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The complementary effects of proximity dimensions on knowledge spillovers

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**THE COMPLEMENTARY EFFECTS OF PROXIMITY
DIMENSIONS ON KNOWLEDGE SPILLOVERS**

**Emanuela Marrocu
Raffaele Paci
Stefano Usai**

WORKING PAPERS

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The complementary effects of proximity dimensions on knowledge spillovers

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Abstract

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

Keywords: knowledge production, spillovers, proximity, human capital, weight matrix.

Jel Classification: C31, O31, O18, O52, R12

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1. Introduction

The accumulation of knowledge in a region depends on its internal capacity of producing innovation and also on its ability to acquire and to put into operation the stock of knowledge generated in other areas. In this view the main determinants of innovations are the internal production inputs, R&D expenditure and human capital, as well as the different channels which facilitate the transmission of the external knowledge towards the receiving region. Among the internal factors, human capital is expected to play a crucial role in the absorption process of external knowledge (Cohen and Levinthal, 1990) and also in the informal process of learning by doing (Nelson and Winter, 1982), which represents a relevant component of the innovation activity.

As far as the transmission channels are concerned the literature has usually focused on geographical proximity following the idea that knowledge spillovers are bounded in space (Jaffe 1989). Thanks to pecuniary and pure knowledge externalities, this implies that firms' (or regions') technological activity benefits from being located close to other firms (regions) producing innovations. However, more recent contributions (Boschma, 2005) have emphasized that the spatial dimension can be supplemented by other forms of a-spatial proximity shaped by institutional, technological, social and organizational links (see also the literature review by Knoben and Oerlemans, 2006).

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

Thus, there is a widespread belief that knowledge transmission can be facilitated by the simultaneous presence of spatial proximity and networking in social, institutional, technological and organizational "space". These different proximity dimensions are expected to exert complementary and reinforcing effects on knowledge transmission (Mattes, 2011). This approach is also in line with recent applied spatial

econometric contributions which have emphasized the “economic” content of the distance concept. Such a content becomes relevant when interactions among spatial units “is determined by purely economic variables, which may have little to do with the spatial configuration of boundaries or geographical distance *per se*” (Corrado and Fingleton, 2011, p. 8)¹.

The original contribution of this paper is to empirically assess the joint and complementary effects of various dimensions of proximity on knowledge spillovers across European regions. Our analysis is carried out within the Knowledge Production Function (KPF) framework, where R&D expenditure and human capital are the main internal inputs, and it is implemented for an ample dataset referring to 276 regions in 29 countries (EU27 plus Norway, Switzerland).

Spatial econometric techniques are adopted in estimating the KPF model in order to account for the regional interconnectivity pattern. Our model selection strategy points out that a spatial autoregressive specification is adequate in capturing the main features of our sample data. Such specification permits to single out the relative importance of the regional internal production factors with respect to spatial spillovers. In order to fully account for the complementarities among all the proximity dimensions considered, the optimal estimation strategy would entail the specification of a comprehensive model which includes all of them at the same time. However, for a spatial autoregressive (SAR) specification, this would require the solution of an order five multivariate optimization problem, which goes beyond the current state of the art (Elhorst, 2010).

As a workable alternative we therefore adopt the SAR model variant which includes two different spatially lagged terms for the dependent variable; this kind of specification, which allows to account for pairs of proximity dimensions at a time, was first proposed in a different setting by Lacombe (2004). Moreover, to obtain at least an approximate measure of the overall spillover effect when all knowledge transmission mechanisms are at work, we carry out a post-estimation exercise based on model combining techniques.

The paper is organised as follows. Section 2 presents the empirical model and describes the data and the different proximity measures. Section 3 deals with the estimation strategy and the spatial

¹ See also the recent contribution by Harris et al. (2011) for a discussion on the specification of the weight matrix in spatial econometrics models.

specification of the model. Section 4 discusses the empirical results. Section 5 concludes.

2. Empirical model and data description

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

The general form of the empirical model for the KPF is specified according to a Cobb-Douglas function where the innovation output (INN) is a function of two production inputs, R&D expenditures (RD) and human capital (HK) and a set of control variables:

$$INN_i = RD_i^{\beta_1} HK_i^{\beta_2} controls_i^\gamma e^{u_i} \quad (1)$$

in this general form, as the proximity factors are not modelled explicitly, the error term is expected to feature spatial dependence. If such factors are assumed to act as an additional determinant of innovation, model (1) can be reformulated in a log-linearised form as follows:

$$inn_i = \beta_1 rd_i + \beta_2 hk_i + \gamma controls_i + \rho proximity\ factors_i + \varepsilon_i \quad (2)$$

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

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 and divided by total population to control for the different size of the regions.² Since patenting activity at

² In case of multiple inventors, we assign a proportional fraction of each patent to the different inventors’ regions of residence. Data on patents are currently

the regional level is quite irregular over time we smooth the variable by computing the average for the years 2005-2007. The traditional input in the KPF is R&D expenditure at the regional level, which is included in the regression after being scaled with respect to GDP. Human capital is measured as the share of population with tertiary education. The vector of control variables includes the population density to allow for possible agglomeration effects and the share of manufacturing activities to account for the regional productive pattern. All the explanatory variables are lagged and averaged over the period 2002-2004. The lags are expected to allow for a congruent response time of the innovation activity to changes in the production inputs and also to avoid potential endogeneity problems; the averaging over a three-year period is carried out to smooth away undue cycle effects. See Table 1 for a detailed description of the variables.

Technological progress at the regional level is a complex process which combines the local production of innovation together with the absorption of externally produced knowledge thanks to the presence of knowledge spillovers across regions. Such spillovers are captured by including in the model the proximity factors defined along the five different dimensions suggested by the literature – geographical, institutional, technological, social and organizational.

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

Institutional proximity indicates that knowledge transmission may be facilitated by the existence of a common institutional framework. Institutions, such as language, laws and norms, can provide a set of standard procedures and mechanisms which, being shared by agents, tend to reduce the degree of uncertainty and transaction costs and, in

gathered in the OECD REGPAT database (Maraut et al., 2008) which provides information on inventive activity and its multiple dimensions (*e.g.* geographical location, technical and institutional origin, individuals and networks).

turn, to favour cooperative behaviours in the regional context (Maskell and Malmberg, 1999; Gertler, 2003). In this paper we follow the simplest way to account for these common factors by including a full set of country dummies.³

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

Social proximity refers to the idea that individuals who have socially embedded relations are more likely to trust each other and therefore to exchange tacit knowledge smoothly (Granovetter, 1985). Within a risky and uncertain phenomenon such as technological progress, this implies that social closeness facilitates firms' capacity to learn, absorb external knowledge and innovate. We measure social proximity by means of co-inventorship relations among multiple inventors of the same patent in case they are resident in different regions. The rationale is that the number and the intensity of links among inventors located in different regions are able to catch the existence of a social network among regions which facilitates the exchange of knowledge. We build a symmetric social matrix S whose generic element s_{ij} is defined as the number of inventors located in region i which have co-operated with inventors located in region j to conceive a

³ Alternatively, institutional proximity can be modelled by means of a weight matrix, whose elements take value 1 if two regions belong to the same country and zero otherwise, as in Paci and Usai (2009) and Hoekman et al. (2009) for their study of knowledge flows across EU regions.

patented invention. The intra-regional relationships are not considered and, therefore, the principal diagonal elements are set to zero.

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

Although we are aware that referring mainly to individuals' characteristics the extension at the aggregate regional level of the social and organisational networks is not straightforward, we believe that it can, nonetheless, provide interesting insights in unveiling what drives knowledge flows across Europe.

3. Estimation strategy and model specification

In order to estimate the KPF model it is necessary to select the most adequate specification which should enable us to properly account for the presence of inter-regional knowledge spillovers and to provide a more reliable estimate of the impact of R&D 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 the different dimensions described in the previous section, which are expected to exert complementary effects reinforcing 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 yield 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 it would be necessary 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 in the spatial econometric literature only a variant of the spatial lag model with two weight matrices has been proposed so far (Lacombe, 2004). We adopt such a variant in section 4.2 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 specifications⁴, 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 (LeSage et al. 2007, Parent and LeSage 2008, Autant-Bernard and LeSage, 2010).

We initially consider 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.

We adopt a specific-to-general approach, starting from a specification which models the interconnectivity among regions by considering one proximity measure at a time, we begin 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.⁵

As it removes spatial spillovers by construction – while our aim is to explicitly measure them – in this study we devote limited attention

⁴ 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).

⁵ Results are not reported in order to save space, but are available from the authors upon request.

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 of the included explanatory variables. For model (1) the estimated SDM returned an insignificant coefficient associated with the spatially lagged dependent variable 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, provided reasonable results for all variables, including the spatial lag, significant and with the expected positive sign. The evidence in favour of the SAR model is plausibly due to fact that, once human capital and the control variables – all spatially correlated to some extent – 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 analysis⁶.

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 spillover effects generated by the dependence structure of the spatial units. The *total* effect caused by a change in one explanatory variable can thus be decomposed into the *direct* effect (the change in region i 's dependent variable caused by a change in one of its own regressors plus the feedback effects) and the *indirect* or spillover effects (the change in region i 's dependent variable caused by a change in region j 's regressor). It is worth noting that feedback and spillover effects occur over time through the simultaneous system of interdependence among regions, so that the effects have to be considered as the result of a new steady state equilibrium. LeSage and Pace (2009) propose summary scalar measures for direct, indirect and total effects along with their dispersion measures, which allow to draw

⁶ Note that in our case the choice of a SAR specification is robust with respect to the critique advanced in Corrado and Fingleton (2011) on the mechanical application of such a model in some empirical analysis. The spatial lag in our estimated model has a precise economic content represented by the knowledge spillovers.

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 WY is the spatial autoregressive term, and ε is the usual iid error term. If the model is reformulated as

$$Y = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1} \varepsilon; Y = \sum_{k=1}^K Q_k(W) x_k + V(W) \varepsilon, \text{ where}$$

$$Q_k(W) = V(W) I_n \beta_k \quad \text{and}$$

$V(W) = (I_n - \rho W)^{-1} = (I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 \dots)$ 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 its 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. Empirical results

4.1 Proximities and networks: a preliminary comparison

In this section we present the results of the SAR model estimated by using the proximity dimensions one at a time; this preliminary analysis allows to carry out comparisons with the previous empirical literature. It is important to remark that all regressions include a set of country dummies to account for institutional closeness, such as sharing a common language and norms.

Following the extensive analysis done by Marrocu et al. (2011) the geographical matrix G is confined to the range 0-600 km since the spatial spillovers are localised and limited in space.⁷ Similar

⁷ The literature has emphasized the localized nature of geographical knowledge spillovers which are often limited in space (Doring and Schnellenbach, 2006). Previous findings for EU15 regions show that knowledge spillovers are

considerations apply to the technological matrix T which generates relevant spillovers only when the similarity index between the two regions is above the threshold of the 0.5 value.

Note that each proximity matrix is maximum-eigenvalue normalized; as emphasised in Kelejian and Prucha (2010), such a normalization is sufficient and avoids strong undue restrictions, as it is the case when the row-standardization method is applied. Moreover, symmetry and the importance of absolute, rather than relative, distance is maintained.⁸

The estimation results for the four KPF models based on a single proximity measure are reported in Table 2. An interesting outcome is the low variability of the estimated coefficients both for the input variables and for the controls. Considering the estimated effects in detail, the total elasticity for R&D goes from 0.21 in model 3 to 0.37 in model 2, while the human capital elasticity ranges from 1.62 in model 4 to 1.96 in model 1. Thus, the first important result is that human capital is more effective than formal research expenditure in determining technology production at the regional level. We find that the total impact of human capital is always higher with respect to R&D in all models, ranging from a multiple of around five in the model with technological distance to above eight in the model with social networks. The creation of new knowledge is often based on informal learning processes and on the ability of exploiting external knowledge and the presence of well educated labour forces plays a key role in these processes. It is also worth noting that indirect effects are always significant and sizeable for human capital, accounting up to 30% and 20% of the total effect in the case of model 2 and 1, respectively.

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

confined to a range of around 300 km (Bottazzi and Peri 2003; Moreno et al. 2005), while a crucial distance of 600 km is found by Dettori et al. (2011).

⁸ When the proximity weight matrix is capturing a “distance decay” type of economic behavior “scaling the rows so that the weights sum to one may result in a loss of that interpretation” (Anselin, 1988, p. 24).

European regions and the one by Usai (2011) for 342 regions in OECD countries, who present point estimates of 2.0 and 1.0, respectively.

As for the controls, the population density turns out to be positive, although it is significant in only one case (the T-matrix model). This means that there are some agglomeration effects at work even though their strength is not substantial, as in Crescenzi et al. (2007). As for the manufacture specialization structure, it is always significant with a coefficient included in a very limited interval going from 0.89 in model 1 (G-matrix) to 1.06 in model 4 (O-matrix). This is an expected result since the production of new technology is higher within the manufacturing sectors.

Looking at the coefficient of the lagged dependent variable, the first remarkable outcome is that it is always positive and statistically significant in all the four models, signalling that technology production in a certain region is positively affected by knowledge spillovers which are transmitted along each of the different proximity dimensions. More specifically, the strongest association (the spatial lag coefficient is equal to 0.29) is captured by the technological proximity which turned out to be the most important channel of knowledge spillovers, whilst geographical proximity ranks second (0.20). As far as the network dimensions are concerned, they have a relatively more modest role: the lagged dependent variable has a coefficient of 0.11 with social proximity and 0.07 with the organizational one.

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

4.2 Models with pairs of proximity matrices

As it has been remarked in the literature, the different types of proximity are expected to be complements as they represent knowledge transmission channels which reinforce each other (Mattes, 2011). From

the empirical point of view this implies that one should allow for all four kinds of proximity in the same estimation model. Unfortunately, the available estimation codes for spatial econometrics do not allow this first best solution and we have to look for second best procedures.

In this section we present the results for the SAR models estimated by including two different proximity-lagged terms at a time in order to account for complementarities between pairs of knowledge spillovers channels. The two-weight matrix SAR model is specified as: $Y = X\beta + \rho_1 W_1 Y + \rho_2 W_2 Y + \varepsilon$ and it requires to solve a bivariate optimization problem over the range of feasible values for the parameters r_1 and r_2 .⁹

This model specification was first proposed by Lacombe (2004) to carry out a policy spending evaluation analysis while controlling for spatial dependence.¹⁰ 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-neighbours) since it also features other a-spatial kinds of links.

The results are reported in Table 3 which shows that, remarkably, most of the previously discussed results maintain their strength and significance. This is the case 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 by an average value of 0.19. The same applies for the proximity measure based on technological similarity, which exhibits a relatively higher impact (average value of 0.31) across all the models when compared with the geographical one. The regional connectivity based on both the social and the organizational proximity shows a weaker degree of dependence, with an estimated coefficient which on average is equal to 0.11 and 0.07, respectively. It is interesting to note that when these matrices are included together (last column in Table 6) both coefficients of the spatially lagged terms are no longer significant, signalling a sort of multicollinearity problem. This is plausibly due to the fact that the

⁹ See LeSage and Pace (2009) for a detailed description of the estimation procedures.

¹⁰ We are very grateful to D.J. Lacombe for making available to us the Matlab scripts to estimate two-weight matrix SAR models.

information contained in the two matrices somehow overlaps (the correlation coefficient is 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 3 we also report the estimated direct, indirect and total effects. It turns out that human capital exhibits higher impacts, both direct and indirect, with respect to R&D, thus proving to be highly productivity-enhancing for regional innovation activities.

It is worth highlighting that spillover effects are significant for all models in the case of human capital, while they are only marginally significant for R&D in the first two models. This results is consistent with the claim that R&D expenditure *per se* is not sufficient to activate knowledge externalities and this, in turn, calls for policies and production devices capable of increasing the absorptive capacity of the regional systems of innovation.

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

4.3 Models comparison and the overall effect of knowledge spillovers

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

Various approaches may be adopted to carry out a selection among estimated models, some are based on testing procedures (Kelejian, 2008; BurrIDGE and Fingleton, 2010), others on the use of information criteria or on the computation of posterior model probabilities or Bayes' factors (LeSage and Pace, 2009). In this paper in order to obtain a possible ranking of the estimated models we apply the Akaike information criterion (AIC). This has the advantage of avoiding several models comparison, as would be the case with the testing approach. Moreover, once the "best" model, defined as the one which minimize the AIC, is found, relative probabilities of minimizing the information loss can be computed for each other model as a function of

the difference between its own AIC value and the minimum one. A weighted multi-model could then be obtained on the basis of such probabilities (Burnham and Anderson, 2002).

The computed AIC values for the ten non-nested estimated models of Table 2 and 3 point out that the “best” model is the one based on the geographical and technological proximity (model 1 of Table 3), followed by model 4 and 5 of Table 3; the other models seem to provide relatively less support¹¹. It is worth remarking that the best performing models are found among those which allow for a certain degree of complementarity among the proximity measures, and such a complementarity turns out to be rather relevant when the technology interconnectivity is involved.

On the basis of the AIC values we compute the relative probabilities¹² described above in order to carry out a tentative exercise to figure out the overall spillover effects when we consider all potential proximities. This is, necessarily, a post-estimation computation where we try to combine the inference drawn from the four one-matrix models (Table 2) and the six two-matrix models (Table 3).

The overall effects are computed analytically on the basis of the weighted average of the estimated coefficients for R&D and human capital obtained from the ten models, which are 0.248 and 1.364 respectively, and the weighted average estimates of the coefficients for the four different kinds of proximity lagged terms. For all measures weights are represented by models’ relative probabilities.

In order to ease the comparison of the strength of proximity dependence, the estimated coefficients of the lagged dependent variables for all combinations of matrices are summarized in Table 4, where the main diagonal reports the lag coefficient estimated in the single-proximity models, while the off-diagonal entries are the coefficients obtained from two-proximity models. The last column report the weighted average calculated on the basis of the models’ probabilities described above. We observe that, on average, dependence among regions is stronger when it is captured by the technological proximity (the average of the estimated coefficients for the technological lagged

¹¹ We obtain exactly the same ranking of the models when we compute the Bayesian or the Hannan-Quinn information criteria.

¹² The probability for model i are computed as: $prob_i = \exp(-(AIC_i - AIC_{MIN})/2) / \sum_j^M \exp(-(AIC_j - AIC_{MIN})/2)$, where M is the number of models and AIC is the bias-adjusted value of the Akaike information criterion.

dependent variable is 0.30). The connectivity appears weaker for the geographical proximity (average equal to 0.16) and the social one (0.02), while the lowest dependence is found for the organizational (0.01) proximity.

In Table 5 we report the direct, indirect and total effects computed by deriving a sort of all-proximities multiplier for both R&D and human capital on the basis of the weighted averages of the relevant parameters.

From this computational exercise, considering the calculated effects at face value, it is possible to design interesting what-if scenarios for the European regions. For example, if we conjecture an 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 60% of the change attributable to direct effects and the remaining 40% 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 128 patents (per million population); this means an addition of 23 patents, 13.7 from a direct internal effect and 9.3 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, even 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 innovation production. Moreover, the finding that in some cases the direct and spillover effects are of the same order of magnitude calls for coordinated efforts at regional, national and European level.

5. Conclusions

In this study we have investigated the complementary role played by five different kinds of proximity in driving knowledge transmission across the European regional innovations systems.

There is by now a widespread consensus among scholars that the transfer of knowledge is significantly favoured, not only by spatial closeness among agents involved in the innovation process, but also by the relations they develop within a-spatial networks, as those shaped by institutional, technological, social and organizational links.

Although in the previous empirical literature the attention has been mostly focused on just one kind of proximity, in particular the geographical one and to a lesser extent the technological one, with the high level of economic and institutional integration within the European production context the concurrent effect of different proximity dimensions can no longer be overlooked (Boschma 2005, Mattes 2011). As a matter of fact such an effect constitutes a crucial factor in facilitating the transmission of the existing knowledge and, in turn, in determining the creation of the new one.

Our analysis is carried out within the Knowledge Production Function theoretical framework by applying some of the recent advances in spatial econometrics to estimate empirical models. These enable us to assess the relative importance of the regional internal production factors with respect to external ones acquired in the form of spillovers and to derive the overall long-run effect on innovation outcomes due to changes in regional inputs.

The KPF empirical models are estimated for a sample of 276 European regions located in 29 countries with reference to the period 2005-2007. On the basis of our model selection strategy, a spatial autoregressive specification turned out to be the most adequate in describing the main characteristics of the sample data considered. The response variable is represented by the patents stock, while the main internal inputs are R&D investments and human capital. The latter is included being a direct determinant of knowledge production but also because it governs the degree of knowledge absorption at the local level. Beside the traditional geographical proximity, we also consider other dimension of regional interconnectivity represented by the institutional one, proxied by a set of country dummies, the technological, based on the specialization productive structure, as well as the social and organizational ones, measured on the basis of inventors and applicant-inventor relationships occurring in different regions.

Although it would be optimal to specify a comprehensive model which simultaneously accounts for all different types of proximity, in the case of a spatial autoregressive model this would require to solve a high order multivariate optimization problem, so that we prefer to leave this extension for future research. As a workable alternative we consider the variant of the SAR models which allows to account for two different types of regional interconnectivity at a time (beside the institutional one, always included thanks to the presence of country dummies) and then

derive the five-proximity overall impact for both R&D and human capital by means of a post-estimation computation.

There are three main results coming out from our analysis. First, human capital is more innovation enhancing with respect to R&D in all models considered. Its total effect, which include the knowledge spillovers coming from proximate regions, is on average six times as higher as the one due to R&D expenditure. Second, spillover effects are significant for human capital in all models considered, while for R&D this is the case just in four models out of ten. This finding indicates that it is the endowment of skilled and well educated people that ensures that knowledge flowing from external sources can effectively be absorbed and transformed in new ideas and innovations; even high levels of R&D do not seem to grant the same desirable result. Third, all proximity measures considered are found to be economically relevant and statistically significant. Comparing the strength of regional association captured by the different “closeness” dimensions, the technological one ranks first, followed by the geographical one; the weakest relations are found for the social and organizational networks. We also find evidence of important complementarities among the different proximities, which turned out to be rather relevant in all the cases in which the technological connectivity is involved. Therefore having a common cognitive base is quite a valuable channel in conveying knowledge.

In conclusion the analysis presented in this paper confirms the great degree of complexity of the knowledge creation and diffusion process in the highly integrated European economic context. Our findings indicate the prominent role played by human capital in driving innovation outcomes and the necessity to extend regional networks in order to bring regions closer and closer and thus favouring both intended and unintended transfers of knowledge.

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Table 1. Data sources and summary statistics

Variable	Definition	Mean	Min	Max	Var. coeff.	Primary Source	Years
Patent	total patents published at EPO, per million population	105.4	0.20	627.6	1.20	EPO	average 2005-2007
Research & Development	total intramural R&D expenditure, over GDP	1.4	0.07	7.6	0.85	Eurostat	average 2002-2004
Human Capital	population 15 and over with tertiary education (ISCED 5-6), over total population	10.5	3.51	23.3	0.39	Eurostat	average 2002-2004
Population density	Population per km ² , thousands	331.3	3.08	9049.6	2.47	Eurostat	average 2002-2004
Manufacture	manufacturing employment, over total employment	17.3	3.67	36.2	0.37	Eurostat	average 2002-2004

Table 2. 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
<i>Production inputs</i>				
R&D	0.257 ** (2.549)	0.255 *** (2.527)	0.191 * (1.837)	0.207 ** (1.992)
Human capital	1.559 *** (5.126)	1.345 *** (4.354)	1.524 *** (4.981)	1.484 *** (4.832)
<i>Control variables</i>				
Population density	0.063 (0.948)	0.113 * (1.794)	0.091 (1.409)	0.095 (1.460)
Manufacture specialisation	0.892 *** (5.062)	0.956 *** (5.610)	1.026 *** (6.077)	1.058 *** (6.283)
Spatial lag (P)	0.202 *** (3.116)	0.293 *** (3.233)	0.115 *** (2.552)	0.072 ** (2.200)
Adj-R ²	0.808	0.809	0.806	0.805
<i>Effects estimates (a)</i>				
R&D				
<i>direct</i>	0.260 **	0.258 ***	0.188 *	0.206 **
<i>indirect</i>	0.067 *	0.110 ***	0.023	0.015
<i>total</i>	0.327 **	0.368 ***	0.212 *	0.221 **
Human capital				
<i>direct</i>	1.559 ***	1.344 ***	1.540 ***	1.499 ***
<i>indirect</i>	0.401 **	0.567 **	0.202 **	0.117 **
<i>total</i>	1.959 ***	1.911 ***	1.742 ***	1.616 ***
<i>Diagnostics</i>				
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 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 3. KPF with two weight matrix models

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

Estimation method: SAR

	1	2	3	4	5	6
Proximity matrices included	G, T	G, S	G, O	T, S	T, O	S, O
<i>Production inputs</i>						
R&D	0.264 *** (2.672)	0.214 ** (2.137)	0.223 ** (2.226)	0.192 ** (1.929)	0.206 ** (2.065)	0.191 * (1.885)
Human capital	1.372 *** (4.613)	1.553 *** (5.140)	1.524 *** (5.043)	1.332 *** (4.448)	1.281 *** (4.270)	1.514 *** (4.952)
<i>Control variables</i>						
Population density	0.042 (0.677)	0.045 (0.725)	0.042 (0.675)	0.069 (1.126)	0.071 (1.143)	0.090 (1.426)
Manufacture specialisation	0.764 *** (4.676)	0.887 *** (5.346)	0.900 *** (5.421)	0.902 *** (5.484)	0.933 *** (5.667)	1.031 *** (6.140)
Spatial lag - 1st proximity matrix	0.213 *** (3.376)	0.172 *** (2.587)	0.183 *** (2.812)	0.312 *** (3.447)	0.320 *** (3.516)	0.095 (1.174)
Spatial lag - 2nd proximity matrix	0.307 *** (3.431)	0.083 * (1.763)	0.057 * (1.734)	0.127 *** (2.805)	0.085 *** (2.648)	0.017 (0.297)
Adj-R ²	0.816	0.811	0.810	0.814	0.814	0.806
<i>Estimated effects</i> ^(a)						
R&D						
<i>direct</i>	0.264 ***	0.215 **	0.223 **	0.194 **	0.206 **	0.193 **
<i>indirect</i>	0.317	0.076	0.072 *	0.161	0.145	0.025
<i>total</i>	0.581 **	0.292 **	0.295 **	0.355 *	0.351 **	0.218 **
Human capital						
<i>direct</i>	1.381 ***	1.554 ***	1.533 ***	1.332 ***	1.295 ***	1.515 ***
<i>indirect</i>	1.651 *	0.549 **	0.498 **	1.089 **	0.921 **	0.196 *
<i>total</i>	3.032 ***	2.103 ***	2.030 ***	2.421 ***	2.216 ***	1.711 ***

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

Table 4. Comparing estimated lag coefficients for different proximities measures

<i>Proximity matrix considered:</i>		<i>Second proximity matrix included:</i>				Weighted average^a
		G	T	S	O	
Geographical proximity	G	0.202	0.213	0.172	0.183	0.162
Technological proximity	T	0.307	0.293	0.312	0.320	0.298
Social proximity	S	0.083	0.127	0.115	0.095	0.018
Organisational proximity	O	0.057	0.085	0.017	0.072	0.008

Diagonal entries are the estimated rho coefficients of the Table 2 one-weight matrix SAR models

Off-diagonal entries are the estimated rho coefficients of the Table 3 two-weight matrix SAR models

All the regressions include also the institutional proximity measured by the country dummies.

^a Weights are given by model probabilities obtained on the basis of AIC values.

Table 5. Combined effects for the KPF inputs

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

	weighted average
R&D	
<i>direct</i>	0.248
<i>indirect</i>	0.164
<i>total</i>	0.413
Human capital	
<i>direct</i>	1.366
<i>indirect</i>	0.903
<i>total</i>	2.269

Effects are computed on the basis of the weighted averages for the inputs coefficients and the spatial autocorrelation coefficients. Weights are given by model probabilities obtained on the basis of AIC values

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