

Intra and inter: regional knowledge spillovers in European Union

Kleoniki Kalapouti · Nikos C. Varsakelis

Published online: 17 July 2014
© Springer Science+Business Media New York 2014

Abstract Aim of this paper is to investigate the impact of intra-regional and inter-regional knowledge spillovers on regional new knowledge production. Knowledge diffusion in a region and between a pair of regions is definitely influenced by separate factors in a clear way. The most important thing, however, is to test the impact of these factors on knowledge spillovers when they operate, not separately but, simultaneously. We apply a knowledge production function to data for 210 European regions for a 12 years period (1995–2006). Our results indicate that the returns to scale with respect to the main inputs of the KPF, are increasing with the absence of spillovers and decreasing when knowledge spillovers exist. Technological diversity facilitates the creation of new ideas and knowledge. The cross regional technological proximity is positive and statistically significant. The spatial proximity is also positive and statistically significant. However, the simultaneous consideration of the spatial and technological proximity significantly influences the marginal effects of these independent variables on new knowledge creation. Thus, when a region is geographically contiguous to weak innovative systems then the knowledge spillovers are stronger between regions which innovate in similar technological fields. When a region is geographically contiguous to regions with high innovative activity the knowledge spillovers are stronger between regions which innovate in different technological fields. Finally, the location of a recipient region on the technological fields' trajectory influences the impact of the technological distance on knowledge transfer.

Keywords Regional knowledge production function · Knowledge spillovers · Technological diversity · European regions

JEL Classification O31 · O33 · O38 · R11

K. Kalapouti · N. C. Varsakelis (✉)
Department of Economics, Aristotle University of Thessaloniki, P.O. Box 184,
54124 Thessalonki, Greece
e-mail: barsak@econ.auth.gr

K. Kalapouti
e-mail: kkalapou@econ.auth.gr

1 Introduction

Modern economies adjust to the new and continuously changing technological and knowledge-based environment mainly through knowledge creation and innovation. Therefore, today, innovation is a key reason of economic and regional growth. The production of new knowledge at regional level is inspired and facilitated not only by the main R&D inputs, researchers and R&D expenditures, but also by the global knowledge. First, the productivity of a Regional Innovation System (RIS) increases with knowledge being transferred by agents who compose the particular RIS, *intra-regional* spillovers. Marshall (1890) supports that specialization of regional economic activity, clustered in the same industry, empowers knowledge diffusion between firms. On the other side, Jacobs (1969) supports that developments coming from different but complementary fields of knowledge enhance knowledge diffusion and, consequently, innovation is facilitated by an industrially diverse environment. Second, literature has also examined the *inter-regional* knowledge spillovers, through the role of physical (geographical or spatial) and technological proximity between regions on knowledge spillovers.

Spatial proximity has been verified by literature as a significant factor in intra regional (Jaffe (1989) Jaffe et al. (1993), Acs et al. (1994) and inter regional knowledge spillovers (Bottazzi and Peri 2003). Technological proximity, agents neighboring in the technology space, is important factor in the explanation of cross firms (Jaffe 1986) and cross regions knowledge spillovers (Maurseth and Verspagen 2002; Bottazzi and Peri 2003).

The aim of this paper is to investigate the effect of intra-regional and inter-regional knowledge spillovers on a regional knowledge production function, using data for 210 EU NUTS-2 regions for the period 1995–2006. We adopt Jaffe's (1988) concept of technological space at cross regional level analysis to capture the impact of technological proximity and the physical contiguity to measure the impact of geographical proximity on inter-regional spillovers. This paper moves forward the previous analysis with the inclusion of a synergetic term of these two measures in order to put into further scrutiny the role of *inter-regional* spillovers. We argue that the simultaneous consideration of the geographical and technological proximity significantly influences the marginal effects of these independent variables on knowledge creation. Finally, we construct an interaction term, consisted of the regional technological diversity and the cross regional technological proximity, in order to investigate how the diversity of regional innovation production influences the role of technological proximity on knowledge transfer across regions.

Our findings indicate that both diversity and specialization does matter. More precisely, when a region is geographically close to strong innovative systems then the knowledge spillovers are stronger when the pair of regions innovates in different technological fields. But when a region is spatially close to weak innovative systems then the knowledge spillovers are stronger when the two regions innovate in similar technological fields. Our results also indicate that a region with low technological diversity receives more knowledge from regions contiguous in the technological space.

The rest of the paper is organized as follows. In Section Two, we discuss the theoretical issues concerning the diffusion of knowledge and we present the research hypotheses. Section Three gives a short description of the methodology and reports the data. Section Four, presents the empirical results and the discussion. Finally, Section Five presents a conclusion along with some policy implications.

2 Theoretical background and hypothesis setting

Region has increasingly been the unit of the economic analysis for new knowledge production. The main reason for this trend is the existence of the agglomeration economies, which usually cannot be counted at national level. The existence of similar or diverse activities at regional level may significantly influence the creation and diffusion of knowledge. Besides, at European Union level, knowledge agents located in a region may exchange knowledge with agents in neighbouring regions of a different country. Therefore, the examination of the impact of technological proximity, technological diversity and geography is more essential at regional rather than at national level.

Doloreux (2002) defined the regional innovation system (RSI) as a social system which involves interactions between sets of agents (private and public) in a systematic way in order to increase and enhance the localized learning capabilities of a region. He underlined four basic elements comprising an RSI: firms, institutions, and knowledge infrastructure and innovation policy. Autio (1998) partitioned the RSI into two sub-systems: The sub-system consisting of those who generate and diffuse knowledge (universities, public research institutions, liaison offices, etc.) and the sub-system consisting of those who apply and exploit knowledge (industrial companies and their customers, collaborators, contactors, and competitors). Communication between the two sub-systems includes among others the transfer of knowledge.

The output of the innovative activity of an innovative unit i (firm, region or country) at time t , X_{it} , is a function of the inputs (Z_{it}) supplied to the unit i and the stock of knowledge (K_t) available in the public domain at time t (Griliches 1979):

$$X_{it} = f(Z_{it}; K_t); Z_{it} = [R_{i,t-k}, H_{it}] \quad (1)$$

where $f(\cdot)$ is the knowledge production function (KPF). The vector of inputs Z_{it} includes the stream of R&D expenditures ($R_{i,t-\tau}$) during the past τ years ($T \geq \tau \geq 0$); and the stock of human resources (H_{it}) (e.g. scientists) at time t . The stock of knowledge K_t available to all innovative units at time t , is the cumulative output of the knowledge production function up to time $t - 1$:

$$K_t = \sum_{i=1}^N \sum_{\tau=1}^T X_{i,t-\tau} \quad (2)$$

where N is the number of innovative units and K_t constitutes the public domain available to all innovative units. K_t measures the knowledge spillovers.

Based on concept of the knowledge production function, empirical literature has assumed that the production of innovation at regional or firm level is the result of inputs and the knowledge spillovers from other regions or businesses. Using three basic inputs of innovation (R&D expenditures, human capital and social capital or tacit knowledge), Tappeiner et al. (2008) found that these inputs exert a statistically significant and economically substantial impact on the level of innovation of a region. Guellec and Pottelberghe de la Potterie (2004), estimated the contribution of several sources of knowledge (business R&D, public R&D and foreign firms R&D) in productivity growth.

The literature argues that the production of innovation in a region or in a business is not only a result of inputs mentioned before, but also a result of knowledge which diffused by other regions or businesses. Romer (1990), assumed that the increase in knowledge level A_j of an agent j depends on the human capital accumulated by the agent and the stock of knowledge A available in the society:

$$\dot{A}_j = \delta H^j A$$

where \dot{A}_j is the creation of new knowledge by the agent j , H^j is the human capital of the agent j and A is the aggregate stock of knowledge. In this paper j stands for regions. Hence, the creation of new knowledge by a region j depends on the aggregate stock of knowledge. The aggregate stock of knowledge consists of the stock of knowledge accumulated in region j , H^j , and the stock of knowledge accumulated by the other regions, $\sum_{k=1}^N A_k$, $k \neq j$.

Romer, in his article, made the assumption that A is non-rivalrous and non-excludable and consequently assigned equal weights to all A_k . However, knowledge diffusion at the very least involves a cost related to knowledge assimilation. As stated by Hirschleifer and Riley (1992, p. 276) "Only rarely does mere disclosure suffice to convey a message; and there are types of information, whose nature and value are not transparent, that are hard for the users to absorb even when offered freely." Thus, an agent may not assimilate new knowledge produced by another agent if its absorptive capacity is insufficient. Absorptive capacity is the ability of an agent to identify, assimilate and exploit knowledge from the environment (Cohen and Levinthal 1989) and then adapt it into the processes and routines that are specific to the agent (Criscuolo and Narula 2002). Thus, we adjust Romer's equation to incorporate weights which are, firstly, related to the absorptive capacity of the receiving region and, secondly, to the communication channel of the transfer of knowledge

from the sender to the recipient region: $\sum_{k=1}^N w_{jk} A_k$, $k \neq j$ where k is the sender region and j

is the recipient. If $w_{jk} = 1$ the recipient region j has the appropriate absorptive capacity to receive knowledge from the region k and the communication channel between the two regions does not produce errors or noise. If $w_{jk} = 0$ the recipient region j does not receive any knowledge from region k either because its absorptive capacity is not considerable or the communication channel is closed or both.

At regional level knowledge spillovers could be classified into two types: (a) *intra-regional spillovers*, spillovers between agents located in the same region, reflecting the structure of the regional innovation system and (b) *inter-regional spillovers*, spillovers between agents located in different regions.

We define the impact of a region's own stock of knowledge on regional innovation output as *intra-regional spillovers* and the impact of the global stock of knowledge, $\sum_{k=1}^N w_{jk} A_k$, $i \neq j$, as *inter-regional spillovers*. *Intra-regional* knowledge spillovers are present when agents, e.g. firms and research institutes, located in the same region exchange knowledge. Two theoretical tracks have been developed to explain the intra-regional knowledge spillovers: the first track is based on the Marshall (1890) analysis and the second follows the Jacob's (1969) analysis. The difference between the two tracks is associated with the impact of diversification of the regional technological or economic activity on knowledge creation.

According to the first theoretical track, firms belonging to the same sector, efficiently decode and exploit sectoral knowledge. Therefore, regional specialization or concentration of the innovative activity in few (or one) technological fields amplifies the knowledge spillovers and subsequently the new knowledge production. Porter (1990), supportive to Marshallian theory, argued that knowledge spillovers are enhanced within specialized and locally clustered industries. Marshall and Porter considered the knowledge diffusion across different industries almost trivial.

Jacobs (1969), on the other hand, argues that a wide range of industries in a region or city increases the knowledge transfer between agents of different industries and leads to the growth of the regional innovative activity. For Jacobs diversity facilitates innovation through the positive externalities of knowledge spillovers.

The previous empirical testing of these theoretical tracks does not provide clear evidence, even though the majority of the findings support diversity. Glaeser et al. (1992) and Feldman and Audretsch (1999), using data from the USA, found that localized industries with diverse but complementary activities are closer to new ideas and innovations than specialized industries. Audretsch and Feldman (1996), also using data from the USA, found that innovative output is located and clustered in industries where knowledge spillovers and new economic knowledge are prevalent. Henderson (1997) argued that even though a big number of US industries are clustered in large cities, these cities' innovative activity is supported by diversity.

Paci and Usai (2000), found a positive relationship between industry specialization and innovative output at NUTS-1 regional level of European Union and Greunz (2004) reached at the same conclusion using data at NUTS-2. On the other hand, Ouwensloot and Rietveld (2000) and Van Oort (2002), using regional data from the Netherlands, recognized the positive correlation between regional diversity and innovative activity. Fritsch and Franke (2004) investigated the role of knowledge spillovers and R&D cooperation on innovation in three German regions. Comparing the R&D expenditures between manufacturing firms in the same industry and in different industries, they found that the production of innovation made by firms in the same industry is the only important source of knowledge spillovers. Moreno et al. (2006) tested for the diversity impact on the regional innovative activity for 175 European regions. They found that specialization is more conducive to agglomeration of innovation in the same sectors than diversity. Fritsch and Slavtchev (2010) come to balance the two conflicting tracks as they investigated the relationship between regional innovation efficiency and diversity across German regions, using a Gini index to measure diversity. They found an optimum level of industrial diversity beyond which an increase in diversity may have a negative impact on innovative efficiency. Finally, Ponds et al. (2010) investigated the impact of regional academic research spillovers on regional innovation activity in Netherlands. They found that the collaborating networks between universities and firms facilitate knowledge spillovers even though these spillovers are geographically bounded.

We assume that each technological field is a system comprising of agents and inter-relations between them. At regional level, these technological fields constitute sub-systems of the regional innovation system. Sometimes, the solutions to technological, and only problems, could not be found inside the sub-system of the technological field. The answers to problems that arise in a sub-system could not come either from its agents per se or from the inter-relations between these agents. In such cases, the answers may reside outside the sub-system, in the *meta-system* (in the terminology of L. Wittgenstein). Thinking beyond the boundaries of the firm and of the technological field may be more creative in dealing with technological problems. Therefore, the regional technological diversity offers to the agents of the various technological fields (sub-systems) the ability to assimilate knowledge from other sub-systems and then adapt it into the processes and routines that are specific to the agent. Thus, we posit the first hypothesis:

Hypothesis 1 The higher the regional innovation diversity the higher the regional innovation productivity.

The investigation of the knowledge transfer across agents located in different regions (*inter-regional spillovers*) includes the analysis of the factors that influence this transfer. Significant part of the literature found that knowledge spillovers are strongly affected by the geographical proximity between the knowledgeable agents. According to Doloreux (2002), the spatial proximity is important for knowledge spillovers because: (a) the spatial agglomerations of firms enhance the regional interactive learning, (b) the cost of knowledge and information transfer falls since the communication channels between the agents produce limited errors or noise, and (c) the tacit knowledge is transferred without semantic difficulties since the agents share a common social and economic environment. Maurseth and Verspagen (2002), using data on patent citations, analyzed the knowledge transfer in a sample of European regions. They found that patent citations increase with geographical proximity between the inventors of the citing and cited patent. Bottazzi and Peri (2003) estimated the impact of R&D externalities on generating profitable new ideas using R&D private inputs available in region i and global knowledge coming from region i and other regions. They found that cross regional knowledge spillovers increase with spatial proximity between regions. Tappeiner et al. (2008) examined different levels of innovation and their spatial distribution in 51 European regions. They found that the higher the spatial proximity of innovation resources the higher innovation activity. Consequently, all these studies implicitly assumed that the weight w in inter-regional spillovers depends on spatial proximity.

However, geographical proximity it is not sufficient to enhance knowledge spillovers across regions. If the regional agents are not sufficiently knowledgeable the absorption and exploitation of the knowledge coming from outside would be limited or in the extreme case negligible. Cohen and Levinthal (1990) introduced the concept of individual firm's absorptive capacity as an important factor influencing knowledge spillovers. Each region builds up its capability to decode and exploit the new knowledge created in other regions. This capability is close to the concept of absorptive capacity. Caragliu and Nijkamp (2012) extended the concept of the absorptive capacity at country and regional level and they found that if a region faces a low absorptive capacity then the region receives knowledge diffused only by its surrounding areas.

A region absorbs knowledge not only when it is created in physically contiguous regions but also in regions, which innovate in similar technological fields. If regions innovate in different technological fields it might not advance for knowledge diffusion. Maurseth and Verspagen (2002), following a similar methodology to Jaffe (1988) at regional level, found that that the patents of pairs of regions that innovate in similar technological fields are more frequently cross cited than other pairs. Greunz (2003) investigated knowledge diffusion in a two-dimensional space, geographical and technological proximities, on the new knowledge creation in 153 European regions. Her results show that when technological proximity is weighted by a geographical decay factor the technological knowledge spillovers increase. Moreno et al. (2005) investigated the spatial distribution of innovative activity and the importance of knowledge spillovers in a KPF context across 175 European regions. They constructed a contiguity and distance matrix weighted by the technological distance matrix. Their results show clearly that innovative activity is getting enforced with the simultaneous existence of technological and geographical proximity.

Regions have higher capacity to absorb the knowledge produced by their technologically neighbor regions and therefore we expect that the inter-regional knowledge spillovers increase with technological proximity. But the simultaneous consideration of physical and technological proximity may change the impact of technological proximity on inter-

regional knowledge spillovers. The knowledge recipient regions which are contiguous to strong innovative sender regions absorb more knowledge the higher (or lower) the technological distance between them.

On the other hand, when a recipient region is contiguous to weak innovative sender regions, it absorbs more knowledge from the sender the lower (or higher) the technological distance between them. Thus, we posit the following hypotheses.

Hypothesis 2a The cross regional spatial proximity has a positive effect on regional innovative activity.

Hypothesis 2b The cross regional technological proximity has a positive effect on regional innovative activity.

Hypothesis 3a If the region is spatially contiguous to weak innovative regions then it absorbs knowledge from other regions that are technologically distant or neighbors.

Hypothesis 3b If the region is geographically contiguous to strong innovative regions then it absorbs knowledge from regions that are technologically distant or neighbors.

In the case of intra-regional knowledge spillovers, we argue that the correlation between technological diversity and knowledge transfer is positive, as suggested by Jacobs. In the case of inter-regional spillovers does the same argument applies too? In other words does diversity or specialization enforces the technological knowledge spillovers across regions? Or this regional diversity is important in the knowledge spillovers between regions that are technologically close or distant? If two regions innovate in different (similar) technological fields, does technological diversity or specialization of the recipient region advance the inter-regional knowledge transfer? Thus, we posit our fourth hypothesis.

Hypothesis 4 The impact of the technological distance on knowledge transfer between a recipient and a sender region is conditioned on the technological diversity (specialization) of the recipient region.

3 The model and data

To test our hypotheses, we estimate the knowledge production function (KPF) (Eq. 1) at regional level. Based on Griliches (1990) arguments, patents have been extensively used as a proxy for the output of knowledge production function. Besides, Acs et al. (2002) compared the literature-based innovation output measures at regional level (as they were published in trade and technical journals) and the “patent” as direct indicators of “innovation”. They found that the number of patents is a reliable output measure of the innovative activity. Bottazzi and Peri (2003), also note that “Although not all inventions are patented, the patented ones have to fulfill minimal standards of novelty”, originality and potential use. Therefore, patents can be considered as a good approximation to ideal data on “economically profitable ideas” which one would like to have for testing theories on innovation” (p. 692).

However, in the relative literature, we found some limitations and reservations as regard the safety of this measure. For instance, According to Pakes and Griliches (1980, p. 378), “patents are a flawed measure (of innovative output) particularly since not all new innovations are patented and since patents differ greatly in their economic impact.” Hall et al. (2001) argued that patents are good indicators of new technology creation but they do not measure the economic value of these technologies. In this paper we discuss more

extensively the drawbacks and limitations in choosing patents as a measure of innovative activity in the data section below.

The vector of inputs consists of the number of researchers in science and technology and the expenditures in research and development. We use annual data on Human Resources in Science and Technology (HRST) as percentage of total population as a proxy of the first input and the total intramural R&D expenditure (GERD) measured as euro per inhabitant as a proxy of the second input. The vector of global knowledge, \mathbf{K}_t , is used to measure the *intra-regional* and *inter-regional* spillovers.

The hypothesis 1 is tested by using the Shannon’s entropy index as a measure of the technological diversity. We calculate the Normalized Shannon’s Entropy Index (NEI) (Kumar et al. 1986):

$$NEI_j = \frac{1}{\ln N} \sum_i^N p_{ij} \log \left(\frac{1}{p_{ij}} \right)$$

where p_{ij} is the patents share of the technological field i in the total innovation activity of region j . N is the number of technological fields, $i = 1, 2, \dots, 121$, j is the number of regions, $j = 1, 2, \dots, 210$. The NEI takes values from 0 to 1. If $NEI_j = 0$ the region produces innovations in one field only. If $NEI_j = 1$, the regionally produced innovations are equally distributed across the 121 technological fields. If the first hypothesis is valid then we expect that the NEI (technological diversity) is positively correlated with the regional innovation activity (number of patents).

Hypotheses 2a and 2b refer to inter-regional knowledge spillovers. Hypothesis 2a is tested using the geographical proximity between the j regions, which has been extensively used in literature. We construct a quadratic matrix \mathbf{GD} for the 210 regions. Each element GD_{jk} of the \mathbf{GD} represents the geographical proximity between regions j and k . It takes the value 1 if the two regions are neighbors and 0 otherwise. Next, we multiply the \mathbf{GD} matrix with the vector of patents \mathbf{P} for each year. The product of this multiplication gives the vector of the global knowledge for region j weighted by the geographical proximity for year t . This variable is denoted as (GDS) in our dataset and varies across regions and time. Bottazzi and Peri (2003) used a similar index, the matrix of geographical distances multiplied with the vector of $\ln(\text{R\&D})$ resources. We regard patents as a more immediate measure of knowledge than the R&D expenditures because R&D expenditure is an input in KPF whereas a patent is the output (Griliches 1990). GDS_j indicates whether the region j is contiguous to strong innovative regions (GDS_j takes high values) or to weak innovative regions (GDS_j takes low values). Since geographical proximity has been used extensively by the literature as a proxy for the tacit knowledge spillovers and research collaboration between institutes closely located, we expect that these knowledge spillovers are significant mainly in the case where the geographically contiguous regions are strongly innovative. Therefore, the estimated coefficient is expected to be statistically significant and positive.

The second hypothesis (2b) is tested using the Romer’s A , the global stock of knowledge, weighted by technological proximity. We use the technological proximity (TP) between regions as measured by the Jaffe’s (1988) technological distance calculated using the patent applications to EPO, disaggregated into the 121 technological fields of the IPC:

$$TP_{jk} = (f_j \times f'_k) (f_j \times f'_j) (f_k \times f'_k)^{-1/2}$$

where $f_j = \frac{P_j^i}{\sum P_i^j}$ and $f_k = \frac{P_k^i}{\sum P_i^k}$, P_i^j is the number of patents of technological field i in region j and P_i^k is the number of patents of technological field i in region k . Since the number of

technological fields is N , there are two vectors: $[N \times 1]_j$ and $[N \times 1]_k$ and the angular separation between f_j and f_k leads to the quadratic matrix \mathbf{TP} . The element TP_{jk} of \mathbf{TP} is a positive correlation index which takes values in $[0, 1]$. If TP_{jk} tends to 0, the regions j and k contact research in different technological fields. On the other hand, if TP_{jk} tends to 1, the regions j and k conduct research in similar technological fields. Finally, if $TP_{jk} = 1$, the regions j and k conduct research in exactly the same fields.

We multiply \mathbf{TP} with the vector of patents \mathbf{P} , the global stock of knowledge. The result is the vector \mathbf{TPS} , whose elements could be regarded as each region’s global knowledge weighted by technological proximity. In Cohen and Levinthal (1989) terminology, we consider \mathbf{TPS} as a proxy for the regional absorptive capacity. A $TPS_j = 0$ is an indication of low absorptive capacity since the region conducts research completely different from those regions which produce high volume of knowledge. In such a case, the “global” knowledge for the region j is usually lower than the global knowledge (the Romer’s A), the unweighted sum of the elements of the vector \mathbf{P} . A high TPS_j is an indication that the region j is technologically contiguous to strongly innovative regions and, therefore, the region j will absorb more knowledge from the public domain. Hence, the estimated coefficient of TPS is expected to be statistically significant and positive.

To test the third hypothesis, that is the synergetic effect between technological and geographical proximity, we use the interaction term (INT_1), the product of GDS and TPS . If INT_1 is statistically significant we might conclude that an interaction effect exists. Finally, the fourth hypothesis is empirically tested via the use of a second interaction term (INT_2), the product of NEI and TPS .

Concluding, the knowledge production function of a region j is represented by the following Cobb-Douglas type KPF:

$$Q_j = E \cdot RS_j^{a_1} \cdot RD_j^{a_2} \cdot e^{a_3 \cdot DIV + a_4 \cdot \log TPS + a_5 GDS + a_6 INT_1 + a_7 INT_2} \tag{3}$$

The time index is omitted for simplicity reasons. The variable Q_j is the total number of patents in region j , RS is the number of researchers in science and technology, RD is the research and development expenditures, DIV is the regional technological diversity measured by NEI , TPS is knowledge spillovers weighted by technological proximity and GDS is knowledge spillovers weighted by geographical proximity. The variables DIV , TPS and GDS are used to capture the various spillover effects for region j . DIV captures intra-regional spillovers whereas TPS and GDS capture inter-regional spillovers. Finally, E could be treated as an estimation of the regional leveraging capacity-efficiency (LCE). Taking logarithms, equation (3) becomes:

$$\log Q_j = \log E + a_1 \log RS_j + a_2 \log RD_j + a_3 \log DIV_j + a_4 \log TPS_j + a_5 \log GDS_j + a_6 INT_{1j} + a_7 INT_{2j} \tag{4}$$

which is the general model to be estimated.

We use a panel data set of 210 European regions at the NUTS-2 level for the period 1995–2006. Our dataset offers a highly diverse landscape since some countries are consisted only of two regions (Bulgaria) and others, such as Germany, are consisted of 37 regions. The innovative activity’s distribution is uneven since some regions present high innovative activity and some others very low, as it is shown in Table 1 (minimum and maximum values of patents). However, almost all the 210 regions increased their innovative activity in the period of 12 years of our sample. Therefore, since there is a variation of innovative activity both across time and across regions, we decide to use panel data analysis.

Table 1 Descriptive statistics

Variable	Mean	Median	Min	Max	SD	Number of observations
Patents	99.9	62.6	0.02	1,006.3	116.36	2,520
RS	23.2	23.1	7.8	46.3	6.8	2,246
RD	306.9	193.5	2.6	2,876.6	340.79	1,256
NEI	0.253	0.281	0	0.505	0.086	2,520
TPS	10,041	10,393	12	50,285	3,928.7	2,520
GDS	573.02	423.45	0.564	3,107.9	559.93	2,520

The data are provided by Eurostat. NUTS-2 regions are administratively independent from each other; they may all participate independently in the programmes of the European Union and may even apply their own tax and economic policies.

We refer to the patents according to their application date rather than their issue date. The application date represents the time at which new knowledge is actually made public. Moreover, in most patent offices, there is a usually long and random time delay between application and issuing of a license (Jaffe 1986). The regional distribution of patent applications is assigned according to the inventor's country or region of residence. If an application has more than one inventor, it is divided equally among all inventors and, subsequently, among their countries of residence. Thus, double counting is avoided. When a patent corresponds to multiple technological fields, it is assigned to the first code of the International Patent Classification (IPC) indicated in the patent.¹ One of the drawbacks of using patent applications at EPO may be that, since EPO acts as single intermediary to participating countries, the cost of double patenting (national and European) may prevent some small firms from demanding an extension of the national patent to European level. On the other hand, as stated by Maurseth and Verspagen (2002), patents filed at the EPO are more likely to have higher average quality. Furthermore, as pointed out by Cefis and Orsenigo (2001), EPO uses a highly homogeneous procedure, so the data are readily comparable to perform comparative analysis. Also, some large corporations with subsidiaries in the EU tend to patent in the USPTO and off shore IP holding companies. Of course, they may have significant knowledge spillovers in terms of new management practices, technologies etc. Also EU patent activity may also reflect the national state support systems since some national agencies co-finance the patent applications by firms increasing that way the number of patent applications. By and large, it is clear that patent is not the perfect measure as an output of a knowledge production function. However, it still remains a fairly good indicator of innovative activity.

Table 1 reports some descriptive statistics and Table 2 reports the correlation between the explanatory variables. Since there is no strong positive or negative correlation between any pair of independent variables, there are no multicollinearity issues in our estimations.

4 Empirical results and discussion

The dataset is balanced since every region is steadily observed for every single year. Estimates are carried out by applying panel data methodology. Due to the lack of space, we

¹ Patent applications to the EPO at the regional level. Eurostat Metadata in SDDS format: summary methodology <http://www.epp.eurostat.ec.europa.eu/>.

Table 2 Correlation matrix

	Ln (patents)	Ln (RS)	Ln (RD)	NEI	Ln (TPS)
Ln (patents)					
Ln (RS)	0.605				
Ln (RD)	0.877	0.669			
NEI	0.695	0.445	0.612		
Ln (TPS)	0.568	0.471	0.563	0.601	
GDS	0.706	0.456	0.563	0.504	0.379

only present the fixed effects (FE) estimations as suggested by the Hausman and Breusch-Pagan tests.

The results of the estimates are shown in Table 3. We present six different fixed effects models all of which include the main KPF inputs, the researchers and the R&D expenditures, but differ in the inclusion of the knowledge spillovers and the interaction terms. Model 1 presents the base regional KPF with the two inputs only, R&D expenditures (*RD*) and researchers (*RS*), without spillover effects. Model 2 introduces the impact of intra-regional spillovers into KPF by including the variable *NEI*. Model 3 introduces the impact of inter-regional spillovers by including the *TPS* and *GDS*. Model 4 includes the interaction term INT_1 . Model 5 incorporates the simultaneous impacts of intra and inter-regional spillovers. Finally, the second interaction term, INT_2 , is included in Model 6.

4.1 Control variables

The dependent variable, the logarithm of patents, is positively correlated with the KPF inputs, *RS* and *RD*. The elasticity of *RD* is statistically significant in all models and ranges from 0.53 (Model 1) to 0.38 (Model 6). However, *RS* is not statistically significant in all models. This finding is similar to previous findings. Bottazzi and Peri (2003), measuring R&D (employment and real spending (private and public) in research and development) in 86 European regions, find a positive and statistically significant correlation between R&D and patents production in each region. Tappeiner et al. (2008) found that the traditional factors of innovative activity, such as expenses on R&D and human capital, in spatial clusters increase the patenting activities. Fritsch and Slavchev (2010), willing to investigate the efficiency of regions by relating regional R&D inputs with output (patents), they found this relation explicitly positive.

The introduction of knowledge spillovers reduces the impact of R&D expenditures on innovation output since the estimated coefficients for both inputs are much higher in Model 1 than in the other five models. This is an indication of the role that knowledge spillovers play in new knowledge production. Not only are the regional resources (inputs) necessary for new knowledge production but also the global knowledge. Hence, the establishment of a mechanism to facilitate the knowledge transfer both inside the regional innovation system and across the regions will improve the efficiency of the RIS by assimilating a higher share of the global knowledge. The influence, however, of the knowledge spillovers on the two inputs estimated coefficients is not similar. The estimated coefficient of the *RD* falls from 0.53 in Model 1 to 0.35 and 0.38 in Models 5 and 6 correspondingly. On the other hand, the coefficient of the *RS* falls from 0.74 in Model 1 to 0.15 and 0.30 in Models 5 and 6 correspondingly. This difference might be attributed to the fact that global

Table 3 Panel Estimation results

Independent variable	Model 1 Knowledge production function	Model 2 Intra regional spillovers	Model 3 Inter regional spillovers	Model 4 Inter regional spillovers	Model 5 Intra and inter regional spillovers	Model 6 Intra and inter regional spillovers
Intercept term	-1.48*** (4.08)	-1.18*** (3.28)	-3.02*** (7.24)	-3.95*** (8.24)	-3.48*** (7.25)	-4.59*** (4.78)
Log (RS)	0.74*** (3.56)	0.59*** (3.02)	0.26 (1.6)	0.21 (1.42)	0.15 (1.05)	0.30** (1.98)
Log (RD)	0.53*** (4.93)	0.48*** (4.75)	0.39*** (4.35)	0.36*** (4.42)	0.35*** (4.19)	0.38*** (4.22)
NEI		1.51*** (4.18)			0.94*** (3.04)	12.11*** (2.83)
Interaction term 2 [Log (TPS*NEI)]						-1.25*** (2.67)
Log (TPS)			0.39*** (5.81)	0.48*** (7.87)	0.43*** (7.26)	0.53*** (5.20)
GDS			0.0002*** (2.88)	0.0082*** (3.68)	0.008*** (3.6)	0.00047*** (5.01)
Interaction term 1 [Log (TPS*GDS)]					-0.00075*** (3.52)	
R ² -Adj	0.95	0.96	0.96	0.96	0.96	0.96
F-statistic test	F(211,1026) = 128.48 (p value = 0)	F(212,1025) = 134.95 (p value = 0)	F(213,1024) = 146.91 (p value = 0)	F(214,1023) = 153.04 (p value = 0)	F(215,1022) = 155.74 (p value = 0)	F(215,1022) = 152.42 (p value = 0)
Hausman test	X ² test(2) = 72.89 (p value = 0)	X ² test(2) = 199.55 (p value = 0)	X ² test(2) = 126.6 (p value = 0)	X ² test(2) = 92.48 (p value = 0)	X ² test(2) = 144.49 (p value = 0)	X ² test(2) = 200.78 (p value = 0)

Log (patents) dependent variable

(a) *t* student in parenthesis. (b) *** Significant at the 0.01 level; ** significant at the 0.05 level. (c) *Log(RS)* is the logarithm of the Human Resources in Science and Technology, *Log(RD)* is the logarithm of the expenditures in Research and Development, *NEI* is the Normalized Shannon's Entropy Index for technological diversity, *Log(TPS)* is the logarithm of the Technology Proximity between the regions, *GDS* is the Geographical proximity between the regions, *Log(TPS) * GDS* is the interactive—synergistic affect between technological proximity and geographical proximity, *Log(TPS) * NEI* is the interactive—synergistic affect between technological proximity and technological diversity

knowledge may actually be a closer substitute to researchers than to R&D expenditures. However, the estimated coefficient of the RS in model 6 suggests that this substitutability is not perfect. The degree of substitutability between R&D expenditures and global knowledge is smaller since the region saves funds from knowledge already existing in the global public domain.

4.2 Returns to scale

The returns to scale with respect to RD and RS, the main inputs of the KPF, are increasing in Model 1, are almost constant in Model 2 and decreasing in the models with knowledge spillovers. The returns to scale are equal to 0.68 in the last model after the introduction of both intra and inter regional spillovers. Hence, the average European regional innovation system operates under decreasing returns to scale for R&D expenditures and researchers. However, if we consider the global knowledge as a third input, the total returns to scale are increasing. But we should emphasize to the importance of the global knowledge in order to achieve increasing returns which otherwise are decreasing. What is important from this finding is that if a RIS plans to spend more resources, in order to increase the output of the KPF, this policy will be efficient only in the case the RIS has, or plans, a mechanism to absorb global knowledge. If not, our findings suggest that more resources may not be as efficient as its planners believed and, therefore, the RIS may waste scarce resources that could be used more efficiently.

4.3 Hypothesis 1

Hypothesis 1 is verified by using the variable *NEI* as a proxy for regional technological variation, which is also positively correlated with patents. This finding implies that technological diversity facilitates the new ideas and knowledge production and increases the innovation productivity. We note that non-linearities between technological diversity and innovation performance, as Fritsch and Slavtchev (2010) found for Germany, are not supported by our data. The positive sign of the *NEI* coefficient suggests that the intra-regional spillovers increase with technological diversity. Our findings support the argument of the Jacob's track of literature that technological diversity facilitates the creation of new knowledge. Furthermore, our findings suggest that in the case where the regional innovation activity is concentrated in few technological fields (and in the extreme case in one field) the region attracts new innovative agents belonging to these technological fields or to the neighboring ones. Therefore, innovative activity increases as long as the agents innovate in these few fields. On the other hand, if a region innovates in a diversity of fields, the attraction of more and diverse agents may contribute to the increase of the regional innovative activity. In the lights of these results, the policy implications are significant. Technological policy usually takes two forms. The first is concentrated in the innovation of specific strategic sectors. The second, which is more decentralized, does not focus on specific sectors. We argue that European regions should apply the second type of technological policy since it facilitates the intra regional knowledge spillovers and consequently the exploitation of the resources devoted to innovation is more efficient.

One of the basic principles of Regional Smart Specialization called *specialized diversification* (OECD 2013) comes to complement the upper suggestion. This substantial principle is revealed mainly by the Smart Specialization's Strategies which involve the adoption, dissemination and adaption of General Purpose Technologies (GPTs) across a wide range of sectors. In the context of these strategies, European Commission laid

emphasis on the “related variety”. This idea arose out of debates as to whether innovation is more likely to occur in regions that are diversified rather than specialized because there are more opportunities afforded, in the former, for knowledge spillovers between different sectors. However, such spillovers are only likely to occur where there is some form of “relatedness” between sectors. Related variety exists where sectors share some form of complementary competences. (Commission of Europe 2013). Additionally, according to Boschma (2014) related variety can boost diversification and true economic renewal in regions by making new recombination between industries. The importance of related variety for regional growth and regional diversification has been confirmed in a number of recent studies (e.g. Frenken et al. 2007; Boschma and Iammarino 2009; Neffke et al. 2011; Boschma et al., 2012; Rigby 2012).

Audretsch and Feldman (1996) using survey data from Levin et al. (1987) to discern the disciplines that form a common science base that contributes to the basis for cross-industry increasing returns, find that the presence of diverse industries within the same science-base in a city leads to increased innovation. Therefore, we can argue that “it is not diversification per se that is important for growth, but the patterns of specialized diversification across related technologies that are important for growth” (McCann and Ortega-Argilés 2013, p. 7).

4.4 Hypothesis 2

Hypothesis 2a is verified by measuring the estimated coefficient of *GDS* which quantifies the direct impact of global knowledge weighted by geographical proximity on new knowledge production. The coefficient is positive and statistically significant in all models. Thus, when a region is spatially contiguous with strong innovative regions the spillovers due to geographical proximity are positive. Hypothesis 2b is verified by measuring the estimated coefficient of *TPS* which quantifies the direct impact of the global knowledge weighted by technological proximity on regional knowledge production. The coefficient is positive and statistically significant in all models and its value is relatively stable. That is, as a region is technologically contiguous to high innovative regions the cross regional spillovers have a greater influence on regional new knowledge production.

4.5 Hypothesis 3

The coefficient of the interaction term (INT_1) is statistically significant and negative. For the analysis below, we use the estimated coefficients of Model 5 as it is representative because incorporates both the intra and inter-regional spillovers:

$$l(Patents) = C + 0.15l(RS) + 0.35l(RD) + 0.94NEI + 0.43l(TPS) + 0.008GDS - 0.00075[l(TPS) \times GDS]$$

The first order partial derivatives of this function with respect to *TPS* and *GDS* are:

$$\frac{\partial l(Patents)}{\partial l(TPS)} = 0.43 - 0.00075GDS \quad (5)$$

$$\frac{\partial l(Patents)}{\partial GDS} = 0.008 - 0.00075TPS \quad (6)$$

According to Hirschberg and Lye (2010), the interaction term in a regression measures the marginal effect of an independent variable depending on the values of another

independent variable. The partial derivatives (5) and (6) are the marginal effects of TPS and GDS. The sign of these marginal effects depends on the values of the other independent variable entering in each marginal effect equation, namely GDS for the Eq. (5) and TPS for the Eq. (6). It is evident from these two equations that the simultaneous consideration of the geographical proximity reduces the impact of the knowledge spillovers due to technological proximity and vice versa. However, it is not clear for what value of GDS (TPS) these marginal effects change sign. Therefore, it is necessary to construct the confidence intervals for these variables following the Fieller theorem as applied by Hirschberg and Lye (2010). We denote as $\beta_4 = 0.43$, $\beta_5 = 0.007$ and $\beta_6 = -0.00075$ from Eqs. (5) and (6).

The sign of the partial derivative $\frac{\partial l(Patents)}{\partial l(TPS)}$ changes at $GDS^* = -\beta_4/\beta_6$ and the sign of the partial derivative $\frac{\partial l(Patents)}{\partial GDS}$ changes at $TPS^* = -\beta_5/\beta_6$. The confidence intervals for GDS^* and TPS^* with $100(1 - \alpha) = 5\%$ are the roots of the quadratic equations $aGDS^2 + 2bGDS + c = 0$ and $aTPS^2 + 2bTPS + c = 0$ correspondingly. Where $a = \beta_6^2 - t_{\alpha/2}^2\sigma_6^2$, $b = -\left(t_{\alpha/2}^2\sigma_{46} - \beta_4\beta_6\right)$ and $c = \beta_4^2 - t_{\alpha/2}^2\sigma_4^2$ for the first equation and $a = \beta_6^2 - t_{\alpha/2}^2\sigma_6^2$, $b = -\left(t_{\alpha/2}^2\sigma_{56} - \beta_5\beta_6\right)$, and $c = \beta_5^2 - t_{\alpha/2}^2\sigma_5^2$ for the second equation. σ_i^2 are the estimated variances of β_i ($i = 4, 5, 6$), σ_{46} and σ_{56} are the covariances between β_4 and β_6 and β_5 and β_6 respectively. $t_{\alpha/2}^2$ is the $\alpha\%$ critical value of t-distribution with $T - k$ degrees of freedom.

The two roots of the first quadratic equation are $(GDS_L, GDS_U) = (-b \pm \sqrt{b^2 - ac})/a$, and the two roots of the first quadratic equation are $(TPS_L, TPS_U) = (-b \pm \sqrt{b^2 - ac})/a$. The two roots define the confidence bounds for GDS^* and TPS^* respectively. Solving for the roots of the first equation we get $GDS_U = 1,215$ and $GDS_L = 350$ and for the second equation $TPS_U = 11.5$ and $TPS_L = 10$. The subscripts $_U$ and $_L$ denote the upper and lower bound of the confidence interval.

The total impact of the TPS on patents by taking into consideration the influence of the geographical proximity has been determined by the corresponding confidence interval. The confidence intervals of the two interacted variables determine the bounds in which the sign of partial derivatives $\frac{\partial l(Patents)}{\partial l(TPS)}$ is uncertain. For values $350 < GDS < 1,215$ the partial derivative is statistically zero and consequently TPS does not influence new patents production. Above and below the upper and lower bounds the signs are definite.

For values $GDS < 350$ the partial derivative $\frac{\partial l(Patents)}{\partial l(TPS)}$ takes positive values but its value is smaller than 0.43, the direct impact. This means that when a region is geographically contiguous to weak innovative systems then the impact of the global knowledge spillovers weighted by technological proximity is still positive. In other words, when a region j is contiguous to a weak innovative region k , then knowledge spillovers from k to j are stronger the lower the technological distance between them. The knowledge spillovers are stronger when the two regions innovate in similar technological fields. In this case inter-regional technological specialization does matter. This result gives an explicit answer to the scenarios presented in hypothesis 3a.

The partial derivative $\frac{\partial l(Patents)}{\partial l(TPS)}$ takes negative values for $GDS > 1,215$. That is when a region is geographically contiguous to regions with high innovative activity, the inter-regional spillovers weighted by technological proximity are increasing when the region

receives knowledge from technologically distant regions. In other words, when a region j is contiguous to a strong innovative region k , the knowledge spillovers from k to j are stronger the higher the technological distance between them. The knowledge spillovers are stronger when the two regions innovate in different technological fields. It seems that even in cross regional knowledge spillovers inter-regional technological diversity does matter. This result gives an explicit answer to the scenarios presented in hypothesis 3b.

4.6 Hypothesis 4

The partial derivative $\frac{\partial l(Patents)}{\partial GDS}$ has positive sign in all models, implying that when a region is spatially contiguous to strong innovative regions the global knowledge spillovers weighted by geographical proximity have a positive impact on regional innovation activity. However, the simultaneous consideration of the technological proximity reduces the impact of the GDS on patents. The partial derivative takes negative values for $TPS > 11.5$ and positive values for $TPS < 10$. But the TPS takes much larger values than 11.5 and, hence, only the first case $TPS > 11.5$ is valid. Thus, the sign of the partial derivative $\frac{\partial l(Patents)}{\partial GDS}$ is clearly negative for every TPS value. The second interaction term (INT_2) is a statistically significant variable with a negative coefficient. We measure the first order partial derivative of the KPF with respect to the TPS using the estimated coefficients of the Model 6.

$$l(Patents) = C + 0.30l(RS) + 0.38l(RD) + 12.11NEI + 0.53l(TPS) + 0.00047GDS - 1.25[l(TPS) \times NEI]$$

$$\frac{\partial l(Patents)}{\partial l(TPS)} = 0.53 - 1.25NEI \tag{7}$$

Following again Hirschberg and Lye (2010), the marginal effect of TPS on patents depends on NEI . We construct the confidence bounds of $\frac{\partial l(Patents)}{\partial l(TPS)}$ function. We denote as $\beta_4 = 0.53$, and $\beta_6 = -1.25$ from equation (7).

The sign of the partial derivative $\frac{\partial l(Patents)}{\partial l(TPS)}$ changes at $NEI^* = -\beta_4/\beta_6$. The confidence interval for NEI^* with $100(1 - \alpha) = 5\%$ is determined by the roots of the quadratic equation $aNEI^2 + 2bNEI + C = 0$ where $a = \beta_6^2 - t_{\alpha/2}^2 \sigma_6^2$, $b = -\left(t_{\alpha/2}^2 \sigma_{46} - \beta_4 \beta_6\right)$ and $c = \beta_4^2 - t_{\alpha/2}^2 \sigma_4^2$. σ_i^2 is the variance of β_i ($i = 4, 6$), σ_{46} is the covariance between β_4 and β_6 , and $t_{\alpha/2}^2$ is the $\alpha\%$ critical value of the t -distribution with $T - k$ degrees of freedom.

Solving for the roots we found that $(NEI_L, NEI_U) = \left(-b \pm \sqrt{b^2 - ac}\right)/a$ where the subscripts U and L denote the upper and lower limit of the confidence interval for NEI^* . We find that $NEI_U = 1.1$ and $NEI_L = 0.3$. The partial derivative $\frac{\partial l(Patents)}{\partial l(TPS)}$ has a positive sign when $NEI < 0.3$ which means that as NEI takes lower values region's j diversity gets lower and then the inter regional knowledge spillovers are higher the lower the technological distance between regions. In other words, when a region j exhibits low technological diversity then the *inter*-regional knowledge spillovers from region k are higher when the two regions innovate in similar technological fields. For values of NEI

between 0.3 and 1 the impact of the global spillovers weighted by technological proximity (*TPS*) is statistically zero. *NEI*, by its structure, cannot take values higher than 1.

4.7 Resources leveraging efficiency

The estimated constant *E* could be considered as an index of the *RIS* ability to efficiently leverage resources. *E*, as an index number, does not provide any information unless it varies across time or across regions. In this paper, the *E* varies across regions and is time invariant. Therefore, the estimated vector **E** of the regional idiosyncratic constants provides information about the differences between the leveraging capacity-efficiency (*LCE*) of the 210 EU regional innovation systems. Since we have assumed that all regions use the same knowledge production function, the *E* is a “shift” parameter: the *KPF* of the regions with higher *E* are located higher in the inputs space than the *KPF* of regions with lower *E*. If, for example, a region has $E^k = 1$ and another region has $E^j = 2$, it could be an indication that the second region can leverage the same resources twice as much as the first one.

We report some regional idiosyncratic *LCE* in Table 4. The first and third columns present the top thirty European regions in terms of patents production and *LCE* correspondingly. The second and fourth columns report the number of patents and the *LCE* correspondingly. The *LCE* index is normalized to unity using as benchmark the highest regional *LCE* (Noord-Brabant region).

From Table 4 we conclude that there are regions which, although they are very high classified in terms of patents production, do not exhibit high *LCE*. For instance, the Île de France region, the region with the highest production of patents, is not present in the list of the 30 regions with the highest *LCE*. This finding might indicate that these regional innovation systems produce high knowledge output by reserving a lot of resources without, however, being supported by the required *LCE*. A possible reason for this phenomenon could be policies which tended to spread “knowledge investment” (e.g. high education and vocational training, public and private R&D) too thinly, not making much of an impact in many areas. Since entrepreneurship and innovation tends to be higher in regions with large market potential, some regions may waste a lot of sources in order to cover many fields of innovative activity.

On the other hand, there are regions with high *LCE* but with lower knowledge output. For example, Rheinhesen-Pfalz region is one of the most efficient regions in terms of *LCE* despite the fact that it is not classified in the top regions with the highest patents production. Mittelfranken, Freiburg and Emilia-Romagna exhibit the same behavior. Regions like the mentioned before, probably have identified more accurately the fields in which they intend to innovate so that they do not consume unnecessary sources. The Smart Specialization concept forms one of the main pillars of the reformed EU Cohesion Policy, which highlights the need for regions to identify and select their own potential sources of innovation and economic growth. In that respect, regions should proceed to self-assessment of their knowledge assets, capabilities and competences and the knowledge agents between whom knowledge is exchanged (McCann and Ortega-Argilés 2013, p. 10).

Table 5 illustrates the twenty regions with the lower *LCE*. These regions belong to the South and Eastern Europe. Because these regions have the lower *LCE* it seems that their *RIS* is characterized by low competences to coordinate and leverage resources allocated to innovation activity. However, the policy implications of our findings suggest that a policy which intends to allocate more resources to innovation activities without improving the

Table 4 The most efficient regional innovation systems

Regions	Patents (average)	Regions	Leveraging capacity —efficiency (LCE)
Île de France (France)	2,817.4	Noord-Brabant (Netherlands)	1
Stuttgart (Germany)	2,292.6	Rheinessen-Pfalz (Germany)	0.992
Oberbayern (Germany)	2,282.8	Vorarlberg (Austria)	0.839
Noord-Brabant (Netherlands)	1,546.7	Mittelfranken (Germany)	0.692
Darmstadt (Germany)	1,423.6	Freiburg (Germany)	0.647
Düsseldorf (Germany)	1,350.4	Lüneburg (Germany)	0.623
Köln (Germany)	1,253.2	Emilia-Romagna (Italy)	0.581
Lombardia (Italy)	1,243.5	Berpfalz (Germany)	0.571
Rhône-Alpes (France)	1,189.8	Niederbayern (Germany)	0.558
Karlsruhe (Germany)	1,147.4	Etelä-Suomi (Finland)	0.531
Freiburg (Germany)	857.6	Schwaben (Germany)	0.518
Rheinessen-Pfalz (Germany)	793.9	Sydsverige (Sweden)	0.505
Tübingen (Germany)	744.5	Detmold (Germany)	0.483
Etelä-Suomi (Finland)	737.1	Länsi-Suomi (Finland)	0.483
Mittelfranken (Germany)	696.5	Gießen (Germany)	0.481
Arnsberg (Germany)	648.6	Münster (Germany)	0.480
Stockholm (Sweden)	643.5	Berfranken (Germany)	0.473
Emilia-Romagna (Italy)	615.3	Unterfranken (Germany)	0.467
Berlin (Germany)	523.3	Niederösterreich (Austria)	0.461
Schwaben (Germany)	495.0	Lombardia (Italy)	0.455
Hovedstaden (Denmark)	486.1	Friuli-Venezia Giulia (Italy)	0.453
Piemonte (Italy)	481.4	Rhône-Alpes (France)	0.450
Veneto (Italy)	455.9	Stuttgart (Germany)	0.448
Unterfranken (Germany)	447.0	Hannover (Germany)	0.447
Västverige (Sweden)	440.0	Luxembourg (Belgium)	0.439
Hannover (Germany)	439.3	Burgenland (Austria)	0.430
Münster (Germany)	432.2	Koblenz (Germany)	0.429
Detmold (Germany)	418.2	Köln (Germany)	0.424
Zuid-Holland (Netherlands)	405.0	Düsseldorf (Germany)	0.424
East Anglia (United Kingdom)	399.2	Luxembourg (Luxembourg)	0.423

coordination and leveraging capacity of the RIS will not be as productive as the policy makers might expect. Technological policy should aim at promoting a strong partnership between businesses, public entities and knowledge institutions.

5 Concluding remarks and policy implications

Aim of this paper was to investigate the determinants of the regional innovative activity. Knowledge spillovers gleaned from the innovative process in and out of a region play a major role in patents production. Intra-regional knowledge spillovers defined and influenced by the degree of diversification of the regional innovative activity. *Inter*-regional

Table 5 The less efficient regional innovation systems

Rank	Regions	Total factor productivity (TFP)
1	Közép-Dunántúl (Hungary)	0.045
2	Norte (Portugal)	0.045
3	Nyugat-Dunántúl (Hungary)	0.044
4	Latvia (Latvia)	0.043
5	Canarias (Spain)	0.042
6	Estonia (Estonia)	0.042
7	Voreia Ellada (Greece)	0.042
8	Andalucía (Spain)	0.041
9	Lódzkie (Poland)	0.036
10	Wielkopolskie (Poland)	0.035
11	Dolnoslaskie (Poland)	0.035
12	Mazowieckie (Poland)	0.032
13	Slaskie (Poland)	0.030
14	Severozápad (Czech Republic)	0.028
15	Lithuania (Lithuania)	0.025
16	Kentriki Ellada (Greece)	0.024
17	Macroregiunea trei (Romania)	0.020
18	Region Północny (Poland)	0.020
19	Region Wschodni (Poland)	0.019
20	Macroregiunea doi (Romania)	0.007

knowledge spillovers defined and influenced by the geographical and technological proximity between each pair of regions. We estimated a regional knowledge production function using data for 210 European regions for a 12 years period (1995–2006).

The dependent variable, the logarithm of patents, is positively correlated with the KPF inputs, *RS* and *RD*. The introduction of knowledge spillovers reduces the impact of these inputs. The influence, however, of the knowledge spillovers on the two inputs estimated coefficients is not similar. The estimated coefficient of the *RD* falls more than the coefficient of the *RS*. This difference might be attributed to the fact that global knowledge may actually be a closer substitute to researchers than to R&D expenditures. The degree of substitutability between the R&D expenditures and global knowledge is smaller since the region saves funds from knowledge already existing in the global public domain. The returns to scale with respect to *RD* and *RS*, the main inputs of the KPF, are increasing in the models without spillovers and decreasing in the models with knowledge spillovers. Hence, the average European regional innovation system operates under decreasing returns to scale for R&D expenditures and researchers. However, if we consider the global knowledge as a third input, the total returns to scale are increasing.

Technological diversity facilitates the new ideas and knowledge production and increases the innovation productivity. Our findings support the argument of the Jacob's track of literature that technological diversity facilitates the creation of new knowledge. In the light of our findings, we argue that European regions should apply a decentralized technological policy because it facilitates the intra regional knowledge spillovers and makes the exploitation of the resources devoted to innovation more efficient. Diversity of

innovative activity in every region is related positively with the output of the regional knowledge production function. This means that intra-regional knowledge spillovers are enhanced when a region innovates in different technological fields.

The estimated coefficient of *TPS* is positive and statistically significant. That is as a region is technologically contiguous to high innovative regions the cross regional spillovers have a greater influence on regional new knowledge production. The estimated coefficient of *GDS* is also positive and statistically significant. Thus, when a region is spatially contiguous with strong innovative regions the spillovers due to geographical proximity are positive. However, the simultaneous consideration of the geographical and technological proximity significantly influences the marginal effects of these independent variables on new knowledge creation. Thus, when a region is geographically contiguous to weak innovative systems then the knowledge spillovers are stronger when the two regions innovate in similar technological fields. When a region is geographically contiguous to regions with high innovative activity the knowledge spillovers are stronger when the two regions innovate in different technological fields.

The structure of the recipient's region innovative activity determines the impact of the global knowledge weighted by technological proximity on regional innovation productivity. When the regional innovation activity is diverse then the impact of the *TPS* is zero or the outcome is not so clear. When the *NEI* is smaller than 0.3 the impact of the *TPS* is positive. That is when the regional innovation activity is concentrated in few technological fields the interregional spillovers increase when the region is technologically contiguous to strong innovation regions. The global knowledge is produced in regions which are technologically closed to this region.

This position gleaned from our estimations, supported also from the context of Regional Smart Specialization. One of the basic principles of Regional Smart Specialization is the specialized diversification. Since, each region is characterized by specific structure, it is able to take advantage of its domains where specific technologies are dominant and to promote diversity of activities in these existing technological fields. Therefore, we can argue that regions which apply specialized diversification across related technologies can achieve growth (McCann and Ortega-Argilés 2013).

Besides, "self-discovery" (Hausmann and Rodrik 2003) is critical for regions' success. The smart specialization suggests that the policy recommendations at regional level may be very different in different places, depending on the region's technological profile, industrial structure and geography. The S^3 platform aims to assist regions and the EU Member States in developing, implementing and reviewing regional smart specialization strategies, and help regions identify high-value added activities which offer the best chances of strengthening their competitiveness (Commission of Europe 2010).

In the light of our results, the "one size fits all" technological policy as applied both by member states and the EU has not proved fruitful. The European regions do not all fit into the same category, since they comprise, for example, peripheral regions, old industrial regions and fragmented metropolitan regions (Todtling and Trippl 2005). The EU should apply a "tailor made" technological policy to increase each region's absorptive capacity. In addition, national and regional authorities should be more committed to applying a potent research and innovation policy and providing good quality research infrastructure at the regional level. According to Feldman and Florida (1994), the existence of technological infrastructure explains the regional concentration of innovative activity in the US. Among other bodies, this technological infrastructure includes research institutions (universities) which provide sources of technological opportunity, as well as networks between universities, industry and business service providers.

The joint policy action of the EU, involving both national and regional authorities, is based on the complementarity principle, and is aimed to expand the stock of knowledge of these regions in the public domain, reduce their technological gap with the strong innovative regions, and enhance their ability to assimilate more knowledge of an increasingly advanced nature.

References

- Acs, Z., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, *31*(7), 1069–1085.
- Acs, Z., Audretsch, D., & Feldman, M. (1994). R&D spillovers and recipient firm size. *The Review of Economics and Statistics*, *76*(2), 336–340.
- Audretsch, D., & Feldman, M. (1996). R & D spillovers and the geography of innovation and production. *The American Economic Review*, *86*(3), 630–640.
- Autio, E. (1998). Evaluation of RTD in regional systems of innovation. *European Planning Studies*, *6*(2), 131–140.
- Boschma, R. (2014). Constructing regional advantage and smart specialisation: Comparison of two European policy concepts. *Scienze Regionali*, *2014*(1), 51–68.
- Boschma, R., & Iammarino, S. (2009). Related variety, trade linkages and regional growth in Italy. *Economic Geography*, *85*(3), 289–311.
- Boschma, R., Minondo, A., & Navarro, M. (2012). Related variety and regional growth in Spain. *Papers in Regional Science*, *91*(2), 241–256.
- Bottazi, L., & Peri, G. (2003). Innovation and spillovers in regions: Evidence from European patent data. *European Economic Review*, *47*(4), 687–710.
- Caragliu, A., & Nijkamp, P. (2012). The impact of regional absorptive capacity on spatial knowledge spillovers: The Cohen and Levinthal model revisited. *Applied Economics*, *44*(11), 1363–1374.
- Cefis, E., & Orsenigo, L. (2001). The persistence of innovative activities: A cross-countries and cross-sectors comparative analysis. *Research Policy*, *30*(7), 1139–1158.
- Cohen, W., & Levinthal, A. (1989). Innovation and learning: The two faces of R&D. *The Economic Journal*, *99*(397), 569–596.
- Cohen, W., & Levinthal, A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–132.
- Commission of Europe (2010). Regional Policy contributing to smart growth in Europe 2020. http://ec.europa.eu/regional_policy/sources/docoffic/official/communic/smart_growth/comm2010_553_en.pdf#page=5&zoom=auto,-17,492.
- Commission of Europe. (2013). The role of clusters in smart specialization strategies. http://ec.europa.eu/research/evaluations/pdf/archive/other_reports_studies_and_documents/clusters_smart_spec2013.pdf.
- Criscuolo, P., Narula, R. (2002). *A novel approach to national technological accumulation and absorptive capacity: Aggregating Cohen and Levinthal*. Working paper, University of Oslo.
- Doloreux, D. (2002). What we should know about regional systems of innovation. *Technology in Society*, *24*(3), 243–263.
- Feldman, M., & Audretsch, D. (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review*, *43*(2), 409–429.
- Feldman, M., & Florida, R. (1994). The geographic sources of innovation: Technological infrastructure and product innovation in the United States. *Annals of the Association of American Geographers*, *84*(2), 210–229.
- Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies*, *41*(5), 685–697.
- Fritsch, M., & Franke, G. (2004). Innovation, regional knowledge spillovers and R&D cooperation. *Research Policy*, *33*(2), 245–255.
- Fritsch, M., & Slavtchev, V. (2010). How does industry specialization affect the efficiency of regional innovation systems? *The Annals of Regional Sciences*, *45*(1), 87–108.
- Glaeser, E., Kallal, H., Scheinkman, J., & Shleifer, A. (1992). Growth in cities. *The Journal of Political Economy*, *100*(6), 1126–1152.
- Greunz, L. (2003). Geographically and technologically mediated knowledge spillovers between European regions. *The Annals of Regional Science*, *37*(4), 657–680.
- Greunz, L. (2004). Industrial structure and innovation-evidence from European regions. *Journal of Evolutionary Economics*, *14*(5), 563–592.

- Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics*, 10(1), 92–116.
- Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, 28(4), 1661–1797.
- Guellec, D., & Pottelsberghe de la Potterie, B. (2004). From R&D to productivity growth: Do the institutional settings and the source of funds of R&D matter? *Oxford Bulletin of Economics and Statistics*, 66(3), 0305–9049.
- Hall, B., Jaffe, A., Trajtenberg, M. (2001). The NBER patent citations data file: Lessons, insights and methodological tools. WP 8498 National Bureau of Economic Research.
- Hausmann, R., & Rodrik, D. (2003). Economic development as self-discovery. *Journal of Development Economics*, 72(2), 603–633.
- Henderson, V. (1997). Medium size cities. *Regional Science and Urban Economics*, 27(6), 583–612.
- Hirschberg, J., & Lye, J. (2010). A reinterpretation of interactions in regressions. *Applied Economics Letters*, 17(5), 427–430.
- Hirschleifer, J., & Riley, J. (1992). *The analytics of uncertainty and information*. Cambridge: Cambridge University Press.
- Jacobs, J. (1969). *The economy of cities*. New York: Vintage.
- Jaffe, A. (1986). Technological opportunity and spillovers of R&D: Evidence from firm's patents, profits and market value. *The American Economic Review*, 76(5), 984–999.
- Jaffe, A. (1988). Demand and supply influences in R&D intensity and productivity growth. *The Review of Economics and Statistics*, 70(3), 431–437.
- Jaffe, A. (1989). Real effects of academic research. *The American Economic Review*, 79(5), 957–970.
- Jaffe, A., Trajtenberg, M., & Hederson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, 108(3), 577–598.
- Kumar, U., Kumar, V., & Kapur, J. N. (1986). Normalized measures of entropy. *International Journal of General Systems*, 12(1), 55–69.
- Levin, R., Alvin, K., Nelson, R., & Winter, S. (1987). Appropriating the returns from industrial research and development. *Brookings Papers on Economic Activity*, 1987(3), 783–820.
- Marshall, A. (1890). *Principles of economics*. London: Macmillan.
- Maurseth, P., & Verspagen, B. (2002). Knowledge spillovers in Europe: A patent citations analysis. *The Scandinavian Journal of Economics*, 104(4), 531–545.
- Mccann, P., Ortega-Argilés, R. (2013). Smart specialization, regional growth and applications to European Union Cohesion Policy. *Regional Studies*. doi:10.1080/00343404.2013.799769.
- Moreno, R., Paci, R., & Usai, S. (2005). Spatial spillovers and innovation activity in European regions. *Environment and Planning A*, 37(10), 1793–1812.
- Moreno, R., Paci, R., & Usai, S. (2006). Innovation clusters in the European regions. *European Planning Studies*, 14(9), 1235–1263.
- Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography*, 87(3), 237–265.
- OECD. (2013). Innovation—Driven growth in regions: The role of smart specialization. <http://www.oecd.org/sti/inno/smart-specialisation.pdf>.
- Ouwensloot, H., & Rietveld, P. (2000). The geography of R&D: Tobit analysis and a Bayesian approach to mapping R&D activities in the Netherlands. *Environment and Planning A*, 32(9), 1673–1688.
- Paci, R., & Usai, S. (2000). Technological enclaves and industrial districts: An analysis of the regional distribution of innovative activity in Europe. *Regional Studies*, 34(2), 97–114.
- Pakes, A., & Griliches, Z. (1980). Patents and R&D at the firm level: A first report. *Economic Letters*, 5(4), 377–381.
- Ponds, R., van Oort, F., & Frenken, K. (2010). Innovation, spillovers and university-industry collaboration: An extended knowledge production function approach. *Journal of Economic Geography*, 10(2), 231–255.
- Porter, M. (1990). *The competitive advantage of nations*. New York: The Free Press.
- Rigby, D. (2012). The geography of knowledge relatedness and technological diversification in U.S. cities. *Papers in Evolutionary Economic Geography*, no. 12.18, Utrecht University.
- Romer, P. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5), 71–102.
- Tappeiner, G., Hauser, C., & Walde, J. (2008). Regional knowledge spillovers: Fact or artifact? *Research Policy*, 37(5), 861–874.
- Todtling, F., & Trippl, M. (2005). One size fits al?: Towards a differentiated regional innovation policy approach. *Research Policy*, 34(8), 1203–1219.
- Van Oort, F. (2002). Innovation and agglomeration economies in the Netherlands. *Journal of Economic and Social Geography*, 93(3), 344–360.