PROXIMITY, NETWORKS AND KNOWLEDGE PRODUCTION IN EUROPE

Emanuela Marrocu, Raffaele Paci, Stefano Usai

University of Cagliari, CRENOS

Abstract
This paper aims at investigating the role of various dimensions of proximity on the innovative capacity of a region within the context of a knowledge production function where we consider as main internal inputs R&D expenditure and human capital. We intend to assess if, and how much, the creation of new ideas in a certain region is the result of a knowledge flows coming from proximate regions. In particular, we examine in details the concept of proximity combining the usual geographical dimension with the institutional, technological, social and organizational proximity. The analysis is implemented for an ample dataset referring to 276 regions in 29 European countries (EU27 plus Norway, Switzerland) for the last decade.
Results show that human capital and R&D are clearly essential for innovative activity but with an impact which is much higher for the former factor. As for the proximity and network effects, we find that geography is important but less than technological and cognitive proximity. Social and organizational networks are also relevant but their role is more modest. Finally, most of these proximities prove to have a complementary role in shaping innovative activity across regions in Europe.

Keywords: knowledge production, spillovers, proximity, networks, human capital
JEL: C31, O31, O18, O52, R12

Acknowledgments: The research leading to these results has received funding from the ESPON project KIT, Knowledge, Innovation, Territory. We would like to thank Barbara Dettori and Marta Foddi for excellent research assistance. We have benefited from valuable comments by participants to the conferences ERSA in Barcelona and EU-REAL in Alghero.

This version, October 2011

1. Introduction

According to the European Council, regional policy, within the Europe 2020 strategy, is essential in unlocking the growth potential of the EU by promoting innovation in all regions. In this perspective, local authorities have a central role, being the institution which deals with all the actors involved in the regional innovation system and its dynamics.

The capacity of a region to generate, transmit and acquire knowledge and innovation depends on many factors: investment in R&D, work force experience, education and training, collaboration networks, technology transfer mechanisms, mobility of researchers, among many others. In particular, the literature has distinguished between the creation of new ideas and inventions and the absorption of innovations generated in other regions. Several works both on the theoretical (Grossman and Helpman, 1990; Rallet and Torre, 1999) and the empirical side (Jaffe, 1989; Coe and Helpman, 1995) have argued and shown that innovation depends on investments in research, knowledge and human capital as much as on interactive learning and on ideas circulation.

Both aspects are strictly related to the concept of proximity across economic agents and how this may affect their ability to connect and, possibly, cooperate within networks. This concept has several dimensions and interpretations, the most common of which applies to geography: spatial concentration is believed crucial in the dynamics of innovation thanks mainly to local spillovers. However, local relations go often together with wider links and networks. In this respect, the spatial dimension may be just a counterpart of other forms of a-spatial proximity: institutional, cognitive or technological, social or relational and organizational, as exhaustively argued and commented by Boschma (2005).

The main object of this paper is to analyse the interaction of these internal and external factors in determining technological performance of European regions. We want to understand how much of the regional inventive activity depends on intra-regional characteristics (mainly R&D expenditure and human capital) and how much on absorptive capacity, i.e. the ability to exploit inter-regional spillovers. The original feature of this contribution is that we extend the usual model of the Knowledge Production Function (KPF) in order to assess the role of different types of proximity and networks in channeling technological spillovers across regions.

Therefore, we try to address the following questions: 1) what is the balance of internal and external factors in shaping regional innovative performance? 2) what kind of proximity drives knowledge spillovers across regions? 3) are these externalities substitute or complementary?

These questions refer to the European regional setting, which represents an extremely interesting case of study because of the high heterogeneity of regions with respect to economic as well as innovative performance (Hollander et al., 2009). The analysis is implemented for an ample dataset referring to 276 regions in 29 countries (EU27 plus Norway, Switzerland) in the first decade of the new century. More specifically, we try to measure the impact of local factors at the beginning of the decade (2002-2004) on innovative performance measured at the second half of the decade (2005-2007). Further, the role of external factors channeled by different dimensions of proximity and network, producing intended and unintended spillovers, are assessed thanks to spatial econometric techniques. We use distinct matrices for each of these dimensions in order to test, first singularly and secondly in pairs, the relative importance of spatial and a-spatial neighborhoods. In particular, it is worth noting that the use of two-weight matrix models, albeit a second best with respect to an all-encompassing model, represents the sole technique currently available. A technique which has never been implemented within the KPF framework.

Main results confirm the importance of investment in R&D and reveal the even greater role of human capital in enhancing innovative activity. More importantly, our empirical analysis shows that geography is not the only dimension which may help knowledge diffusion and not even the most important one. Technological proximity always proves the most relevant, while social and organizational networks may have a complementary decisive role. All these results have potentially fruitful policy consequences.

The paper is structured as follows. Section 2 analyses the different concepts of proximity used in the empirical literature on knowledge production function and presents our proximity measures across regions. Section 3 deals with the definition of the empirical KPF model, the description of the variables and the discussion of some estimation issues. Section 4 presents the results of the KPF model estimated using one proximity matrix at a time. In section 5 the issue of complementarities among proximity dimensions is investigated and the overall effect of knowledge spillovers is computed. Section 6 concludes.

2. Proximity dimensions: concepts and measures

The idea that technological progress is a complex process which combines the direct production of innovation at the local level together with the absorption of the knowledge produced in the global setting is by now widely shared. Endogenous growth and New Economic Geography literature provide theoretical backing to this idea, which is based on the presence of knowledge spillovers both within and across regions and countries. Such 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 can access information less costly and they can share tacit knowledge (a local public good) through face to face contacts. Nonetheless, the French School of Proximity argues that geographical proximity is neither necessary nor sufficient and that there may be a separate role for a-spatial links among economic entities (see Carrincazeaux and Coris, 2011, for a recent review). The exchange of knowledge and technological interdependence, in other words, may be related, according to Boschma (2005), to proximities across agents with respect to at least four other dimensions: institutional, technological (or cognitive), social (or relational) and organizational.

In this section we first provide a definition of the five concepts of proximity and analyse how they have been measured in the empirical studies based on the KPF and then we suggest our measures for the case of the European regions.

2.1 Definitions and previous literature

Institutional proximity means that the effective transmission of knowledge may be facilitated by the presence of a common institutional framework. Institutions, such as laws and norms, can provide a set of standard procedures and mechanisms which are shared by agents and, therefore, taken for granted. This mutual endowment proves relevant in reducing uncertainty and lowering transaction costs and, thus, favouring cooperative behaviours in the regional context (Maskell and Malmberg, 1999; Gertler, 2003)

Technological (or cognitive) proximity indicates that knowledge transfer requires appropriate absorptive capacity (Cohen and Levinthal, 1990), which entails, among others, an homogenous cognitive base with respect to the original knowledge in order to understand and process it effectively[1]. In practical terms we expect that economic agents which share a similar knowledge base, or territories which have in common a similar specialisation structure, can exchange information more easily and less costly, and this may favour innovation.

Social (or relational) proximity refers to the fact that economic relationships may reflect social ties and vice versa (Granovetter, 1985). In the context of innovation processes, this implies that social closeness facilitates firms capacity to learn, absorb external knowledge and innovate since this breeds trust which lowers transaction costs and facilitate collaboration. This aspect can be particularly relevant in a risky and uncertain phenomenon such as technological progress.

Organisational proximity refers to the relations within the same group or organisation which influence the individual capacity to acquire new knowledge coming from different agents. It thus reduces uncertainty and incentives to opportunistic behaviours since it provides an area of definition

[1] The concept of absorptive capacity does not depend only on cognitive proximity and has a wider application at the level of firms, sectors, regions and nations. In particular, Iammarino (2005) observes that the ability of a region to absorb and generate new knowledge depends on skills which are people- and institution-embodied, that is human capital and R&D investments.

of practices and strategies within a set of rules based on an organizational arrangement (Kirat and Lung, 1999). Such an arrangement can be either within or among firms and takes different forms along a range which goes from informal relations among companies to formally organised firms.

The different dimensions of proximity discussed above can be seen as a critical condition for firms interaction and cooperation aimed at innovation. Boschma and Frenken (2010), in particular, explain how proximity (or similarity) can act as a driving force for the formation and the evolution of networks. The interconnected role of proximity and networks on local innovation performance is going to be analysed thanks to the KPF approach, introduced by Griliches (1979) to study the relationship, at the firm level, between knowledge inputs and outputs. Since then it has been extensively used to analyze how such a relationship works both at the firm and at the territorial level. In particular, regional KPF's have been estimated to assess the role of internal as much as external factors on regional innovation systems. The seminal paper is due to Jaffe (1989), who proves the existence of geographically mediated spillovers from university research to commercial innovation among US metropolitan areas. The main results of this paper have been later extended and strengthened by many other authors who observe the presence of local externalities both within and across regions in the USA (Acs et al., 1992; Anselin et al., 1997; O´hUallacha´in and Leslie, 2007). Most of these studies introduce the concept of geographical proximity and test for its importance by means of spatial econometric techniques.

Along the same vein, several studies have been proposed for the EU regions (Tappeiner et al., 2008; Acosta et al., 2009; Buesa et al., 2010 are among the latest contributions).[2] All in all, these studies find that innovation performance is partly due to internal factors and partly to spillovers which flow from one region to another. Contrary to the studies on the US, some of these papers start introducing other possible dimensions of proximity to assess their role on knowledge production together with the geographical one. In particular Bottazzi and Peri (2003), Greunz (2003) and Moreno et al. (2005) investigate inter-regional knowledge spillovers across European regions, trying to assess if technological proximity influences the creation of new knowledge within European regions. Results show that interregional knowledge spillovers exist both between close-by regions and between regions with similar technological profiles. This indicates that geographical distance is not the only dimension to be investigated and that knowledge spillovers may be affected also by cognitive distance. Furthermore, all these studies consider institutional proximity (measured by means of country dummies) and find it relevant in discriminating among more and less innovative regions.

[2] The only contributions which analyse different continents at the regional level are Crescenzi et al. (2007) for US and EU with data coming from USPTO and EPO respectively and Usai (2011) on OECD regions with homogenous information coming from the Patent Cooperation Treaty.

There are only few contributions which examine the role of social/relational networks[3] together with geographical proximity within a KPF. Maggioni et al. (2007), Kroll (2009) and Ponds et al. (2010) find that both the local neighborhood and the co-operation based connectedness to other regions matter for the local process of knowledge generation. The former paper measures social proximity by means of cooperation networks for the fifth framework programme, the second one uses co-patenting across regions, whilst the latter uses co-publications. Other contributions have introduced various features of inventors' network in a KPF framework: Lobo and Strumsky (2008) for the case of USA MSA's and Miguelez and Moreno (2010) for the European NUTS2 regions. They all find that the scale and extent of networks have a positive impact on innovative performance. However, none of these studies implement this concept in order to measure proximity for each couple of regions but rather as a regional indicator which measures its degree of connectivity and openness.

Finally, to the best of our knowledge, there are no contributions which focus directly on the role of organizational proximity on regional innovation performance. The only partial exceptions is the paper by Sorensen et al. (2006) where organizational proximity is considered as a determinant of knowledge flows proxied by citations. The use of micro data allows to introduce organizational proximity as a binary variable which is equal to unity when the citation comes from employees of the same firm even though they reside in different regions. Another interesting study on the impact of organizational proximity on innovation, even though at the firm level, is Oerlemans and Meeus (2005), who, thanks to survey based micro data on the Netherlands, conclude that interregional relations with business agents (users and suppliers) are conducive to a better innovative performance.

2.2 Our proximity measures at the regional level

In this section we analyze in details the measures of the five types of proximity considered in the KPF estimation[4]; the summary statistics are reported in Table 1.

Geographical proximity. This is the standard and widely used indicator of proximity measured by the distance in Km between the centroids of each couple of regions. This measure is preferred with respect to the contiguity matrix since it allows to consider all the potential

---

[3] The social proximity has been also included in studies of R&D cooperation networks, such as that of Autant-Bernard et al. (2007), who find that the probability of collaboration is influenced by each individual's position within the network and in particular that social distance seems to matter more than geographical distance. In the same vein, Hoekman et al. (2009), with data on inter-regional research collaboration measured by scientific publications and patents in Europe, find negative effects of both geographical and institutional distance on research collaboration.

[4] See the recent contribution by Harris et al. (2011) for a discussion on the specification of the weight matrix in spatial econometrics models.

interactions among regions so that spillovers are not limited to those regions which share a border. The median spatial distance across regions in Europe is 1270 km ranging from a lowest value of 18 km among Belgium regions to the maximum distance, that is 4574 km, between Cyprus and Ireland. In the econometric analysis we use the inverse of the distance so that high values indicates more proximate regions and thus a higher probability to exchange knowledge. Moreover, we will assess which is the most relevant distance range in determining knowledge spillovers.

Institutional proximity. Knowledge is transmitted more easily when individuals and firms share the same institutional framework, a common language and similar cultural, ethnic and religious values. A simple way to account for these time invariant common factors is to include country dummies or, alternatively, model institutional proximity by means of a weight matrix, whose elements take value 1 if two regions belong to the same country and zero otherwise.[5] We anticipate here that the empirical specification based on such a proximity matrix is outperformed by the estimation which includes country dummies to account for the importance of institutional similarity across regions.

Technological proximity. In order to attract new knowledge from outside, firms and regions need to build up an absorptive capacity around the existing knowledge base and carry out technological activity in similar fields. In other words, cognitive capacity is bounded and only companies and regions sharing an analogous knowledge base may exchange information and knowledge and learn from each other. To measure the technological, or cognitive, proximity across regions we have computed a similarity index between region *i* and region *j*, based on the distribution of patenting activity among 44 sectors, defined as:

$$t_{ij} = 1 - \left(\frac{1}{2}\sum_{k=1}^{K=44}\left|l_{ik} - l_{jk}\right|\right)$$

where l_{ik} is the sectoral share of sector *k* in region *i*. The coefficient t_{ij} is defined between zero (perfect dissimilarity of the sectoral distribution) and one (perfect similarity); thus, the higher the index value, the more similar in the technological structure are the two regions, the higher is the probability that they can exchange knowledge. The index has been computed for each couple of regions to build up a technological proximity matrix *T* with generic element t_{ij}.[6]

In Table 1 we see that the two most technologically distant regions (Ionia Nisia and Notio Aigaio in Greece) have an index of 0.05. Interestingly, the higher degree of technological similarity

[5] A similar matrix is used by Paci and Usai (2009) to analyse how institutional factors positively affect the flows of knowledge for the case of EU15 regions.

[6] We have also computed a matrix based on the correlation coefficient among the sectoral patent shares between regions *i* and *j* as in Jaffe (1986) and Moreno et al. (2005). The matrices based on the similarity and correlation coefficients are highly correlated (r=0.91) and they give very similar results; therefore in the following sections we present only the results based on the similarity index.

(0.94) is found in two not spatially contiguous regions, located in different countries: Piedmont in Italy and Niederbayern in Germany. The econometric estimation allows to test if regions with a similar technological specialization, for instance in high tech industries, and therefore with a common cognitive background are more likely to benefit from mutual knowledge flows independently from their geographical location.

In order to test the robustness of the technological matrix based on patenting activity we have computed another matrix based on the sectoral distribution of employment which is available for 17 manufacturing and knowledge intensive service sectors. In section 4.2 we present the results for both matrices and we show that the matrix based on the finer distribution of patenting activity is more able to grasp the cognitive similarity among territorial units favoring the exchange of knowledge.

Social proximity. The main idea is that individuals who have socially embedded relations are more likely to trust each other and therefore to exchange tacit knowledge smoothly. It is clear that social proximity refers mainly to individuals' characteristic and its measurement at the regional level is not an easy task. The approach we follow in this paper is to measure this proximity by means of co-inventorship relations among multiple inventors of the same patent in case they are resident in different regions. As a result, the generic element s_{ij} of the symmetric social matrix S is defined as the number of inventors located in region i which have co-operated with inventors located in region j to conceive a patented invention. In this matrix we do not consider the intra-regional relationships, the principal diagonal elements are therefore set to zero. The rationale is that the number and the intensity of links among inventors located in different regions is able to catch the existence of a social network between regions which facilitates the exchange of knowledge.[7]

Table 1 shows that the number of non-zero links (co-inventorships) in the matrix represents only a small fraction (18%) of all potential relationships, while the remaining 82% of cells is empty. The highest social interaction (137) is reached by the two contiguous German regions of Düsseldorf and Köln, followed by other couples of contiguous German regions located in the industrialized area of Baden-Wurttemberg: Karlsruhe with Rheinhessen-Pfalz and Stuttgart with Karlsruhe. Thus there is a geographically defined cluster of regions characterized by a strong social relationships measured by co-inventorships. As expected, spatial proximity favors social interactions among inventors although, from Table 1, we can see that the correlation coefficient between the

[7] We also compute another matrix to measure the social interaction based on migration flows. The idea is that a migration flow between two areas creates a bilateral link which may favor the exchange of knowledge. Unfortunately, data on migration flows, with the specification of the origin and destination, are available only at the national level so we have regionalized them using the population shares. Not surprisingly, results were not satisfactory.

geographical and social proximity matrices is positive even though its magnitude is quite modest (0.12).[8]

Organizational proximity. Organizational proximity refers to the connections within the same organization or group which explain the capacity of an agent to acquire knowledge coming from a multitude of different actors. For example, we can think of establishments belonging to the same firm, departments of the same university or inventors working for the same company. As for social proximity, however, the organisational proximity is mainly about the attributes of agents and companies rather than regions. We measure organizational proximity by the affiliation to the same organization of the applicant and the inventors of a patent (see Maggioni et al., 2011). Given this definition, we are not considering the case in which the applicant and the inventor are equivalent as much as the case in which they are different but located in the same region. As a result the main diagonal is set to zero. A characteristic of the applicant-inventor matrix is that it is not symmetric. In other words, the relationships originated by the applicant in region i with inventors resident in region j are different with respect to the links between applicant in region j and inventors living in region i. 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 regions i and j.

As for the previous types of proximity, we expect a positive influence of organizational networks in the process of knowledge creation and diffusion since it is believed to reduce uncertainty and opportunism. We have to notice that this is a not completely satisfactory measure for organizational proximity, which is quite complex to define even at the micro level. Moreover, it is quite difficult to differentiate empirically organizational and social proximity. Indeed, the correlation coefficients between the two proximity matrices reported in Table 1 is 0.74.

Table 1 shows that the number of non-zero links in the organizational matrix amount to 17% of total possible relationships among European regions. Interestingly, the highest value (480) is reached by two far-away regions in France: Ile de France and Rhone Alpes. The former hosts the capital, Paris, where most French companies locate their headquarters, whist the latter is renowned for its scientific parks and research laboratories which are apparently linked to parent companies. In such a case the hypothesis, to be tested empirically, is that the two regions are characterized by a high organizational proximity which should help them in exchanging knowledge.

[8] It is interesting to notice that the correlation coefficient with the contiguity matrix is much higher (0.39) signaling that strong social relationships are more likely to develop among contiguous regions.

3. The empirical KPF model

In this section we first present the econometric model used to investigate the determinants of the process of knowledge creation and diffusion in Europe, followed by a description of the data used for the dependent variable and for the production inputs considered. We then discuss in detail some methodological issues related to the specification of the empirical model.

3.1 Empirical model and data description

The literature on the determinants of innovative activity at firms and regional level has been traditionally based on the estimation of a KPF where the output is measured by the patenting activity and the input by the R&D expenditure. We follow this approach but we augment the KPF by introducing human capital as an additional input given its well known effects on knowledge creation. Indeed, in the case of traditional sectors and small enterprises the creation of innovation is not necessarily the result of a formal investment in research but it is often derived either from an informal process of learning by doing (Nelson and Winter, 1982) and from the absorption of external knowledge (Abreu et al., 2008). Firms' and regions' ability to understand, interpret and exploit internal and external knowledge[9] relies on prior experiences embodied in individual skills and, more generally, in a well educated labour force. Moreover, in the light of the discussion above, we explicitly consider the presence of spillover effects coming from "proximate" regions which may enhance the impact of internal factors thanks to indirect effects.

Thus, the general form of the empirical model for the KPF is specified according to a log-linearized Cobb-Douglas function as:

$$inn_i = \beta_1 rd_i + \beta_2 hk_i + \phi \; controls_i + \gamma \;\; proximity \;\; factors + \varepsilon_i \qquad (1)$$

where lower case letters indicate log-transformed variables. More specifically, the innovation output *inn* is proxied by the yearly average of patents per capita in 2005-2007, *rd* indicates R&D expenditures over GDP, *hk* is the share of graduates over population. As control variables we include, the population density to control for possible agglomeration/congestion effects and the regional share of manufacturing activities to account for the regional productive pattern. Note that all the explanatory variables included in the model are averaged over the three-year period 2002-2004 to smooth away cycle effects and to avoid potential endogeneity problems.

[9] Caragliu and Nijkamp (2011) show that spillover effects on productivity may work both within and across regions, since low absorptive capacity may hinder not only the exploitation of knowledge produced in other regions but also that produced locally.

Proximity factors are included in the model in order to capture the potential role of spillovers effects running along the five different dimensions suggested by the literature – geographical, institutional, technological, social and organizational. We discuss the specific form in which such proximity factors enter the model in the next section where we present our estimation strategy. Before that, we provide a detailed description of the main sample features of the other variables included in our empirical model (see Appendix 2 for a detailed description of the variables).

As a proxy of the innovative activity we use the number of patents application filed at the European Patent Office (EPO) classified by priority year and by inventor's region. In case of multiple inventors we assign a proportional fraction of each patent to the different inventors' regions of residence. Since patenting activity, especially at the regional level, is quite irregular over time we smooth the variable by computing a three-year average. Moreover, to control for the different size of the regions, the number of patent is divided by total population. Thus our dependent variable is measured as the yearly average of patents per million inhabitants in 2005-2007. The summary statistics, reported in Table 2, show the substantial differences in patenting activity among European regions ranging from nearly zero in Sud-Vest Oltenia in Romania to 627 in the German region of Stuttgart. The high value (1.2) of the coefficient of variation (CV) confirms the great degree of spatial concentration of innovative activity which is clustered in the north-centre of Europe while a scarce patenting activity is performed by the eastern and southern regions.

The traditional input in the KPF is the R&D expenditure computed as a share of GDP. The average R&D expenditure in Europe is 1.4% with a minimum of 0.07% and a maximum of 7.6% in Braunschweig (Germany). In this case, yet again, the spatial distribution in Europe is quite concentrated (CV=0.85) in Scandinavia, Central Europe (Germany, Switzerland, France) and in Southern England.

As an additional input, expected to influence the process of knowledge production at the local level, we consider the availability of human capital. Following a well established literature we measure human capital as the share of population with tertiary education (ISCED 5-6) over total population. The spatial distribution of this variable across European regions appears more uniform (CV=0.39) and with a clearly identifiable national pattern. A high endowment of human capital characterizes the Scandinavian countries, UK, Germany, Spain while lower values are generally detected in the Eastern countries, France and Italy.

3.2 Estimation strategy and model specification

In order to estimate model (1) it is necessary to select the most adequate *proximity* specification which enables us to properly account for the presence of knowledge spillovers and to provide a more reliable estimate of the impact of RD and human capital on patenting activity.

As argued in section 2, spillover effects do not depend only on the geographical proximity among regions – although this has been quite a useful simplifying assumption for some time – but crucially also on the degree of similarity among agents involved in the innovation activity. Such a similarity can be measured along other dimensions which are expected to exert complementary effects, which in turn reinforce each other over time.

For this reason, ideally it would be preferable to specify a comprehensive model which accounts for all possible proximity factors at the same time. However, this would be possible only if one relies on a linear least square specification, which entails that spillovers yields their effects only through the explanatory variables of the model. On the other hand, if such effects are also due to the dependent variable itself, as it is more reasonable to assume, then a spatial autoregressive specification is to be preferred; but in this case a spatial lag model would require to solve a multivariate optimization problem, of order five in our case, over the range of feasible values for the autoregressive parameters. Note, however that so far in the spatial econometric literature only a variant of the spatial lag model with two weight matrices has been proposed (Lacombe, 2004), and we adopt such a variant in section 5.1 in order to account for two proximity measures at a time.

In order to select the most adequate specification for model (1) we carried out an extensive preliminary analysis by considering five alternative spatial specifications[10], which should enable us to account for the well documented spatial dependence for geo-referenced data in general, and for the knowledge diffusion process in particular (Moreno et al. 2005, LeSage et al. 2007, Parent and LeSage 2008, Autant-Bernard and LeSage, 2010).

We initially considered the following specifications (i) Spatial Error Model (SEM), which allows only for spatial dependence in the disturbance term, (ii) the Spatial Autoregressive Model (SAR), which includes the spatial lag of the dependent variable, (iii) the Spatial Durbin Model (SDM), which includes the spatially lagged terms for both the dependent and the independent variables, (iv) the Spatial Least Square (SLX) model, which includes spatial lags only for the explanatory variables and finally (v) its variant, the Spatial Durbin error model (SDEM), which also allows for spatially correlated errors[11]. We adopt a specific-to-general approach by starting from a specification which models the interconnectivity among the regions by considering one proximity

---

[10] For a comprehensive description of spatial models and related specifications, estimation and testing issues refer to Le Sage and Pace (2009) to the outstanding discussion of the book key issues and implications in Elhorst (2010).

[11] We are very grateful to J. LeSage and R. K. Pace for making publicly available the Matlab scripts used for the analysis carried out in this paper in the websites spatial-econometrics.com and spatial-statistics.com.

measure at a time, we start with the most commonly used in empirical studies, i.e. the geographical proximity. In what follows we briefly discuss the main results of the specification analysis.[12]

As it removes spatial spillovers by construction – while our aim is to explicitly measure them – we devoted limited attention to the SEM model. In the case of the SDM, LeSage and Pace (2009) argue that it is to be preferred when there are omitted variables featuring a spatial pattern correlated with the one characterizing the included explanatory variables. For model (1) the estimated SDM returned an insignificant coefficient associated with the dependent variable spatially lagged term, this in turn yields indirect and total effects that are not significant at conventional levels. The SDM specification does not seem to be supported by our data and it is outperformed by the SAR specification, which, on the contrary, yielded reasonable results with all variables, including the spatial lag, significant and exhibiting the expected sign. The evidence in favour of the SAR model is plausibly due to fact that once human capital and the control variables – all being to some extent spatially correlated – are included in the mean equation of the model unobservable factors are no longer an issue. In capturing the presence of spillovers, the autoregressive structure of the SAR model turned out to be superior also with respect to the simpler SLX and the SDEM alternatives. For this reasons the SAR specification is the preferred one and it will be adopted in the subsequent analysis to investigate the role of different kinds of proximity in inducing knowledge spillovers.

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 due to the presence of the spatially lagged dependent variable; this induces feedback loops and spillovers effects generated by the dependence structure among the spatial units. The *total* effect caused by a change in one explanatory variables 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 interdependences among regions, so that the effects have to be considered as the result of a new steady state equilibrium. LeSage and Pace (2009) proposed summary scalar measures for direct, indirect and total effects along with their dispersion measures, which allow to draw inference on their statistical significance. More specifically, the SAR model is defined as: $Y = X\beta + \rho WY + \varepsilon$, where Y is the dependent variable, X is a set of K explanatory variables, W is a (normalized) proximity/spatial matrix, so that

[12] Results are not report in order to save space, but are available from the authors upon request.

WY is the spatial autoregressive term, and ε is the usual iid error term. If the model is reformulated as $Y = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1}\varepsilon$; $Y = \sum_{k=1}^{K} Q_k(W)x_k + V(W)\varepsilon$, where $Q_k(W) = V(W)I_n\beta_k$ and $V(W) = (I_n - \rho W)^{-1} = (I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 ...)$ with I_n being the identity matrix, then the effect of a change in the explanatory variable x_k occurring in region i on the dependent value of the same region is given by the partial derivative $\partial y_i / \partial x_{ki} = Q_k(W)_{ii}$, while the effect on region i dependent variable arising from a change x_k variable in region j is represented by the partial derivative $\partial y_i / \partial x_{kj} = Q_k(W)_{ij}$. The main diagonal elements of the matrix $Q_k(W)$ are the own partial derivatives, which represent the direct effects and are summarized by their average value; the off-diagonal entries of the same matrix are the cross-partial derivatives, the indirect or spillover effects, which are summarized by computing the average of the row sums of the elements of the matrix excluding the diagonal ones. The total effect is obtained as the sum of the direct and indirect effect.

4. The KPF model with different proximities

In this section, we consider the different proximities as alternative measures by relying on the simplifying assumption that, in principle, they are all equally relevant proxies for capturing the closeness among regions and that their relative importance can be established only on empirical grounds.

4.1 Geographical proximity

In Table 3 we present the results of the SAR model estimated by using the geographical matrix. In the first column we report the OLS results along with the robust LM diagnostic designed to test whether the potential spatial dependence in the residuals is due to the omitted lagged dependent variable term. The test is computed using as a spatial weight matrix the inverse distance in kilometers between each possible pair of regions (G); it is normalized by dividing each element by its maximum eigenvalue.[13] As expected, the test is highly significant leading to the rejection of the null of non spatially correlated residuals for the OLS regression.

In column 2 we therefore report the spatial lag model; the coefficients of both productive inputs and of the spatially lagged dependent variable are highly significant, as it is the case for the direct, indirect and total effects. However, the LM error test still detects the presence of spatially

[13] Such normalization is sufficient and avoids strong undue restrictions, as it is the case when the row-standardization method is applied (Keleijan and Prucha, 2010). Moreover, the importance of absolute, rather than relative, distance is maintained.

correlated residuals, pointing out that the complexity of the inter-connectivity among the regions is not entirely captured by the geographical weight matrix.

This provides a further rationale to investigate whether other proximity measures have a role to play in unveiling other aspects of the innovation process. A simple way to account for a-spatial proximity dimensions is to include in model 3 a set of country dummies to proxy ~~for~~ institutional factors, while still tackling the regional interconnectivity by means of the geographical proximity measure.[14] Almost all dummy coefficients are statistically significant, pointing out that national effects are indeed relevant: they make the spatial residual correlation no longer significant and their inclusion changes the relative magnitude of the productive inputs coefficients and effects, with human capital now outperforming R&D. This provides evidence that when institutional factors are overlooked the R&D effect seems to be overestimated, while the opposite is true for human capital.

The literature has emphasized the localized nature of spatial knowledge spillovers which are somehow limited in space (see the survey by Doring and Schnellenbach, 2006). More specifically, since previous findings for the case of the EU15 regions pointed out that knowledge spillovers were confined to a range of around 300 kilometers (Bottazzi and Peri 2003; Moreno et al. 2005) we investigate whether this is still the case for our wider sample of EU27 regions. We consider several possible ranges, each one 300 km wide, starting from the shortest one (0-300 km) up to the one limited by the median distance (1200 km) between all possible regions' pairs. We thus re-estimate the SAR model with the geographical matrix constructed accordingly, and select the best specification among those models yielding a spatial lag term coefficient still significant at the 5% level. This was the case for the first two distance bands considered, so we conclude that knowledge spillovers exhibit a relevant spatial pattern up to the 600 km distance.[15] The model estimated with a 0-600 km geographical matrix is reported in column 4 of Table 3; as expected, when higher distances are considered (model 5) the spatially lagged term becomes irrelevant signaling that spillovers have exhausted their effects in space.

Model 4 of Table 3 is the preferred specification when proximity is measured only along the geographical dimension. The estimated coefficient for both R&D and human capital are both significant and quite similar to the ones obtained from model 3. More specifically, the R&D shows an estimated direct elasticity of 0.26 and an indirect one of about in 0.07, thus direct effects account for almost the 80% of the total effect estimated in 0.33 and the spillovers for the remaining 20%. Comparing our findings with similar studies on the European regions, we see that our direct effect

[14] We also account for institutional proximity in regression 2 by replacing the geographical matrix with the full Institutional matrix (see section 2). In this case the results are not satisfactory as the residual spatial correlation is still present, so we prefer in the rest of the paper to proxy the institutional dimension by country dummies.

[15] A similar crucial distance for the effectiveness of spatial spillovers is also found by Dettori et al. (2011) estimating a Total Factor Productivity model for the EU15 regions.

is very similar to the elasticity of 0.26 estimated by Moreno et al. (2005) for 17 EU countries. While Bottazzi and Peri (2003) for a sample of patents of 86 regions in 12 European countries found a higher value of 0.8. However both studies do not consider the indirect effects coming from other regions.

As for human capital, we find a direct elasticity of 1.55, which is much higher than the one estimated for R&D. This is an important result offering further support to the idea that a high endowment of well educated labour forces in a region strongly enhances the innovative activity, once we control for the R&D expenditure. In some industries the process of knowledge production is not derived by formal R&D activity but is rather the result of the capacity of human capital to produce new ideas. Moreover, we have also to consider the indirect effect of human capital which has an elasticity of 0.40; thus the total effect of human capital on innovation reaches almost the value 2. The only two comparable studies are the one by Greunz (2003) for 153 NUTS2 regions and the one by Usai (2011) for 342 regions in OECD countries, which report estimates of 2.0 and 1.0, respectively.

Another interesting comparison applies to the value of the coefficient of the lagged dependent variable, which measures the strength of spatial dependence. For the case of the geographical proximity matrix, this value goes from 0.09 for EU regions in Moreno et al. (2005) to a much higher 0.4 for the US in Carlino et al. (2007). In the middle we find the estimate suggested in Usai (2011), 0.18, which refers to both US and EU, quite similar to the one of 0.20 we find for our wide European sample.

4.2 Technological proximity

In Table 4 we consider the results of the SAR models estimated with the technological proximity; as before, all specifications also include the country dummies to account for the institutional proximity.

In model 1 we as a weight matrix we use the similarity matrix based on the distribution of patenting activity among 44 sectors. The production inputs are both significant with the estimated coefficients similar to the one obtained with the geographical proximity and the spatial lag is positive and significant. However the indirect effects of R&D and human capital are not significant signaling that the technological proximity matrix we are using is not able to adequately account for the spillovers coming from the technological proximate regions. Therefore, we test whether the spillovers are effective only when the technological similarity between the two regions is above a certain threshold. Following the methodology used in the previous section for the case of the geographical proximity, we estimate several regressions with the technological matrix restricted to different values of the similarity index. It turns out that the technological spillovers are most effective when the similarity index is above the 0.5 value. The results reported in model 2 show that now the indirect effects are positive and highly significant. Conversely, if we restrict the technological matrix to similarity values lower that 0.5 (specification 3) we find a negative value for the lag dependent coefficient.

To assess the robustness of these results we have computed a second technological proximity matrix using the employment distribution among 17 manufacturing and knowledge intensive service sectors. Results are reported in specifications 4-6 using the full matrix, a similarity index greater and lower than 0.5, respectively. The magnitude of the estimated coefficients for the production inputs and the spatial lag are very similar to the ones obtained with patenting activity. However the indirect effect are never significant even when a similarity index greater than 0.5 is considered. The technological matrix based on patenting activity seems to perform better probably because it considers a detailed breakdown of the production structure (44 vs 17 sectors), which allows for a more accurate measurement of the degree of similarity among the regions. Moreover, since we are assessing how the cognitive proximity influences the knowledge spillovers, it is not surprising that the innovation activity turns out to represent the most adequate measure for the sectoral composition of the regional economy.

In summary, model 2 is the preferred specification with the technological matrix. The spatial dependence coefficient for the technological proximity shows a value of 0.29. Previous comparable studies for the cognitive proximity are Moreno et al. (2005) with a value the spatial lag coefficient of 0.05 and Greunz (2003) with an estimate of 0.25 who also reports that technological association is stronger than the geographical one (estimated coefficient of 0.22) like in our study.

The direct elasticities for both R&D (0.26) and human capital (1.3) are very similar to the one obtained from the model based on the G matrix, while the indirect ones (0.11 and 0.56 respectively) appear slightly greater in magnitude. In both cases it is confirmed that the impact of the human capital input is much higher than the R&D one. The capacity of a region to absorb external knowledge requires an internal effort of research expenditure but, most importantly, it entails the availability of well educated population to understand, manipulate and make effective the flow of knowledge coming from outside.

The process of knowledge spillover across regions seems to be affected not only by the geographical distance but even more notably by the technological proximity. Moreover this process is effective only if a certain threshold of similarity among regions is reached. For a certain region the possibility to benefit knowledge spillover requires a relatively high cognitive similarity with respect to the region where the original knowledge is produced.

4.3 Social and organizational networks

In Table 5 we present the results of the SAR models based on the social and organisational proximity dimensions. The social network refers to co-inventorship relations across agents living in different regions while the organizational proximity is traced thanks to the association of inventors and applicants residing in different regions. Focusing on the last two columns we find that, interestingly, the coefficients of the innovative inputs – R&D and human capital – appear all positive and significant and their magnitude is remarkably stable. Looking at the coefficients of the dependent lagged variable they are always positive and significant which implies that knowledge flows across regions also thanks to social and organizational networks. However, the strength of these ties is relatively low since it reaches the value of 0.11 for the social matrix and 0.07 for the organizational one. Nonetheless, it is worth noting that, according to the LM test on the estimated residuals, both models are able to capture the proximity dependence present in the data, as it was the case for the preferred models based on the geographical matrix and on the technological one.

The only previous study which provide an analogous econometric setting, where the relational/social matrix (based on FP5 links) is introduced as a weight matrix, is Maggioni et al. (2007), albeit they estimate a SEM rather than a SAR one. Nonetheless, their coefficient is comparable with ours, since their value is between 0.25 and 0.36, even though with a marginal significance. A much closer elasticity is found, on the contrary, in Ponds et al. (2010) where a SLX model is estimated. The value of the coefficient of the network-university R&D is, as matter of fact, comprised within an interval from 0.08 and 0.12. Unfortunately, results on organizational proximity are not comparable to any previous study since, as we have emphasized in section 2, this is the first time that the role of this proximity dimension is tested at the regional level.

In Table 5 we find that direct and indirect effects for R&D are neither strong nor always significant in the case of the social proximity model while only direct effects are significant in the organizational model. On the contrary, we have further evidence on the robustness of the result on human capital, whose direct and indirect effects are always at work in the two models. As for the total effects, they are all significant even though only marginally for the R&D spillovers moving along the social networks.

In conclusion, these results confirm that the production pattern of innovation is shaped not only by spatial and technological proximities but also by the presence of co-operative and relational proximity which emerges through social and organizational networks. This is a critical aspect since it implies that spillovers may have a double nature, as argued by Maggioni et al. (2007): an unintended and an intended one. In the former case geographical and technological neighbourhood may be conducive of a trickling down process of knowledge diffusion which is not due to economic agents' decisions. In the latter case, technological and scientific knowledge travels across a-spatial networks, which can be structured thanks to formal or informal agreements, and are composed of agents and institutions which exchange ideas on a voluntary base (Cowan and Jonard, 2004).

4.4 Proximities and networks: a preliminary comparison

Finally, we extend our comparison to the whole set of four models based on one weight matrix. In Table 5, to facilitate the comparisons, we reproduce the preferred models derived using the geographical matrix G (table 3, eq. 4) the technological matrix T (table 4, eq. 2).

A worth noting result is the low variability of the estimated coefficients both for the input variables and for the controls. As far as the former are concerned, the elasticity for R&D goes from 0.19 in model 3 to 0.25 in both model 1 and 2, while the elasticity of human capital ranges from a minimum of 1.34 in model 2 to a maximum of 1.56 in model 1. As for the controls, the population density turns out to be positive, although it is significant in only one case (the T-matrix model) thus there are some agglomeration effects at work even though their strength is not so relevant.[16] As for the manufacture specialization structure, it is always significant with an elasticity ranging within a very limited interval going from 0.89 in model 1 (G-matrix) to 1.02 in model 3 (S-matrix). This is an expected result since the production of new technology is still higher within the manufacturing sectors.

Looking at the elasticity of the lagged dependent variable, we conclude that technological proximity is the most important channel of knowledge spillovers, whilst geographical neighbours comes second. As far as the networks are concerned, they have a relatively more modest role, confirming previous results by Maggioni et al. (2007) and Ponds et al. (2010). In particular, it is worth noting that in the former paper the relative size of the geographical and relational elasticities are comparable with those reported above (their values are 0.6 and 0.3 respectively whilst ours are 0.2 and 0.1).

Finally, when we focus on direct and indirect effects, we find that such stability implies that the total impact due to human capital with respect to R&D is always higher in all models, ranging from a multiple of around five in the model with technological distance and almost eight in the model with social networks.

Due to model uncertainty it is quite a difficult task to select a preferred model among the one presented in Table 5, although they provide quite interesting evidence on the role played by the knowledge productive inputs and on the relevance of different regional connectivity measures. It is

[16] We have also used another measure of agglomeration - the settlement structure typology - but it turned out to be never significant.

the object of current research to undertake a model comparison by applying the recent approach proposed by LeSage and Pace (2009), based on the computation of posterior model probabilities or Bayes' factors, which is particularly suitable for the case of non-nested models, as it is the case for SAR models estimated with alternative weight matrices. The posterior model probabilities can also be used to obtain - rather than a preferred model - a *combined* one resulting from the average of all possible alternative specifications. This route seems very promising for future research since the combined model is expected to encompass all the relevant dimensions of the complex interconnectivity linking the European regions in the production process of knowledge.

5. Assessing the complementarities of the proximity dimensions

In section 4 we have examined the effect of proximity matrices one by one, implicitly assuming that each dimension generates an independent effect on knowledge spillovers. However, we are well aware that the different types of proximity are complements and that they represent knowledge transmission channels which reinforce each other (Mattes, 2011). From the empirical point of view this implies that all the four proximity matrices should be included together in the 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 section 5.1 to account for the complementarities among proximity measures we include them in pairs in the estimation model. Moreover, in section 5.2 we try to compute an overall effect of the knowledge spillovers by combining all the estimation results.

5.1 KPF models with pairs of proximity matrices

In this section we present the results for the SAR models estimated by including two different proximity weight matrices at a time in order to account for the complementarities among the different proximity dimensions. This model was first proposed by Lacombe (2004) to carry out a policy spending evaluation analysis while controlling for spatial dependence.[17] Such models are a useful estimation device when the connectivity among spatial units cannot be entirely captured by the traditional geographical measures (distance, contiguity, nearest-neighbors) since it also features other a-spatial kinds of links.[18]

---

[17] We are very grateful to D.J. Lacombe for making available to us the Matlab scripts to estimate two-weight matrix SAR models.

[18] 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 optimization problem over the range of feasible values for the parameters ρ_1 and ρ_2 . See LeSage and Pace (2009) for a detailed description of the estimation procedures.

The results are reported in Table 6 which shows that, remarkably, most results maintain their strength and significance. This is the case 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) and it is estimated in about 0.19. The same applies for the proximity measure based on technological similarity, which exhibits across all the models a relatively higher impact (average value 0.31) when compared with the geographical one. The regional connectivity based on both the social and the organizational proximity show a weaker degree of dependence, with an estimated coefficient which on average is equal to 0.11 and 0.07, respectively. It is interesting to note that when this matrices are included together (last column in Table 6) both the coefficients of the spatially lagged terms are no longer significant, signaling a sort of multicollinearity problem. This is plausibly due to the fact that the information contained in the two matrices somehow overlaps (the correlation coefficient is estimated in 0.74).

As far as the knowledge production inputs, R&D and human capital, 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 6 we also report the computed direct, indirect and total effects[19]. It turns out that human capital exhibits higher impacts, both direct and indirect, with respect to R&D, thus proving to be quite productivity enhancing for the regional innovation activities. Overall the model that yields the highest total impacts is the first one, when the interdependence among regions is captured by the geographical pattern and the technological network. Note that spillovers effects are rather relevant, as they are almost of the same order of magnitude as the direct ones (for R&D the direct effect is calculated in 0.26 and the indirect one in 0.20, for human capital they amount to 1.37 and 1.06, respectively).

5.2 Figuring out the overall effect of knowledge spillovers

In this section we carry out a tentative exercise to figure out the overall spillover effects when all proximities are taken into account. This is, necessarily, a post-estimation computation where we try to combine the inference drawn from both the four one-matrix models (Table 5) and the six two-matrix models (Table 6). We emphasize once again that the first best strategy would be to obtain the overall effects from a comprehensive general model, nonetheless we believe that this kind of exercise may be informative on how the different proximities may interact in the European regional context.

[19] Differently from the case with one weight matrix models, for two-weight matrices models the effects are computed analytically and not by simulation, so for this case no dispersion measures are provided.

The overall effects are computed analytically on the basis of the average estimates of the coefficients of R&D and human capital obtained from the ten models, which are 0.22 and 1.45 respectively, and the average estimates of the coefficients for the four different kinds of proximity lagged terms. In order to ease the comparison of the strength of proximity dependence the estimated coefficients of the lagged dependent variable terms for all combinations of matrices are summarized in Table 7, where the main diagonal reports the lag coefficient estimated in the single weight matrix models. We observe that, on average, the 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 strength is lower for the geographical proximity (average equal to 0.19), while the lowest dependence is found for the social (0.11) and the organizational (0.07) proximity.

In the middle column of Table 8 we report the direct, indirect and total effects computed by deriving a sort of all- proximities multiplier for both R&D and human capital[20]. The values are similar to those obtained from the two-matrix SAR model based on the geographical and the technological interconnections (first column in Table 6), signalling that this kind of proximity are the ones that are more innovation enhancing.

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 increase of the ratio between R&D expenditure and GDP of 10%, from an average European actual value of 1.4% to 1.56%, this will generate a total increase of patents (per million population) from the observed average value of 105 to the new computed value of 109 (with half of the change attributable to direct effects and half to spillovers). On the contrary, if the 10% increase refers to human capital, (the share of graduates on population) from the average European value of 10.5% to 11.6%, this would yield a total effect on the production of knowledge that determines a total increase from 105 to 132 patents (per million population); this means an addition of 27 patents, 14.5 from a direct internal effect and 12.5 from a knowledge spillover effect thanks to the absorption capacity of the local well educated labour forces.

We think that the computation of the all-proximity multiplier for the two KPF inputs, although it has to be considered with all the caveats that this kind of exercise requires, provides useful indications on the relative role of R&D and human capital in determining the innovation production; moreover, the finding that the directs effects and spillover effects are in most cases of the same order of magnitude calls for coordinated efforts at regional, national and European level.

---

[20] For comparison purposes in Table 8 we also report the effects computed considering the lowest (column ‘min’) and the highest (column ‘max’) estimated coefficients for R&D and human capital and for the coefficients of the four different lagged terms.

6. Concluding remarks

Both economists and politicians agree that the availability of knowledge and its diffusion are crucial ingredients for regional growth in Europe. The same agreement is shared for the idea that the diffusion of innovation depends on the relative position of regions along different dimensions, which go beyond the geographical space. Several authors, from different schools of thoughts, believe that knowledge transmission can be facilitated by the simultaneous presence of proximity and networking in social, institutional, technological and organizational "space". In spite of this common belief, most studies in the past have relied on geographical proximity as a sort of all-encompassing connectivity measure. Thus, they have overlooked the concurrent effects of other types of proximities in order to understand their substitutability or complementarity and, therefore, to assess their relative importance. However the most recent contributions in this field have emphasized the importance of considering the effects of the spatial and a-spatial dimensions of proximity all together (Boschma 2005, Mattes, 2011). This would also allow to take into consideration the intended (co-operative and relational proximity) and the unintended (geographical and technological closeness) nature of these relationships (Maggioni et al. 2007).

In this paper, moving along the research line of KPF, we focus on the creation and production of new knowledge and how this is affected by a set of internal production inputs, where, in addition to R&D expenditure, we also include human capital. Moreover, the use of spatial models with proximity effects allow to investigate on the impact of the external factors and thus to evaluate their role in knowledge transmission. The chosen field of analysis is the European space, which represents the most important economic system characterized by high heterogeneity at the regional and country level in innovative performance, a reflection of differences in investments in R&D and human capital. Furthermore, regions in Europe clearly feature diverse scenarios with respect to institutional, technological, organizational and social characteristics and their respective networks.

The different proximity dimensions are expected to exert complementary and reinforcing effects on knowledge transmission. Therefore, the optimal estimation strategy would be the specification of a comprehensive model which accounts for all possible proximity factors at the same time. However, in presence of our preferred spatial autoregressive (SAR) specification, it would require to solve an order five multivariate optimization problem which goes beyond the current state of the art (Elhorst, 2011). The estimation of a SAR model permits to compute the direct and the indirect effects of the explanatory variables and to assess the relative importance of the internal endowments of production factors with respect to the spatial spillover effects.

Thus, as a first approximation, we consider the four proximity dimensions as alternative measures introducing them one at a time in the model, while the institutional proximity is considered throughout the whole estimations, by means of country dummies. We start with the usual investigation of the geographical dependence and, in light of previous empirical analyses, we examine the potential decay effect of spillovers along space founding that, in the wider Europe, knowledge spillovers are effective until a distance of 600 km. Looking at the cognitive proximity, it appears that technological similarity is relevant in channeling spillovers from one region to another one and, also in this case, we find that the transmission of knowledge is effective only above a certain threshold of proximity between the cognitive structure of the two regions (i.e. for a similarity index greater than 0.5). Finally, also the social and organizational proximities, which channel intended spillovers, also turn out to represent significant knowledge transmission mechanisms.

In the second step, thanks to a two-weight matrix SAR model, we estimate models based on all possible couples of proximity matrices. This allows us to take into account, at least partially, the issue of complementarity of these different connectivity matrices and to compute the overall effect of knowledge spillovers.

In general, the results presented in this paper, while confirming some outcomes of the previous literature, introduce interesting novelties. As far as the internal factors are concerned, we find that both R&D and human capital are essential components for technological progress but with quite a different magnitude. The latter, once institutional proximity is considered, has an impact which is around six times higher than the former. This outcome is a clear indication of the importance of a skillful and qualified labour force for incremental technological progress based on continuous learning and experience accumulation.

Regarding the external factors, we ascertain that all dimensions of proximities are significantly related to innovative performance and they represent complementary channels of knowledge transmission. Nonetheless, we find that their relative influence differs significantly. Cognitive or technological proximity has an average impact, across our estimations, which is 1.5 times that of geographical proximity and at least five times higher than that of social and organizational networking. The existence of a common knowledge and productive base can be, in other words, more important than information sharing which happens at the local level thanks to spatial proximity. Moreover, we prove that the social and organizational dimensions are important too, although their impact is relatively more modest. Besides, these two dimensions turn out to be not always substitute since the two proxies suffers from some overlapping. In general, our results confirm that the complexity of the inter-connectivity among regions is not entirely captured by the geographical weight matrix and that there are other forms of a-spatial proximity which concur in capturing the complementary channels through which the creation and diffusion of knowledge take place among the European regions.

Finally, we find evidence that a relevant part of the total effects of R&D expenditures and human capital endowments on the knowledge creation in a certain region derives from the spillover effect coming from other regions which are interconnected in a variety of dimensions. These estimated indirect effects vary according with the proximity dimension employed, but they are crucial in determining feedback and spillover impacts which occur through the simultaneous system of interdependences among regions.

There are at least two main policy implications which can be drawn from the outcomes of the present paper. The first is the importance of policies aiming at increasing the endowments of well educated labor forces, given their strong and pervasive role in determining both the internal creation and the external diffusion and absorption of knowledge. The impact of graduates on innovation activities is much stronger than formal R&D expenditures. New ideas, inventions, product and process innovations come mainly from the inventive capacity of well educated people and thus university education must be adequately supported in Europe. The second policy implication derives from the presence of relevant spillovers which calls for coordination policies aimed at supporting and encouraging the formation of dense networks among regional innovation systems. Moreover, the fact that technological proximity matter even more than the geographical one in determining spillovers means that knowledge diffusion is facilitated within an a-spatial technological clusters, where regions which share a common cognitive base are more likely to cooperate and exchange knowledge. This suggests the implementation of specific industrial policies to support the formation and the functioning throughout Europe of such a-spatial industrial clusters characterized by proximate technology. Most importantly, the objective to transform EU in an Innovation Union envisages the strengthening of the knowledge base by promoting excellence in education and skills development and the need of reducing the policy fragmentation by ensuring consistency of EU, national and regional strategies to enhance cooperation in research, science and innovation.

References

Abreu M., Grinevich V., Kitson M. and Savona M. (2008) Absorptive capacity and regional patterns of innovation, *DIUS RR*-08-11.

Acosta M., Coronado D., León M.D. and Martínez M.Á. (2009) Production of University Technological Knowledge in European Regions: Evidence from Patent Data, *Regional Studies*, 43, 1167-1181.

Acs Z.J., Anselin, L. and Varga A. (2002) Patents and innovation counts as measures of regional production of new knowledge, *Research Policy*, 31, 1069-1085.

Anselin L., Acs Z.J., and Varga A. (1997) Local Geographic Spillovers between University Research and High Technology Innovations, *Journal of Urban Economics*, 42, 422-448.

Autant-Bernard C. and J. LeSage (2010) Quantifying knowledge spillovers using spatial econometric models, *Journal of Regional Science*, 20, 1-26

Autant-Bernard C., Billand P., Frachisse D. and Massard N. (2007) Social distance versus spatial distance in R&D cooperation: Empirical evidence from European collaboration choices in micro and nanotechnologies, *Papers in Regional Science*, 86, 495-519.

Boschma R.A. (2005) Proximity and innovation. A critical assessment, *Regional Studies* 39, 61–74.

Boschma, R. and K. Frenken (2010) The spatial evolution of innovation networks. A proximity perspective, in: R. Boschma and R. Martin (eds) *Handbook of Evolutionary Economic Geography*. Cheltenham: Edward Elgar.

Bottazzi L. and Peri G. (2003) Innovation and spillovers in regions: Evidence from European patent data, *European Economic Review*, 47, 687-710.

Buesa M., Heijs J. and Baumert T. (2010) The determinants of regional innovation in Europe: A combined factorial and regression knowledge production function approach, *Research Policy* 39, 722–735.

Caragliu A. and Nijkamp P. (2011) The impact of regional absorptive capacity on spatial knowledge spillovers, *Applied Economics*, DOI: 10.1080/00036846.2010.539549.

Carlino G.A., Chatterjee S. and Hunt R.M. (2007) Urban Density and the Rate of Innovation, *Journal of Urban Economics*, 61, 389-419.

Carrincazeaux C. and Coris M. (2011) Proximity and Innovation, in Cooke P, Asheim B.T. and Boschma R. (eds) *Handbook of Regional Innovation and Growth*. Cheltenham: Edward Elgar.

Coe D. T. and Helpman E. (1995) International R&D spillovers, *European Economic Review*, 39, 859-887.

Cohen W. M. and Levinthal D.A. (1990) Absorptive capacity: a new perspective on learning an innovation, *Administrative Science Quarterly*, 35, 128-152.

Cowan R and Jonard N. (2004) Network structure and the diffusion of knowledge, *Journal of Economic Dynamics and Control*, 28, 1557–1575.

Crescenzi R., Rodriguez-Pose A. and Storper M. (2007) The territorial dynamics of innovation: a Europe–United States comparative analysis, *Journal of Economic Geography*, 7, 673–709.

Dettori B., Marrocu E. and Paci R. (2011) Total factor productivity, intangible assets and spatial dependence in the European regions, *Regional Studies*, DOI: 10.1080/00343404.2010.529288

Doring T. and Schnellenbach J. (2006) What do we know about geographical knowledge spillovers and regional growth?: a survey of the literature, *Regional Studies*, 40, 375–395.

Elhorst, J.P. (2010) Applied Spatial Econometrics: raising the bar, *Spatial Economic Analysis*, 5, 10-28.

Gertler M.S. (2003) Tacit knowledge and the economic geography of context, or The undefinable tacitness of being (there), *Journal of Economic Geography*, 3, 75-99.

Granovetter, M. (1985) Economic action and social structure: the problem of embeddedness. *American Journal of Sociology* 91, 481-510.

Greunz, L. (2003) Geographically and Technologically Mediated Knowledge Spillovers between European Regions, *Annals of Regional Science*, 37, 657-80.

Griliches Z. (1979) Issues in Assessing the Contribution of Research and Development to Productivity Growth, *Bell Journal of Economics*, 10, 92-116.

Grossman G.M and Helpman E. (1990) Trade, Innovation, and Growth, *American Economic Review*, 80, 86-91.

Harris R., Moffat J. and Kravtsova V. (2011), In search of 'W', *Spatial Economic Analysis*, 6, 249-270.

Hoekman J., Frenken K. and van Oort F. (2009) The geography of collaborative knowledge production in Europe, *The Annals of Regional Science* 43, 721-738.

Hollander H., Tarantola S. and Loschky A. (2009) Regional Innovation Scoreboard (RIS) 2009, ProInno Europe.

Iammarino S. (2005) An Evolutionary Integrated View of Regional Systems of Innovation: Concepts, Measures and Historical Perspective, *European Planning Studies*, 13, 495-517.

Jaffe A.B. (1986) Technological Opportunity and Spillovers of R&D: evidence from Firms' Patents, Profits and Market Value, *American Economic Review*, 76, 984-1001.

Jaffe A.B. (1989) Real Effects of Academic Research, *American Economic Review*, 79, 957-70.

Kelejian H.H. and Prucha I.R. (2010) Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances, *Journal of Econometrics*, 157, 53-67.

Kirat T. and Lung Y. (1999) Innovation and proximity - Territories as loci of collective learning processes, *European Urban and Regional Studies* 6, 27-38.

Knoben J. and Oerlemans L.A.G. (2006) Proximity and inter-organizational collaboration: A literature review, *International Journal of Management Reviews*, 8, 71–89

Kroll H. (2009) Spillovers and Proximity in Perspective. A Network Approach to Improving the Operationalisation of Proximity, *Fraunhofer Working Papers Firms and Region*, No. R2/2009

Lacombe D.J. (2004) Does econometric methodology matter? An analysis of public policy using spatial econometric techniques, *Geographical Analysis*, 36, 105-118.

LeSage J.P. and Pace R.K. (2009) Introduction to Spatial Econometrics. Boca Raton: CRC.

LeSage J. P., Fischer M.M. and Scherngell T. (2007) Knowledge Spillovers across Europe. Evidence from a Poisson Spatial Interaction Model with Spatial Effects, *Papers in Regional Science*, 86, 393-421.

Lobo J. and Strumsky D. (2008) Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects, *Journal of Urban Economics* 63, 871-84

Maggioni M.A., Nosvelli M. and Uberti T.E. (2007) Space versus networks in the geography of innovation: A European analysis, *Papers in Regional Science*, 86, 471–493.

Maggioni M.A., Uberti T.E. and Usai S. (2011) Treating Patents as Relational Data: Knowledge Transfers and Spillovers across Italian Provinces, *Industry & Innovation*, 18, 39-67

Maskell P. and Malmberg A. (1999) The competitiveness of firms and regions. 'Ubiquitification' and the importance of localized learning, *European Urban and Regional Studies* 6, 9–25.

Mattes J. (2011) Dimensions of Proximity and Knowledge Bases: Innovation between Spatial and Non-spatial Factors, *Regional Studies*, DOI:10.1080/00343404.2011.552493.

Miguelez E. and Moreno R. (2010) Research Networks and Inventors' Mobility as Drivers of Innovation: Evidence from Europe, *IREA Working Papers 201001*, University of Barcelona.

Moreno R., Paci R. and Usai S. (2005) Spatial spillovers and innovation activity in European Regions, *Environment and Planning A*, 37, 1793-1812.

Nelson R.R. and Winter S.G. (1982) *An Evolutionary Theory of Economic Change.* Cambridge, MA: Harvard University Press.

O´hUallacha´in B. and Leslie T., (2007) Rethinking the regional knowledge production function, *Journal of Economic Geography*, 7, 737-752.

Oerlemans L., and Meeus M. (2005) Do organizational and spatial proximity impact on firm performance? *Regional Studies,* 39, 89–104.

Paci R. and Usai S. (2009) Knowledge flows across the European regions, *Annals of Regional Science,* 43, 669-690.

Parent O. and LeSage J. (2008) Using the Variance Structure of the Conditional Autoregressive Specification to Model Knowledge Spillovers, *Journal of Applied Econometrics*, 23, 235-256.

Ponds R., van Oort F. and Frenken K. (2010) Innovation, spillovers and university-industry collaboration: An extended knowledge production function approach, *Journal of Economic Geography*, 10, 231–55.

Rallet A. and Torre A. (1999) Is geographical proximity necessary in the innovation networks in the era of the global economy?, *GeoJournal*, 49, 373–380.

Sorensen O., Rivkin J.W and Fleming L. (2006) Complexity, networks and knowledge flow, *Research Policy*, 35, 994–1017.

Tappeiner G., Hauser C. and Walde J. (2008) Regional knowledge spillovers: Fact or artifact?, *Research Policy*, 37, 861–874.

Usai S. (2011) The geography of inventive activity in OECD regions, *Regional Studies*, 45, 711-731.

Appendix 1. Regions and NUTS level

Code	Country	NUTS	Regions
AT	Austria	2	9
BE	Belgium	2	11
BG	Bulgaria	2	6
CH	Switzerland	2	7
CY	Cyprus	0	1
CZ	Czech Republic	2	8
DE	Germany	2	39
DK	Denmark	2	5
EE	Estonia	0	1
ES	Spain (a)	2	16
FI	Finland	2	5
FR	France (a)	2	22
GR	Greece	2	13
HU	Hungary	2	7
IE	Ireland	2	2
IT	Italy	2	21
LT	Lithuania	0	1
LU	Luxembourg	0	1
LV	Latvia	0	1
MT	Malta	0	1
NL	Netherlands	2	12
NO	Norway	2	7
PL	Poland	2	16
PT	Portugal (a)	2	5
RO	Romania	2	8
SE	Sweden	2	8
SI	Slovenia	2	2
SK	Slovakia	2	4
UK	United Kingdom	2	37

(a) Territories outside Europe are not considered

Appendix 2. Data sources and definition for variables and proximity matrices

Variable		Primary Source	Years	Definition
Patent	INN	OCSE Pat-Reg	average 2005-2007	total patents published at EPO, per million population
Research & Development	RD	Eurostat	average 2002-2004	total intramural R&D expenditure, over GDP
Human Capital	HK	Eurostat	average 2002-2004	population aged 15 and over with tertiary education (ISCED 5-6), over total population
Population density	DEN	Eurostat	average 2002-2004	Population per km^2, thousands
Manufacture specialisation	MAN	Eurostat	average 2002-2004	manufacturing employment over total employment
Settlement Structure Typology	SST	ESPON project 3.1 BBR	1999	1=less densely populated without centres, 2=less densely populated with centres, 3=densely populated without large centers, 4=less densely populated with large centres, 5= densely populated with large centres, 6=very densely populated with large centres

Proximity matrix		Primary Source	Years	Definition
Geographical	G	own calculation		inverse of distance in Km
Institutional	I	own calculation		binary matrix: value 1 if the two regions belong to the same country and 0 otherwise
Technological (patent)	T	OCSE Pat-Reg	average 2002-2004	similarity index based on 44 sectoral shares of patenting activity
Technological (employment)	Te	Eurostat, Structural Business Statistics	1999	similarity index based on 17 manufacture and knowledge intensive sectoral shares of employment
Social	S	OCSE Pat-Reg	average 2002-2004	co-inventorship relation among multiple inventors of the same patent by inventors' region (intra regions relationships are not considered)
Organisational	O	OCSE Pat-Reg	average 2002-2004	applicant-inventors relation of the same patent by region of residence (intra regions relationships are not considered)

Table 1. Summary statistics for proximity matrices

Proximity matrices	Units of measurement	Min	Max	Mean	Var. coeff.	Links % *
Geographical	km	17,86	4574,57	1370,15	0,56	-
Technological	index [0 , 1]	0,05	0,94	0,70	0,18	-
Social	num links	0,00	137,84	0,16	10,68	18,18
Organisational	num links	0,00	480,13	0,58	10,52	17,11

* % of total cells, excluding the principal diagonal

	Correlation coefficients		
	Geographical	Technological	Social
Technological	0,200		
Social	0,120	0,070	
Organisational	0,113	0,069	0,740

Table 2. Summary statistics for dependent and exogenous variables

Variable	Unit of measurement	Min	Max	Mean	Var. coeff.
Patent	per million pop	0,20	627,6	105,4	1,20
Research & Development	over GDP, %	0,07	7,6	1,4	0,85
Human Capital	over total population, %	3,51	23,3	10,5	0,39
Population density	thousands per km^2	3,08	9049,6	331,3	2,47
Manufacture specialisation	over total empl., %	3,67	36,2	17,3	0,37

Table 3. KPF with geographical proximity (G)

Dependent variable: Patents, 2005-2007 average per capita values

	1	2	3	4	5
Estimation method:	OLS	SAR	SAR	SAR	SAR
Range in Km included:		full	full	0-600 km	over 600 km
Production inputs					
R&D	1,372 ***	1,044 ***	0,271 ***	0,257 **	0,247 **
	(12.159)	(10.118)	(2.683)	(2.549)	(2.386)
Human capital	0,934 ***	0,863 ***	1,535 ***	1,559 ***	1,529 ***
	(3.737)	(3.960)	(5.063)	(5.126)	(4.913)
Control variables					
Population density	0,063	-0,227 ***	0,048	0,063	0,13 **
	(0.912)	(-3.305)	(0.713)	(0.948)	(2.036)
Manufacture specialisation	0,594 ***	0,290	0,863 ***	0,892 ***	1,069 ***
	(2.861)	(1.580)	(4.875)	(5.062)	(6.295)
Spatial lag (r)		0,557 ***	0,330 ***	0,202 ***	-0,023
		(9.359)	(3.396)	(3.116)	(0.135)
Country dummies			yes	yes	yes
Adj-R^2	0,586	0,662	0,810	0,808	0,801
Effects estimates (a)					
R&D					
direct		1,047 ***	0,270 ***	0,260 **	0,247 **
indirect		1,334 ***	0,146 *	0,067 *	0,004
total		2,381 ***	0,416 **	0,327 **	0,251 **
Human capital					
direct		0,874 ***	1,546 ***	1,559 ***	1,535 ***
indirect		1,117 ***	0,827 **	0,401 **	0,000
total		1,991 ***	2,373 ***	1,959 ***	1,535 ***
Diagnostics					
Robust LM test - spatial lag	17,61				
p-value	0,00				
LM error test for SAR model residuals		56,68	0,01	0,01	0,01
p-value		0,00	0,92	0,92	0,92

Observations: 276 regions

All variables are log-transformed

For all the explanatory variables the values are averages over the period 2002-2004

All regressions include a constant

The proximity weight matrix is the inverse distance matrix (G), max-eigenvalue normalized

Asymptotic t-statistics in parenthesis; significance: *** 1%; ** 5%; * 10%

(a) We report only the effects for the main interest explanatory variables

Table 4. KPF with technological proximity

Dependent variable: Patents, 2005-2007 average per capita values Estimation method: SAR

	1	2	3	4	5	6
Technological proximity matrix:	Patent	Patent	Patent	Empl.	Empl.	Empl.
Range of similarity index included:	full	>0.5	<0.5	full	>0.5	<0.5
Production inputs						
R&D	0,254 **	0,255 ***	0,259 **	0,235 **	0,213 **	0,184 *
	(2.518)	(2.527)	(2.551)	(2.272)	(2.040)	(1.743)
Human capital	1,326 ***	1,345 ***	1,401 ***	1,502 ***	1,493 ***	1,505 ***
	(4.286)	(4.354)	(4.542)	(4.852)	(4.843)	(4.911)
Control variables						
Population density	0,112 *	0,113 *	0,121 *	0,137 **	0,146 **	0,155 **
	(1.780)	(1.794)	(1.928)	(2.133)	(2.271)	(2.428)
Manufacture specialisation	0,913	0,956 ***	1,013 ***	1,051 ***	1,034 ***	1,023 ***
	(5.272)	(5.610)	(5.999)	(6.163)	(6.067)	(6.045)
Spatial lag (r)	0,493 ***	0,293 ***	-0,055 ***	0,238	0,263 *	-0,057 *
	(3.364)	(3.233)	(2.785)	(1.035)	(1.718)	(2.349)
Country dummies	yes	yes	yes	yes	yes	yes
Adj-R^2	0,809	0,809	0,807	0,803	0,804	0,805
Effects estimates (a)						
R&D						
direct	0,250 **	0,258 ***	0,260 **	0,231 **	0,213 **	0,184 *
indirect	0,287	0,110 ***	-0,014 *	0,120	0,083	-0,009
total	0,538 *	0,368 ***	0,247 **	0,351	0,296 *	0,175 *
Human capital						
direct	1,344 ***	1,344 ***	1,387 ***	1,508 ***	1,496 ***	1,511 ***
indirect	1,484	0,567 **	-0,071 **	0,795	0,612	-0,080
total	2,828 **	1,911 ***	1,316 ***	2,304	2,107 ***	1,431 ***
Diagnostics						
LM error test for SAR model residuals	0,029	0,029	0,029	0,745	0,745	0,744
p-value	0,864	0,864	0,864	0,388	0,388	0,388

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

Table 5. KPF with different proximity measures: Geographical (G), Technological (T), Social (S) and Organisational (O)

Dependent variable: Patents, 2005-2007 average per capita values   Estimation method: SAR

	1	2	3	4
Proximity matrix:	G	T	S	O
Production inputs				
R&D	0,257 **	0,255 ***	0,191 *	0,207 **
	(2.549)	(2.527)	(1.837)	(1.992)
Human capital	1,559 ***	1,345 ***	1,524 ***	1,484 ***
	(5.126)	(4.354)	(4.981)	(4.832)
Control variables				
Population density	0,063	0,113 *	0,091	0,095
	(0.948)	(1.794)	(1.409)	(1.460)
Manufacture specialisation	0,892 ***	0,956 ***	1,026 ***	1,058 ***
	(5.062)	(5.610)	(6.077)	(6.283)
Spatial lag (r)	0,202 ***	0,293 ***	0,115 ***	0,072 **
	(3.116)	(3.233)	(2.552)	(2.200)
Country dummies	yes	yes	yes	yes
Adj-R^2	0,808	0,809	0,806	0,805
Effects estimates (a)				
R&D				
direct	0,260 **	0,258 ***	0,188 *	0,206 **
indirect	0,067 *	0,110 ***	0,023	0,015
total	0,327 **	0,368 ***	0,212 *	0,221 **
Human capital				
direct	1,559 ***	1,344 ***	1,540 ***	1,499 ***
indirect	0,401 **	0,567 **	0,202 **	0,117 **
total	1,959 ***	1,911 ***	1,742 ***	1,616 ***
Diagnostics				
LM error test for SAR model residuals	0,011	0,029	0,293	0,009
p-value	0,918	0,864	0,589	0,923

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 , T=technological .
We report also the results for matrix G (0-600 km) from Table 3 eq.4; and matrix T (index>0.5) from Table 4 eq. 2.
Asymptotic t-statistics in parenthesis; significance: *** 1%; ** 5%; * 10%
(a) We report only the effects for the main interest explanatory variables

Table 6. KPF with two weight matrix SAR models

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	0,264 ***	0,214 **	0,223 **	0,192 **	0,206 **	0,191 *
	(2.672)	(2.137)	(2.226)	(1.929)	(2.065)	(1.885)
Human capital	1,372 ***	1,553 ***	1,524 ***	1,332 ***	1,281 ***	1,514 ***
	(4.613)	(5.140)	(5.043)	(4.448)	(4.270)	(4.952)
Control variables						
Population density	0,042	0,045	0,042	0,069	0,071	0,090
	(0.677)	(0.725)	(0.675)	(1.126)	(1.143)	(1.426)
Manufacture specialisation	0,764 ***	0,887 ***	0,900 ***	0,902 ***	0,933 ***	1,031 ***
	(4.676)	(5.346)	(5.421)	(5.484)	(5.667)	(6.140)
Spatial lag - 1st proximity matrix	0,213 ***	0,172 ***	0,183 ***	0,312 ***	0,320 ***	0,095
	(3.376)	(2.587)	(2.812)	(3.447)	(3.516)	(1.174)
Spatial lag - 2nd proximity matrix	0,307 ***	0,083 *	0,057 *	0,127 ***	0,085 ***	0,017
	(3.431)	(1.763)	(1.734)	(2.805)	(2.648)	(0.297)
Country dummies	yes	yes	yes	yes	yes	yes
Adj-R^2	0,816	0,811	0,810	0,814	0,814	0,806
Computed effects [(a)]						
R&D						
direct	0,265	0,215	0,224	0,192	0,206	0,191
indirect	0,204	0,030	0,032	0,094	0,101	0,021
total	0,469	0,245	0,256	0,286	0,307	0,212
Human capital						
direct	1,375	1,554	1,525	1,333	1,282	1,514
indirect	1,061	0,220	0,222	0,652	0,629	0,163
total	2,436	1,775	1,747	1,985	1,910	1,677

Observations: 276 regions

All variables are log-transformed

For all the explanatory variables the values are averages over the period 2002-2004

All models include country dummies

All proximity matrices are max-eigenvalue normalized; G=geographical (0-600 km), T=technological (index >0.5), S=social and O=organisational.

Asymptotic t-statistics in parenthesis; significance: *** 1%; ** 5%; * 10%

[(a)] The effects are computed analytically and not by simulation, in this case no dispersion measures are provided.

Table 7. Comparing estimated lag coefficients for different proximities measures

		Second proximity matrix included:				
Proximity matrix considered:		G	T	S	O	**Average**
Geographical proximity	G	*0,202*	0,213	0,172	0,183	**0,193**
Technological proximity	T	0,307	*0,293*	0,312	0,320	**0,308**
Social proximity	S	0,083	0,127	*0,115*	0.095 (a)	**0,108**
Organisational proximity	O	0,057	0,085	0.017 (a)	*0,072*	**0,071**

Diagonal entries are the estimated rho coefficients of the Table 5 one-weight matrix SAR models
Off-diagonal entries are the estimated rho coefficients of the Table 6 two-weight matrix SAR models
All the regressions include also the insitutional proximity measured by the country dummies.
(a) not statistically significant
The average is computed only for statistically significant coefficients

Table 8. Computed effects for the KPF inputs across the 10 SAR models

Dependent variable : Patents, 2005-2007 average per capita values

		min[b]	average[a]	max[b]
Direct	R&D	0,192	0,221	0,265
Direct	Human capital	1,284	1,453	1,565
Indirect	R&D	0,143	0,192	0,266
Indirect	Human capital	0,954	1,266	1,572
Total	R&D	0,334	0,413	0,531
Total	Human capital	2,237	2,719	3,136

[a] Effects are calculated by averaging the information obtained from the 4 single (Table 5) and 6 double (Table 6) estimated SAR models

Average estimated coefficients: 0.220 for R&D and 1.449 for Human capital; average values of rhos are those reported in table 7

[b] Effects are calculated by considering the lowest/highest estimated values obtained from the 10 estimated SAR models for the coefficients of R&D, Human capital and spatial lag term