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The Complementary Effects of Proximity Dimensions on Knowledge Spillovers

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ABSTRACT *The purpose of this paper is to analyse the effect of various proximity dimensions on the innovative capacity of 276 regions in Europe within a knowledge production function model, where R&D and human capital are included as the main internal inputs. We combine the standard geographical proximity with the technological, social and organizational ones to assess whether they are substitutes or complements in channelling knowledge spillovers. Results show that all proximities have a significant complementary role in generating an important flow of knowledge across regions, with technological closeness showing the most important effect.*

Effets complémentaires des dimensions de proximité sur les « retombées » de connaissances

RESUME *l'objet de la présente communication est d'analyser l'effet de différentes dimensions de proximité concernant la capacité d'innovation de 276 régions d'Europe, dans le cadre d'un modèle de fonction de production des connaissances, où l'étude et la recherche, ainsi que le capital humain, sont incorporés au titre d'entrées internes principales. Nous allions la proximité géographique standard aux proximités technologiques, sociales et organisationnelles, afin d'évaluer si elles jouent un rôle substitutif ou complémentaire dans l'acheminement des « retombées » de connaissances. Les résultats montrent que toutes les proximités jouent un rôle complémentaire significatif dans la production d'un important flux de connaissances dans les différentes régions, le rapprochement technologique présentant l'effet le plus important.*

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Los efectos complementarios de las dimensiones de proximidad sobre los desbordamientos de conocimiento

EXTRACTO *El propósito de este estudio es analizar el efecto de varias dimensiones de proximidad sobre la capacidad innovadora de 276 regiones de Europa, dentro de un modelo de función de producción de conocimiento, donde I+D y el capital humano se incluyen como las principales aportaciones internas. Combinamos la proximidad geográfica estándar con la tecnológica, social y organizacional para evaluar si son sustitutas o complementos a la hora de canalizar los desbordamientos de conocimiento. Los resultados muestran que todas las proximidades tienen una función complementaria significativa en generar un flujo importante de conocimiento a través de regiones, siendo la proximidad tecnológica la que muestra el efecto más importante.*

邻近性维度对知识溢出的补足效应

摘　要：本论文旨在通过一个知识生产函数模型来分析各种邻近性维度对欧洲 276 个地区的创新能力产生的影响，其中研发和人力资本将作为主要的内部投入包括在其中。我们将标准的地理邻近性与技术、社会和组织邻近性结合在一起，评估它们在传输知识溢出过程中是否起到替代或补充作用。结果表明，所有邻近性都在重要跨地区知识流的生成过程中起到意义重大的补足作用，而技术邻近性的影响最为重 大。

KEYWORDS: *Knowledge production; spillovers; proximity; human capital; spatial models*

JEL CLASSIFICATION: C31; O31; O18; O52; R12

1. Introduction

In any economic system, the accumulation of knowledge depends on the economy's internal capacity to produce innovation and also on its ability to acquire the stock of knowledge generated in other areas and put it to work. Robust theoretical and empirical support to this assumption has been provided by both the macroeconomic literature on international technology diffusion at the country level (Grossman & Helpman, 1990; Coe & Helpman, 1995; Keller, 2004) and by the regional science literature (Jaffe et al., 1993; Audretsch & Feldman, 1996; Anselin et al., 1997). According to this framework, the main determinants of innovations are the internal production inputs, Research and Development (R&D) expenditure and human capital, as well as the different channels which facilitate the transmission of the external knowledge towards the receiving economy. Among the internal factors, human capital is expected to play a crucial role both in the development process (Benhabib & Spiegel, 1994) and in the absorption of external knowledge (Cohen & Levinthal, 1990).[1] Moreover, the competence and ability of human resources are essential in the informal process of learning by doing (Nelson & Winter, 1982), which represents a relevant component of the knowledge activity—often tacit and informal by nature (Dosi & Teece, 1998).

As far as the transmission channels are concerned, the literature has usually focused on geographical proximity, following the idea that knowledge spillovers are bounded in space (Jaffe, 1989). Since pecuniary and pure knowledge externalities are at work, firms' (or regions') technological activity benefits from being located close to other firms (regions) producing innovations. However, more recent contributions (Boschma, 2005) have emphasized that the spatial dimension can be supplemented by other forms of a-spatial proximity shaped by institutional, technological, social and organizational links.

Indeed, the importance of cognitive, relational and cooperative ties among agents—rather than pure spatial closeness—has been the key focus of the French School of Proximity in the analysis of the drivers of knowledge exchanges (see the recent review by Carrincazeaux & Coris, 2011). Another relevant concept for the analysis of knowledge flows is the distinction between unintended and intended spillovers (Maggioni et al., 2007). Geographical and technological proximity may induce a process of knowledge diffusion that does not depend directly on economic agents' decisions. In the case of intended spillovers, knowledge flows through a-spatial networks, within which agents exchange ideas on a voluntary basis thanks to formal or to informal agreements (Cowan & Jonard, 2004).

Thus, there is a widespread belief that knowledge transmission can be facilitated by the simultaneous presence of spatial proximity and networking in social, institutional, technological and organizational 'space'. These different proximity dimensions are expected to exert complementary and reinforcing effects on knowledge transmission (Mattes, 2012). This approach is also in line with recent applied spatial econometric contributions, which emphasize the need to move beyond the pure geographical distance measure and to unveil the 'economic' content of the selected interconnectivity structure. Such content becomes relevant when the interaction among spatial units 'is determined by purely economic variables, which may have little to do with the spatial configuration of boundaries or geographical distance *per se*' (Corrado and Fingleton, 2012, p. 8).[2]

The original contribution of this paper is to assess empirically the joint and the complementary effectiveness of four different dimensions of proximity—geographical, technological, social and organizational—in channelling knowledge spillovers at the aggregate regional level in Europe. Our aim is to give a wide-ranging picture of the knowledge diffusion process and, therefore, we apply our analysis to an ample data-set referring to 276 regions in 29 countries (EU27 plus Norway, Switzerland) over the last decade.[3]

Our analysis is carried out within the Knowledge Production Function (KPF) framework, and the use of spatial econometric techniques allows us to model explicitly the role of knowledge spillovers transmitted through the different proximity channels mentioned above. Thus, we assess the impacts of R&D expenditure and human capital as the main internal inputs of knowledge production and provide an assessment of the multiplier effects due to the external sources of innovation. The empirical analysis is performed by controlling for other economic, territorial and industrial characteristics of the regional economy. Unobserved factors influencing the regional performance within the same country are controlled for by including the full set of country dummies. These enable us to also account for institutional elements, like common norms, legal system and common language.

Our model selection strategy points out that a spatial autoregressive (SAR) specification is adequate to model the regional interconnectivity pattern which enables the transmission of knowledge across proximate territories. In order to fully account for the complementarities among all the proximity dimensions considered, the optimal estimation strategy would entail the specification of a comprehensive model which includes all of them at the same time. However, for a SAR specification, this goes beyond the current state-of-the-art (Elhorst, 2010) as it would require the formulation of new econometric tools. As a workable alternative we, therefore, adopt the SAR model variant which includes two spatially lagged terms for the dependent variable, computed on the basis of two different proximity dimensions. This kind of specification, which allows to account for one pair of proximity dimensions at a time, was first proposed in a different setting by Lacombe (2004). Moreover, to obtain an approximate measure of the overall multiplier effect resulting from the simultaneous working of all knowledge transmission mechanisms, we carry out a post-estimation exercise based on model combining techniques.

The paper is organized as follows. Section 2 presents the empirical model and describes the data and the different proximity measures. Section 3 deals with the estimation strategy and the empirical specification of the model. Section 4 discusses the empirical results. Section 5 concludes.

2. Empirical Model and Data

2.1. The Empirical Model of Knowledge Creation

The creation of innovation is not necessarily the result of a formal investment in research, but it is often derived from an informal process of learning by doing or through the absorption of external knowledge. The ability of firms and regions to interpret and to exploit internal and external knowledge relies on prior experiences embodied in individual skills and, more generally, in a well-educated labour force. Therefore, our analysis of the determinants of innovation activity at the regional level is based on the estimation of a KPF model (Griliches, 1979), where we include both internal and external factors (Jaffe, 1989). As internal input, together with the traditional R&D expenditure, we introduce human capital, given its well-known effects on knowledge production and absorption at the local level. External factors are accounted for by explicitly assessing the relevance of knowledge spillovers coming from 'proximate' regions, which may enhance the overall impact of internal factors thanks to multiplier effects.

Following the vast empirical literature on KPF, we specify the general form of our econometric model as a Cobb-Douglas function, where the innovation output (*INN*) is a function of two production inputs, R&D expenditures (*RD*) and human capital (*HK*) and a set of control variables:

$$\mathrm{INN}_i = \mathrm{RD}_i^{\beta_1}\mathrm{HK}_i^{\beta_2}\mathrm{controls}^{\gamma}e^{u_i} \tag{1}$$

In Model (1), if proximity factors are relevant, the error term is expected to feature cross-regional dependence; if such factors are assumed to act as an additional determinant of innovation, they can be modelled explicitly so that model (1) can be reformulated in a log-linearised form as follows:

$$\mathrm{inn}_i = \beta_1\mathrm{rd}_i + \beta_2\mathrm{hk}_i + \gamma\ \mathrm{controls}_i + \rho\ \mathrm{proximity\ factors}_i + \varepsilon_i \tag{2}$$

where lower case letters indicate log-transformed variables and ε_i is now an i.i.d. error term.[4]

The KPF approach has been followed in several contributions applied to different geographical contexts. Limiting our attention to the European case, the KPF function with spatial features has been employed by Bottazzi & Peri (2003), Greunz (2003), Moreno et al. (2005), Rodriguez-Pose and Crescenzi (2008), Parent &

LeSage (2008) and Autant-Bernard and LeSage (2010). In general, the results prove that the spatial external spillovers are relevant in influencing the knowledge capacity of a specific region and that they decay over the geographical space.

Few studies have also investigated the role of other types of proximity in influencing the exchange of knowledge among regions. More specifically, Greunz (2003) and Moreno et al. (2005) included a measure of technological proximity for each pair of regions' production structures showing that interregional knowledge spillovers are stronger between regions with similar technological profiles. Other contributions assessed the positive role of social networks on the process of knowledge creation in Europe, using various measures of social proximity like the cooperation networks for the European Research Fifth Framework Programme (Maggioni et al., 2007),[5] co-publications (Ponds et al., 2010) and inventors networks (Miguelez and Moreno, 2013). The influence of geographical and institutional proximity on social interactions, measured by inter-regional scientific publications and patent co-inventorship, was investigated by Hoekman et al. (2009). However, in these studies, the extent of social networks in a certain region is used to appraise its degree of connectivity and openness, but the whole social matrix providing a social distance measure for any pair of regions is not considered, differently from the case of geographical and technological distances. Finally, most of the above mentioned contributions include also a set of country dummies to account for institutional elements and find it relevant in discriminating between high- and low-innovative groups of regions.

2.2. Data Description and Proximity Measures

As a proxy of innovative activity, we use the number of patent applications[6] filed at the European Patent Office (EPO) classified by priority year and by inventor's region and divided by total population to control for the different size of the regions.[7] Since patenting activity at the regional level is quite irregular over time, we smooth the variable by computing the average for the years 2005–2007. The traditional input in the KPF is R&D expenditure at the regional level, which is included in the regression after being scaled with respect to gross domestic product (GDP). Human capital is measured as the share of population with tertiary education.

The vector of control variables includes GDP per capita to account for the different levels of economic development across European regions,[8] the share of manufacturing activities to account for the regional productive pattern, population density to allow for possible agglomeration effects and social capital, which is expected to improve the efficiency and the economic local performance by decreasing the transaction costs and by facilitating the coordination among actors (Knack & Keefer, 1997). Following La Porta et al. (1997), as a social capital variable, we consider the level of general trust measured by the share of population who state their belief in people's helpfulness, as reported by the European Social Survey.

All the explanatory variables are lagged with respect to the dependent variable so that they are averaged over the period 2002–2004. The averaging over a three-year period is carried out to smooth away undue cycle effects, while lags are expected to allow for a congruent response time of the innovation activity to changes in the production inputs and to avoid potential endogeneity problems. See Table 1 for a detailed description of the variables.

Table 1. Data sources and summary statistics

Variable	Definition	Mean	Minimum	Maximum	Variation coefficient	Primary source	Years
Patent	Total patents published at EPO, per million population	105.45	0.20	627.57	1.20	EPO	Average 2005–2007
Research & Development	Total intramural R&D expenditure, over GDP	1.42	0.07	7.59	0.85	Eurostat	Average 2002–2004
Human Capital	Population 15 and over with tertiary education (ISCED 5-6), over total population	10.52	3.51	23.33	0.39	Eurostat	Average 2002–2004
GDP	GDP per capita indicator, takes value 1 for regions with values above the average and zero otherwise	0.56	0.00	1.00	0.89	Eurostat	Average 2002–2004
Manufacture	Manufacturing employment, over total employment	17.25	3.67	36.23	0.37	Eurostat	Average 2002–2004
Population density	Population per km^2, thousands	331.35	3.08	9049.64	2.47	Eurostat	Average 2002–2004
Social Capital	General trust, population that feel people helpful (highest 3 scores),%	70.47	24.70	100.00	0.20	European Social Survey	2004

Technological progress at the regional level is a complex process which combines the local production of innovation together with the absorption of externally produced knowledge. This 'spills over' proximate territories through a number of underlying mechanisms is operating along four different dimensions suggested by the literature—geographical, technological, social and organizational.[9]

Before describing in detail how we operationalised the different proximity notions at the aggregate regional level, it is important to underline that the actual transmission of knowledge takes place at the micro-level as a result of interactions occurring among agents (scientists, researchers, inventors and firms) in specific areas or sectors. Such interactions are expected to bring about inter-regional relationships yielding positive effects on local economic outcomes, as is the case for the knowledge creation and diffusion process, which is the main focus of our analysis. In general, such positive effects are related to the fact that knowledge transmission is facilitated by reductions in transaction costs. While it is widely recognized that this is a direct result of nearness in space, less evidence has been provided so far on the fact that the same result could be obtained by other forms of closeness, as those related to sharing a similar cultural (common language and norms) or cognitive (common technological expertise) base. Social embeddedness and organizational membership are also expected to reduce uncertainty and encourage the exchange of knowledge as they foster increasing levels of trust and cooperative behaviour, ultimately leading to reduced transaction costs. All these mechanisms promote intended knowledge exchanges, mainly through market-based mechanisms, as much as unintended exchange among agents which take place in both spatial and a-spatial dimensions. In what follows, we present how we measured such proximity dimensions at the regional aggregate level for our sample of 276 NUTS2 territories.

Knowledge spillovers are obviously related to the geographical dimension since close-by agents are believed to have a better innovative performance because of pecuniary and pure technological advantages. More specifically, they enjoy cheaper access to information, and they can share tacit knowledge (a local public good) through face-to-face contacts. The standard and widely used indicator of spatial proximity is the distance in kilometres between the centroids of each couple of regions. In the econometric analysis, we use the inverse of the distance so that high values indicate more proximate regions and thus a higher probability of exchanging knowledge.

Technological (or cognitive) proximity facilitates knowledge transfer when a proper absorptive capacity is necessary (Cohen & Levinthal, 1990); a homogenous cognitive base with respect to the original knowledge is required in order to understand and process the additional knowledge effectively. We expect that economic agents who share a similar knowledge base, or territories which have a similar specialization structure, can exchange knowledge more easily and less costly, and this may favour innovation. To measure the technological proximity across regions, we compute a similarity index, t_{ij}, between region i and region j, based on the distribution of patenting activity among 44 sectors. The index is computed for each couple of regions to build up a technological proximity matrix T where each generic element is defined between zero (perfect dissimilarity of the sectoral distribution) and one (perfect similarity); thus, the higher the index value, the more similar the technological structure of the two regions and the higher the probability that they exchange knowledge.

Social proximity refers to the idea that individuals who have socially embedded relations are more likely to trust each other and, therefore, to exchange tacit knowledge smoothly (Granovetter, 1985). Within a risky and uncertain phenomenon such as technological progress, this implies that social closeness facilitates firms' capacity to learn, absorb external knowledge and innovate. Starting from these individual relationships, derived from inventors' utility maximizing behaviour, we measure social proximity by means of co-inventorship relations among multiple inventors of the same patent in case they are resident in different regions. The rationale is that the number and the intensity of links among inventors located in different regions can catch the existence of a social network among regions which facilitates the exchange of knowledge. We build a symmetric social matrix S whose generic element, s_{ij}, is defined as the number of inventors located in region i which have cooperated with inventors located in region j to conceive a patented invention. The intra-regional relationships are not considered and, therefore, the principal diagonal elements are set to zero.

Organizational proximity refers to the relations within the same group or organization which influence the individual capacity to acquire new knowledge coming from different agents. It reduces uncertainty and incentives to opportunistic behaviour since it provides an area of definition of practices and strategies within a set of rules based on organizational arrangements (Kirat & Lung, 1999). Following Maggioni et al. (2011), we measure organizational proximity by building a matrix based on the affiliation to the same organization by the applicant and the inventors of a patent when they are located in different regions. Since we are interested in the total number of organizational relationships between the two regions, we sum up mirror cells so that the generic element, o_{ij}, of the organizational matrix O is defined as the total number of bilateral relationships between applicants and inventors located in the pair of regions i and j. We expect a positive influence of organizational networks in the process of knowledge creation and diffusion since they are believed to reduce uncertainty and opportunism.

From the description above, it is evident that knowledge diffusion is a very complex phenomenon and the computation of fully reliable measures of the different transmission channels at the regional level is a challenging task. We are aware that the four proximity measures suggested in this study are not devoid of measurement problems, especially for the case of social and organizational proximities.[10] By restricting our ample geographical coverage in favour of a more confined but disaggregated territorial and sectoral context, it would be possible to provide a more accurate measure of the micro-level knowledge transmission mechanisms, as suggested in Breschi & Lissoni (2001). This should also allow to explore the sectoral dimension in order to assess to what extent such transmission is characterized by either intra- or inter-sectoral flows and how much it is associated to related variety. Moreover, the measurement of social and organizational relationships could benefit from the availability of better indicators related to commuting, time distance and cooperative agreements as it is done by Andersson & Grasjö (2009) for the case of Swedish municipalities or by Fitjar & Rodriguez-Pose (2011) for the case of Norwegian firms. Similarly, the focus on disaggregated sectors may enable us to obtain more accurate indicators to measure institutional, cognitive and organizational networks as in Balland et al. (2013) for the videogame industry.

Overall, we think that for analysing knowledge transmission at the regional level our contribution, based on four different proximity dimensions, may represent a valuable attempt to account for the interconnectivity structure of the whole European territory by moving beyond the straightforward catch-all geographical proximity and considering connectivity patterns more closely related to real social and economic relationships (Corrado & Fingleton, 2012).[11]

3. Estimation Strategy and Model Specification

In order to estimate the KPF model, it is necessary to select the most adequate specification in order to properly account for the interconnectivity structure among the European regions and thus provide a more reliable estimate of the impact of both internal and external endowments of R&D and human capital on patenting activity.

As argued in Section 2, innovation activity is likely to exhibit cross-regional dependence due to the emergence of a number of interactions among agents, firms and institutions located in different regions. On the basis of a preliminary investigation, we rule out that such dependence can be considered as a nuisance yielding non-spherical errors since spatial lagrange multiplier (LM) tests indicate the presence of spillovers effects.[12] The occurrence of spillovers is in line with evidence on increasing returns to scale and regional disparities induced by agglomeration effects, which have been rationalized by the endogenous growth (starting with Romer, 1986) and new economic geography theories. According to the taxonomy suggested by Anselin (2003), spillovers could be local or global in nature and can be represented by basically three main spatial specifications: the spatial least squares model (SLX), which features local externalities captured by the spatially lagged exogenous variables; on the contrary, the SAR, thanks to the spatial lag of the dependent variable, yields global spillovers. Both kinds of externalities are featured by the third encompassing model, the spatial Durbin model (SDM), which includes spatial lags for both the response and the explanatory variables. Clearly, discriminating among these different specifications can be very difficult; as argued in Anselin (2003), the problem can be approached either from an entirely empirical perspective by relying on specification tests, or on the basis of substantive theoretical arguments which identify a priori the nature of externalities.

In light of the knowledge transmission mechanism described in the theoretical section, innovation externalities are believed to be more global in nature since all locations in the system are assumed to be related to each other through a multi-dimensional structure of networks and interactions. On these grounds, we first focused on the estimation of the general Spatial Durbin model. However, this specification yields implausible results with spillover effects being either not significant or with the wrong sign.[13] This result may be due to the intrinsic characteristics of the SDM specification, which entails a very complex externalities structure, and puts too strong a requirement on the data, especially at the territorial level considered in this study (NUTS 2 regions). Moreover, at such regional scale, it is reasonable to argue that the enhancing effects on knowledge production transmitted by proximate regions are more likely related to their innovation realizations rather than to their own efforts to produce them.

Therefore, on the basis of these substantive arguments, we proceed by considering the SAR model. Conditioned on our sample data, it turned out to provide an adequate specification of the global externalities governing the diffusion process of innovations. The related structural model implies that the effect of a given explanatory variable is the result of all the interactions among regions that have taken place across space and over time. Identification of the effects is obtained on the basis of the decaying behaviour of the distance or similarity measures. Thus, inference on the estimated coefficients allows to explain the interconnectivity pattern for all the locations as a function of the exogenous variables.[14] Moreover, it is worth emphasizing that although the spatial lag of the dependent variable might in principle pick up factors different from knowledge spillovers, this is very unlikely in the case of the models proposed in this paper because we find that such spillovers remain positive and significant even after controlling for a comprehensive set of possible confounding factors; namely, country-specific ones (27 country dummies are included), GDP per capita, industrial specialization structure, agglomeration and social capital.

In modelling the regional innovation activity, we adopt a specific-to-general approach, starting from a SAR specification which models the interconnectivity among regions by considering one proximity measure at a time. We begin with the proximity most commonly used in empirical studies, i.e. the geographical one, and then we proceed with the other ones. In order to account for the complementarity among them, ideally it would be preferable to specify a comprehensive model which accounts for all possible proximity factors at the same time. This would require solving an order four-multivariate optimisation problem over the range of feasible values for the autoregressive parameters and thus would entail the development a new spatial econometric toolbox, which, however, goes beyond the scope of this study. As a matter of fact, in the spatial econometric literature only a variant of the spatial lag model with two spatially lagged terms for the dependent variable has been proposed so far (Lacombe, 2004). Therefore, in this study, proximity complementarity is preliminarily analysed by adopting such a variant of the SAR model and deriving, in a later phase, encompassing results by resorting to model combining techniques.

Before proceeding with the detailed discussion of the results, it is worth recalling that in the case of the SAR model, the effects of the explanatory variables no longer coincide with the estimated coefficients because of the presence of the spatially lagged dependent variable; this induces feedback loops and spillover effects generated by the dependence structure of the spatial units. The *total* effect caused by a change in one explanatory variable can thus be decomposed into the *direct* effect (the change in region *i*'s dependent variable caused by a change in one of its own regressors plus the feedback effects) and the *indirect* or spillover effects (the change in region *i*'s dependent variable caused by a change in region *j*'s regressor). It is worth noting that feedback and spillover effects occur over time through the simultaneous system of interdependence among regions so that the effects have to be considered as the result of a new steady-state equilibrium. LeSage & Pace (2009) propose summary scalar measures for direct, indirect and total effects along with their dispersion measures, which allow to draw inference on their statistical significance.

4. Empirical Results

4.1. Proximities and Networks: A Preliminary Comparison

In this section, we present the results of the SAR model estimated by using the four proximity dimensions one at a time; this first stage analysis allows to carry out comparisons with the previous empirical literature. It is important to remark that all regressions include a full set of national dummies to account for unobserved factors shared among regions within the same country. The inclusion of the country dummies allows also to control for institutional elements such as common language, laws and norms which, being shared by agents, tend to reduce transaction costs and the degree of uncertainty favouring the cooperative behaviours in the regional context (Maskell & Malmberg, 1999; Gertler, 2003).

Following the extensive analysis done by Marrocu et al. (2013), the geographical matrix G is confined to the range 0–600 km since the spatial spillovers are localized and limited in space.[15] Similar considerations apply to the technological matrix T, which generates relevant spillovers only when the similarity index between the two regions is above the threshold of the 0.5 value.

Note that each proximity matrix is maximum-eigenvalue normalized; as emphasized in Kelejian & Prucha (2010), such a normalization is sufficient and avoids strong undue restrictions, as it is the case when the row-standardization method is applied. Moreover, symmetry and the importance of absolute, rather than relative, distance is maintained.[16]

The estimation results for the four KPF models based on a single proximity measure are reported in Table 2. An interesting outcome is the low variability of the estimated coefficients both for the input variables and for the controls. Considering the estimated effects in detail, the total elasticity for R&D goes from 0.19, when the regional connectivity is proxied by the social matrix, to 0.33 in the technology proximity-based model. In the latter model, the highest elasticity is also found for human capital (1.95), while the organizational-based model yields its lowest value (1.64). Thus, the first important result is that human capital is more effective than formal research expenditure in determining knowledge production at the regional level. We find that the total impact of human capital is always higher with respect to R&D in all models, ranging from a multiple of around six in the model with technological similarity to above nine in the model with social networks. As the creation of new knowledge is often based on informal learning processes and on the ability to exploit external knowledge, a well-educated labour force plays a key role in these processes. It is also worth noting that indirect effects are almost always significant and sizeable for human capital, accounting for up to 32% of the total effect in the case of the technology based model and 16% with the geography based one.

Comparisons with previous similar studies on European regions, where no direct/indirect/total effects were reported, could be made only on the basis of the estimated inputs' coefficients. Our R&D estimated coefficients are similar to the one of 0.26 reported by Moreno et al. (2005) for 17 countries, while Bottazzi & Peri (2003) present a higher value of 0.8 for 86 regions in EU12. For human capital, the only two comparable studies are the one by Greunz (2003) for 153 European regions and the one by Usai (2011) for 342 regions in OECD countries, who present point estimates of 2.0 and 1.0, respectively.

As for the controls, the GDP per capita indicator and the manufacture specialization structure exhibit positive and significant coefficients across the four models, indicating that knowledge creation exhibits a significant correlations with both high-income levels and manufacturing productions. On the other hand, social capital and population density turn out to be not significant; for the latter it is plausibly because the agglomeration effects it was meant to capture are already accounted for by the GDP variable.[17]

Turning to the coefficient of the lagged dependent variable, the first remarkable outcome is that it is always positive and statistically significant in all

Table 2. KPF – SAR models with different proximity measures: geographical (G), technological (T), social (S) and organizational (O)

Dependent variable: Patents, 2005-2007 average per capita values								
	1		2		3		4	
Proximity matrix	G		T		S		O	
Production inputs								
R&D	0.224**	(2.233)	0.222**	(2.239)	0.170*	(1.655)	0.181*	(1.772)
Human capital	1.613***	(5.174)	1.330***	(4.222)	1.572***	(5.039)	1.537***	(4.917)
Control variables								
GDP per capita indicator	0.470***	(2.723)	0.594***	(3.609)	0.522***	(3.081)	0.538***	(3.189)
Manufacture specialisation	0.870***	(4.911)	0.832***	(4.758)	0.956***	(5.548)	0.977***	(5.665)
Population density	0.028	(0.419)	0.057	(0.894)	0.046	(0.698)	0.047	(0.718)
Social capital	−0.009	(−1.116)	−0.003	(−0.404)	−0.008	(−0.990)	−0.007	(−0.958)
Spatial lag (ρ)	0.156**	(2.321)	0.306***	(3.418)	0.091**	(1.999)	0.058*	(1.766)
Country dummies	Yes		Yes		Yes		Yes	
Square Corr (actual, fitted values)	0.836		0.839		0.834		0.834	
Effects estimates[a]								
R&D								
Direct	0.224**		0.222**		0.170*		0.181*	
Indirect	0.044		0.103*		0.016		0.010	
Total	0.268**		0.325**		0.186*		0.192*	
Human capital								
Direct	1.613***		1.330***		1.591***		1.539***	
Indirect	0.311*		0.615**		0.164*		0.096	
Total	1.924***		1.944***		1.755***		1.635***	
Diagnostics								
LM error test for SAR model residuals	0.120		0.010		0.104		0.000	
p-value	0.729		0.919		0.747		0.984	

Notes: Observations: 276 regions. All variables are log-transformed. For all the explanatory variables the values are averages over the period 2002–2004. All proximity matrices are max-eigenvalue normalized. Asymptotic *t*-statistics in parenthesis; significance: ***1%; **5%; *10%.

[a] We report only the effects for the main interest explanatory variables.

four models, signalling that each of the different proximity measures captures the cross-regional dependence arising from the knowledge transmission mechanisms described in Section 2. More specifically, the strongest association (the spatial lag coefficient is equal to 0.31) is found for the technological proximity, which turns out to be the most important channel of knowledge spillovers, whilst geographical proximity ranks second (0.16). As far as the network dimensions are concerned, they have a relatively more modest role: the spatially lagged dependent variable exhibits a coefficient of 0.09 when it is computed using the social proximity and 0.06 in the case of the organizational one.

Comparing our results for the lagged dependent variable coefficient with previous studies, it turns out that the coefficient of the geographical proximity matrix goes from 0.09, for EU regions in Moreno et al. (2005), to 0.18 in Usai (2011) that refers to both the USA and EU, to a much higher value of 0.4, for the USA in Carlino et al. (2007). For the technological proximity, previous comparable studies are that of Moreno et al. (2005) with a lag coefficient equal to 0.05 and that of Greunz (2003) with an estimate of 0.25, who also emphasizes that technological association is stronger than the geographical one. Our findings related to a lower effect of the social dimension confirm previous results by Maggioni et al. (2007), who found that geographical proximity has an effect that is double with respect to the relational one.

Finally, it is worth noting that the diagnostics tests (bottom panel of Table 2) are not significant across the four models, indicating that there is no remaining spatial correlation in the residuals; therefore, all the proximity measures considered are adequate candidates for capturing regional interconnectivity. This result lends further support to the SAR model, since, had the spatial functional form been mis-specified, this would have shown up in the residuals yielding significant diagnostic tests.

4.2. Models with Pairs of Proximity Matrices

As it has been remarked in the literature, the different types of proximity are expected to exhibit complementary traits as they represent knowledge transmission channels which reinforce each other over time and across space (Mattes, 2012). From the empirical point of view, this implies that one should include all the kinds of proximity in the same estimation model. Unfortunately, the available estimation codes for spatial econometrics do not allow this first best solution, and we have to look for second-best procedures.

In this section, we present the results for the SAR models estimated by including two different proximity-lagged terms at a time, in order to account for complementarities between pairs of knowledge spillovers channels. The two-weight matrix SAR model is specified as: $Y = X\beta + \rho_1 W_1 Y + \rho_2 W_2 Y + \varepsilon$, and it requires to solve a bivariate optimisation problem over the range of feasible values for the parameters ρ_1 and ρ_2.[18] This model specification was first proposed by Lacombe (2004) to carry out a policy spending evaluation analysis within a spatial framework.[19] Such models are a useful estimation device when the connectivity among spatial units cannot be entirely captured by the traditional geographical measures (distance, contiguity and nearest-neighbours) since it also features other a-spatial kinds of links.

Results are reported in Table 3 which shows that, remarkably, most of the previously discussed results maintain their strength and significance. This is the case

Table 3. KPF – SAR models with two proximity dimensions

	Dependent variable: Patents, 2005-2007 average per capita values											
	1		2		3		4		5		6	
Proximity matrices included	G, T		G, S		G, O		T, S		T, O		S, O	
Production inputs												
R&D	0.233**	(2.379)	0.189*	(1.895)	0.196**	(1.966)	0.175*	(1.780)	0.184*	(1.874)	0.171*	(1.696)
Human capital	1.383***	(4.546)	1.616***	(5.220)	1.590***	(5.136)	1.335***	(4.377)	1.288***	(4.222)	1.562***	(5.009)
Control variables												
GDP per capita indicator	0.477***	(2.930)	0.437***	(2.639)	0.440***	(2.660)	0.528***	(3.236)	0.542***	(3.321)	0.523***	(3.135)
Manufacture specialisation	0.724***	(4.313)	0.871***	(5.095)	0.881***	(5.156)	0.809***	(4.807)	0.829***	(4.919)	0.961***	(5.584)
Population density	0.012	(0.183)	0.014	(0.212)	0.011	(0.166)	0.028	(0.446)	0.027	(0.428)	0.045	(0.690)
Social capital	−0.005	(−0.656)	−0.009	(−1.181)	−0.009	(−1.175)	−0.004	(−0.514)	−0.004	(−0.473)	−0.008	(−0.990)
Spatial lag - 1st proximity matrix	0.162**	(2.467)	0.136**	(1.986)	0.145**	(2.146)	0.317***	(3.533)	0.325***	(3.607)	0.070	(0.870)
Spatial lag - 2nd proximity matrix	0.310***	(3.468)	0.071	(1.507)	0.049	(1.506)	0.100**	(2.205)	0.069**	(2.169)	0.018	(0.314)
Country dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Square Corr (actual, fitted values)	0.842		0.837		0.837		0.842		0.842		0.834	
Estimated effects[a]												
R&D												
Direct	0.234**		0.191**		0.196**		0.176*		0.186*		0.173*	
Indirect	0.237		0.052		0.048		0.140		0.128		0.017	
Total	0.471**		0.243*		0.245**		0.316*		0.314*		0.190*	
Human capital												
Direct	1.383***		1.616***		1.590***		1.335***		1.288***		1.562***	
Indirect	1.396*		0.437**		0.388**		1.052**		0.871*		0.152	
Total	2.780***		2.053***		1.979***		2.387***		2.159***		1.714***	

Notes: Observations: 276 regions. All variables are log-transformed. For all the explanatory variables the values are averages over the period 2002–2004. All proximity matrices are max-eigenvalue normalized; G = geographical (0–600 km); T = technological (index >0.5), S = social and O = organizational. Asymptotic *t*-statistics in parenthesis; significance: ***1%; **5%; *10%.

[a] We report only the effects for the main interest explanatory variables.

for the main determinants of knowledge production—R&D and human capital—the controls and the spatially lagged dependent variables. In particular, the strength of the geographical connectivity is confirmed, for all the three models where this is considered (first three columns), with an estimated simple average value of 0.15. The same applies for the proximity measure based on technological similarity, which exhibits a relatively higher impact (average value of 0.32) when compared with the geographical one. The regional connectivity based on both the social and the organizational proximity shows a weaker degree of dependence, with an estimated coefficient which, on average, is equal to 0.08 and 0.05, respectively. Note that when these matrices are included together (last column in Table 3), both coefficients of the spatially lagged terms are no longer significant, signalling a sort of multicollinearity problem. This is possibly due to the fact that, as remarked in Section 2.2, there is some overlapping in the information contained in the two matrices.

As far as the knowledge production inputs, R&D and human capital are concerned, the results provided in the previous section are broadly confirmed. The estimated coefficients are significant in all the six estimated models. In the bottom panel of Table 3, we also report the estimated direct, indirect and total effects. It turns out that human capital exhibits higher impacts, both direct and indirect, with respect to R&D, thus proving to be highly productivity-enhancing for regional innovation activities.

Finally, it is worth highlighting that spillover effects are significant for all models but only in the case of human capital, as it was the case for the specifications presented in Table 2. This result is consistent with the claim that R&D expenditure *per se* is not sufficient to activate knowledge externalities[20] and this, in turn, calls for policies and production devices capable of increasing the absorptive capacity of the regional systems of innovation.

Overall, the model that yields the highest total impacts is the first one, when the interdependence among regions is captured by the geographical and the technological patterns. Note that spillover effects are rather relevant, as in certain cases, they are almost of the same order of magnitude as the direct ones.

4.3. Model Comparison and the Overall Effect of Knowledge Spillovers

Although all the estimated models provide promising evidence on the role played by the knowledge productive inputs and on the relevance of different regional transmission channels, it is quite difficult to select a preferred model among those presented in Tables 2 and 3.

Various approaches may be adopted to carry out a selection from the estimated models, some are based on testing procedures (Kelejian, 2008; Burridge & Fingleton, 2010), and others on the use of information criteria or on the computation of posterior model probabilities or Bayes' factors (LeSage & Pace, 2009). In this paper, we apply the Akaike information criterion (AIC) to obtain a possible ranking of the estimated models. This has the advantage of avoiding several model comparisons, as would be the case with the testing approach. Moreover, once the 'best' model, defined as the one which minimize the AIC, is found; relative probabilities of minimizing the information loss can be computed for each remaining model as a function of the difference between its own AIC value and the minimum one. A weighted multi-model could be then obtained on the basis of such probabilities (Burnham & Anderson, 2002).

The computed AIC values for the 10 non-nested estimated models of Tables 2 and 3 point out that the 'best' model is the one based on the geographical and technological proximity (Model 1 of Table 3), followed by Models 4 and 5 of Table 3; the other models seem to provide relatively less support.[21] It is worth remarking that the best-performing models are found among those which allow for a certain degree of complementarity among the proximity measures, and that such a complementarity turns out to be rather relevant when the technology interconnectivity is involved.

On the basis of the AIC values, we thus compute the relative probabilities[22] described above in order to carry out a tentative exercise to figure out the overall spillover effects when all potential proximities are taken into account. This is, necessarily, a post-estimation computation carried out to combine the inference drawn from the four one-matrix models (Table 2) and the six two-matrix models (Table 3). The overall effects are computed analytically on the basis of the weighted average of the estimated coefficients for R&D and human capital obtained from the 10 models, which are 0.21 and 1.35, respectively, and the weighted average estimates of the coefficients for the four different kinds of proximity lagged terms. For all measures, the weights are represented by the models' relative probabilities.

In order to ease the comparison of the strength of proximity dependence, the estimated coefficients of the lagged dependent variables for all combinations of matrices are summarized in Table 4, where the main diagonal reports the lag coefficient estimated in the single-proximity models, while the off-diagonal entries are the coefficients obtained from two-proximity models. The last column reports the weighted average calculated on the basis of the models' probabilities described above. We observe that, on average, dependence among regions is stronger when it is captured by the technological proximity (the average of the estimated coefficients for the technological lagged dependent variable is 0.31). The connectivity appears weaker for the geographical proximity (0.072) and the social one (0.025), while the lowest dependence is found for the organizational (0.016) proximity.

In Table 5, we report the direct, indirect and total effects computed by deriving an all-proximity multiplier for both R&D and human capital on the basis of the weighted averages of the relevant parameters. From this computational exercise, considering the calculated effects at face value, it is possible to design interesting what-if scenarios for the European regions. For example, if we conjecture an

Table 4. Comparing estimated coefficients of spatial lags for different proximities measures

	Second proximity matrix included				
Proximity matrix considered	G	T	S	O	Weighted average[a]
Geographical proximity G	0.156	0.162	0.136	0.145	0.072
Technological proximity T	0.310	0.306	0.317	0.325	0.310
Social proximity S	0.071	0.100	0.091	0.070	0.025
organizational proximity O	0.049	0.069	0.018	0.058	0.016

Notes: Diagonal entries are the estimated rho coefficients of the Table 2 one-weight matrix SAR models; Off-diagonal entries are the estimated rho coefficients of the Table 3 two-weight matrix SAR models; All the regressions include also the institutional proximity measured by the country dummies.
[a] Weights are given by model probabilities obtained on the basis of AIC values.

Table 5. Combined effects of the KPF inputs

	Weighted average
R&D	
Direct	0.207
Indirect	0.113
Total	0.320
Human capital	
Direct	1.350
Indirect	0.741
Total	2.091

Notes: Dependent variable: Patents, 2005–2007 average per capita values. Effects are computed on the basis of the weighted averages for the inputs coefficients and the spatial autocorrelation coefficients. Weights are given by model probabilities obtained on the basis of AIC values.

increase of 10% of the R&D/GDP ratio so that the actual European average value increases from 1.4% to 1.56%, this should generate a total increase of patents (per million population) of 3.2 units, from the observed average value of 105 to the new computed value of 108.2 (with 65% of the change attributable to direct effects and the remaining 35% to spillovers). On the contrary, if the 10% increase refers to human capital, entailing an increase in the share of graduates from the European average value of 10.5% to 11.6%, this would yield a total increase of 20.9 patents (per million population), 13.5 units generated by regional internal efforts and 7.4 units by knowledge spillovers, made effective by the absorption capacity of the local well-educated labour force.

We think that the computation of the all-proximity multiplier for the two KPF inputs, even with all the caveats that this kind of exercise requires, provides useful indications on the relative role and importance of R&D and human capital in determining innovation. Moreover, the finding that, on average spillovers account for one-third of the total effect calls for coordination policies at regional, national and European level. These policies should recognize that regions are part of different geographical, cognitive, social and organizational structures and networks and that these dimensions require appropriate actions to favour their specific positive impacts.

5. Conclusions

In this study, we have investigated the complementary role played by four different kinds of proximity in driving knowledge transmission across the European regional innovations systems. There is by now a widespread consensus among scholars that the transfer of knowledge is significantly favoured not only by spatial closeness among agents involved in the innovation process but also by the relations they develop within a-spatial networks, such as those shaped by institutional, technological, social and organizational links.

Nonetheless, in previous empirical literature, the attention has been mostly focused on just one kind of proximity, usually the geographical one or, to a lesser extent, the technological one. At the same time several authors (Boschma, 2005; Mattes, 2012) have argued that, with the increasing level of economic and institutional integration within the European production context, the concurrent effect of different proximity dimensions can no longer be overlooked.

This paper contributes to the current debate by operationalising four proximity dimensions for the European regions and by analysing, for the first time, their complementary role in enhancing innovation diffusion. Our empirical analysis is carried out for a sample of 276 European regions within the prevailing KPF framework where the response variable is represented by the patents stock, while the main internal inputs are R&D investments and human capital. In the case of our sample data, the SAR model turned out to be the most adequate specification to assess the influence of external factors transmitted along different dimensions in the form of spillovers. Beside the traditional geographical proximity, we also consider other regional interconnectivity channels represented by the technological base, measured by the specialization productive structure, as well as the social and organizational networks, measured on the basis of inventors and applicant-inventor relationships occurring across different regions. The overall four-proximity multiplier for both R&D and human capital is derived on the basis of model averaging techniques applied to the various non-nested estimated models.

Four main results emerge from our empirical analysis. First, in all models considered, human capital is more innovation enhancing than R&D: its total effect, which includes knowledge spillovers transmitted by proximate regions, is on average seven times higher than the one associated with R&D expenditure. Second, spillover effects are significant for human capital in all models considered. This original finding indicates that it is the endowment of skilled and well-educated people which ensures that knowledge produced by external sources can be effectively absorbed and transformed into new ideas and innovations, while high levels of R&D do not seem to grant the same desirable result. Third, all proximity dimensions considered are found to play a significant role in channelling knowledge flows. Comparing the strength of regional association captured by the different 'closeness' dimensions, the technological one ranks first, followed by the geographical one; the weakest relations are found for the social and organizational networks. Fourth, we find evidence of important complementarities among the different proximities. This turns out to be rather relevant in all the cases in which the technological connectivity is involved, signalling that a common cognitive base appears to be a crucial element for conveying knowledge across regions.

Overall, the analysis presented in this paper confirms the great degree of complexity of the knowledge creation and diffusion process in the highly integrated European economic context. Our findings highlight the prominent role played by human capital in driving knowledge transfers and innovation creation and the importance of extending and strengthening regional interconnectivity along both spatial and a-spatial dimensions.

We expect the key findings summarized above to be reinforced by further investigations overcoming the limitations of the current study, which were fully discussed in Sections 2 and 3 and are mainly related to the methodology and the data. Regarding the methodology, the optimal estimation strategy would require the specification of a comprehensive model which includes all proximity dimensions to fully account for their complementarities. The data limitation is mainly related to the purpose of the present study, that is, to provide a general analysis of the knowledge transmission mechanisms throughout Europe, which has required the use of aggregate data since detailed information is currently available only for limited geographical contexts or for specific productive sectors.

We plan to extend and improve our research agenda to deal with the above limitations. First of all, it is important to investigate explicitly the agents' decision processes which are behind knowledge transmission and how such processes are affected by each type of proximity. Moreover, forthcoming analyses could benefit from the use of more disaggregated data at the sectoral and territorial level. Sectoral analysis is expected to provide insights on which economic sectors are more conducive to knowledge spillovers, on the relative importance of intra- vs. inter-sectoral technological flows and on the specific role of sector variety and relatedness on innovation and growth. A finer territorial scale, restricting the analysis to a few specific countries, would allow to use better qualitative and quantitative information on important phenomena such as migration, commuting, formal and informal agreements and exchanges. Such information should prove instrumental to build better indicators of economic, social and organizational interactions, in order to discriminate between intended and unintended spillovers as well as between pecuniary and pure technological externalities.

Notes

1. More generally, Abramovitz (1986) links the capacity of a country to absorb more advanced technologies to its ‘social capability’, formed up by human capital endowments and political, commercial, industrial and financial institutions.
2. See also the recent contribution by Harris et al. (2011) for a discussion on the specification of the weight matrix in spatial econometrics models.
3. For 23 European countries, we consider the NUTS 2 regional level, while for 6 small countries (Cyprus, Estonia, Lithuania, Luxembourg, Latvia and Malta) the national (NUTS 0) level is analysed.
4. In a preliminary investigation, we also estimate the more flexible functional form represented by the translog production function. However, once the basic KPF model is augmented with controls and spatial covariates, all the non-linear terms in RD and HK turn out to be not significant. For this reason, we prefer to carry out the empirical analysis by adopting the widely applied Cobb-Douglas specification. It is worth noting that this choice enables us to compare our results with those provided in previous contributions.
5. Basile et al. (2012) in a study on regional productivity growth employ a similar measure of relational proximity.
6. Among the few available indicators of technology output at the local level, patents are the most frequently used, even though all researchers admit that they have some drawbacks (Griliches, 1979). For example, one should not forget that the value distribution of patents is skewed and that many inventions are not legally protected because they are not patentable or inventors may prefer to protect their inventions using other methods, such as secrecy.
7. In case of multiple inventors, we assign a proportional fraction of each patent to the different inventors’ regions of residence. Data on patents are currently gathered in the OECD REGPAT database (Maraut et al., 2008), which provides information on inventive activity and its multiple dimensions (e.g. geographical location, technical and institutional origin, individuals and networks).
8. Following Usai (2011), the GDP per capita is included as an indicator which takes value 1 for regions with a GDP per capita level above the European average and zero, otherwise. The indicator is preferred to the level of the variable since the latter induces multicollinearity problems with the other regressors, in particular with the share of R&D.
9. In a preliminary version, institutional proximity, based on a weight matrix whose elements take value 1 if two regions belong to the same country and zero otherwise, was considered too. However, this attempt did not provide statistically significant results since such institutional matrix partially overlaps information contained in the set of country dummies.
10. It is worth noting that the proposed proximity measures show a low degree of correlation, with the exception of the social and organizational matrices which exhibit a high overlapping (the sample correlation coefficient is estimated in 0.74) since they are both derived from patenting activities.
11. Anselin (2010) emphasizes the need for more adequate representation of spatial processes, derived on the basis of agents’ social and economic interaction.
12. With respect to Model (2), the LM-error test has a p-value of 0.86, while the LM-lag test exhibits a p-value of 0.02. Note that the preliminary analysis was mostly based on the geographical proximity.
13. The SLX model and the spatial Durbin error model yielded the same kind of results for the lagged explanatory variables.

14. It is worth noting that the results obtained from the spatial specifications, discussed above, may be influenced by spatial heterogeneity. Differently, from the case when panel data are used, which allow to treat the problem by including fixed or random cross-section and time effects, it is difficult to deal with heterogeneity when using cross-section data. However, the inclusion of three different control variables along with the complete set of national dummies is expected to alleviate the problem. The estimation of more involving models, which explicitly deal with spatial heterogeneity, such as those comprising the existence of spatial regimes or varying coefficients over space, goes beyond the scope of this paper.
15. The literature has emphasized the localized nature of geographical knowledge spillovers which are often limited in space (Doring & Schnellenbach, 2006). Previous findings for EU15 regions show that knowledge spillovers are confined to a range of around 300 km (Bottazzi & Peri, 2003; Moreno et al., 2005), while a crucial distance of 600 km is found by Dettori et al. (2012).
16. When the proximity weight matrix is capturing a 'distance decay' type of economic behaviour 'scaling the rows so that the weights sum to one may result in a loss of that interpretation' (Anselin, 1988, p. 24).
17. Similar results are obtained when the population density variable in replaced by the Settlement Structure Typology (ESPON Project, 1999) variable. Differently from density, the latter is a discrete variable which accounts for both population density and the existence of urban centres; it takes values from 1 (for regions less densely populated without centres) to 6 (for regions very densely populated with large centres).
18. See LeSage & Pace (2009) for a detailed description of the estimation procedures.
19. We are very grateful to D.J. Lacombe for making available to us the Matlab scripts to estimate two-weight matrix SAR models.
20. This is likely due to the fact that a large part of R&D expenditure is represented by researches' wages, whose effect is evidently captured by the human capital variable. Moreover, it is often the case that expenditures classified as R&D are not directly related to research activities but rather to infrastructures and logistics, so they have basically no effect on proximate regions. A similar result has been found by Crescenzi & Rodriguez-Pose (2013) for the case of the USA.
21. The same ranking of the models is obtained when computing either the Bayesian or the Hannan–Quinn information criteria.
22. The probability for model i are computed as: $\text{prob}_i = \exp\left(-(\text{AIC}_i - \text{AIC}_{\text{MIN}})/2\right) / \sum_j^M \exp\left(-(\text{AIC}_j - \text{AIC}_{\text{MIN}})/2\right)$, where M is the number of models and AIC is the bias-adjusted value of the AIC.

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