Proximity, Networking and Knowledge Production in Europe: what lessons for innovation policy?

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Abstract
This paper aims at investigating the role of different types of proximity on the technological activity of a region within the context of a knowledge production function, where R&D expenditure and human capital are the main internal inputs. We thus assess to what extent the creation of new ideas in a certain region is enhanced by knowledge flows coming from proximate regions. In particular, we examine in detail different kinds of proximity by 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) over the last decade. Results show that human capital and R&D are clearly essential for innovative activity with the former being much more effective in driving the production of knowledge. As for the proximity and network effects, we find that technological proximity outperforms the geographic one, while a limited role is played by social and organizational networks. As a result, the first policy message is that European regions still need to focus on policies aimed at increasing the endowments of well-educated labour force and therefore their knowledge base. Furthermore, we need innovation policies based on each region's specific innovation potential, due to the existing differences in geographical, cognitive, institutional, social and organizational structures and networks.

Keywords: technological production, proximity, networks, human capital
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1. Introduction

The current economic downturn is forcing countries and regions to design policies which are able to balance short and long run effects in the most effective way, while saving resources. The European Union is trying to achieve such goals with a complex set of interventions where the European innovation strategy, as set out in the Innovation Union document, is the crucial instrument to achieve sustainable and inclusive growth in the long run. This strategy, essentially, targets the ability of each region to improve its internal and, most importantly, external links, since regions need to confront themselves with the worldwide scenario at large to improve their connections and cooperation with other territories, clusters and innovation players.

It is widely recognised that the capacity of a region to generate, transmit and acquire knowledge and innovation depends on a multifaceted set of factors: investment in R&D, work force experience, education and training, collaboration networks, technology transfer mechanisms, researchers' and workers' mobility, 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 theoretical (Grossman and Helpman, 1990; Rallet and Torre, 1999, Antonelli, 2008) and empirical grounds (Jaffe, 1989; Coe and Helpman, 1995), have argued that innovation depends on investments in research and human capital as much as on interactive learning, knowledge diffusion and circulation of ideas.

Both sets of aspects are strictly related to the concept of closeness of economic agents and how proximity affects their ability to connect and, possibly, cooperate within systemic networks at different territorial levels. The concept of closeness has several dimensions and may have different implications; obviously, the most common one refers to geography: spatial concentration is believed to be 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).

In this perspective, the general object of this paper is to analyse how external factors interact with the regions' internal ones in determining the technological performance of the European territories. More specifically, the main and original contribution of our work is to investigate to what extent the regional inventive activity depends on intra-regional characteristics (mainly R&D expenditure and human capital) and on regions' ability to absorb inter-regional knowledge spillovers channelled and diffused by different types of proximity. These aspects are investigated by applying spatial econometric techniques to a Knowledge Production Function (KPF) model.

With respect to its traditional formulation, this is augmented with extra-regional factors, mediated by different kinds of proximity and networks (institutional, geographical, technological, social and organizational), which are expected to enhance a region's innovative activity. Our analysis is based on an ample dataset referring to 276 regions in 29 countries (EU27 plus Norway and Switzerland) over the last decade.

The regional scenario of the enlarged Europe examined in the paper represents an extremely interesting case study, as the high heterogeneity in terms of economic as well as innovative regional performance (Hollander et al., 2009) asks for coordinated policy interventions both at the national and regional level. Such interventions, defined in the Research and Innovation Strategies for Smart Specialisation (RIS3 strategies) document, are intended to provide a coherent national and regional plan/framework to ensure knowledge development.

The paper, therefore, addresses the following main research questions: 1) what is the balance of internal and external factors in shaping regional innovative performance? 2) what kind of connections are most effective in driving knowledge spillovers across regions? 3) what lessons can be gained from such results to design more effective innovation policies?

Our main results confirm the importance of investment in R&D and reveal that human capital plays an even greater role in fostering innovative activity and in generating inflows of knowledge relevant to region's existing knowledge base. More importantly, our analysis shows that geography is not the only dimension which may favour knowledge diffusion and not even the most important one. Technological proximity proves to be the most relevant, while social and organizational networks are also significant although their role is modest. This implies that policy interventions have to be coordinated with several different instruments and along diverse dimensions to be effective in reaching the overall innovation targets.

The paper is structured as follows. Section 2 analyses the different concepts of proximity used in the empirical literature and presents our proximity measures across regions. Section 3 deals with the definition of the empirical KPF model and the description of the variables. In the following sections we present the results of the models estimated by adopting different proximity measures. More specifically, section 4 focuses on geographical and institutional dimensions of interconnectivity, section 5 on the technological one, while the social and organisational closeness are discussed in section 6. In section 7 some concluding comments and policy implications are presented.

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. Economic literature from different schools of thoughts provides theoretical backing to this idea, which is based on the presence of local spillovers both within and across regions and countries (see Castellacci, 2007 and Christ, 2009, for recent surveys). 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[1]. More specifically, they have less costly access to information and they can share tacit knowledge (a local public good) through face to face contacts. Nonetheless, the French School of Proximity (Kirat and Lung, 1999; Torre and Gilly, 2000) 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 at least four other dimensions of proximity across agents: institutional, technological (or cognitive), social (or relational) and organizational.

2.1 Definitions and previous literature

In this section we provide a definition of these four concepts of proximity and a description of their measurement, as suggested in the empirical literature on the estimation of regional KPF.

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 in lowering transaction costs and, thus, favours cooperative behaviours in the regional context (Maskell and Malmberg, 1999; Gertler, 2003).

Technological (or cognitive) proximity indicates that knowledge transfer requires specific and appropriate absorptive capacity (Cohen and Levinthal, 1990), which entails, among others, a homogenous cognitive base with respect to the original knowledge in order to understand and

[1] Antonelli et al. (2008) argue that there may be an optimal size of local knowledge pools since a low innovation network density reduces access to external knowledge whilst an excessively large one enhances congestion and reduces appropriability.

process the new incoming knowledge effectively[2]. In practical terms, we expect that economic agents who 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 social nearness breeds trust which, in turn, lowers transaction costs and facilitates collaboration. This aspect can be particularly relevant for 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 reduces uncertainty and incentives to opportunistic behaviour since it provides an area of definition of practices and strategies within a set of rules based on organizational arrangements (Kirat and Lung, 1999). Such arrangements can be either within or among firms and may take 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 crucial 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 can be analysed thanks to the KPF approach, introduced by Griliches (1979) to study the relationship between knowledge inputs and outputs at the firm level. Since then it has been extensively used to analyse how this relationship works both at the firm and at the territorial level. In particular, regional KPFs have been estimated to assess the role of both internal and external factors on regional innovation systems. The seminal paper by Jaffe (1989), who proves the existence of geographically mediated spillovers from university research to commercial innovation in US metropolitan areas. The main results of his paper have been later extended and strengthened by many other authors who provide evidence in favour 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 its importance by means of spatial econometric techniques.

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[2] 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.

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).[3] These studies find that innovation performance is partly due to internal factors and partly to spillovers which flow from one region to another. Unlike the USA studies, some of these articles add other possible dimensions of proximity and assess their role on knowledge production. In particular, Bottazzi and Peri (2003), Greunz (2003) and Moreno et al. (2005) investigate inter-regional knowledge spillovers across European regions, testing whether 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 distant regions with similar technological profiles. This indicates that geographical distance is not the only dimension to be investigated and that knowledge spillovers may be induced also by cognitive closeness. Furthermore, all these studies consider institutional proximity (measured by means of country dummies) and find it relevant in indentifying the more and less innovative regions.

Only few contributions examine the role of social or relational networks[4] together with geographical proximity within a KPF[5]. Maggioni et al. (2007), Kroll (2009) and Ponds et al. (2010) find that both the local neighbourhood and the connections with other regions based on co-operation matter for the local process of knowledge generation. The first article measures social proximity by means of cooperation networks for the Fifth Framework Programme, the second one uses co-patenting across regions, whilst the third uses co-publications. Other contributions have introduced various features of inventors' network in a KPF framework: Lobo and Strumsky (2008) for the case of the USA, MSA's and Miguelez and Moreno (2011) 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 operationalizes this concept in order to gauge proximity for each couple of regions[6], but rather they use it as a regional indicator which measures the region's degree of connectivity and openness.

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[3] The only contributions which analyze 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 on Patent Cooperation Treaty applications.

[4] 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 also that social distance seems to matter more than geographical distance. In the same vein, Hoekman et al. (2009) find negative effects of both geographical and institutional distance on research collaboration, using data on inter-regional research collaboration measured by scientific publications and patents in Europe.

[5] An interesting parallel study which has tried to provide a measure of different proximities, namely relational, social and technological, to assess their role in affecting productivity growth, rather than innovative activity, has been recently proposed by Basile et al. (2012).

[6] It is worth noting that Rodriguez-Pose and Crescenzi (2008) use the concept of 'social filter', a composite index describing the socio-economic realm of each region, in their study of regional growth in Europe. Moreover, the role of the social filter is assessed not only within regional borders but also across regions. This external role is, however, mediated only along the geographical dimension.

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 exception is the article 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 introducing organizational proximity as a binary variable which is equal to unity when the citation comes from employees of the same firm, even when they reside in different regions. Another interesting study on the impact of organizational proximity on innovation, although at the firm level, is Oerlemans and Meeus (2005), who, using survey-based micro data on the Netherlands, conclude that interregional relations with business agents (users and suppliers) lead to a better innovative performance.

2.2 Proximity measures at the regional level

In this section we analyse in detail how we operationalize the five concepts of proximities presented above into measures to be used later in the KPF estimation. For each dimension we try to clarify the mechanisms which link the micro level (agents, firms) where the closeness measures operate and the aggregate regional level which is investigated in the paper.

All proximity measures considered in this paper are computed at the NUTS (Nomenclature des Unités Territoriales Statistiques) 2 level (see Appendix 1).[7] Although we are aware that some proximity notions, as it is particularly the case for the social and organizational ones, were initially formulated for firm level kind of connections, we think that if a significant impact is found, even at an aggregate territorial scale, this is to be interpreted as evidence in favour of the existence of underlying micro mechanisms, which are effective and pervasive in driving knowledge creation across regions. As for the social and organizational proximity, although they are both based on the network notion it is worth remarking that accounting for the sources of network creation and development goes beyond the scope of this paper. Following the traditional regional science literature, we consider both social and organizational structures to be the result of fixed or slowly evolving networks (Corrado and Fingleton, 2012).

In Table 1 we summarize the main descriptive statistics of the proximity measures considered, along with their correlation matrix.

Geographical proximity. This is the standard and widely used indicator of proximity, it is measured by the distance in km between the centroids of any two regions. This measure is preferred to the contiguity matrix since it allows one to consider all the potential interactions among

[7] For the small European countries (Cyprus, Estonia, Lithuania, Luxembourg, Latvia, Malta) the regional breakdown is not available so they are considered at the country (NUTS0) level. Although we acknowledge that the NUTS2 territorial scale may be too aggregate to unveil all potential spillovers, nonetheless it is the observational level for which consistent regional data is made available by statistical offices, thus enabling us to consider the widest possible coverage of the European territory.

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's 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 indicate more proximate regions and thus a higher probability to exchange knowledge. Moreover, we 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. Thus two regions belonging to the same national institution are expected to have higher knowledge exchange. A simple, and widely used, way to account for these time invariant common factors is to include a full set of country dummies. Alternatively, we 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.[8] 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. Note also that the inclusion of national indicators is also suitable to account for the potential adverse influence due to "border effects"; the international trade literature (Anderson and Wincoop, 2004) has largely emphasized how such effects may inhibit trade among countries, and this can analogously happen in this case of knowledge flows when the regional and the national boundaries coincide (Parent and LeSage, 2012).

Technological proximity. In order to attract new knowledge from outside, firms and regions may need to build up absorptive capacity around the existing knowledge base and carry out technological activity in similar fields. In other words, cognitive capacity is bounded and companies and regions sharing an analogous knowledge base may exchange information and knowledge and learn from each other more easily. To measure the technological, or cognitive, proximity across regions we compute a similarity index between region *i* and region *j*, based on the distribution of patenting activity among 44 sectors,[9] defined as:

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

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

[9] Compared to other studies our sectoral breakdown is quite fine and informative. For instance, Parent and LeSage (2012) consider 8 sectors in analyzing knowledge determinants for the whole economic regional system of nine Western European countries.

where l_{ik} is the sectoral share of sector k in region i. The index 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 the technological structure of the two regions and the higher the probability that they can exchange knowledge. The index is computed for each couple of regions to build up a technological proximity matrix T with generic element t_{ij}.[10] The 44 sectors are defined on the basis of patenting activity measured at 2-digit SIC level and they mainly refer to manufacturing industries where most of the patenting activity is performed.

In Table 1 we show that the two most technologically distant regions (Ionia Nisia and Notio Aigaio in Greece) exhibit an index of 0.05. Interestingly, the higher degree of technological similarity (0.94) is found in two non-adjacent regions, located in different countries: Piedmont in Italy and Niederbayern in Germany. The econometric estimation allows to test whether 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, regardless of their geographical location.

In order to test the robustness of the technological proximity measure based on patenting activity we have also computed a matrix based on the sectoral distribution of employment, which is available for seventeen 2-digit NACE manufacturing and 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 better able to grasp the informative content of the cognitive similarity among territorial units.

Social proximity. The main idea is that individuals who have socially embedded relations and networks are more likely to trust each other and therefore to exchange tacit knowledge smoothly. At the macro level this implies that regions where network members reside are facilitated in exchanging knowledge. In this paper we measure social proximity by means of co-inventorship relations among multiple inventors of the same patent in case they are resident in different regions. 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

[10] 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 (the sample correlation coefficient is 0.91) and they give very similar results; therefore in the following sections we present only the results based on the similarity index. It is worth noting that this index may be also instrumental to construct a measure of cognitive distance across firms (as in Colombelli et al., 2012, in this issue)

number and the intensity of links among inventors located in different regions are able to catch the existence of a social network between regions which facilitates the exchange of knowledge.

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. 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 strong social relationships measured by co-inventorships. As expected, spatial proximity favours social interactions among inventors although, from Table 1, we can see that the correlation coefficient between the geographical and social proximity matrices is quite small (0.12).[11]

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 employees working for the same company. We follow Picci (2010) and Maggioni et al. (2011b) who measure proximity across nations and regions, respectively, by using the affiliation to the same organization of the applicant and the inventors of a patent. Given this definition, we are not considering the case in which the applicant and the inventor are the same 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 with the previous types of proximity, we expect a positive influence of organizational networks in the process of knowledge creation and diffusion since they are believed to reduce uncertainty and opportunism. Table 1 shows that the number of non-zero links in the organizational matrix amounts to 17% of total possible relationships among European regions. Interestingly, the highest value (480) is reached by two distant regions within France: Île de France and Rhône Alpes. The former hosts the capital, Paris, where most French companies locate their headquarters, whilst

[11] 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.

the latter is renowned for its scientific parks and research laboratories which are apparently linked to parent companies. In this case the hypothesis, to be tested empirically, is that the two regions are characterized by a high organizational proximity which should facilitate the knowledge exchange between them.

It is worth pointing out that both social and organization proximity measures are not completely satisfactory[12], the phenomena they are intended to capture are very complex and their measurement is a challenging task even at the micro level. However, we think that our contribution is, at least partly, successful attempt at responding to Anselin's (2010) solicitation for a more and more adequate representation of the spatial processes by deriving their interconnectivity structure on the basis of agents' social and economic interaction. This aspect is becoming increasingly relevant and deserves further investigation, in future analysis we intend to search for different proxies of social and organization closeness in order to reduce their overlapping and thus to gain a better understanding of their distinctive role in conducing knowledge flows.

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.

The literature on the determinants of innovative activity at firms' and regional level has been traditionally based on the estimation of a KPF model, 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 specification 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) or from the absorption of external knowledge (Abreu et al., 2008). Firms' and regions' ability to understand, interpret and exploit internal and external knowledge relies on prior experiences embodied in individual skills and, more generally, in a well-educated labour force (Engelbrecht, 2002 and Archibugi and Filippetti, 2011). In light of the discussion above, we also explicitly consider the presence of external factors coming from "proximate" regions, which may enhance the impact of the internal ones thanks to spillover effects.

[12] As a matter of fact it is quite difficult to obtain a non-overlapping measure of organizational and social proximity. Indeed, the correlation coefficient between the two proximity matrices reported in Table 1 is 0.74.

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

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

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 population share of graduates. As control variables we include the population density and the regional share of manufacturing activities. See Appendix 2 for a detailed description of the variables.

More specifically, as a proxy of 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 patents is divided by total population. Thus our dependent variable (*inn*) is measured as the yearly average of patents per million inhabitants in 2005-2007. The summary statistics, reported in Table 2, show substantial differences in patenting activity among European regions, ranging from near zero in Sud-Vest Oltenia, 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 little patenting activity is performed by the eastern and southern regions.

The traditional input in the KPF is R&D expenditure, rescaled for GDP, which shows an average value of 1.4. 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). 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.

Population density is included to account for possible agglomeration effects, which especially in urban contexts are associated with more intensive innovation activity. Audretsch and

Feldman (1996) emphasize that the location of manufacturing activity is one of most relevant factors that explain the spatial distribution of innovative activity, thus to control for this aspect related to the local productive pattern, we also include the regional share of manufacturing activities.

Note that all the explanatory variables included in model (1) are averaged over the three-year period 2002-2004. The average values are expected to smooth away undue business cycle effects, the lags with respect to the dependent variable are necessary to allow for a congruent time horizon for the productive inputs to unfold their effects. Moreover, lagged explanatory variables should also avoid potential endogeneity problems.

Proximity factors are included in the model in order to capture the potential role of spillover effects running along the five different dimensions suggested by the literature – geographical, institutional, technological, social and organizational.

Since the presence of spillovers induces spatial correlation in the patenting activity among the regions, the proximity factors have to be modelled accordingly. The spatial econometric literature provides two basic models to account for the existence of spillovers: the Spatial Autoregressive (SAR) model, which features a spatial regressor given by the weighted average of the all-other region response variable, and the Spatial Durbin (SD) Model, which extends the SAR model by including also the weighted average of the explanatory variables. For both specifications the weights represent the assumed interconnectivity structure among the spatial units.

It is worth remarking that, in this paper, we do not consider the Spatial Error Model (SEM), which entails spatial dependence only in the model errors, as it removes spillovers by construction. Within the SEM model, spatial dependence is not the focus of the analysis, but it is seen as a nuisance which yields non-spherical error, so it is treated just to ensure unbiased variance estimators.

Note also that we rule out the SD Model on substantive grounds, for this specification implies that the influence of neighbouring territories on the innovative performance of a certain region is mediated also by their internal inputs, i.e. R&D investments and human capital endowments, conditional on a given connectivity structure. This amounts to assuming that neighbours' R&D investments are thoroughly productive and that human capital feature a considerable degree of mobility among regions. As both these assumptions are hardly realistic in the European context,[13] we argue that it is more reasonable to envisage that innovation spillovers

[13] For instance, some expenditures classified as R&D are not directly related to knowledge activities (as is the case of research laboratory buildings) and 50% of R&D is made of researchers wages, so that it is more plausible to allow for the existence of R&D spillovers in the case of the general level of production than in the case of the specific knowledge

work through the effective level of knowledge achieved by neighbouring regions, which is proxied by the number of patent applications. Therefore, our preferred specification is the spatial autoregressive one, formalized as follows:

$$inn_i = \beta_1 rd_i + \beta_2 hk_i + \phi\ controls_i + \rho W\ inn_i + \varepsilon_i \qquad (2)$$

where W is a weight matrix, which describes the interconnectivity among regions according to one of the proximity dimensions previously discussed.[14]

In model (2), due to the presence of the spatially lagged dependent variable the interpretation of the coefficients as partial derivative no longer holds. The *total* effect on the innovation response variable caused by a unit change in one of the internal factors - either R&D or human capital - has a complex structure and can be decomposed into a *direct* and an *indirect* effect. The *direct* effect measures the change in region *i*'s dependent variable caused by a change in one of its own regressors plus a series of feedback effects (region *i* is neighbour to its neighbours so affecting them will receive in turn a feedback influence), while the *indirect* or spillover effects is due to a change in another region's regressor. It is worth noting that feedback and spillover effects occur over time through the simultaneous system of interdependence among regions, so that the effects have to be considered as the result of a new steady state equilibrium. LeSage and Pace (2009) propose summary scalar measures for direct, indirect and total effects along with their dispersion measures, which allow to draw inference on their statistical significance.

In the subsequent sections we analyse spillovers by considering one proximity dimension at a time, starting with the traditional geographical one and then following with the technological, the social and finally the organizational proximity. As will be explained in greater detail in the next section, regional institutional closeness is better dealt with by including the complete set of country dummies, so we do not propose a SAR model with the dependent variable lagged term based on the institutional structure. As the national dummies can be considered as additional control variables, the institutional kind of proximity is always included in the empirical models along with one of the other four connectivity measures.

Although it would be more reasonable to assume that all the proximity channels are simultaneously at work, possibly reinforcing each other in a complementary guise, this would entail

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creation process. This is also confirmed by a preliminary econometric investigation based on the SD model, which resulted in not significant spillovers effects.

[14] The SAR specification has recently been criticized (Partridge et al., 2012 and Gibbons and Overman, 2012) for lacking identification of the ρ parameter (see model 2) when the weight matrix is block-diagonal and idempotent. In our case the weight matrices considered do not share such properties. Moreover, Gibbons and Overman interpret ρ parameter as the causal effect of the neighbouring response variable. However, LeSage and Pace (2009) warn against such interpretation and Elhorst (2010) explains very clearly that the spillovers (indirect) effects have the complex structure of a multiplier term whose size and sign depend on both the estimated coefficients and on the weights matrix. We provide a brief description of direct and indirect effects in the main text.

the specification of a quite complex interconnectivity structure, which poses challenging econometric technical aspects to solve.[15] Therefore in this study we confine our attention to the estimation of one-proximity models; if complementarities are indeed present our results provide lower-bound effects, which are expected to be amplified when allowing for the complete set of proximity interconnections among regions.[16] Notwithstanding this limitation of our analysis, the evidence we find is very insightful and can serve as a basis for some suggestive policy prescriptions.

4. Geographical proximity

Table 3 presents the results based on the SAR model estimated by assuming that the regional interconnectivity is represented by the geographical proximity.

Following a specific-to-general approach (Florax et al., 2003), our analysis starts with the estimation of a basic model which does not include any spatial regressor, so that if omitted spillovers are relevant, they will be part of the error term, which consequently will feature spatial autocorrelation. OLS Estimates of the basic model are reported in the first two columns of Table 3; the regression model in the second column includes also the set of country dummies. We carried out the Robust LM tests to detect either generic spatial dependence in the error term (LM-error) or in the omitted lagged dependent variable (spillover) term (LM-spatial lag). The test are computed using as a spatial weight matrix the inverse distance in kilometres between each possible pair of regions (*G*); it is normalized by dividing each element by its maximum eigenvalue. Both tests are highly significant for the first regression, but in the second one it is evident that the result of the LM-error test is entirely due to the omission of the national countries. As expected, these account for a great deal of spatial heterogeneity among the regions. The significance of the LM-spatial lag test in column (2) indicates that the model is better specified by including the spatial lag of the response variable. In columns (3) and (4) we thus report the results of the SAR model estimated without and with the country dummies. Note that the LM error test for the SAR residuals of regression (3) is significant, thus indicating that the complexity of the inter-connectivity among the regions is not entirely captured by the geographical weight matrix and that national features are indeed relevant; when these are included in regression (4) the SAR models yields approximately

[15] This would require to estimate a SAR model with four different dependent variable lagged terms and to solve a multivariate optimization problem of order four over the range of all possible values of the autoregressive parameters. No off-the-shelf econometric tools are currently available. In a recent companion paper (Marrocu et al. 2011) we have managed to estimate two-proximity SAR models and provide evidence of remarkable complementarities between geographical closeness and technological similarity.

[16] Note that on the basis of the sample correlation coefficients reported in Table 1, with the exception of the social and organizational matrices, all the other proximities exhibit a low degree of overlapping, so their single influences can reasonably expected to add up.

white noise residuals (the LM error test is no longer significant)[17]. Note that comparing model (3) with model (4) shows that the inclusion of the country dummies, most of which are statistically significant, 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. It is important to remark that in both models (3) and (4) direct, indirect and total effects are significant for both R&D and human capital, these results thus provide evidence that a region's own internal knowledge production factors are enhanced by being located in highly innovative areas.

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 kilometres (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 value (1200 km) of the distance distribution for the 75900 pairs of regions included in our sample. 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 (0-300 and 301-600) and for the wider 0-600 km band. Note that the 600 km distance approximately corresponds to the first quintile of the distance distribution. The model estimated with a 0-600 km geographical matrix is reported in column 5 of Table 3; as expected, when longer distances are considered (greater than 600 km, model 6) the spatially lagged term becomes irrelevant, signalling that spillovers are likely to have exhausted their effects in space. Conditional on the scale of our territorial units, our results suggests that knowledge flows among regions are likely to be bounded within a 600 km range. 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.

Model 5 of Table 3 is the preferred specification when proximity is measured only along the geographical dimension. The estimated coefficient for R&D and human capital are both significant and quite similar to the ones obtained from model 4. More specifically, the R&D shows an

[17] We have also estimated an alternative version of regression (3) by replacing the geographical matrix with the institutional proximity one (see section 2). In this case the model residuals still feature spatial correlation autocorrelation, signaling that such a matrix is not sufficient to account for both national similarity and interconnectivity among the regions. For these reasons in the subsequent analysis we prefer to account for institutional factors by including the complete set of country dummies, while tackling the regional interrelationships by means of one of four different proximity matrices.

estimated direct elasticity of 0.26 and an indirect one of about 0.07, thus direct effects account for almost 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 is very similar to the elasticity of 0.26 estimated by Moreno et al. (2005) for 17 EU countries. For a sample of patents of 86 regions in 12 European countries, Bottazzi and Peri (2003) found a higher value of 0.8. However neither study considers the indirect effects coming from other regions.

As for human capital, we find a direct elasticity of 1.56, which is much higher than the one estimated for R&D. This is an important result which lends further support to the idea that an endowment of well-educated labour force in a given region strongly enhances the innovative activity, once we account 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.

As for the controls, the population density give contrasting results and it is not significant in our preferred specification (model 5).[18] The manufacture specialization structure appears positive and significant with a coefficient of 0.89 in model 4 confirming that the production of new technology is higher within the manufacturing sectors.

Another interesting comparison can be made for 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, a value close to the 0.20 we find for our wide European sample.

5. 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.

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

In model 1, 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; the spatially autoregressive coefficient is also positive and significant. However, the indirect effects of R&D and human capital are not significant, signalling 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 any two regions is above a certain threshold. Following the methodology illustrated in the previous section, we estimate several regressions with the technological matrix restricted to different values of the similarity index. It turns out that the technological spillovers can be detected 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 spatially lagged dependent variable coefficient.

To assess the robustness of these results we consider another technological proximity matrix based on the similarity indices computed for the employment distribution of 17 manufacturing and knowledge intensive service sectors. Results are reported in specifications 4-6 using the full matrix, and matrices with similarity indices greater and lower than 0.5, respectively. The magnitude of the estimated coefficients for the production inputs and the spatial lag is very similar to that of the coefficients obtained with patenting activity. However the indirect effects are never significant even when a similarity indices 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 when proximity is measured in terms of the regional cognitive base. The spatial dependence coefficient for the technological proximity shows a value of 0.29. Previous comparable studies for the technological 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).

The direct elasticities for both R&D (0.26) and human capital (1.3) are very similar to the ones obtained from the model based on the geographical 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, handle 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 given region to benefit from knowledge spillovers, a relatively high cognitive similarity is required with respect to the region where the original knowledge is produced.

6. 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 by associating inventors and applicants residing in different regions. We find that, for both social and organizational proximity, the strength of the regional interconnection is much lower (0.11 and 0.07, respectively) when compared to the one found for the geographical and the technological proximities. The 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. We have further evidence of 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 when the specification is based on social networks.

These results, however, are very relevant when considered in the light of the inherent difficulties faced in computing the social and the organizational proximity matrices and of the territorial level considered: since positive evidence is found even at the aggregate NUTS2 level this signals that effective knowledge exchanges are taking place in the underlying individual and firm levels. The only previous study which provides an analogous KPF econometric setting, where the relational/social matrix (based on FP5 links) is introduced as a weight matrix, is Maggioni et al. (2007), although they estimate a SEM rather than a SAR model. They find evidence of interconnectivity in the social space even though the coefficient is not always significant. Another interesting outcome is proposed by Ponds et al. (2010), who estimate a model including only the spatial lagged terms for the explanatory variables. The value of the coefficient of the network-university R&D is comprised within an interval from 0.08 and 0.12, quite close to our values.

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 dimension is tested at the regional level.

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. The simultaneous presence of these proximity dimensions implies that spillovers may have a dual nature, as argued by Maggioni et al. (2007 and 2011a): one unintended and one intended. In the former case, geographical vicinity, for example, may give rise to a trickling down process of knowledge diffusion which is not connected to economic agents' decisions. In the latter case, knowledge may travel across a-spatial networks, which can be structured through formal or informal agreements, and are due to agents and institutions which exchange ideas on a voluntary basis (Cowan and Jonard, 2004).

7. Concluding remarks and policy implications

Economists and politicians both agree that the availability of knowledge and its diffusion are crucial ingredients for fostering economic development in Europe both at the regional and national level. A similar agreement is now emerging about the idea that the diffusion of innovation depends on the relative position of each region with respect to different dimensions which go beyond the geographical space. These dimensions are mainly a-spatial and include the institutional, technological, social and organizational ones. In this paper, moving along the research line of the KPF model, we have examined these issues reaching interesting and original results on the role of internal and external factors in promoting knowledge creation at the regional level.

As far as the internal factors are concerned, we find that both R&D and human capital are essential components of technological progress, even though with quite a distinct magnitude. Once institutional proximity is considered, the latter exhibits almost six times the impact of the former. This outcome is a clear indication of the effectiveness of skilful and qualified labour force in ensuring incremental technological progress based on pervasive and continuous learning, ideas circulation and experience accumulation. This is particularly true in current economic systems where the continuous emergence of new technological trajectories calls for an encompassing and systemic capacity to understand, acquire and control original knowledge and innovations.

Regarding the external factors, we establish that all dimensions of interregional proximity and connectivity are significantly related to innovative performance, representing effective channels of knowledge transmission. Nonetheless, we find that their relative strength differs significantly.

The strongest association was found for the cognitive or technological proximity: 1.5 times higher than the one based on geographical proximity and up to three-four times higher than that of social and organizational networking. The existence of a common knowledge and productive base can thus be more important than unintended interactions due to spatial proximity. Moreover, we prove that intended interactions, which model social and organizational networks, are important too, although their relevance is relatively more modest. As a consequence, we find that a sizeable part of the total effects of R&D investments and human capital endowments on the knowledge creation in a certain region derives from spillover effects coming from other regions along a composite system of interregional connections. In other words, the intensity of indirect effects vary with the proximity dimension employed, but they are all fundamental in channelling knowledge through a variety of regional interdependences.

It is worth underlining that the results associated with social and organizational proximities are likely to be driven by the inherent difficulties faced in measuring their precise content. This represents a limitation of the current study, which we plan to address in future analyses by exploiting the additional explanatory power of alternative data sources at the micro level (i.e. European social survey), which are expected to provide more reliable measures of social closeness at regional level. Another limitation, which deserves further consideration in future extensions, is related to the assessment of potential complementarities among the different proximity dimensions. The development of a comprehensive econometric framework would enable us to account for the complete range of complementarities, which are supposed to exist among the proximity dimensions, and to provide a more rigorous measure of the overall knowledge multiplier. Moreover, further research is necessary to unveil the underlying links between the aggregate regional macro level and the micro level, where individual behavior and relations are shaped along each dimension of proximity. As a matter of fact, there is strong need for micro-econometric analyses on the causal effects of industrial and regional policies, such as those by Criscuolo et al. (2012) and Antonelli and Crespi (2012), to acquire more specific indications on the more effective interventions and instruments to be implemented.

Notwithstanding these limitations, the current analysis has provided relevant empirical findings which allow for a better understanding of the processes of knowledge creation and diffusion in Europe. This enables us to formulate a number of policy recommendations, some with a more general relevance and some others specific to the proximity dimension considered.

Among the former, the first policy advice is that European regions still need to focus on actions aimed at increasing the endowments of well-educated labour force, given their strong and pervasive role in determining both the internal creation and the external 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 education in general and universities in particular have to be central in any innovation policy.

The second general policy implication derives from the existence of several channels of interregional spillovers and externalities, which calls for a coordinated strategy able to achieve the optimal social outcome with differentiated interventions. It is increasingly clear that there is no "one size fits all" policy (Todling and Trippl, 2005) and that regions need to set different targets to be achieved with diverse instruments. In general, policies should aim directly at investments in knowledge diffusion and absorption rather than merely investments in research and development for new ideas. Actually, this is one of the basic ideas behind the smart specialisation strategy which promotes place-based policies recently at the centre of a heated debate (see Barca, 2009 and World Bank, 2009). Thanks to such policy support, each region is expected to strengthen its competitive advantages by acquiring as much as possible from ongoing knowledge flows and, at the same time, spreading the benefits of innovation throughout the entire regional economy (Asheim et al. 2011).

In order to derive the specific policy recommendations implied by the five different spillovers transmission channels analyzed in this study, we follow the path traced in Boschma (2005).

First of all, the presence of flows of knowledge which move along the technological space implies that regions should try to develop a balanced policy to create a common wide knowledge base and specific industrial platforms to maximize the absorptive capacity and its effective application. Practically, policies should support and encourage the formation of dense specialised networks among regional innovation systems, which go beyond geographical clusters. The fact that technological proximity matters even more than the geographical one in transmitting spillovers means that knowledge diffusion is facilitated within a-spatial technological clusters. This suggests the implementation of specific industrial policies to support the functioning throughout Europe of such a-spatial industrial clusters characterized by proximate technology.

Secondly, the presence of spatial externalities encourages regions to find a position along this dimension, which favours local spillovers without cutting off global pipelines of information. The risk of losing global innovation opportunities is likely to arise when regions become part of local enclaves based only on spatially bounded externalities, as recently theorized by Boschma and Frenken (2010), who have proposed the so-called proximity paradox. While proximity may help agents to connect and exchange knowledge, too much proximity on any of the dimensions might harm their innovative performance (see Broekel and Boschma, 2012, for an interesting analysis of such a paradox in the Dutch aviation).

Furthermore, the empirical relevance of institutional proximity implies that public coordination in the form of common procedures and standards may be crucial for avoiding opportunistic, or merely inefficient, behaviours due to lack of trust among agents in different regions. Thus, a process of effective homogenization of norms and procedures for the whole of Europe is required to help the creation of a real institutional closeness among all European areas. At the same time implementation procedures should not translate in excessive bureaucracy favouring inertia and delaying the integration with different institutional and cultural settings.

Finally, externalities arising from social and organizational interregional relations require policies designed specifically to sustain those areas where the absence or the shortage of either social or organizational capital may hamper the creation of such networks. Since these networks have an intended voluntary nature, policies have to provide a balanced set of incentives to motivate more cooperative attitudes towards economic agents located in proximate regions. Nonetheless, such inclusive policies should ensure that social relations to not happen at the detriment of market relations and competitive behaviours.

All in all, 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 enhancement of mechanisms underlying the diffusion of knowledge and the circulation of ideas. This will facilitate the catching up of laggard and more fragile areas and, at the same time, increase the potential innovative output of Europe within global competition. Such a goal clearly entails enhanced consistency of EU strategies at the European, national and regional level. Strategies which recognise that each region innovation potential is unique because of different geographical, cognitive, social, institutional and organizational structures and networks, and each region requires specific local platform policies based on differentiated knowledge structures.

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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	EPO	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 centres, 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

	Sample 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

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

	1	2	3	4	5	6
Model:	Linear	Linear	SAR	SAR	SAR	SAR
Estimation method:	OLS	OLS	ML	ML	ML	ML
Range in Km included:			full	full	0-600 km	over 600 km
Production inputs						
R&D	1.372 ***	0.249 **	1.044 ***	0.271 ***	0.257 **	0.247 **
	(12.159)	(2.274)	(10.118)	(2.683)	(2.549)	(2.386)
Human capital	0.934 ***	1.524 ***	0.863 ***	1.535 ***	1.559 ***	1.529 ***
	(3.737)	(4.624)	(3.960)	(5.063)	(5.126)	(4.913)
Control variables						
Population density	0.063	0.129 *	-0.227 ***	0.048	0.063	0.13 **
	(0.912)	(1.906)	(-3.305)	(0.713)	(0.948)	(2.036)
Manufacture specialisation	0.594 ***	1.069 ***	0.290	0.863 ***	0.892 ***	1.069 ***
	(2.861)	(5.906)	(1.580)	(4.875)	(5.062)	(6.295)
Spatial autoregressive coefficient (ρ)			0.557 ***	0.330 ***	0.202 ***	-0.023
			(9.359)	(3.396)	(3.116)	(0.135)
Country dummies		yes		yes	yes	yes
Adj-R^2/ Sq. Corr. (actual, fitted values)	0.586	0.801	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 error	97.311	0.254				
p-value	0.000	0.614				
Robust LM test - spatial lag	79.064	12.790				
p-value	0.000	0.000				
LM error test for SAR model residuals			56.680	0.011	0.011	0.011
p-value			0.000	0.918	0.918	0.918

Observations: N=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

SAR Models:	**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 autoregressive coefficient (ρ)	0.493 ***	0.293 ***	-0.055 ***	0.238	0.263 *	-0.057 *
	(3.364)	(3.233)	(2.785)	(1.035)	(1.718)	(2.349)
Square correlation (actual, fitted	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: N=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

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 Social (S) and Organisational (O) proximity

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

SAR Models:	1	2
Proximity matrix:	S	O
Production inputs		
R&D	0.191 *	0.207 **
	(1.837)	(1.992)
Human capital	1.524 ***	1.484 ***
	(4.981)	(4.832)
Control variables		
Population density	0.091	0.095
	(1.409)	(1.460)
Manufacture specialisation	1.026 ***	1.058 ***
	(6.077)	(6.283)
Spatial autoregressive coefficient (ρ)	0.115 ***	0.072 **
	(2.552)	(2.200)
Square correlation (actual, fitted values)	0.806	0.805
Effects estimates (a)		
R&D		
direct	0.188 *	0.206 **
indirect	0.023	0.015
total	0.212 *	0.221 **
Human capital		
direct	1.540 ***	1.499 ***
indirect	0.202 **	0.117 **
total	1.742 ***	1.616 ***
Diagnostics		
LM error test for SAR model residuals	0.293	0.009
p-value	0.589	0.923

Observations: N=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
Asymptotic t-statistics in parenthesis; significance: *** 1%; ** 5%; * 10%
(a) We report only the effects for the main interest explanatory variables