unobservable determinants of inventive output, as well as random shocks.

The additional factors included in *IF* are meant to control for systematic effects that may be present in the invention process and might enhance or hinder the production of new knowledge. First, in light of the theoretical and empirical literature, human capital is considered, that is, the proportion of people with the necessary competences and skills. Secondly, it is hypothesized that agglomeration processes may be catalysed with a higher density of economic exchanges and contacts. Thirdly, regions, and especially countries, may show remarkable differences in the institutions and strategies for technological change which form the so-called regional or national innovation system.

Finally, the theoretical and empirical literature suggests that the production of knowledge in a region may depend not only on its own research efforts, but also on the knowledge stock available in the whole economy and on its ability to exploit it. In other words, knowledge may spill over from other regions (especially nearby ones). Many factors external to the region can act as determinants of technological activity, channelled 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. The general framework (equation 1) consequently can be modified to introduce an additional vector of external factors, *EF*, reflecting the fact that invention generated in one region may spill over and help knowledge formation in other regions:

$$I_i = RD_i^{\partial_1} IF_i^{\partial_2} EF_i^{\partial_3} e_i \tag{2}$$

This extended model can capture the spatial dependence of the invention phenomena, visually apparent in the graphs in the fourth section, which was quantified and statistically documented through the Moran tests. One should, therefore, expect the estimates of the coefficients of *EF* to be significant.

However, instead of estimating directly model 2, one starts with model 1– or equation (2) and equation (1) – because one first needs to understand the best way to introduce spatial dependence in the regression from a technical point of view. Therefore, one begins by assuming that any new knowledge produced in a given period by a region, denoted by *I*, is related to its R&D efforts in previous periods (*RD*) and to a vector of internal factors:

$$IF = (HK, DENS, NAT, DU, DR, DCAP \text{ and } DGDP)$$

The dependent variable *I* is the number of patents per capita, per million inhabitants, to be more exact, as it is common in most studies of regional or national KPF.[9]

As for the independent variables, the input of inventive activities (*RD*) is measured by the share of gross domestic product invested in R&D activities. Among the other potentially relevant internal factors,[10] density of population (*DENS*) is introduced as a proxy for the agglomeration forces,[11] and the availability of human capital (*HK*) at the regional level with the index of tertiary education, defined as the percentage of population completing a tertiary education degree.

Further, a set of dummies is inserted. First of all, several dummies are included that classify regions with respect to their rural (*DR*) or urban (*DU*)[12] nature. Then, regions are further differentiated with respect to their main specialization by introducing a dummy (*DCAP*), which is equal to 1 when it refers to a capital region; and zero otherwise. This is because capital regions are often specialized in services and their inventive activity may not show up in patent production which is mostly concentrated in manufacturing. The set of dummies is finally completed with a dummy (*DGDP*), which discriminates rich regions with respect to less developed regions since the former may enjoy several advantages in terms of technological opportunity. The use of a dummy[13] is again motivated by the fact that it is difficult to measure differences in technological opportunities.

Moreover, a set of national dummies (*NAT*) is included in order to control for any national fixed-effect, such as institutional and other structural factors, which may affect either the inventive activity or the propensity to appropriate its results by patenting. The function to be estimated hypothesizes Cobb–Douglas technology, which can be written in logarithmic form as follows:

$$\begin{aligned}\log I_{i,t} = {} & \beta_1 \log RD_{i,t-s} + \beta_2 \log DENS_{i,t-s} \\ & + \beta_3 \log HK_{i,t-s} + \sum_{c=1}^{n} \delta_c NAT_{ic} + \gamma_1 DU_i \\ & + \gamma_2 DR_i + \gamma_3 DCAP_i + \gamma_4 DGDP_{i,t-s} + \varepsilon_{i,t}\end{aligned} \tag{3}$$

where the coefficients can be interpreted as elasticities. It is worth noting that all independent variables but the dummies are lagged, since inputs are expected to take some time to produce effects on the output, which is a very plausible assumption in the case of patents as they come at the end of a lengthy inventive process. Moreover, this procedure can avoid problems of endogeneity.

This empirical exercise directly addresses interregional externalities in the generation of invention through the use of spatial econometrics techniques. In other words, a set of Lagrange multiplier tests is used, that is for residual spatial autocorrelation (LM-ERR) and for a spatially lagged dependent variable (LM-LAG), which are computed for a physical contiguity matrix (W) giving rise to a binary and symmetric matrix with elements equal to 1 in the case of two neighbouring regions; and zero otherwise. This is done not only to assess the existence of spatial dependence in the specification, but also to ascertain its possible form: a substantive or a nuisance model.[14] The former is the one that is always selected through tests; it is specified as follows:

$$\begin{aligned}\log I_{i,t} = {} & \beta_1 \log RD_{i,t-q} + \beta_2 \log DENS_{i,t-s} \\ & + \beta_3 \log HK_{i,t-s} + \beta_4 W \log I \\ & + \sum_{c=1}^{n} \delta_c NAT_{ic} + \gamma_1 DU_i + \gamma_2 DR_i \\ & + \gamma_3 DCAP_i + \gamma_4 DGDP_{i,t-s} + \varepsilon_{i,t}\end{aligned} \tag{4}$$

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

This paper is based on the latest available international comparable data on patents made available by the OECD. The indicators for invention activity have been identified as the number of PCT applications which are available for seven years from 1998 to 2004. Data for the dependent variable refer to the second period (2001–2004), whilst data for the explanatory variables refer to the first period (1998–2000).

Other indicators at the regional level are included in the OECD Regional Database (ORDB), which provides quantitative information on socio-economic issues. Unfortunately, there are several missing values for some important indicators in a handful of countries. In particular, regional data could not be gathered for R&D in Japan and Korea. This makes the preliminary analysis focus basically on the comparison of the European and the North American areas. Although this aspect may limit the representativeness of the sample, it should be remembered that PCT data for Japan show a possible under-valuation of its inventive capacity, which would have biased the analysis (even though national dummies are meant to control partially for such cases).

It is also worth noting that no regionalized data for patents are present for some countries among those included in the analysis, namely Denmark, Iceland, Ireland, Luxembourg, and New Zealand. Also for Mexico and Turkey, data are not regionalized, but they are not included in the econometric analysis since other pieces of information are also missing.

Another important observation regarding data refers to the UK case, where the number of regions for which the econometric analysis is performed (twelve) does not coincide with that provided in the descriptive analysis (thirty-seven regions). This is due to the fact that R&D data are only available at this higher level of disaggregation. Finally, it should be remembered that some regions (eleven) are excluded from the analysis since they display zero values and therefore their logarithm was not feasible.

The econometric analysis is therefore performed with 271 observations referring to twenty-six nations out of a potential thirty countries (Mexico, Turkey, Japan, and Korea are the excluded countries).

Since a cross-section is being estimated and data refer to several years, it was decided to smooth out possible transient effects and to approximate long-run values by using each variable as an average of three years' worth of data. More specifically, since the production of knowledge takes time, a time lag between R&D expenditure and the invention yield is assumed. As a result, variable *I* refers to the period 2001–2004, whereas *DENS* and *RD* refer to 1998–2000. It should be noted that as far as *RD* is concerned, this information is gathered with different frequency in different countries and therefore it might not necessarily be a three-year average for all countries.

Econometric results

The main econometric results are summarized in Table 4, which shows in the first two columns the results for the KPF for the whole sample of OECD regions. The model works remarkably well, since almost 90% of the variance of the dependent variable is explained by the set of explanatory variables. However, as expected, the OLS estimation reported in column 1 suffers from spatial autocorrelation, and the estimation of the spatial-lag model by maximum likelihood (ML) is the suggested specification.

Column 2, therefore, proposes the ML estimation of equation (4). The results are interesting. In particular, it was found that the elasticity of patents with respect to R&D expenditure is around 0.45 and statistically significant. This result confirms the consensus found in the literature. The elasticity changes from 0.20 to 0.90 in the United States (JAFFE, 1989; ACS *et al.*, 1992; ANSELIN *et al.*, 1997), and from 0.25 to 0.80 in the European case (MORENO *et al.*, 2005; BOTTAZZI and PERI, 2003).

The other main factor that contributes to inventive performance, human capital, is positive and significant with an impact which is more than double than that of R&D (0.99). Local agglomeration factors, measured by density of population, have some impact, but a much lower one, since the elasticity is around 0.07. As for the dummies that take into account the nature and the environment of the regions, urban or rural, only the latter's coefficient is significant with the expected negative sign. The capital dummy is negative, signalling the presence of a specialization (mainly in services) which is not conducive to the type of inventive activity that is patented. However, it should be also acknowledged that this negative result may be due to the unit of analysis chosen for capitals, which often is geographically smaller than their economic area of influence. Finally, the coefficient of the dummy for high-income countries is significant and, as expected, positive.

As for the institutional factors, coefficients for the national dummies are in general significant with different values and sign depending on country performance. They can be interpreted as a reflection of the general efficiency of research influenced by countrywide institutional settings as well as the productivity effects of the knowledge diffused throughout the country.

Finally, as regards the external factors, it is found that the lagged value of the dependent variable, which measures interregional linkages, is positive and significant with an elasticity of 0.18 (almost one-third of internal effects of regional R&D). Moreover, the significant value of the likelihood ratio (LR) tests implies the statistical adequacy of the spatial-lag models.

Also in Table 4, columns 3–6 are devoted to the estimation of the model separately for Europe and North America. This exercise allows one to assess the

Table 4. Knowledge Production Function (KPF) estimation

	OECD		Europe		North America	
Variables	OLS	ML	OLS	ML	OLS	ML
Log (*RD*)	0.486	0.446	0.498	0.461	0.548	0.479
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (*HK*)	1.094	0.991	1.072	0.886	1.061	1.086
	(0.000)	(0.000)	(0.000)	(0.000)	(0.262)	(0.008)
Log (*DENS*)	0.070	0.073	0.054	0.059	0.069	0.076
	(0.092)	(0.045)	(0.438)	(0.320)	(0.182)	(0.093)
W log (I)		0.182		0.229		0.153
		(0.000)		(0.000)		(0.016)
Controls						
Rural dummy	−0.201	−0.202	−0.142	−0.130	−0.236	−0.279
	(0.050)	(0.026)	(0.280)	(0.248)	(0.197)	(0.080)
Urban dummy	0.099	0.049	0.268	0.230	−0.271	−0.342
	(0.452)	(0.679)	(0.104)	(0.103)	(0.243)	(0.092)
Capital dummy	−0.543	−0.419	−0.515	−0.338	−0.815	−0.821
	(0.003)	(0.010)	(0.019)	(0.073)	(0.440)	(0.018)
GDP dummy	0.810	0.652	0.935	0.713	0.466	0.375
	(0.000)	(0.000)	(0.000)	(0.000)	(0.078)	(0.103)
NAT dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number observed	271	271	201	201	61	61
R^2-adjusted	0.889	0.906	0.901	0.920	0.679	0.747
LIK	−208.184	−194.813	−156.856	−143.291	−38.144	−35.489
AIC	480.367	455.625	369.713	344.583	94.288	90.978
SC	595.635	574.495	462.205	440.379	113.286	112.087
Moran's I	4.074		3.619		1.656	
	(0.000)		(0.000)		(0.098)	
LM-ERR	0.002	0.090	0.401	0.065	0.013	0.143
	(0.968)	(0.764)	(0.526)	(0.799)	(0.909)	(0.706)
LM-LAG	20.551		22.653		3.990	
	(0.000)		(0.000)		(0.046)	

Note: AIC, Akaike information criterion; GDP, gross domestic product; LIK, likelihood; LM-ERR, Lagrange multiplier test for residual spatial autocorrelation; LM-LAG, Lagrange multiplier test for a spatially lagged dependent variable; ML, maximum likelihood; NAT, national; OECD, Organisation for Economic Co-operation and Development; OLS, ordinary least-squares; SC, Schwarz information criterion. Probabilities are given in parentheses.

differences in elasticities in North America and Europe, as suggested by CRESCENZI *et al.* (2007).

Results show that the regions in these two macro-areas use similar technologies for the production of knowledge, even though some interesting specific features appear. This sub-section focuses on columns 4 and 6, since in both cases it is necessary to estimate the spatial-lag model. The first thing to notice is that the model fits the European case much better than the North American case, since the power of explanation of the regression is far higher in the former case (around 0.92) than in the latter (0.74). In spite of this difference, there is a remarkable similarity in the whole set of coefficients, especially with respect to R&D efforts (even though it is slightly higher in Europe). More evident differences appear in the other two coefficients under examination, that is, *HK* and *DENS*. *HK* is positive and significant in both Europe and North America, but with a higher value in North America. As for the agglomeration effects, this variable shows a positive sign in both cases, but it loses its significance in Europe, while holding it in the North American case. As for the dummies, it is found that the rural dummy keeps its significance in the North American model together with the capital region, whilst the gross domestic product (GDP) dummy keeps its sign, but its significance is only at the 10% level. On the contrary, the rural and urban dummies are both insignificant in the European Union model, where the capital region dummy is no longer significant and only the GDP dummy is significant.

Spatial dependence is always present in both models and it is taken account of with the included lagged dependent variable. The coefficient is slightly higher in Europe (0.22) with respect to the OECD-wide result, whilst it is slightly lower in North America (0.15). To some extent, this difference can be related to the fact that regions in Europe are much smaller than in North America, where potential spillovers are more likely within regions than among regions.

Robustness checks

This sub-section implements some robustness checks to the main results shown and discussed previously.[15]

Table 5. Knowledge Production Function (KPF) estimation with interactive dummies

	OECD		Europe		North America	
Variables	OLS	ML	OLS	ML	OLS	ML
Log (*RD*)	0.571	0.586	0.600	0.619	0.768	0.605
	(0.000)	(0.000)	(0.000)	(0.000)	(0.292)	(0.332)
Log (*HK*)	1.087	0.953	0.969	0.780	1.020	1.408
	(0.000)	(0.000)	(0.000)	(0.000)	(0.474)	(0.253)
Log (*DENS*)	0.100	0.106	0.126	0.114	0.073	0.081
	(0.015)	(0.004)	(0.080)	(0.062)	(0.171)	(0.074)
W log (*I*)		0.176		0.223		0.160
		(0.000)		(0.000)		(0.013)
*DGDP**log(*RD*)	−0.104	−0.191	−0.155	−0.262	−0.230	−0.141
	(0.399)	(0.085)	(0.291)	(0.041)	(0.753)	(0.823)
*DGDP**log(*HK*)	−0.488	0.359	−0.433	−0.201	0.000	−0.400
	(0.002)	(0.011)	(0.027)	(0.246)	(0.999)	(0.747)
Controls						
Rural dummy	−0.203	−0.210	−0.950	−0.102	−0.232	−0.277
	(0.042)	(0.017)	(0.462)	(0.357)	(0.213)	(0.081)
Urban dummy	0.078	0.021	0.187	0.152	−0.264	−0.339
	(0.548)	(0.854)	(0.253)	(0.278)	(0.263)	(0.093)
Capital dummy	−0.478	−0.377	−0.445	−0.300	−0.784	−0.763
	(0.007)	(0.018)	(0.038)	(0.105)	(0.062)	(0.031)
GDP dummy	1.953	1.507	1.895	1.192	0.473	1.455
	(0.000)	(0.000)	(0.000)	(0.002)	(0.902)	(0.663)
NAT dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number observed	271	271	201	201	61	61
R^2-adjusted	0.893	0.911	0.905	0.923	0.668	0.750
LIK	−199.977	−187.269	−151.127	−138.559	−37.986	−35.142
AIC	467.955	444.538	362.255	339.117	97.972	94.283
SC	590.427	570.613	461.354	441.520	121.192	119.614
Moran's *I*	0.660		3.454		1.613	
	(0.000)		(0.001)		(0.107)	
LM-ERR	0.157	0.016	0.547	0.069	0.000	0.033
	(0.692)	(0.900)	(0.460)	(0.793)	(0.990)	(0.856)
LM-LAG	20.693		21.230		4.510	
	(0.000)		(0.000)		(0.034)	

Note: AIC, Akaike information criterion; GDP, gross domestic product; LIK, likelihood; LM-ERR, Lagrange multiplier test for residual spatial autocorrelation; LM-LAG, Lagrange multiplier test for a spatially lagged dependent variable; ML, maximum likelihood; NAT, national; OECD, Organisation for Economic Co-operation and Development; OLS, ordinary least-squares; SC, Schwarz information criterion. Probabilities are given in parentheses.

Table 5 assessed the robustness of the role of the main determinants of inventive activity, that is, R&D efforts and human capital, with respect to the GDP dummy which separates the sample into two parts: rich and poor regions. This modification of the model is motivated by the belief that the role of these factors may change along the process of economic growth of regions. The interactive dummies should therefore have a negative sign if the effect of *RD* and *HK* decreases as GDP augments. The results shown in column 1 imply that the impact of R&D and *HK* is relatively lower when the GDP per-capita levels are higher. The model is less robust when it is implemented for the two macro-areas. In these cases, only does the interaction of GDP with *RD* in the European Union case keep its significance. In the North American case, the interactive dummies introduce a distortion in the whole model and their use is found to be inappropriate.

As anticipated when commenting on Table 3, the use of just a physical contiguity matrix limited to neighbouring regions may not capture all potential knowledge spillovers, since space is better represented as a continuum. Consequently, distance matrices can be applied in order to test if the results rest on the application of a different kind of matrix in order to measure geographical proximity. In other words, a distance matrix is used instead of the contiguity matrix. The former is made of values where each cell reports the inverse of distance for each pair of regions. Thus, this weight matrix has only non-zero elements for each observation pair that is assumed to interact. For this reason, as performed for the Moran index, it was used only for the analysis referring to the continental macro-areas of Europe and North America, since here distances are homogenous at least to some extent. The results in Table 6 show that the OLS estimation indicates that spatial autocorrelation has to be corrected in

Table 6. Knowledge Production Function (KPF) estimation with distance matrix

	Europe		North America
Variables	OLS	ML	OLS
Log (*RD*)	0.600	0.677	0.548
	(0.000)	(0.000)	(0.000)
Log (*HK*)	0.969	0.624	1.061
	(0.000)	(0.001)	(0.262)
Log (*DENS*)	0.126	0.075	0.069
	(0.080)	(0.229)	(0.182)
W log (*I*)		0.012	
		(0.000)	
DGDP * log(*RD*)	−0.155	−0.209	
	(0.291)	(0.103)	
DGDP * log(*HK*)	−0.433	−0.169	
	(0.027)	(0.340)	
Controls			
Rural dummy	−0.950	−0.088	−0.236
	(0.462)	(0.433)	(0.197)
Urban dummy	0.187	0.189	−0.271
	(0.253)	(0.183)	(0.243)
Capital dummy	−0.445	−0.232	−0.815
	(0.038)	(0.223)	(0.044)
GDP dummy	1.895	1.032	0.466
	(0.000)	(0.012)	(0.078)
NAT dummies	Yes	Yes	Yes
Number observed	201	201	61
R^2-adjusted	0.905	0.922	0.679
LIK	−151.127	−139.517	−38.144
AIC	362.255	341.034	94.288
SC	461.354	443.436	113.286
Moran's *I*	7.125		2.852
	(0.000)		(0.004)
LM-ERR	0.780	0.069	1.355
	(0.377)	(0.793)	(0.244)
LM-LAG	21.236		0.043
	(0.000)		(0.836)

Note: AIC, Akaike information criterion; GDP, gross domestic product; LIK, likelihood; LM-ERR, Lagrange multiplier test for residual spatial autocorrelation; LM-LAG, Lagrange multiplier test for a spatially lagged dependent variable; ML, maximum likelihood; NAT, national; OLS, ordinary least-squares; SC, Schwarz information criterion. Probabilities are given in parentheses.

Table 7. Knowledge Production Function (KPF) estimation with spatial lag of RD

	OECD	Europe		North America
Variables	OLS	OLS		OLS
Log (*RD*)	0.603	0.633	0.627	0.507
	(0.000)	(0.000)	(0.000)	(0.000)
Log (*HK*)	1.064	0.940	0.964	1.011
	(0.000)	(0.000)	(0.000)	(0.033)
Log (*DENS*)	0.089	0.118	0.126	0.057
	(0.031)	(0.926)	(0.072)	(0.277)
W log (*RD*)	0.253	0.312	0.289	0.214
	(0.006)	(0.010)	(0.160)	(0.200)
W2 log (*RD*)			0.280	
			(0.051)	
*DGDP**log(*RD*)	−0.155	−0.180	−0.162	
	(0.209)	(0.217)	(0.261)	
*DGDP**log(*HK*)	−0.483	−0.424	−0.393	
	(0.002)	(0.028)	(0.041)	
Controls				
Rural dummy	−0.201	−0.092	−0.641	−0.245
	(0.041)	(0.471)	(0.613)	(0.178)
Urban dummy	0.062	0.163	0.151	−0.283
	(0.627)	(0.311)	(0.343)	(0.220)
Capital dummy	−0.434	−0.396	−0.415	−0.858
	(0.014)	(0.062)	(0.048)	(0.034)
GDP dummy	1.923	1.818	1.690	0.513
	(0.000)	(0.000)	(0.000)	(0.054)
NAT dummies	Yes	Yes	Yes	Yes
Number observed	271	201	201	61
R^2-adjusted	0.897	0.908	0.909	0.683
LIK	−195.657	−147.144	−144.877	−37.154
AIC	461.314	356.289	353.755	94.307
SC	587.388	458.691	459.460	115.416
Moran's *I*	3.306	3.379	3.290	1.069
	(0.001)	(0.001)	(0.001)	(0.285)
LM-ERR	0.347	0.566	0.466	0.123
	(0.556)	(0.452)	(0.495)	(0.726)
LM-LAG	14.480	15.139	12.472	2.724
	(0.000)	(0.000)	(0.000)	(0.099)

Note: AIC, Akaike information criterion; GDP, gross domestic product; LIK, likelihood; LM-ERR, Lagrange multiplier test for residual spatial autocorrelation; LM-LAG, Lagrange multiplier test for a spatially lagged dependent variable; NAT, national; OLS, ordinary least-squares; SC, Schwarz information criterion. Probabilities are given in parentheses.

order to obtain accurate estimates only in the European Union case. This result can again be attributed to the different geographical setting in the two continents: Europe with relatively small regions and North America with relatively large regions. The model is therefore corrected only in the European Union case with the spatial-lag model reported in column 3. The main results prove robust. The only main difference is the fact that now the coefficient of the spatial lag of the dependent variable is much lower since it applies not only to neighbouring regions, but also to close and far away regions at the same time. Nonetheless, the elasticities have the expected sign and significance.

Another interesting extension of the model is based on the assumption that the knowledge available in the neighbouring regions can be generated by their research efforts rather than by their research output (that is, spatially lagged patents as in model 4). This means that one can envisage a sensitivity analysis of the previous results with respect to other proxies for interregional knowledge flows, as follows:

$$\begin{aligned}\log I_{i,t} &= \beta_1 \log RD_{i,t-q} + \beta_2 \log DENS_{i,t-s} \\ &\quad + \beta_3 \log HK_{i,t-s} + \beta_4 W \log RD \\ &\quad + \sum_{c=1}^{n} \delta_c NAT_{ic} + \gamma_1 DU_i + \gamma_2 DR_i \\ &\quad + \gamma_3 DCAP_i + \gamma_4 DGDP_{i,t-s} + \varepsilon_{i,t}\end{aligned} \tag{5}$$

where $W\log RD$ is a spatial lag for the invention input. The method of estimation is OLS, since there are no endogeneity problems.

Table 7 reports the extremely interesting results of the estimation of equation (5). R&D performed in nearby regions is significant and its value is almost half the elasticity of internal R&D. Spatial autocorrelation is, however, still present and therefore should be eliminated by means of the usual spatial-lag model. Results (not shown) prove that the spatial lag of the *RD* variable does not keep its significance when the lag of the dependent variable is inserted. The latter is a stronger proxy for interregional knowledge flows.

The same model is estimated for the European Union and the North American cases, too. The results deserve some attention. For the European case, it is found that the R&D efforts of neighbouring regions are relevant from a statistical and quantitative point of view. On the contrary, for North America, a positive coefficient is still found, but one cannot reject the hypothesis that is not statistically different from zero. Again, however, in both models spatial autocorrelation is still detected and the LM tests suggest the use of the spatial-lag model. As above, the spatial lag of the dependent variable prevails with respect to the spatial lag of *RD*.[16]

CONCLUSIONS

This paper is the first systematic attempt to analyse comparatively the distribution of inventive activity across regions in Organisation for Economic Co-operation and Development (OECD) countries with a set of homogenous measures for both input and output in the process of knowledge production and dissemination.

The descriptive analysis shows that there are important differences in the inventive performance of regions in OECD countries. Such performance is clustered in some areas in Continental Europe, in North America, and, to a lesser extent, in Japan. The presence of spatial dependence is also detected with some specific tests. This spatial dependence is increasing with time and the consequent dispersion of invention activities is rising in almost all OECD countries, except North America. Some convergence is detected at the country level, but not at the regional level.

In spite of some regularities that characterize the four macro-areas of Europe, North America, Asia, and Oceania, there are important differences across countries that probably indicate the relevance of a national innovation system which is above regional performance.

The estimation of the knowledge production function (KPF) shows that the model which links inventive output to main inputs is at work across regions in OECD countries. Some particular results deserve highlighting. Research and development (R&D) is a very important determinant, and human capital is even more so. Agglomeration economies measured by population density also prove significant, even though their elasticity is relatively lower. The performance of neighbouring regions is an important determinant of inventive performance, which suggests the existence of important diffusion effects across space. Inventive performance is not favoured in rural regions and it is more facilitated in rich areas. Institutional factors that differentiate each country are still relevant. The impacts of *RD* and *HK* are not necessarily monotonous, but they decrease as the country becomes richer.

These results are differentiated with respect to two macro-areas for which it was possible to estimate two separate models: Europe and North America. In the former, the main results found for the OECD hold. On the contrary, in North America, a higher impact of human capital and a significant impact of agglomeration economies, which becomes non-significant in some models in Europe, are found. In both cases it is found that diffusion of invention goes across regions, but this phenomenon appears to be less strong in North America than in Europe.

As for future work, given the exploratory nature of this analysis, many research avenues are worth pursuing. One interesting path is the analysis of the KPF model at the sectoral level in order to assess the characteristics of some of the externalities at the local industrial level. In particular, this kind of analysis would allow a discrimination to be made among specialization and diversity externalities, a discrimination which is crucial in order to gain some useful policy implications. Another important avenue for future investigation is the one referring to the analysis at a lower level of territorial disaggregation in order to assess the robustness of the results with respect to this smaller dimension.

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NOTES

1. It should be remembered that KRUGMAN (1991) has the merit of reviving a research tradition which had an important previous contribution in both Economics and Geography (for an overview of the literature, see BRAKMAN *et al.*, 2009).

2. Note that since 2000 there has been an important European Union initiative called the European Trend Chart on Innovation which provides several indicators on innovation (based on input and output data and on the Community Innovation Survey) at the regional level and a synthetic measure of them.
3. In particular, the author is aware that a propensity to patent inventions differs across industries, and therefore patents tend to overestimate the inventive activity of countries specialized in patent-intensive industries. This potential bias is, at least partially, corrected in the econometric analysis thanks to national dummies.
4. PCT data are selected from a couple of newly built databases recently introduced in the research of inventive activity thanks to the OECD (MARAUT *et al.*, 2008): the Triadic Patent Family data set (DERNIS and KHAN, 2004) and the PCT itself. While both data sets contain patent data that do not suffer (or suffer less) from the usual home bias effect of the EPO, USPTO, and JPTO data, only the former is easily regionalized.
5. The PCT provides an international system for filing patent applications (WIPO, 2007). In other words, the PCT procedure consists of an international phase followed by a national or regional phase, and it has great advantages for the applicant, the patent offices, and the general public: (1) compared with a procedure outside the PCT, the applicant has up to eighteen more months to reflect on the desirability of seeking protection in foreign countries; (2) the search and examination work of patent offices can be considerably reduced or virtually eliminated thanks to the international search report; and (3) since each international application is published together with an international search report, third parties are in a better position to formulate a well-founded opinion about the patentability of the claimed invention.
6. In the OECD Regional Database (ORDB), regions in each member country are classified at two territorial levels (TLs): TL2 (335 macro-regions) and TL3 (1679 micro-regions). For European countries, this classification is largely consistent with the Eurostat NUTS-2 and NUTS-3 regions (Nomenclature des Unités Territoriales Statistiques – NUTS). The classification is officially established (and relatively stable) in all OECD member countries and used by central governments as a framework for implementing regional policies.
7. Moran's *I* index has also been computed for a complementary variable computed in such a way to normalize patent per capita with country averages in order to remove differences due to country differences. Results are similar to those reported in Table 3.
8. For the same reason, distance matrices are not used in the regressions below when they refer to the whole of the OECD countries, but are taken into account when they refer to Europe and North America where most distances are across land.
9. The use of patents per capita instead of the count of patents is motivated not only by the fact that this allows comparisons with results of previous research. One also needs to take into account regional heterogeneity in terms of demographic dimensions and therefore in terms of potential for innovative activity. Further, from a technical point of view, the use of patents per capita reduces the risk of incurring in problems of heteroskedasticity.
10. Different variables have been used in the literature to proxy other internal factors and agglomeration economies, such as employment in the business sector and high-technology employment (ANSELIN *et al.*, 1997), the relative importance of large firms in the geographical area (VARGA, 2000), and the quota of manufacturing firms (MORENO *et al.*, 2005).
11. Density is an inaccurate measure of agglomeration even though it is largely used in the literature, starting from CICCONE and HALL (1996). In fact, it should be remembered that regional size can be relevant too and that, consequently, high density levels do not necessarily imply large agglomerations (for example, Monaco), while large agglomerations may be associated with relatively low density levels (for example, Central Florida, Phoenix or Atlanta). This problem is related to the fact that the unit of analysis is less than perfect. The author will attempt to deal with this issue by taking into account differences in regional dimension directly in the dependent variable, that is, patent divided by population.
12. Note that regions are classified with respect to three modalities: rural, urban and intermediate. Such a classification is provided by the ORDB.
13. The complete series for GDP is not used in order to avoid potential problems of collinearity with the *RD* and *HK* variables. Therefore, it is preferable to introduce a dummy in order to use this piece of information. Regions take a value of 1 when their GDP per capita is above the average; and zero otherwise.
14. The nuisance model represents a second way to incorporate spatial autocorrelation into the knowledge production function by specifying a spatial process for the disturbance term. Although unbiased, the OLS estimators will be no longer efficient. In the case of spatial error autocorrelation, OLS parameter estimates are inefficient, whereas in the presence of spatial lag, dependence parameters become not only biased, but also inconsistent (ANSELIN, 1988; ANSELIN and FLORAX, 1995).
15. For more checks on the robustness of results, see USAI (2008). In particular, one interesting extension refers to the enlargement of the sample of countries in order to include Japan and Korea, two leaders in the technological competition in many sectors. This operation is made possible through the estimation of some indicators that are not directly provided in the ORDB. Results are surprisingly stable with respect to both the sign and their significance. One interesting difference is that the dummy for the capital region becomes only marginally significant in the ML model probably due to the fact that the Tokyo and the Seoul regions in these two countries are central in their respective national invention systems.
16. In the two models (OECD and EU), the aim is to try to insert the spatial lag of the second order (neighbours of neighbours) to see if the relationship extends beyond the first ring of regions. Results show that the second lag is positive and also significant (confirming MORENO *et al.*, 2005), but spatial autocorrelation does not completely disappear. The insertion of a third lag of *RD* did not give significant coefficient and spatial autocorrelation is still detected.

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