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THE IMPACT OF RELATIONAL SPILLOVERS FROM JOINT RESEARCH PROJECTS ON KNOWLEDGE CREATION ACROSS EUROPEAN REGIONS

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ABSTRACT

This paper investigates the impact of "relational" spillovers arising from participation in European research networks on knowledge creation across European regions. We use links in EU Framework Programmes (from the Fourth to the Seventh) to weight foreign R&D in order to construct a relational distance matrix across 257 European regions over the period 1995-2010. We, then, assess the impact of relational spillovers on regional patent applications controlling also for local spatial spillovers. We find that relational spillovers matter for knowledge creation although spatial contiguity remains a crucial factor. We also find that spillovers are higher when regions with different levels of R&D participate in European networks.

Keywords: Relational spillovers, R&D collaboration, knowledge, EU Framework Programmes, spatial correlation, patents.

JEL Classification: O31, R12, C23

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1. Introduction

The European Union in both the Lisbon Strategy and, more recently, in the Strategy Europe 2020 strongly emphasizes the crucial role of innovation for Europe's long run growth. Among the different instruments used to foster innovation, the EU has devoted a relevant and increasing amount of resources to finance Framework Programmes (FP) encouraging collaboration across different EU regions/countries. Behind the implementation of such policies is the idea that international knowledge flows are a major factor in world growth. This view has been supported by a large body of literature showing the importance of technology spillovers[1] for growth and productivity (for a review see Cincera and Van Pottelsberghe de la Potterie, 2001; Hall et al., 2010). However, most of the studies find that knowledge spillovers are geographically concentrated (see, among others, Jaffe et al., 1993; Jaffe et al., 1999; Maurseth and Verspagen, 2002). This is consistent with the fact that knowledge is imperfectly codified, linked to the experience of the scientists or "attached" to people, so that it diffuses mostly via personal contacts and face-to-face interactions that are facilitated by geographical proximity.

Recently, some authors (Boschma, 2005; Maggioni and Uberti, 2011) have argued that the importance of geographical proximity cannot be assessed in isolation, but should always be examined in relation to other dimensions of proximity that may provide alternative solutions to the problem of coordination (Boschma, 2005).

The different role of geographical and relational proximity in the creation and diffusion of knowledge bear important consequences for the geographical distribution of innovation activities in Europe and for policies devoted to support the creation and spreading of knowledge among European countries/regions. In fact, the geographical concentration of knowledge spillovers can lead to an uneven distribution of innovation activities exacerbating income disparities between the core and the periphery (Bottazzi and Peri, 2003; Crescenzi and Rodriguez-Pose, 2011).

In this perspective, in order to be consistent with its Cohesion policy, the European Union should evaluate what kind of knowledge transfers/spillovers occur within EU research networks and to what extent the decrease in "relational" distance brought about by research networks could overcome the possibly diverging impact of geographically clustered spillovers.

Framework Programmes have special characteristics that make them particularly interesting for evaluating the role of relational spillovers. In fact, participation in EU funded projects creates

[1]Spillovers differ from technology transfers since the former refer to an unintended transfer of knowledge (externality) while the latter occur when there is a voluntary exchange of knowledge and eventually a price is attached to the transaction of knowledge. Empirically distinguishing between spillovers and knowledge transfers is not an easy task, in this paper we will, therefore, use the two terms interchangeably.

supranational networks potentially able to give rise to international knowledge transfers based on “relational” distance, going beyond geographical proximity. If geographical proximity is important for exchanging knowledge since it favours personal interactions, participation in international research programmes can be a way of reconciling the need of “face to face” contacts (through the mobility of researchers during and after the project) with knowledge exchange via interactions over long distances. But what kind of networks are favoured by the EU initiative and what kind of networks are more effective in fostering knowledge transfers/spillovers?

On the one hand, regions at the technological frontier have an incentive to collaborate with partners from other research intensive regions in order to create networks of excellence; on the other hand the European Union encourages participation of scientifically laggard regions to FP networks[2]. For these regions participation in FP can be a mean to partly close their scientific and technological gap with the more advanced partners.

The aim of this paper is to assess the role of relational R&D spillovers arising from participation to EU Framework Programmes for knowledge generation (patents) across European regions. Differently from previous studies (reviewed in the next Section) our focus is on the additional effect of relational spillovers with respect to spatial spillovers and on assessing which kind of collaborations (if any) are more effective in generating spillovers. For that purpose, in our empirical analysis, we allow for the extent of spillovers to vary between regions cooperating with similar or dissimilar (in terms of R&D) regions.

The paper is organised as follows: the next Section discusses other papers dealing with the estimation of relational spillovers at the regional level and introduces our research hypotheses and econometric methodology; Section 3 describes the data and presents descriptive statistics on EU regional innovation networks based on collaborations in FP; Section 4 presents the results of the econometric estimations, while Section 5 concludes and draws policy implications.

2. Measuring relational spillovers

2.1 Previous literature

Recently several papers have investigated the role of geographical spillovers for regional growth (Peri, 2004; Bottazzi and Peri, 2003; Moreno et al 2005; Rodriguez-Pose and Crescenzi, 2008; 2011), mainly finding that spillovers are very localized and exist only within short distances (between 200 and 300 km).

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[2]Although there is no explicit reference to this criterion the chance of obtaining EU funding increases when the network includes regions with different levels of R&D capabilities and in particular regions from countries recently joining the EU.

This argument is also supported by other studies in the field of the geography of innovation stating that geography matters because it enhances interpersonal relationships and face-to-face contacts, thus making easier to transfer tacit knowledge (Zucker et al. 1998; Almeida and Kogut 1999; Singh 2005; Balconi et al. 2004; Breschi and Lissoni 2006; Mairesse and Turner 2006).

However, the special role of geographical distance with respect to other types of distances has been questioned by a seminal paper of Boschma (2005) claiming that geographical proximity per se is neither a necessary nor a sufficient condition for learning to take place. Cognitive, organizational, social and institutional distances may be equally relevant, although they may be strengthened by geographical proximity. Similarly Autant-Bernard et al. (2007a) argue that the proper impact of the geographical dimension has to be assessed in relation to other types of proximity.

In this context Singh (2005) finds that geographical proximity (being in the same region or firm) has little additional effect on the probability of knowledge flow among inventors who already have close network ties (past collaborations). Similarly, Breschi and Lissoni (2009) find that, after controlling for inventors mobility and for the resulting co-invention network, the residual effect of spatial proximity on knowledge diffusion is strongly reduced.

Ponds et al. (2007), using data on co-publications in the Netherlands, find that geographical proximity in more important for collaboration in the absence of institutional proximity and conclude that spatial contiguity is a way of overcoming the institutional differences between organizations.

D'Este et al. (2013) find that the role of geographical proximity in the formation of new partnerships between universities and firms is weakened when firms are located in dense clusters and, particularly, in the case of technologically related clusters.

Crescenzi et al. (2014), using co-patenting between UK inventors, find important differences between the proximities that help inventors collaborate for the first time, the factors shaping repeated interactions, and the behaviour of serial inventors. While physical proximity is critical to start co-operating, once a relationship has been established, other forms of proximity (organizational, social and ethnic links) become more important and, for serial inventors, geography does no longer matter.

In a context that is much closer to our contribution, i.e. estimating a knowledge production function on a sample of European regions, Marrocu et al. (2013) analyze the role of different types of proximity on regional innovation finding that technological proximity outperforms geographic proximity, whilst a limited role is played by social and organizational networks.

These, and other similar findings, suggest the role of "relational" distance in addition to geographical distance as a source of knowledge flows.

European Framework Programmes provide data that may be used to measure relational proximity. In fact the Programmes are specifically designed to encourage the creation of linkages among researchers of different and often geographically distant regions.

This data have been so far analyzed mainly with the purpose of looking at the structure of research networks and at the factors that facilitate their formation (Breschi and Cusmano 2004; Maggioni et al. 2007, 2011; Autant-Bernard et al. 2007b, Scherngell and Barber 2009; Ortega and Aguillo 2010; Scherngell and Barber 2011; Hoekman et al. 2013; Wanzenböck et al. 2014), while only few papers have looked at the impact of participation in EU framework programmes on knowledge transfers between regions (Maggioni et al. 2007; Hoekman et al. 2013) or countries (Di Cagno et al. 2013).

In particular, Breschi and Cusmano (2004) studied the R&D joint ventures of the 3rd and 4th Framework Programmes finding that there was a preferential attachment phenomenon between both calls. Autant-Bernard et al (2007b), using data on collaborative projects submitted to the European 6th Framework Program, find that the firms' position within a network (measured by their number of links with other organisations in the previous 5th Framework Program) matters more than their geographical location to explain the incentives to cooperate in R&D. Maggioni and Uberti (2009) apply Network Analysis techniques to the configuration of international knowledge flows between European regions showing that geographic distance is still relevant for determining the structure of *inter*-regional knowledge flows. Functional and, above all, sectoral distances also play a relevant role. Ortega and Aguillo (2010) explore the role of each country in the health thematic area of the 6th Framework Programme (6FP) of the EU using social network analysis (SNA) finding that there is a strong relationship between R&D indicators and the structural position of each country in the network. Scherngell and Barber (2009) investigate the geography of R&D collaborations across European regions by using spatial interaction modeling techniques providing evidence that geographical distance significantly affects patterns of cross-region R&D collaborations in Europe. Scherngell and Barber (2011) use data on joint research projects funded by the fifth European Framework Programme (FP) to proxy cross-region collaborative activities. The results of the spatial analysis provide evidence that geographical factors significantly affect patterns of industrial R&D collaboration while in the public research sector the effects of geography are much smaller. However, the results show that technological distance is the most important factor for both industry and public research cooperative activities. Wanzenböck et al. (2014) focuses on the embeddedness of regions in research and development (R&D) networks within European Union Framework Programmes by estimating how distinct regional factors affect a region's network positioning. Panel spatial Durbin error models (SDEM) reveal that region-internal knowledge production capacities, a region's level of economic development as well as spatial spillovers are important determinants for a region's positioning in the European Union-funded R&D network.

More relevant to our contribution are the few studies that use data from EU framework programmes to estimate the impact of relational distance on knowledge creation at the regional level (Maggioni et al. 2007; Hoekman et al. 2013). In particular, Maggioni et al (2007) investigate the role of both geographical and relational distance finding that spatial proximity and geographical centrality are always significant in determining the co-patenting activity whereas joint collaborations also appear as another important factor. They also estimate a knowledge production function using two spatial error models based respectively on geographical and relational (co-participation to EU projects) distance matrixes. They find that relational networks influence the behavior of regional innovation systems, but that spatial proximity plays a more relevant role in determining their performance.

Hoekman et al. (2013), using a regionalized dataset of joint FP participations and joint co-publication activities, study whether the acquisition and effect of FP funding is disproportionally concentrated in the leading research regions. They show that the returns to FP funding are highest when involving scientifically lagging regions concluding that the current FP policy is in line with the EU Cohesion policy.

Our paper is related to both contributions. Similarly to Maggioni et al. (2007) we look at the respective role of geographical and relational proximity for knowledge creation, however we adopt a spatial lag of X (R&D) model (SLX) (Lesage, 2014) of the knowledge production function including, at the same time, R&D weighted by two different distance matrixes, one based on geographical distance across regions and the second based on relational distance. This allows disentangling the additional effect of R&D relational spillovers over geographical ones. Similarly to Hoekman et al. (2013) we ask whether the effect of FP funding varies across regions. However, while Hoekman et al (2013) investigates this issue indirectly (by looking at the composition of FP networks), we directly estimate whether relational R&D spillovers are higher among regions that are similar or different in terms of R&D intensity (with positive or negative local Moran statistics).

2.2 Research hypotheses and econometric methodology

Our main hypothesis is that i) *relational spillovers matter for knowledge creation and have an additional effect with respect to geographical ones.* Our second hypothesis is that ii) *spillovers are higher for those regions that participate intensively to research networks*: i.e. it is not only important with whom you cooperate but also how much a region cooperates. Finally, we expect that iii) *the rewards to participation in European FP differ according to degree of similarity/difference in R&D intensity between participants.*

In order to test these hypotheses we estimate a knowledge production function at the regional level allowing for relational R&D spillovers. Our basic equation is the following:

$$PAT_t=RD_{t-s}\beta_1 + W_{t-s}RD_{t-s}\beta_2+HC_{t-s}\beta_3+PD_{t-s}\beta_4+\lambda_t e_N+v_t \qquad (1)$$

where PAT_t denotes a Nx1 vector of patent applications to the EPO divided by population (consisting of one observation for every region in period *t*); RD denotes R&D expenditures divided by GDP (a Nx1 vector consisting of one observation for every region in period *t-s*, where *s* denotes the time lag between the depend and the explanatory variables); HC are human resources in science and technology divided by population; PD is population divided by the region's area[3]; W_{t-s} is an NxN non negative row standardized relational weights matrix, with diagonal elements are all equal to zero, for period *t-s*; β_1, β_2, β_3, β_4 are response parameters; λ_t denotes a time specific effect, which is multiplied by a Nx1 vector of units elements and v_t is a Nx1 vector of residuals for every spatial unit with zero mean and variance σ^2.

Due to the variability of data over time, patents are computed as averages over the periods 1997-2000, 2001-2004, 2005-2008 and 2009-2010. Since there exists a time lag between inputs and outputs in the production of new knowledge all explanatory variables (including the relational matrix) are computed as averages over the periods 1995-1998, 1999-2002, 2003-2006 and 2007-2010[4]. Overall we have a panel of 257 regions over four time periods.

In order to test the robustness of our results to this basic equation, we first add country dummies, then geographical spillovers and finally the total amount of regional collaborations per capita and the interaction between this variable and relational spillovers. In some specifications, we also distinguish R&D (and R&D spillovers) by sector of performance (business enterprise R&D, government R&D and higher education R&D). Finally, we estimate the equation allowing for different parameters between regions cooperating with similar (in terms of R&D) regions (with positive local Moran) and regions cooperating with regions that differ in terms of R&D (with a negative local Moran).

Our specification only takes into account "local" R&D spillovers by estimating a spatial lag of X (R&D) model (SLX) (Lesage, 2014). This means assuming that the outcome (patents) of each region *i* are affected by the R&D expenditures only of regions cooperating in the same network,

[3] Source data on patent applications to the European Patents Office (EPO), R&D expenditure, GDP, human resources in science and technology (HRST), population and geographical: Eurostat, sub-national section (NUTS 2 level). We use the terms regions and NUTS2 (Nomenclature des Unitès Territoriales Statistiques) as synonymous.

[4] We call the four periods, 1995-1998, 1999-2002, 2003-2006 and 2007-2010, FP4, FP5, FP6 and FP7, respectively, in accordance with EU Framework Programmes nomenclature and their temporal extension. The same structure can be applied to patents for their reference point.

ruling out higher order effects possibly arising from the indirect impact of the R&D of regions cooperating with regions with whom region *i* cooperates (neighbours to the neighbours indirect effects). In this respect our paper differs from Maggioni et al. (2007) estimating a spatial error model and from Marrocu et al. (2013) estimating a spatial lag model. Our choice is dictated by different reasons described in a recent paper by Vega and Elhorst (2013) and already discussed in Gibbons and Overman (2012). First, the SLX model is the simplest among the spatial models used to take into account local spatial spillover effects. Moreover, the SLX overcomes some identification problems of an alternative model, such as the spatial Durbin model (SDM) which contains both a spatially lagged endogenous variable and spatially lagged exogenous variables[5]. Finally, the spatial autoregressive model (SAR) and the spatial error model (SEM) do not allow disentangling which variables are responsible for spillovers.

3. Regional collaborations in EU Framework Programmes

Framework Programmes (FPs) are the context under which research and technological development EU policies are implemented. FPs are multiannual and include both direct and indirect actions: direct actions are implemented by research institutes directly depending on the European Commission (such as the Joint Research Centre) whereas indirect actions are implemented by Member States bodies. Indirect actions have a top-down structure: this means that the thematic and sector priorities (according to the European Commission classification) which will be supported are selected *a priori* according to the goal of the FPs[6]. Specific calls for proposals are published during the implementation phase of FPs, thus enabling candidates to present specific RTD projects. EU funding is granted to those projects approved by the European Commission (supported by a group of independent experts for the technical assessment). Due to the EC rules, the eligible project has multilateral nature: it involves more actors (firms and/or universities and/or research centres) from different regions. A project, therefore, creates links among the participants, or differently, links among regions where the actors involved operate. Considering all projects funded, we can construct a collaborative, or relational, matrix, one for each FP.

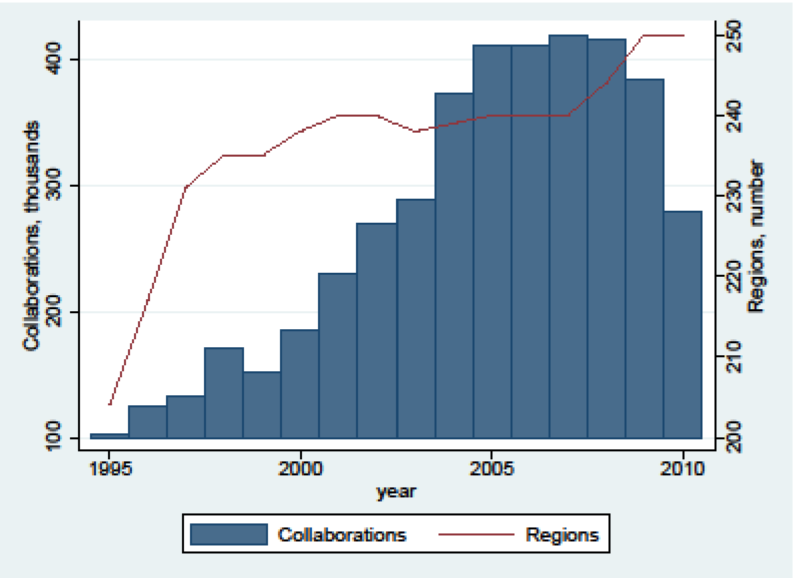
[5] Gibbons and Overman (2012) point out that in the SDM it is difficult to disentangle endogenous and exogenous interactions effects

[6] FPs are proposed by the European Commission and adopted by the Council and the European Parliament under the co-decision procedure.

3.1 Regional data from EUPRO database

Data from regional collaborations in EU Framework Programmes are extracted from EUPRO database that contains information on organisations participating in FP funded projects[7]. To obtain our relational weight matrices, we follow Scherngell and Barber (2009) and construct region-by-region collaboration matrices containing the FP collaboration intensities between all regional pairs for each year over the period of observation[8]. The entries of the matrices give information on the number of links between two regions in a specific year, i.e. collaborative R&D projects between organisations located in these regions. Figure 1 shows, for each year, the absolute number of collaborations created from 1995 to 2010 and the number of participating regions (Y-axes, right side). We can observe that the number of both regions participating in EU funded projects and inter-regional FP collaborations increase considerably over the period of observation. This may be traced back to the fact that the amount of EU financial resource allocated under FPs has risen from 3,408.9, in the 2000 budget, to 6,471.3 Million EUR in the 2008 budget[9].

Figure 1: FPs Collaborations



Source: EUPRO database.

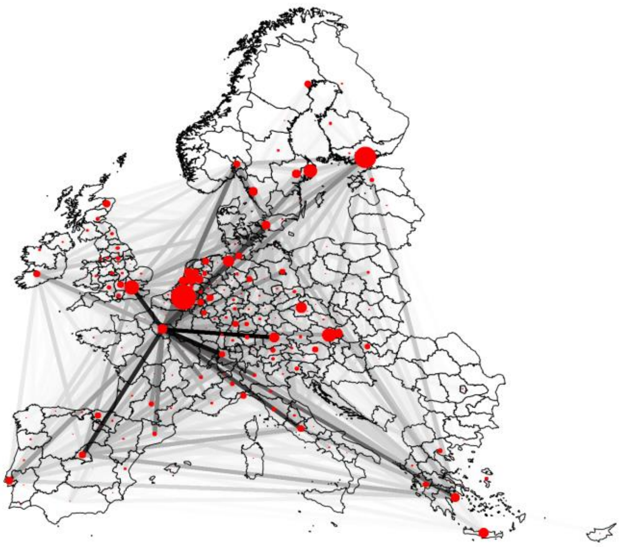
[7] EUPRO is constructed and maintained by AIT (Austrian Institute of Technology). It provides systematic information on funded projects, such as project name, project objectives and achievements, etc., as well as on participating organizations including the full name, type of organization, the full address and the assignment of each organization to specific NUTS regions of Europe. To relate FP participations to the respective NUTS-2 level, we use – if available – the location of the participating department. In this way, bias towards headquarters of large organizations can be reduced.

[8] In the estimations we use averages over the four time periods 1995-1998, 1999-2002, 2003-2006 and 2007-2010.

[9] Source: EU budget 2008 - Financial Report.

Furthermore, Figure 2 shows the role of regions in the FPs based on their average collaboration intensity per capita (and the average number of linkages a region has with other regions, over the period 1995 – 2010). Based on the size of the nodes we can see that the regions Bruxelles-Capitale, Helsinki-Uusimaa, Prov. Brabant Wallon, Inner London and Wien (in order of rank) have the highest visibility in the network of FP collaborations, related to their regional population. Moreover, the transparency of the lines represents the number of collaboration between two regions, indicating that Île de France is the most central region with the highest number of linkages to other regions.

Figure 2: R&D collaboration in the EU Framework Programmes across European NUTS-2 regions



Notes: Average values for the period 1995 - 2010 are used. Node size corresponds to a region's total number of collaborations (p.c.), line transparency corresponds to the number of joint FP projects between two regions.

Source: EUPRO database

3.2 Descriptive statistics (data analysis with spatial tools)

In Table 1[10], we summarize the descriptive statistics for the main variables of the knowledge production function (KPF), as described in the section 2.2. As we have explained, data are computed at NUTS 2 level[11] and due to the variability of data over time, they are also computed as average over a four year period, except for collaborations, where the numerator are the counts in the interval. This variable, indeed, measures the propensity to cooperate of region *i*. Collaborations are, also, a proxy both for outwards attractiveness of a region and its capacity to absorb knowledge generated elsewhere, jointly with quality and quantity of its human capital. The average value of collaborations per million population is around 960, with a maximum value of 13,096 for the Région de Bruxelles - Capital. As expected, higher values are registered in regions of Central and Northern Europe, whereas lower values characterize Southern and Eastern Europe (see also Figure 3). This variable, along with the other variables in Table 1, shows a strong variability between units, lesser over time (within dimension), as measured by standard deviation, and pointed out in Figure 1 (more regions involved and more links among them over time).

For patents per million population, the (global) mean is 90.84, with values greater than 600 observed in two regions: Stuttgart Oberbayern (Germany) and Noord-Brabant (Netherlands). Low patenting activity (less than one patent per capita) is found in some regions of Southern Europe (Spain, Greece, Portugal and South of Italy) and in a large part of Eastern European regions. Looking at the evolution over time, it is possible to remark that in the recent years there are significant improvements in Eastern countries (see also Figure 3).

For the R&D expenditure over GDP, a standard input of KPF, the average R&D intensity in Europe is 1.37% with a minimum of 0.09% in Notio Aigaio (Greece) and a maximum of 8.08% in Brabant Wallon (Belgium). In this case, once again, the spatial distribution in Europe appears quite dispersed. R&D intensity can be decomposed at a sectorial level: first, the business sector (mean value is 0.86%); second, the government spending on R&D (mean value is 0.32), and finally, the higher education sector, HES (mean value is 0.18). At a country level, the HES R&D expenditure together with the government spending on R&D count more than business R&D expenditure in Eastern country and Italy as well (characterized by a lower level in these variables and other ones, compared to the other large countries).

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[10] In the table, the standard deviation of variable x_{it} is decomposed into a between ($\overline{x_i}$) and within (x_{it} -$\overline{x_i}$ +$\overline{\overline{x}}$, the global mean x being added back in make results comparable) component.

[11] For some countries, the smaller ones (Cyprus, Latvia, Lithuania, Luxembourg, Malta and Estonia), and others (Denmark, Norway, Slovenia and Switzerland), the regional breakdown is not available either in Eurostat or in EUPRO database. In this case we have considered the country level (NUTS0). We have chosen this approach because we would consider the widest possible coverage of the European territory (EU27 plus Switzerland and Norway). In addition, we use all information (data at NUTS 1 level and NUTS 0 level) to fill the gap in the missing values in our dataset, so that we can obtain a balanced panel.

We also consider the availability of human capital as an additional input, expected to influence the process of knowledge production at the local level. We measure human capital with human resources in science and technology over total population[12]. This variable has lower dispersion across the European regions compared to other variables, and it shows a clearly identifiable national pattern. A high endowment of human capital characterizes the Scandinavian countries, the UK, Germany, while lower values are generally detected in the Eastern countries (except for Baltic countries) France and Italy. In the last period, some regions have recorded particularly high values (over 36%): Praha, Helsinki-Uusimaa, Stockholm, East Anglia and Inner London.

Table 1: Descriptive statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
Patent (per million population)	overall	90.8447	113.0128	0.0788	705.7323	N = 1028
	between		111.6807	0.2336	590.8845	n = 257
	Within		18.3240	-64.3083	205.6925	T = 4
R&D/GDP, %	overall	1.3762	1.2113	0.0901	8.0806	N = 1028
	between		1.2043	0.1041	7.6910	n = 257
	Within		0.1451	0.5621	2.2276	T = 4
Business R&D/GDP, %	overall	0.8695	0.9971	0.0103	7.5747	N = 1028
	between		0.9921	0.0132	7.1026	n = 257
	Within		0.1138	0.2166	1.4596	T = 4
Government R&D/GDP, %	overall	0.1812	0.2353	0	2.0299	N = 1028
	between		0.2327	0	1.5655	n = 257
	Within		0.0371	-0.0912	0.6456	T = 4
HES R&D/GDP, %	overall	0.3260	0.2632	0.0008	1.6340	N = 1028
	between		0.2600	0.0016	1.5244	n = 257
	Within		0.0438	0.1503	0.5842	T = 4
HRST/POPULATION, %	overall	17.5017	6.2321	3.3414	44.1581	N = 1028
	between		5.4978	7.3352	34.9986	n = 257
	Within		2.9499	-5.3010	27.1196	T = 4
Collaborations (per million population)	overall	968.7207	1361.9240	0	13096.8300	N = 1028
	between		1209.4240	0	8555.5380	n = 257
	within		629.6061	-3968.1780	5510.0160	T = 4

Note: in the table, the standard deviation of variable x_{it} is decomposed into a between ($\overline{x_i}$) and within (x_{it} -$\overline{x_i}$ +$\overline{\overline{x}}$, the global mean $\overline{\overline{x}}$ being added back in make results comparable) component. Since the within number refers to the deviation from each individual's average, some of those deviations must be negative. Source: EUROSTAT

[12] In the Human resources in science and technology *(HRST)* statistics are persons with the tertiary level of education or employed in a science and technology occupation for which a high qualification is normally required and the innovation potential is high, according to the *Canberra Manual* (OECD and Eurostat, 1995).

The paper analyses the influence of space and relational distance on knowledge creation. At the base of the analysis, we have a matrix indicating the strength of links among regions. Then, we use this matrix to estimate R&D spillovers. For each period FP_t, the spillovers are computed as a product of row-standardized weight matrices *W*, relational (*rel)* or geographical (*geo*), and a R&D intensity vector: otherwise, the matrix product *Wx* is a R&D intensity spatial (relational) lag variable.

In order to visualize these links we use spatial tools, in particular Moran's statistic (Moran's I) and Local indicators of spatial association, or LISA (Anselin, 1995; Pisati, 2001). The first measure is an index of global spatial (relational) autocorrelation: in presence of either positive or negative values, the spatial distribution of the variable of interest *x* shows a systematic pattern, meaning that the value taken on by *x* at each location *i* tends to be similar to the values taken on by *x* at (spatially or relationally) contiguous locations. The second is an estimate of local spatial (relational) autocorrelation.

In Figures 2 and 3 (two Moran scatterplots[13]) we plot Moran's statistics both in the first (FP4) and last period (FP7). The first plot is based on matrix *geo,* the second is based on matrixes *rel*. By comparing FP4 and FP7 we can infer whether spatial and relational R&D correlation has increased or decreased over time. Moreover, the figures also help us to identify differences in the underlying matrixes: as noted by Pace et al. (2013) while it is not possible to directly compare two or more weight matrixes, it is useful to survey the resulting spatial lag variable (*Wx*).

First, we can observe that R&D spatial correlation, in both FP4 and FP7, is higher than relational correlation. This means that, while regions with similar levels of R&D expenditure tend to be spatially clustered, collaborations in FP might involve also regions with different levels of R&D expenditure (the number of regions located in quadrants with negative correlation is higher when using relational distance). Secondly, for both matrixes, spatial (relational) correlation in R&D declines over time. This is partly due to the behaviour of some Eastern European regions that have performed remarkably well over time, so that some of them presenting low values of R&D at the beginning (with low R&D spatial/relational neighbors) have moved to high values at the end of the period. The decline in relational correlation in R&D is consistent with the increasing effort of the European Commission to stimulate the creation of networks involving also laggard regions.

[13] The Moran scatterplot is a plot of spatial lag variable, *Wx*, versus *x*, where *x* denotes, in our case, standardized R&D intensity. The oblique line represents the linear regression line obtained by regressing *Wx* on *x*, and its slope equals Moran's I.

Figure 3: Moran scatterplot (space matrixes)

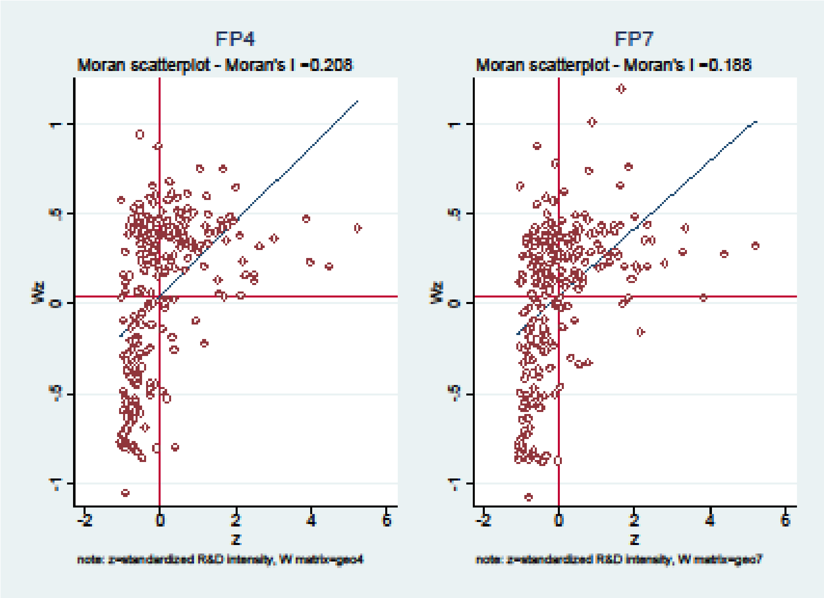


Figure 4: Moran scatterplot (relational matrixes)

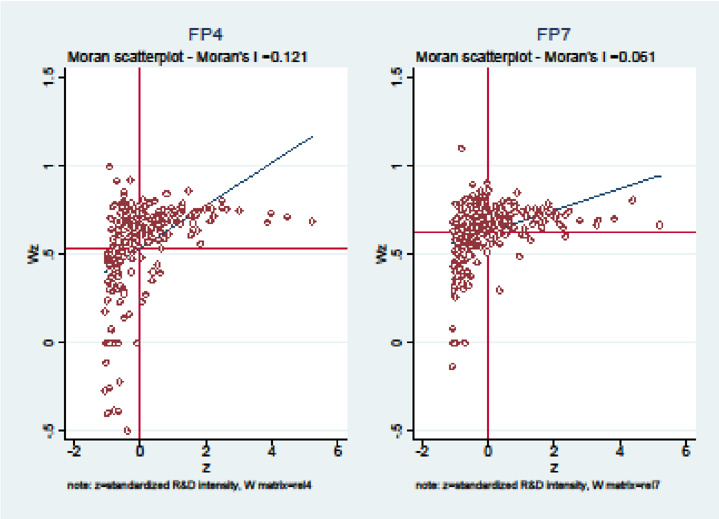


Figure 5: Geographical LISA

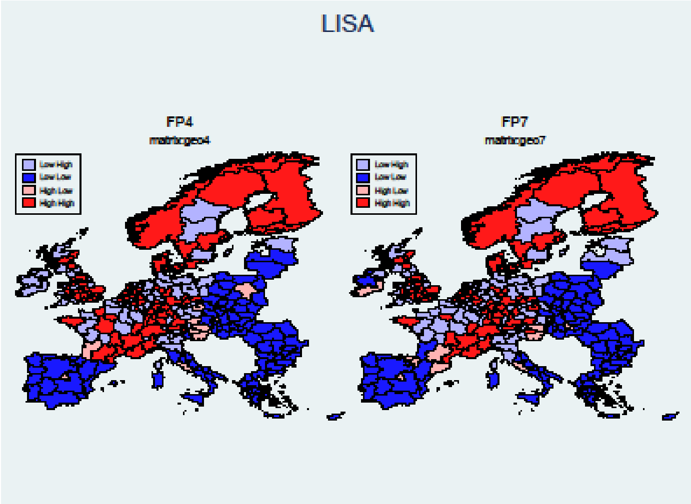
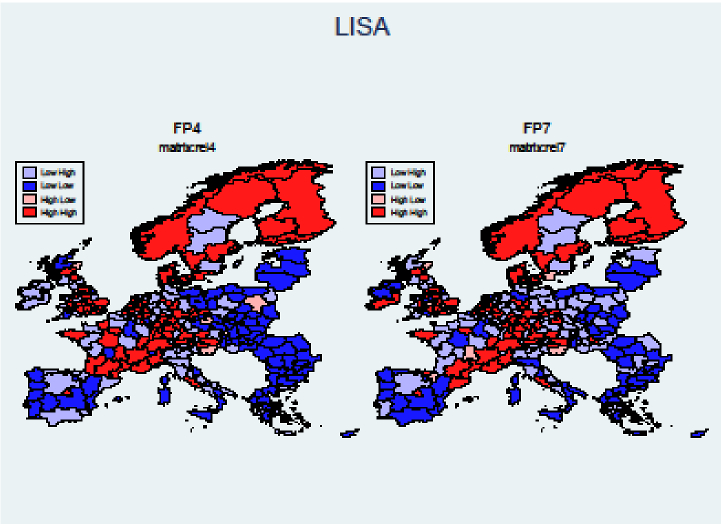


Figure 6: Relational LISA



4. Relational spillovers and knowledge creation in European regions: regression results

Table 2 reports the results of the estimation of equation[14] (1) with four different specifications. Results are based on GLS estimations of a spatial lag of X (R&D) model (SLX) (Lesage, 2014). In the first column we introduce relational R&D spillovers into a knowledge production function controlling for regional R&D, human capital, population density and time dummies; in column (2) we add country dummies; in column (3) we add geographical R&D spillovers; in column (4) we control also for the amount of collaborations in FP and we allow the impact of relational spillovers to depend on the amount of R&D collaborations.

[14] We use feasible generalized least squares (GLS) estimator to fit our panel-data linear model.

Table 2: Relational spillovers and knowledge creation: GLS results

	(1)	(2)	(3)	(4)
	Patents	Patents	Patents	Patents
R&D intensity	1.056***	0.510***	0.542***	0.414***
	(45.58)	(41.00)	(37.40)	(27.66)
Human capital	1.105***	0.504***	0.387***	0.404***
	(23.43)	(11.16)	(8.06)	(9.09)
Relational spillovers	1.529***	0.453***	0.161	0.723***
	(8.41)	(5.02)	(1.75)	(4.92)
Population density	0.0146	0.0840***	0.115***	0.0606***
	(1.68)	(8.51)	(11.03)	(5.57)
_Ifp_5	-0.166***	0.0441**	-0.0157	0.0159
	(-6.07)	(2.75)	(-0.88)	(1.01)
_Ifp_6	-0.224***	0.0857***	0.0289	0.0319
	(-7.36)	(4.57)	(1.42)	(1.68)
_Ifp_7	-0.857***	-0.352***	-0.469***	-0.403***
	(-23.05)	(-15.21)	(-18.75)	(-15.07)
Geographical spillovers			1.481***	
			(26.83)	
Collaborations				0.513***
				(3.53)
RSPILL*Collaborations				0.108**
				(2.92)
Constant	2.824***	-4.357***	0.676	-3.705***
	(4.13)	(-11.83)	(1.61)	(-6.19)
Country dummies	NO	YES	YES	YES
chi2	17371.690	84896.720	63060.405	3.93e+05
rho-squared	0.625	0.873	0.897	0.878
N	970	970	970	970
N_groups	252	252	252	252
N_time	4	4	4	4

t statistics in parentheses

Coefficients are heteroskedasticity-consistent

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: rho-squared are the square of correlation coefficient between the patents and their predicted values.

The results show that relational spillovers are always positive and significant, although their size decreases when country dummies and geographical spillovers are controlled for (in particular the coefficient decreases from 1.53 to 0.45 when country dummies are introduced and to 0.16 when also geographical spillovers are accounted for). The additional explanatory power of relational spillovers with respect to geographical spillovers confirms the results of Maggioni et al. (2007), based on binary relational and geographical proximity matrixes and on a spatial error model. The regression results also show that patents increase with R&D expenditure, human capital and population density. Finally, the impact of geographical R&D spillovers is large and highly significant, indicating that physical proximity is still very important for knowledge transmission.

The way in which relational spillovers are computed (by row standardising the matrix of regional collaborations) allows spillovers to increase when regions cooperate with more R&D intensive regions, but neglects the possible impact of the total amount of research collaborations on knowledge creation. When introducing this variable in the regression, we find that regional patents depend positively on the total amount of regional collaborations. Moreover, the size of relational R&D spillovers increases with the size of total research collaborations in FP (the interaction term between relational spillovers and total collaborations is positive and significant). These results show that relational spillovers are underestimated when total collaborations are not accounted for.

Table 3 looks at the possible different impact of R&D and R&D spillovers when one distinguishes by the R&D sector of performance (business enterprise, government, higher education).

The results show that, in all specifications, business enterprise and higher education R&D and their associated relational spillovers are positive and significant, while government R&D and its associated relational spillovers are negative and significant. The positive relational spillovers/knowledge transfers associated to higher education R&D are in line with the strong participation of universities to European FP. Less expected is the result on public R&D, although consistent with the findings of Maggioni at al. (2007) who provide as a possible explanation the fact that publicly funded R&D primarily addresses basic research which rarely produces patentable (or patented) results. Table 3 (column 3) shows that the results on relational spillovers are also robust to controlling for geographical spillovers. It is interesting also to observe that, differently from relational spillovers, the only significant geographical spillovers are found for business enterprise R&D. These results are consistent with those found by Scherngell and Barber (2011) providing evidence that geographical factors significantly affect patterns of industrial R&D collaboration, while in the public research sector effects of geography are much smaller.

Our findings confirm that the production pattern of innovation is shaped not only by spatial proximities but also by the presence of relational proximity which emerges through participation to research networks. Marrocu et al. (2013) argue that the simultaneous presence of different proximity dimensions implies that spillovers may have a dual nature: one unintended and one intended. Our results show that in the business enterprise R&D sector both types of spillovers occur, while in the higher education sector intended spillovers (or, more properly, knowledge transfer) based on agents and institutions which exchange ideas on a voluntary basis prevail.

Table 3: Relational spillovers and knowledge creation: GLS results by R&D sector of performance

	(1)	(2)	(3)
	Patents	Patents	Patents
Business enterprise R&D intensity BERD	0.809***	0.528***	0.496***
	(73.21)	(50.01)	(51.22)
Government R&D intensity GERD	-0.0258***	-0.0251***	-0.0214***
	(-10.99)	(-5.72)	(-7.08)
Higher education R&D intensity HERD	0.127***	0.0188**	0.0161**
	(13.65)	(2.84)	(2.82)
Human capital	0.789***	0.570***	0.424***
	(21.52)	(12.19)	(9.45)
Relational spillovers BERD	1.637***	0.566***	0.160*
	(15.35)	(7.52)	(2.29)
Relational spillovers GERD	-2.076***	-0.725***	-0.547***
	(-15.32)	(-9.26)	(-8.17)
Relational spillovers HERD	1.696***	0.331	0.705***
	(7.54)	(1.92)	(4.58)
Population density	0.0247***	0.0843***	0.126***
	(3.36)	(11.26)	(13.38)
_Ifp_5	-0.557***	-0.117***	-0.122***
	(-18.70)	(-4.97)	(-5.21)
_Ifp_6	-0.585***	-0.0666*	-0.0914**
	(-16.49)	(-2.25)	(-3.11)
_Ifp_7	-1.241***	-0.505***	-0.579***
	(-24.48)	(-11.30)	(-12.90)
Relational spillovers BERD			0.837***
			(19.26)
Relational spillovers GERD			-0.0428
			(-0.82)
Relational spillovers HERD			-0.0742
			(-0.99)
Constant	0.745	-5.724***	-1.815*
	(0.71)	(-8.10)	(-2.47)
Country dummies	NO	YES	YES
chi2	44033.560	1.30e+05	45996.238
rho-squared	0.728	0.900	0.915
N	970	970	970
N_groups	252	252	252
N_time	4	4	4

t statistics in parentheses

Coefficients are heteroskedasticity-consistent

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: rho-squared are the square of correlation coefficient between the patents and their predicted values.

But what kind of networks is more likely to favour knowledge spillovers? And should European policy encourage the formation of “networks of excellence” or rather the formation of networks involving regions with different levels of R&D activity by pursuing an innovation policy in line with the Cohesion policy? Although we cannot directly answer this question, we try to provide an indirect answer by looking at spillovers accruing to regions participating with similar (in terms of R&D) or different regions on the basis of the local Moran coefficient (positive or negative). Table 4 reports the results of the knowledge production function allowing for different results across two groups of regions (similar/different) on the basis of the value of the local Moran based on the relational distance matrix (positive/negative).

Table 4: Relational spillovers and knowledge creation: GLS results by type of regions

	(1)	(2)		(3)	(4)	
	Moran<0	Moran>0	Difference	Moran<0	Moran>0	Difference
R&D intensity	0.362***	0.587***	-0.225***	0.463***	0.654***	0.191***
	(16.50)	(25.24)	(-7.28)	(15.04)	(36.25)	(-5.53)
Human capital	0.968***	0.0103	0.958***	0.772***	0.0937**	0.678***
	(14.69)	(0.20)	(11.19)	(11.34)	(2.61)	(8.71)
Relational spillovers	0.902***	0.330**	0.572***	0.673***	0.0647	0.608***
	(6.58)	(2.88)	(2.90)	(4.44)	(1.30)	(3.64)
Population density	0.124***	0.0965***	0.028	0.103***	0.0952***	0.008
	(8.42)	(6.91)	(0.92)	(6.39)	(6.98)	(0.22)
_Ifp_5	0.0184	0.0538**	-0.036	-0.0292	-0.0494**	0.02
	(0.72)	(3.20)	(-1.22)	(-1.19)	(-2.97)	(0.79)
_Ifp_6	0.0290	0.123***	-0.094***	0.00205	0.0112	-0.009
	(1.04)	(5.79)	(-2.93)	(0.07)	(0.59)	(-0.05)
_Ifp_7	-0.483***	-0.267***	-0.216***	-0.584***	-0.483***	-0.101**
	(-14.16)	(-10.17)	(-4.69)	(-15.92)	(-22.40)	(-2.23)
Geographical spillovers				1.376***	1.516***	-0.14
				(19.50)	(19.27)	(-0.65)
Constant	-2.457***	-5.776***	3.319***	2.764***	0.220	2.544***
	(-4.29)	(-12.82)	(4.23)	(4.27)	(0.59)	(3.53)
Country dummies	YES	YES	YES	YES	YES	YES
chi2	1.66e+05	12023.274		67966.259	64263.178	
rho-squared	0.851	0.713		0.880	0.776	
N	593	377		593	377	
N_groups	169	110		169	110	
N_time	4	4		4	4	

t statistics in parentheses

Coefficients are heteroskedasticity-consistent

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: rho-squared are the square of correlation coefficient between the patents and their predicted values.

The table shows that, in the regression including only relational spillovers, these are much lower between "similar" regions than between "different" regions (the coefficient for the first group is 0.33 while for the second group it increases to 0.90). Moreover, in the regression including also geographical R&D spillovers, relational spillovers are not significant for the group of "similar" regions while they are positive and significant with a coefficient of 0.67 for the group of "different" regions. The two groups also differ in the impact of R&D and human capital, with R&D being more important for the group of regions cooperating with regions with similar R&D expenditure and human capital being more important for the group of regions cooperating with regions that are different in terms of R&D expenditure. Overall, these results suggest that participation to FP is particularly beneficial for regions that are not at the scientific frontier but have a sufficient level of human capital allowing absorbing the knowledge of more R&D intensive partners. This evidence supports the claim of Hoekman et al. (2013) suggesting that the returns to FP funding are highest when involving scientifically lagging regions. In this respect, the current FP policy, encouraging network formation across regions with different levels of development (and, therefore, with different research capabilities) appears to be in line with the EU cohesion policy.

5. Conclusions

This paper has investigated the additional contribution of relational with respect to geographical spillovers in the process of knowledge creation across European regions. Two main findings emerge from the empirical analysis. First, the results of the econometric estimations show the existence of a simultaneous positive impact of both unintended (geographically based) and intended (collaborations based) R&D spillovers on knowledge generation. Secondly, the positive impact of relational spillovers is significantly higher in networks involving regions with heterogeneous levels of R&D. However, this strictly depends on regions having a sufficient level of absorption capacities (the impact of human capital is higher in heterogeneous networks).

The first result strengthens the findings of Maggioni et al. (2007) on the importance of relational spillovers for knowledge generation while also allowing disentangling their additional effect with respect to geographical ones. The second result adds to the existing literature by showing that, in order to evaluate the size of R&D spillovers, it is important to distinguish between different types of research networks since they may be more or less efficient in spreading knowledge across regions.

Both results have relevant policy implications. In particular, they show that any successful attempt to facilitate knowledge transfer across regions with different levels of research capabilities is important to counterbalance the natural tendency of knowledge to localise in certain areas leading to cumulative processes of knowledge accumulation and divergence. This apparently supports the effectiveness of European Framework Programmes in enhancing knowledge flows and at the same time in helping to spread knowledge across regions with various levels of R&D. However, considering the consistent and increasing amount of resources invested in such programmes, future research should aim at comparing the costs and benefits of such policies. Moreover, while geographical proximity naturally facilitates face to face interactions, a crucial question in order to fully evaluate the impact of FP is whether relational proximity intentionally created through participation in R&D networks produces a once for all transfer of knowledge or contributes to initiate long lasting research relationships sustaining continuous processes of knowledge exchange. Finally, the differential impact of public and private R&D and their associated spillovers on patents' generation, emerging from the empirical analysis, raises the question on whether networks with a different composition of private and public participants are more or less efficient in creating knowledge spillovers. Future research with more detailed data on the composition of FP would allow shedding more light on this issue that deserves further investigation.

References

Almeida, P. - Kogut, B. (1999), Localization of knowledge and the mobility of engineers, *Management Science*, 45, 905-917.

Anselin, L. (1995), Local Indicators of Spatial Association – LISA, *Geographical Analysis*, 27(2), 93–115.

Autant-Bernard, C. – Billand, P. - Frachisse, D. - Massard, N. (2007a), Social distance versus spatial distance in R&D cooperation: Empirical evidence from European collaboration choices in micro and nanotechnologies, *Papers in Regional Science*, 86 (3), 495-519.

Autant-Bernard, C. – Mairesse, J. - Massard, N. (2007b), Spatial knowledge diffusion through collaborative networks, *Papers in Regional Science*, 86 (3), 341-350.

Balconi, M. – Breschi, S. and Lissoni, F. (2004), Networks of investors and the role of academia: An exploration of Italian patent data, *Research Policy*, 33, 127-145.

Boschma, R. (2005), Proximity and Innovation: A Critical Assessment, *Regional Studies*, 39 (1) 61-74.

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

Breschi, S. - Cusmano, L. (2004), Unveiling the texture of a European Research Area: Emergence of oligarchic networks under EU Framework Programmes, *International Journal of Technology Management*, 27(8), 747-772.

Breschi, S.- Lissoni, F. (2006), Mobility and social networks: Localized knowledge spillovers revisited, KTeS WP142, Bocconi University.

Breschi, S. - Lissoni, F. (2009), Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows, *Journal of Economic Geography*, 9 (4), 439-468.

Cincera M. - Van Pottelsberghe de la Potterie B. (2001), International R&D spillovers: a survey, *Cahiers Economiques de Bruxelles*, 169 (1er trimestre), 3-32.

Crescenzi, R. - Rodriguez-Pose A. (2011**)** Innovation and regional growth in the European Union, Advances in spatial science. Springer, Berlin, Germany. ISBN 9783642177606.

Crescenzi, R. - Nathan, M. - Rodríguez-Pose, A. (2014) Do inventors talk to strangers? on proximity and collaborative knowledge creation. SERC Discussion Papers, SERCDP0153. Spatial Economics Research Centre (SERC), London School of Economics and Political Science, London, UK.

D'Este, P. - Guy, F. - Iammarino, S. (2013) Shaping the formation of university-industry research collaborations: what type of proximity does really matter? *Journal of Economic Geography*, 13 (4). 537-558.

Di Cagno, D. - Fabrizi, A. - Meliciani, V. (2013) The impact of participation in European joint research projects on knowledge creation and economic growth The Journal of Technology Transfer, 1-23.

European Communities (2009), EU budget 2008 - Financial report, Luxembourg. Available at http://ec.europa.eu/budget/library/biblio/publications/2008/fin_report/fin_report_08_en.pdf.

Gibbons, S.- Overman, H.G. (2012) Mostly pointless special econometrics, *Journal of Regional Science*, 52 (2), 172-191.

Hall B. H. - Mairesse,J. - Mohnen, P. (2010), Measuring the Returns to R&D, *NBER Working Papers 15622*, National Bureau of Economic Research, Inc.

Hoekman J. - Scherngell T. - Frenken, K.- Tijssen, R. (2013), Acquisition of European research funds and its effect on international scientific collaboration, *Journal of Economic Geography*, 13, 23-52.

Jaffee, A.B.- Trajtenberg, M. - Henderson, R. (1993), Geographic localization of knowledge spillovers as evidenced by patent citations, *Quarterly Journal of Economics*, 108, 577-598.

Jaffee, A.B.- Trajtenberg, M., (1999), International Knowledge flows: Evidence from patent citations, *Economics of Innovation and new Technology*, 8 (1-2), 105-136.

Lesage, James P., (2014) What Regional Scientists Need to Know About Spatial Econometrics, doi.org/10.2139/ssrn.2420725.

Mairesse, J. - Turner, L. (2006), Measurement and Explanation of the Intensity of Co-publication in Scientific Research: An Analysis at the Laboratory Level, in *New Frontiers in the Economics of Innovation and New Technology: Essays in honour of Paul David*, eds. Antonelli, C. - Foray, D. - Hall, B.H.- Steinmueller, E., Edward Elgar Publishing, 255-295.

Maggioni, M. A. – Nosvelli, M. – Uberti, T.E. (2007), Space versus networks in the geography of innovation: A European analysis, *Papers in Regional Science*, 86 (3), 271-293.

Maggioni, M. – Uberti, T.E. (2009), Knowledge networks across Europe: which distance matters?, *The Annals of Regional Science*, 43, 691-720.

Maggioni, M. - Uberti, T.E. (2011), Networks and geography in the economics of knowledge Flows, *Quality and Quantity*, 45,1031-1051.

Marrocu, E. - Paci, R. - Usai, S. (2013), Proximity, networking and knowledge production in Europe: What lessons for innovation policy?, *Technological Forecasting and Social Change*, 80, 1484-1498.

Maurseth, P.B. - Verspagen, B. (2002), Knowledge spillovers in Europe: A patent citation analysis, *Scandinavian Journal of Economics*, 104 (4), 531-545.

Moreno, R. - Paci, R. - Usai, S. (2005), Spatial spillovers and innovation activity in European regions, *Environment and Planning*, 37 (10), 1793-1812.

OECD/ EU/Eurostat, GD (1995), The Measurement of Human Resources Devoted to S&T – *Canberra Manual*.

Ortega, J.L.- Aguillo, I.F. (2010), Shaping the European research collaboration in the 6th Framework Programme health thematic area through network analysis, *Scientometrics*, 85 (1), 377-386.

Pace, R.K.- Lesage, J.P. - Shuang, Z. (2013), Interpretation and Computation of Estimates from Regression Models using Spatial Filtering, *Spatial Economic Analysis*, 8 (3), 352-369.

Peri, G. (2004) Knowledge Flows and Productivity, *Rivista di Politica Economica*, 21-59.

Pisati, M. (2001), Tools for Spatial Data Analysis, *Stata Technical Bulletin*, 60, 21-37.

Ponds, R. - van Oort, F. - Koen, F. (2007), The geographical and institutional proximity of research collaboration, *Papers in Regional Science*, 86, (3), 423-443.

Rodriguez-Pose, A. - Crescenzi, R. (2008), Research and development spillovers, innovation system, and genesis of regional growth in Europe, *Regional Studies*, 42 (1), 51-67.

Scherngell, T. - Barber, M. J. (2009), Spatial interaction modelling of cross-region R&D collaborations: empirical evidence from the 5th EU framework programme, *Papers in Regional Science*, 88(3), 531-546.

Scherngell, T. - Barber, M. J. (2011), Distinct spatial characteristics of industrial and public research collaborations: evidence from the fifth EU Framework Programme, *The Annals of Regional Science*, 46 (2), 247-266.

Singh, J. (2005), Collaborative Networks as Determinants of Knowledge Diffusion Patterns, *Management Science*, 51(5), 756-770.

Vega, S. H. - Elhorst, P. (2013), On spatial econometric models, spillover effects, and W, *ERSA conference papers*. No. ersa13p222, European Regional Science Association.

Wanzenböck, I. - Scherngella, T. - Lata, R. (2014), Embeddedness of European Regions in European Union-Funded Research and Development (R&D) Networks: A Spatial Econometric Perspective, *Regional Studies*, 1-21.

Zucker, L.G. - Darby, M. - Armstrong, J. (1998), Intellectual capital and the firm: The technology of geographically localized knowledge spillovers, *Economic Inquiry*, 36, 65-86.