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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 the EU Framework Programmes (from the Fourth to the Seventh) to weigh 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 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.

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[2] 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 bears important consequences for the geographical distribution of innovation activities in Europe and for policies devoted to support the creation and dispersion 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/

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[1] Responsibility for the information and views set out in this article lies entirely with the author.

[2] 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.

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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 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, participation in international research programmes can be a way of reconciling the need for "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 lagging regions to FP networks.[3] For these regions, participation in FP can be a means 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 in EU Framework Programmes for knowledge generation (patents) across European regions. In contrast to 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 other similar or dissimilar (in terms of R&D intensity) regions.

The paper is organized 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

The role of R&D spillovers for regional growth has been deeply investigated recently by many authors showing that the relevance of such spillovers is very localized.[4] This result is supported by other studies in the field of the geography of innovation stating that proximity matters since it enhances interpersonal relationships and face-to-face contacts, thus making it easier to transfer tacit knowledge.[5]

However, the special role of geographical distance with respect to other types of distances has been questioned by Boschma (2005) and Autant-Bernard et al. (2007a) claiming that geographical proximity per sé is neither a necessary nor a sufficient condition for learning to take place: other types of proximity such as cognitive, organizational, social and institutional distances may be equally relevant, although they could be enhanced by geographical 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 flows between inventors who already have close network ties (past collaborations). Further, Breschi and Lissoni (2009) show that after controlling for inventor mobility and for the resulting co-invention network, the residual effect of spatial proximity on knowledge diffusion is strongly reduced.[6] More recently, using co-patenting between UK inventors, Crescenzi et al. (2014) show that while physical proximity is crucial in starting a collaboration, once a relationship has been established other forms of proximity (organizational, social and ethnic links) become more relevant and, in the case of serial inventors, geography no longer matters.

These, and other similar findings, suggest that quantifying the role of "relational" distance, with respect to "geographical" distance, as a source of knowledge flows is an interesting research topic deserving deeper investigation. With this aim Marrocu et al. (2013) analyse the role of different types of proximity on regional innovation for a sample of European regions, finding that technological proximity outperforms geographic proximity, whilst a limited role is played by social and organizational networks.

European Framework Programmes provide data that fit especially well when measuring relational proximity: they are in fact specifically designed to encourage the creation of linkages among researchers of different and often geographically distant regions. However, this data has been analysed so far mainly with the purpose of looking at the structure of research networks and aimed at investigating the factors that facilitate their formation,[7] while only a few papers have looked at the impact of participation in EU Framework Programmes on knowledge transfers (Maggioni et al., 2007; Hoekman et al., 2013; Di Cagno et al., 2013).

To the best of our knowledge, the only studies that use the data extracted from EU Framework Programmes to estimate the impact of relational distance on knowledge creation at the regional level, as done in this paper, are those of Maggioni et al. (2007) and 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 matrices. They find that relational networks influence the behaviour of regional innovation systems, but that spatial proximity plays a more relevant role in determining their performance.

Using a regionalized dataset of joint FP participations and joint co-publication activities, Hoekman et al. (2013) 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 contribution builds on these two studies: similarly to Maggioni et al. (2007), it aims at investigating the respective role of geographical and relational proximity for knowledge creation while, in line with Hoekman et al. (2013), it asks whether the effect of FP funding varies across regions. However, differently from Maggioni et al. (2007), it contributes to the literature by disentangling the additional effect of R&D relational spillovers and geographical spillovers by adopting 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 matrices; one based on geographical distance across regions and the second based on relational distance. At the same time, in contrast to Hoekman et al. (2013), it formally tests whether relational R&D

[3] 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.

[4] Peri (2004), Bottazzi and Peri (2003), Moreno et al. (2005) and Rodriguez-Pose and Crescenzi (2008 and 2011).

[5] Zucker et al. (1998), Almeida and Kogut (1999), Singh (2005), Balconi et al. (2004), Breschi and Lissoni (2006) and Mairesse and Turner (2006).

[6] An analogous effect is found by Ponds et al. (2007), using data on co-publications in the Netherlands and by D'Este et al. (2013) in which the role of geographical proximity in the formation of new partnerships between universities and firms is weakened when firms are located in dense and technologically related clusters.

[7] 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) and Wanzenböck et al. (2014).

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

On the basis of the literature reviewed in the previous section, there appears to be some evidence of the relevance of both geographical and relational spillovers for knowledge creation. However, there is no direct evidence of whether relational spillovers are additional to geographical ones. The first aim of this paper is to shed light on this neglected issue. In particular, since one of the main aims of FP is to create collaborations also among geographically distant regions, our main hypothesis is that i) *relational spillovers have an additional effect with respect to geographical spillovers on knowledge creation*. Testing this hypothesis indirectly sheds light on the effectiveness of FP — a crucial issue considering the large and increasing amount of European resources invested in such programmes.

The literature on spillovers, mostly relying on different standardised weighting matrices (see, for example Maggioni et al. (2007); Marrocu et al. (2013)), does not take into account the overall level of collaborations among regions. Our second hypothesis is that ii) *spillovers are higher for those regions that participate intensively in research networks*; it is not only important with whom you cooperate but also how much a region cooperates, i.e. the regional total number of links, or "openness" to international networks, matters for knowledge creation in addition to relational spillovers.

Finally, the literature has mainly neglected the importance of the composition of the networks for the effectiveness of knowledge spillovers. In a different context, i.e. without measuring spillovers, Hoekman et al. (2013) show that the returns to FP funding are highest when involving scientifically lagging regions. We, therefore, ask whether spillovers are more easily created among regions that are similar or dissimilar in terms of their R&D intensities. On the one hand, similar regions can exchange knowledge more easily; on the other hand scientifically lagging regions may have more to learn from high R&D spending regions. Although we do not have a strong a priori hypothesis on the "best" composition of research networks, we expect that iii) *the rewards to participation in European FP are higher when FP include partners with dissimilar levels of R&D expenditures* (*high and low*) *conditional on regions having the sufficient level of human capital or* "*absorptive capacity*". A confirmation of this hypothesis would be in line with the result of Hoekman et al. (2013), suggesting that the current FP policy is in line with the EU Cohesion policy.

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:

$$\mathrm{PAT_t} = \mathrm{RD}_{t-s}\beta_1 + \mathrm{W}_{t-s}\mathrm{RD}_{t-s}\beta_2 + \mathrm{HC}_{t-s}\beta_3 + \mathrm{PD}_{t-s}\beta_4 + \lambda_{t\mathrm{e}\mathrm{N}} + \mathrm{v}_t \quad (1)$$

where $\mathrm{PAT_t}$ denotes a $\mathrm{N} \times 1$ 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 $\mathrm{N} \times 1$ vector consisting of one observation for every region in period $t - s$, where s denotes the time lag between the dependent and the explanatory variables); HC are human resources in science and technology divided by population; PD is population divided by the region's area[8]; W_{t-s} is an $\mathrm{N} \times \mathrm{N}$ non negative row standardized relational weights matrix for period $t - s$ with diagonal elements all equal to zero; β_1, β_2, β_3, and β_4 are response parameters; λ_t denotes a time specific effect, which is multiplied by a $\mathrm{N} \times 1$ vector of unit elements and v_t is a $\mathrm{N} \times 1$ vector of residuals for every spatial unit with zero mean and variance σ^2.

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 regional collaborations 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).

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.[9] Lagged explanatory variables should also avoid potential endogeneity problems. Overall we have a panel of 257 regions over four time periods. Due to the short time dimension of the data, we pool the data over time and use the feasible generalized least squares (GLS) estimator to fit the model. GLS allows taking into account possible heteroscedasticity in the error term. Finally, to detect multicollinearity problems, we look at correlation coefficients and variance inflation factor (VIF).

Our specification only takes into account "local" R&D spillovers by estimating a spatial lag of X (R&D) model (SLX) (Lesage, 2014). Assuming that the outcomes (patents) of each region *i* are affected by the R&D expenditures only of the regions cooperating in the same network, we can rule 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). Differently from our paper, Maggioni et al. (2007) estimate a spatial error model and Marrocu et al. (2013) estimate 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.[10] Finally, the spatial autoregressive model (SAR) and the spatial error model (SEM) do not allow disentangling which variables are responsible for spillovers.

Starting from Eq. (1) and then adding geographical spillovers and the total amount of regional collaborations per capita allows testing for our first and second hypotheses. In particular, the first hypothesis (*relational spillovers matter for knowledge creation and have an additional effect with respect to geographical spillovers*) is tested by looking at the significance of relational spillovers (the coefficient β_2) in the regression including geographical spillovers: a positive and significant β_2 would support the hypothesis. The second hypothesis (*spillovers are higher for those regions that participate intensively in research networks*) is tested by looking at the significance of the total amount of regional collaborations per capita. Finally, in order to test the third hypothesis (*the rewards to participation in European FP are higher when FP include partners with dissimilar levels of R&D expenditures*), we estimate Eq. (1) allowing for different parameters between two groups of regions. The first group includes regions cooperating with other regions having a similar level of R&D intensity. The second group includes regions cooperating with other regions with dissimilar levels of R&D intensity.[11] We then test whether the coefficient on relational spillovers is higher for the second group of regions.

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

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

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

[11] The two groups are identified on the basis of the Moran coefficient, see Section 4.

3. Regional collaborations in EU Framework Programmes

Framework Programmes (FPs) are the context under which EU policies for research and technological development 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 priorities (according to the European Commission classification) which will be supported are selected a priori according to the goal of the FPs.[12] 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 put, links among regions where the actors involved operate. Considering all projects funded, we can construct a collaborative, or relational matrix for each FP.

3.1. Regional data from the EUPRO database

Data from regional collaborations in EU Framework Programmes are extracted from the EUPRO database that contains information on organisations participating in FP funded projects.[13] 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.[14] 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. Fig. 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 resources allocated under FPs has risen from 3408.9 in the 2000 budget, to 6471.3 Million EUR in the 2008 budget.[15]

Table 1 displays a Top20 ranking of regions according to the number of linkages (column 3), the number of linkages per capita (column 5) and the regional pairs showing the highest number of inter-regional collaborations on average over the period of observation (column 7). Regarding the total number of collaborations in FP, the table shows that the region of Île de France (FR10) is one of the key regions and a central hub concentrating the highest number of linkages. Also the regions of Denmark (DK00), Switzerland (CH00), London (UKI1) and Oberbayern (DE21) show a high number of inter-regional FP collaborations in general, and in particular with Île de France. A list of Top20 ranking regions and NUTS codes is provided in Appendix B.

Table 2 gives further details on the relational weight matrices to be implemented in the empirical model. The summary statistics show that European regions get more densely connected in relational space over time. We can, for example, observe considerable increases in the mean number of linkages from the first period (1995–1998) to the last period considered (2007–2010). Moreover, the number of regions with zero linkages to other regions is considerably decreasing over time, reflecting the ongoing process of pan-European integration in FP collaboration. However, the number of linkages, i.e. the intensity of FP collaboration, is highly skewed across the regions.

3.2. Descriptive statistics (data analysis with spatial tools)

In Table 3,[16] we summarize the descriptive statistics for the main variables of the knowledge production function (KPF), as described in Section 2.2. We report the correlation matrix and variance inflation factor (VIF) values in Appendix A. As we have explained, the data is computed at the NUTS2 level[17] and, due to the variability of data over time, is computed as an average over a four year period. For each region, collaborations is the row-total of the relational weight matrices divided by population. This variable measures the propensity of region i to cooperate. Collaborations are also a proxy both for outwards attractiveness of a region and for its capacity to absorb knowledge generated elsewhere, jointly with quality and quantity of its human capital. As expected, higher values are registered in regions of Central and Northern Europe, whereas lower values characterize Southern and Eastern Europe. This variable, along with the other variables in Table 3, shows a strong variability between units, less over time (within dimension), as measured by standard deviation, and pointed out in Fig. 1 (more regions involved and more linkages 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 million population) 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 (data available on request).

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 sectoral 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 countries and Italy (characterized by a lower level in these variables and other ones when compared to the other large countries).

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.[18] This variable has lower dispersion across the European regions compared to other variables,

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

[13] 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, 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.

[14] In the estimations we use sums over the four time periods 1995–1998, 1999–2002, 2003–2006 and 2007–2010.

[15] Source: European Communities (2009), EU budget 2008 — Financial Report.

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

[17] 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 NUTS1 level and NUTS0 level) to fill the gap in the missing values in our dataset, so that we can obtain a balanced panel.

[18] 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).

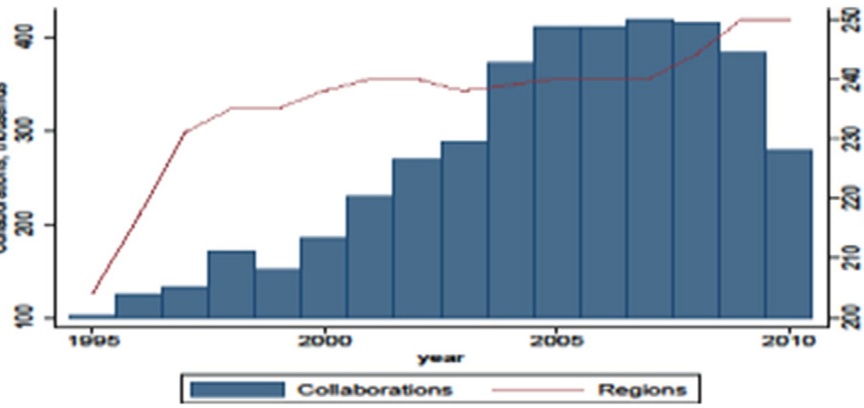

Fig. 1. FPs collaborations.
Source: EUPRO database.

Table 1
Top 20 regions and regional pairs according to the number of linkages.

Rank[a]	Region	Number of linkages	Region	Number of linkages (p.c.)	Regional pair	Number of linkages
1	FR10	150,175	BE10	0.0131	DE21–FR10	5,526
2	DK00	65,106	FI1B	0.0121	CH00–FR10	5,219
3	CH00	62,066	BE31	0.0084	FR10–UKI1	4,860
4	UKI1	57,895	UKI1	0.0202	ES30–FR10	4,683
5	DE21	56,424	AT13	0.0136	DK00–FR10	4,072
6	ES30	55,393	BE24	0.0098	FR10–ITI4	4,060
7	EL30	49,172	SE11	0.0125	FR10–ITC4	3,523
8	ITI4	48,870	NL31	0.0092	DEA2–FR10	3,325
9	ITC4	48,486	DE50	0.0052	FR10–EL30	3,282
10	NL33	43,009	CZ01	0.0125	FR10–NL33	3,102
11	NO00	42,190	DE21	0.0092	FR10–NO01	2,997
12	FI1B	41,908	EL43	0.0299	BE10–FR10	2,897
13	DEA2	39,905	FR10	0.0093	FR10–FR71	2,678
14	ES51	38,740	EL30	0.0058	ES51–FR10	2,667
15	BE10	34,675	NL33	0.0342	FI1B–FR10	2,523
16	SE11	33,887	SK01	0.0183	FR10–SE11	2,505
17	AT13	31,092	SE23	0.0192	FR10–ITC1	2,399
18	FR71	29,326	DK00	0.0050	FR10–FR62	2,316
19	NL32	29,188	SE12	0.0113	DK00–NO01	2,311
20	PT17	28,204	NL32	0.0104	DE30–FR10	2,180

[a] All values are calculated as the average over the observed period 1995–2010.

and it shows a clearly identifiable national pattern. A high endowment of human capital characterizes the Scandinavian countries, the UK, and Germany, while lower values are generally detected for France, Italy and Eastern countries (except for Baltic countries). In the last period, some regions have recorded particularly high values (over 36%): Praha, Helsinki-Uusimaa, Stockholm, East Anglia and Inner London.

Finally, looking at correlation coefficients (see Appendix A), we find generally positive, although not particularly high values. Exceptions are the very high (above 0.8) correlation coefficients between business, government and higher education R&D relational spillovers and, to a lesser extent (values around or above 0.6) for geographical spillovers. Similar indications emerge from the VIF suggesting some possible problems of multicollinearity only for some of these variables (an issue we will come back in the econometric analysis).

Table 2
Descriptive statistics of the relational weight matrices.

	1995–1998	1999–2002	2003–2006	2007–2010
Density of the matrix	0.45	0.55	0.62	0.61
Non-zero elements of the matrix	29,718	36,646	40,718	40,430
Regions without linkages	21	16	15	6
Mean no. of linkages	16.10	25.25	44.90	45.31
Max no. of linkages	2490	3782	8575	8675
SD no. of linkages	67.99	99.06	188.25	198.48

This 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 the 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 Figs. 2 and 3 (two Moran scatterplots[19]) 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 matrices *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 matrices: as noted by Pace et al. (2013) while it is not possible to directly compare two or more weight matrices, 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 intensity tend to be spatially clustered, collaborations in FP might involve also regions with different levels of R&D intensity (the number of regions located in quadrants with negative correlation is higher when using relational distance).

Secondly, for both matrices, spatial and relational correlation in R&D intensity declines over time, but the decline in relational correlation is higher than that in geographical correlation. To shed more light on how the different regions affect the Moran coefficient, Figs. 4 and 5 provide information on the localization in a map of regions in the four quadrants of Figs. 2 and 3. In Fig. 4, we can observe that regions with low levels of R&D intensity surrounded by other regions with low R&D intensity are more frequently located in Southern and Eastern Europe. At the same time, geographical clusters of high R&D intensive regions prevail in Northern Europe and in the area between Northern Italy, Austria, South of France and South of Germany. A more mixed pattern is found in the UK and in the rest of Europe. In Fig. 5, we observe

[19] 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.

Table 3
Descriptive statistics.

Variable		Mean	Std. Dev.	Min	Max	Observations
Patent (per million population)	Overall	90.84465	113.0128	0.0787997	705.7324	N = 1028
	Between		111.6807	0.2335537	590.8845	n = 257
	Within		18.32396	−64.30827	205.6925	T = 4
R&D/GDP, %	Overall	1.376166	1.211298	0.0901267	8.080558	N = 1028
	Between		1.204333	0.1041226	7.691028	n = 257
	Within		0.1451292	0.5621051	2.227633	T = 4
Business R&D/GDP, %	Overall	0.8694985	0.9971312	0.0103019	7.574735	N = 1028
	Between		0.9920606	0.0131727	7.102596	n = 257
	Within		0.1138477	0.2166495	1.45955	T = 4
Government R&D/GDP, %	Overall	0.1812484	0.2352526	3.89E−07	2.029898	N = 1028
	Between		0.2326565	4.93E−07	1.565497	n = 257
	Within		0.0370521	−0.0912118	0.6456492	T = 4
HES R&D/GDP, %	Overall	0.32599	0.2632462	0.000796	1.633954	N = 1028
	Between		0.2599517	0.0015907	1.524395	n = 257
	Within		0.0438301	0.1502923	0.5842198	T = 4
HRST/POPULATION, %	Overall	17.50165	6.23214	3.341367	44.1581	N = 1028
	Between		5.497825	7.3352	34.99855	n = 257
	Within		2.949879	−5.30099	27.11959	T = 4
Collaborations (per million population)	Overall	968.7207	1361.924	0	13,096.83	N = 1028
	Between		1209.424	0	8555.538	n = 257
	Within		629.6061	−3968.178	5510.016	T = 4

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.

that, in FP4, in some areas of Southern Europe (particularly Italy and Spain), there are a relevant number of regions with low R&D intensities cooperating with regions having high R&D intensities. The number of such regions increases in FP7 including also Greek and Eastern European regions, thus contributing to reduce relational correlations.

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

Table 4 reports the results of the estimation of Eq. (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.

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 geographical spillovers are accounted for). The additional explanatory power of relational spillovers with respect to geographical spillovers confirms our first hypothesis. This result adds to that of Maggioni et al. (2007), based on binary relational and geographical proximity matrices and on a spatial error model unable to capture the joint impact of both types of proximity. The finding is in line with the reasoning that R&D spillovers follow the routes of distinct knowledge transmission mechanisms, based not only on geographical distance but also established for example in the form of knowledge

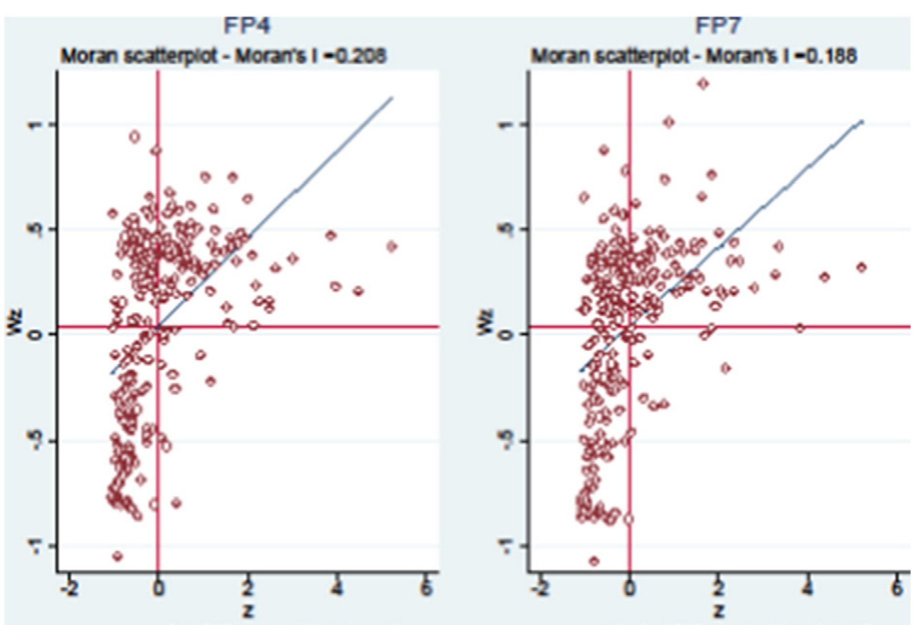

Fig. 2. Moran scatterplot (space matrixes).

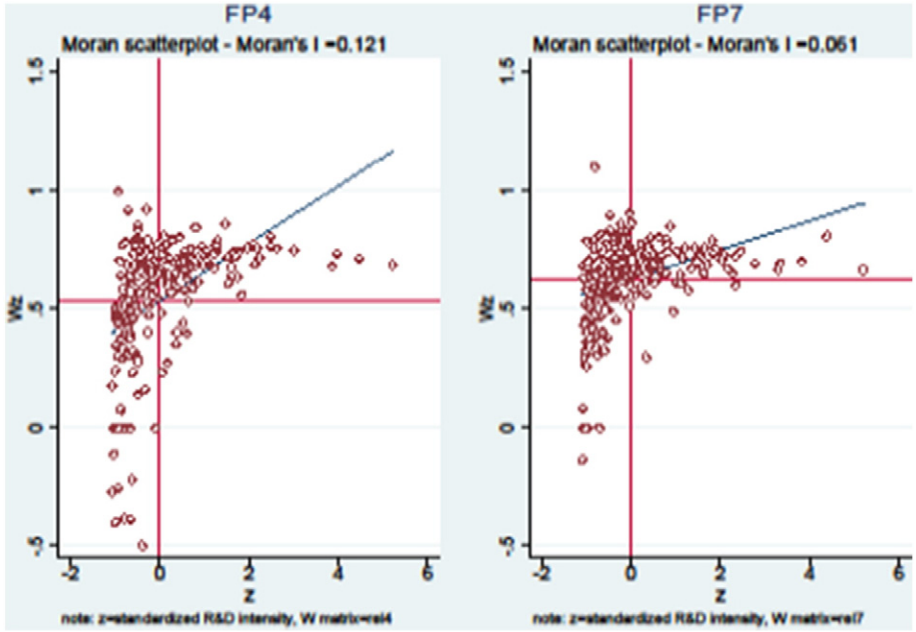

Fig. 3. Moran scatterplot (relational matrixes).

networks involving geographically distant regions (Autant-Bernard et al., 2007b).

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 support our second hypothesis showing that the importance of research networks is underestimated when total collaborations are not accounted for.

Table 6 looks at the possible different impacts of R&D and R&D spillovers when one distinguishes by the R&D sector of performance (business enterprise, government, higher education).

To control for the possible presence of multicollinearity between relational (geographical) R&D spillovers, as indicated by the high correlation coefficients (see Appendix A), we conduct an iterated principal-factor analysis by means of which we retain two common factors. Table 5 shows the matrix obtained after an orthogonal rotation (criterion varimax). This last operation makes it easier to explain the relationships between variables and factors. In the last column, we report the

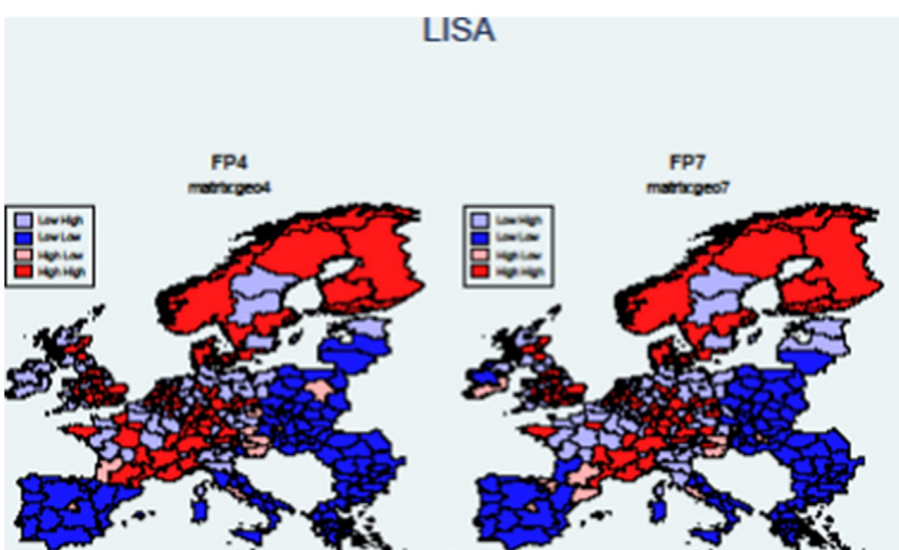

Fig. 4. Geographical LISA.

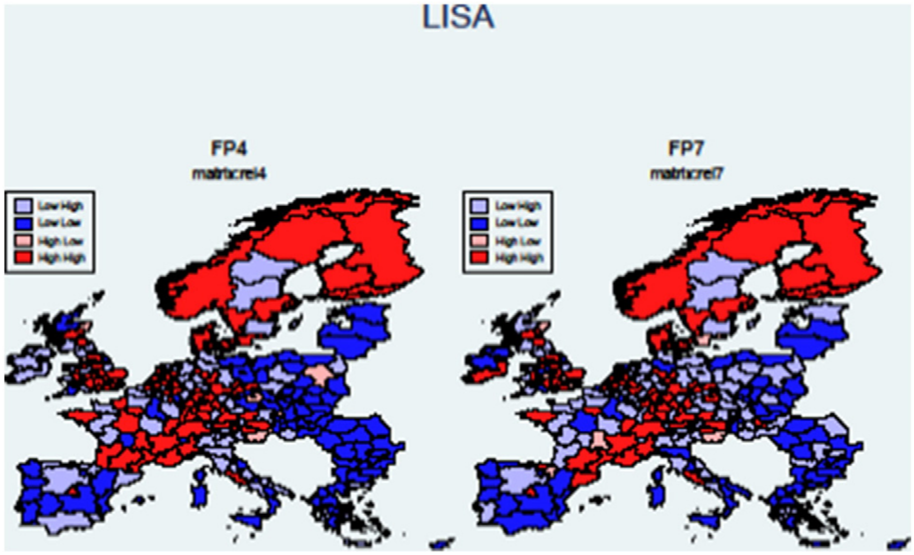

Fig. 5. Relational LISA.

uniqueness, that is the percentage of variance for the variable that is not explained by retained factors. For both relational and geographical spillovers, factor1 is mostly defined by BERD/HERD sectors and factor2 by GERD/BERD sectors.

Table 4
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***
	(45.60)	(41.00)	(37.40)	(27.66)
Human capital	1.104***	0.504***	0.387***	0.404***
	(23.42)	(11.16)	(8.06)	(9.08)
Relational spillovers	1.524***	0.453***	0.160*	0.722***
	(8.39)	(5.02)	(1.75)	(4.91)
Population density	0.0149*	0.0841***	0.115***	0.0606***
	(1.71)	(8.51)	(11.03)	(5.57)
Geographical spillovers			1.481***	
			(26.83)	
Collaborations				0.512***
				(3.53)
RSPILL ∗ Collaborations				0.108***
				(2.92)
_Ifp_5	−0.166***	0.0441***	−0.0157	0.0159
	(−6.07)	(2.75)	(−0.88)	(1.01)
_Ifp_6	−0.224***	0.0858***	0.0290	0.0319*
	(−7.35)	(4.57)	(1.42)	(1.68)
_Ifp_7	−0.856***	−0.352***	−0.469***	−0.403***
	(−23.05)	(−15.21)	(−18.75)	(−15.07)
Constant	2.804***	−4.359***	0.674	−3.710***
	(4.10)	(−11.84)	(1.61)	(−6.20)
Country dummies	No	Yes	Yes	Yes
chi2	17,384.207	84,936.651	63,191.681	4.03e+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

Notes: t statistics in parentheses.
Coefficients are heteroskedasticity-consistent.
Rho-squared are the square of correlation coefficients between the patents and their predicted values.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

The results in Table 6 (column 1) show that 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. Table 6 (column 2) shows that the results on relational spillovers are also robust to controlling for geographical spillovers. It is interesting to observe that, differently from relational spillovers, the only significant geographical spillovers are found in business enterprise R&D.

Due to the high correlation between private, higher education and government R&D spillovers (both relational and geographical), columns 3 to 5 of Table 6 introduce linear combinations of geographic and relational spillovers resulting from principal-factor analysis. The results show that the first relational and geographical factors (that are mostly defined by BERD/HERD) are always positive and significant, while the second factor (mostly defined by GERD/BERD) is negative and significant when looking at relational spillovers and positive and significant when looking at geographical spillovers.

Overall, it appears that, in the case of relational spillovers, public R&D exerts a negative impact on patent creation. Maggioni et al. (2007) provide as a possible explanation the fact that publicly funded R&D primarily addresses basic research which rarely produces patentable (or patented) results. However, when looking at geographical spillovers, it appears difficult to disentangle the impact of private, higher education and government R&D spillovers. In fact, while the last two are not significant when introduced simultaneously in the regression (column 3), when grouped into principal factors they show up as positive and significant.

Overall, our findings confirm that the production pattern of innovation is shaped not only by spatial proximities but also by the presence of

Table 5
Iterated principal-factor analysis.

Variable	Factor1	Factor2	Uniqueness
Relational spillovers BERD	0.8324	0.3117	0.2099
Relational spillovers GERD	0.3891	0.3829	0.7020
Relational spillovers HERD	0.7896	0.0643	0.3724
Geographical spillovers BERD	0.7508	0.5896	0.0888
Geographical spillovers GERD	0.5493	0.6001	0.3381
Geographical spillovers HERD	0.7405	0.4156	0.2789

Table 6
Relational spillovers and knowledge creation: GLS results by R&D sector of performance.

	(1)	(2)	(3)	(4)	(5)	(6)
	Patents	Patents	Patents	Patents	Patents	Patents
Business enterprise R&D intensity BERD	0.528***	0.496***	0.538***	0.517***	0.550***	0.504***
	(50.00)	(51.22)	(45.77)	(55.61)	(49.04)	(58.71)
Government R&D intensity GERD	−0.0251***	−0.0214***	−0.0290***	−0.0262***	−0.0338***	−0.0256***
	(−5.72)	(−7.08)	(−6.09)	(−10.98)	(−7.88)	(−8.93)
Higher education R&D intensity HERD	0.0188***	0.0161***	0.0140*	0.0377***	0.00883	0.0292***
	(2.84)	(2.82)	(1.89)	(5.46)	(1.42)	(5.08)
Human capital	0.570***	0.424***	0.538***	0.396***	0.569***	0.441***
	(12.18)	(9.45)	(10.53)	(8.38)	(12.35)	(10.03)
Population density	0.0843***	0.126***	0.0789***	0.130***	0.0887***	0.137***
	(11.25)	(13.38)	(9.16)	(14.21)	(10.72)	(15.42)
Relational spillovers BERD	0.566***	0.160**				
	(7.51)	(2.28)				
Relational spillovers GERD	−0.723***	−0.545***				
	(−9.23)	(−8.15)				
Relational spillovers HERD	0.328*	0.703***				
	(1.90)	(4.56)				
Geographical spillovers BERD		0.837***				
		(19.26)				
Geographical spillovers GERD		−0.0428				
		(−0.82)				
Geographical spillovers HERD		−0.0741				
		(−0.99)				
Relational factor_1			0.0823***	0.0434***	0.191***	0.136***
			(4.54)	(3.50)	(8.10)	(7.38)
Geographical factor_1				0.844***		0.572***
				(27.66)		(18.39)
Relational factor_2					−0.268***	−0.209***
					(−10.14)	(−8.27)
Geographical factor_2						0.311***
						(11.01)
_Ifp_5	−0.117***	−0.122***	−0.00545	−0.108***	−0.118***	−0.120***
	(−4.95)	(−5.19)	(−0.28)	(−6.78)	(−5.28)	(−5.93)
_Ifp_6	−0.0660**	−0.0910***	0.0266	−0.0947***	−0.123***	−0.124***
	(−2.22)	(−3.09)	(1.15)	(−5.01)	(−4.55)	(−4.97)
_Ifp_7	−0.504***	−0.579***	−0.419***	−0.628***	−0.645***	−0.692***
	(−11.28)	(−12.89)	(−13.32)	(−23.90)	(−16.25)	(−18.22)
Constant	−5.734***	−1.822**	−5.814***	−6.277***	−5.742***	−6.393***
	(−8.11)	(−2.48)	(−46.28)	(−54.75)	(−49.00)	(−62.38)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
chi2	1.29 + 05	45,828.044	43,914.004	58,640.486	5.61e + 05	94,435.417
Rho-squared	0.900	0.916	0.897	0.909	0.899	0.912
N	970	970	970	970	970	970
N_groups	252	252	252	252	252	252
N_time	4	4	4	4	4	4

Notes: *t* statistics in parentheses.
Coefficients are heteroskedasticity-consistent.
Rho-squared are the square of correlation coefficients between the patents and their predicted values.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

relational proximity which emerges through participation in 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. In the higher education sector intended spillovers (or, more properly, knowledge transfer based on agents and institutions which exchange ideas on a voluntary basis) seem to prevail.

But what kind of networks are 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 in regions participating with similar or dissimilar regions (in terms of R&D intensity) on the basis of the local Moran coefficient (positive or negative). In particular, similar regions are those located in Fig. 3 in the left bottom and top right quadrants (low R&D intensive regions cooperating with low R&D intensive regions and high R&D intensive regions cooperating with high R&D intensive regions). Dissimilar regions are those located in the right bottom and top left quadrants in Fig. 3 (high R&D intensive regions cooperating with low R&D intensive regions). Table 7 reports the results of the estimation of the knowledge production function allowing for different coefficients across two groups of regions (similar/different) on the basis of the value of the local Moran computed on the relational distance matrix (positive/negative).

The table shows that, in the regression including only relational spillovers, spillovers 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 geographical R&D spillovers, relational spillovers are not

Table 7
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***
	(16.52)	(25.25)	(−7.28)	(15.05)	(36.26)	(−5.53)
Human capital	0.968***	0.0103	0.958***	0.772***	0.0937***	0.678***
	(14.70)	(0.20)	(11.19)	(11.34)	(2.61)	(8.71)
Relational spillovers	0.901***	0.330***	0.572***	0.672***	0.0646	0.608***
	(6.58)	(2.88)	(2.90)	(4.43)	(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)
Geographical spillovers				1.376***	1.516***	−0.14
				(19.51)	(19.27)	(0.65)
_Ifp_5	0.0185	0.0538***	−0.036	−0.0291	−0.0494***	0.02
	(0.72)	(3.20)	(−1.22)	(−1.18)	(−2.97)	(0.79)
_Ifp_6	0.0291	0.123***	−0.094***	0.00216	0.0113	−0.009
	(1.05)	(5.80)	(−2.93)	(0.08)	(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)	(−22.39)	(−2.23)
Constant	−2.460***	−5.777***	3.319***	2.761***	0.220	2.544***
	(−4.30)	(−12.83)	(4.23)	(4.27)	(0.59)	(3.53)
Country dummies	Yes	Yes		Yes	Yes	
chi2	1.71e+05	12,022.948		67,722.681	64,316.837	
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	

Notes: *t* statistics in parentheses.
Coefficients are heteroskedasticity-consistent.
rho-squared are the square of correlation coefficients between the patents and their predicted values.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

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 that have similar R&D expenditure, and human capital being more important for the group of regions cooperating with other regions that are different in terms of R&D expenditure. Overall, these results suggest that participation in FP is particularly beneficial for regions that are not at the scientific frontier but have a sufficient level of human capital allowing them to absorb 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 spillovers 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 creation. Secondly, the positive impact of relational spillovers is significantly higher in networks involving regions with heterogeneous levels of R&D. However, this effect strictly relies 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 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 for any attempt to facilitate knowledge transfer across regions with different levels of research capabilities to be successful it is important to counterbalance the natural tendency of knowledge to localise in certain areas leading to cumulative processes of knowledge accumulation and divergence. This 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 an 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 patent generation, emerging from the empirical analysis, raises the question of 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 make it possible to shed more light on this issue that deserves further investigation.

Appendix A. Correlation matrix and variance inflation factors

id	Variable	1	2	3	4	5	6	7	8	9	10	11	VIF	1/VIF
1	Business R&D/GDP	1.000											3.500	0.286
2	Government R&D/GDP	0.268	1.000										1.690	0.592
3	HES R&D/GDP	0.363	0.326	1.000									1.580	0.631
4	HRST/POPULATION	0.473	0.414	0.471	1.000								4.220	0.237
5	Population density	0.054	0.137	0.223	0.267	1.000							2.100	0.476
6	REL spillovers BERD	0.311	0.113	0.354	0.380	0.101	1.000						3.250	0.308
7	REL spillovers GERD	0.209	0.128	0.291	0.214	0.088	0.827	1.000					1.890	0.529
8	REL spillovers HERD	0.227	0.112	0.344	0.379	0.068	0.914	0.839	1.000				6.370	0.157
9	GEO spillovers BERD	0.435	0.131	0.314	0.537	0.187	0.508	0.315	0.399	1.000			14.220	0.070
10	GEO spillovers GERD	0.293	0.149	0.215	0.343	0.091	0.351	0.300	0.276	0.634	1.000		4.930	0.203
11	GEO spillovers HERD	0.365	0.108	0.334	0.532	0.059	0.528	0.349	0.512	0.784	0.591	1.000	9.860	0.101

Note: we estimate variance inflation factors (VIF) for the reported independent variables after running a linear regression (country and time dummies VIF are not reported). The dependent variable is patents.

Appendix B. Top20 ranking regions

Ranking	NUTS2_code	Country	NUTS2_label
1	FR10	France	Île de France
2	DK00	Denmark	Denmark
3	CH00	Switzerland	Switzerland
4	UKI1	United Kingdom	Inner London
5	DE21	Germany	Oberbayern
6	ES30	Spain	Comunidad de Madrid
7	EL30	Greece	Attiki
8	ITI4	Italy	Lazio
9	ITC4	Italy	Lombardia
10	NL33	Netherlands	Zuid-Holland
11	NO00	Norway	Norway
12	FI1B	Finland	Helsinki-Uusimaa
13	DEA2	Germany	Köln
14	ES51	Spain	Cataluña
15	BE10	Belgium	Région de Bruxelles-Capitale/Gewest
16	SE11	Sweden	Stockholm
17	AT13	Austria	Wien
18	FR71	France	Rhône-Alpes
19	NL32	Netherlands	Noord-Holland
20	PT17	Portugal	Lisboa

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