ISSN 2532-5604

CSCC Centro di ricerca sulle Scienze Cognitive e la Comunicazione
Cognitive Science and Communication Research Centre

CSCC Working Papers 02/11

Does intentional mean hierarchical? Knowledge flows and innovative performance of European regions

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CSCC Working Papers 02/11

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ISSN 2532-5604
CSCC Working Papers
[Online]

Does intentional mean hierarchical?

Knowledge flows and innovative performance of European regions[♦]

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ABSTRACT

The production of scientific and technical knowledge is mostly concentrated in specific locations (high-tech clusters, innovative industrial agglomerations, hot spots, excellence centres, technologically advanced regions). Knowledge flows very easily within these geographical enclaves; however, scientific and technical knowledge does flow also between different enclaves. Aim of this paper is to analyse how knowledge flows between these agglomerations of innovative inputs, and what are the effects of such flows on the innovative performance, measured by patents application intensity, of an individual location. To do so we estimate a regional knowledge production function and we estimate, through appropriate spatial econometric estimation techniques, the effect of both geographical and relational autocorrelation (as measured by participation to joint research networks funded by the EU). Furthermore we are able to model the unobservable structure and link value of actual knowledge flows within these joint research networks. Our research methodology showed that knowledge flows within inter-regional research networks along a non symmetrical hierarchical structure in which knowledge produced by network participants is exploited by the coordinator.

Keywords: Framework Programmes, Networks, Spatial econometrics

Jel Code: C01, C52

[♦] Comments and suggestions on earlier versions of this paper, by participants at the 7th European Meeting on Applied Evolutionary Economics, SSSUP, Pisa; Dimetic Conference on "Regional Innovation and Growth: theory, empirics and policy analysis", Pècs; Deams - University of Trieste and Kites-Bocconi seminars, as well as discussions with E Bergman, S. Beretta, K. Frenken, G. Fagiolo, L Togni are gratefully acknowledged.

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1. Introduction

Scientific and technical knowledge is mostly generated by specially dedicated actors (universities, research centres, firms) which, for a number of reasons[1], tend to co-locate in specific sites, thus determining the birth and development of what are called: high-tech clusters, innovative industrial agglomerations, hot spots, excellence centres, technologically advanced regions (Swann et al. 1998; Bresnahan et al. 2001; Maggioni 2002; Braunerhjelm and Feldman 2006). Knowledge flows very easily within these geographical enclaves – because of the high mobility of inventors and highly qualified workers, the strict interaction of producers and sub-suppliers of specialised inputs, and the more general phenomenon of knowledge diffusion. However, scientific and technical knowledge does flow also between different enclaves and some breakthrough technology was indeed developed thanks to the joint efforts of scientists and technicians working in different geographical locations.

Aim of this paper is to analyse how knowledge flows between these agglomerations of innovative inputs (which, for convenience, we operationalise as NUTS2 level regions for all EU-15 countries), and what are the effects of such flows on the innovative performance – as measured by patent application intensity – of an individual region.

In doing so we build on Maggioni et al. (2007) where we assumed that knowledge can be diffused and exchanged either through an unintentional diffusive pattern based on spatial contiguity, or according to intentional relations based on a-spatial networks.

According to the first pattern, the geographical selection process leading to a hierarchical structure of the location of innovative activities goes together with an increasing role of 'unintended' spatial knowledge spillovers that, from excellence centres, extend their positive effects to other agents (firms, universities, research centres) located in neighbourhood areas. So relevant regions present both an 'attractivity' potential and a 'diffusive capacity' (Acs et al. 2002). Each innovative region extends its influence over the neighbouring territories through a trickling down process of spatial diffusion (underlining the role of different forms of localised knowledge spillovers). According to this perspective, thus space matters most and knowledge flows following geographical patterns.

According to the second pattern, knowledge is mainly exchanged according to voluntary 'barter' and increased through learning by interacting procedures, within specialised networks which are intentionally established between crucial nodes (Cowan and Jonard 2004). On the other hand, technological and scientific knowledge, developed within the region, is diffused and exchanged through a set of a-spatial networks (often structured in formal and contractual agreements between institutions) connecting each region with other regions, irrespectively of their geographical contiguity. According to this perspective, relational networks matter most and knowledge spreads following intentional patterns, which may have little correlation with geographical contiguity.

In Maggioni et al (2007) the analysis – built on spatial econometric techniques based on different "spatial weight matrices" either according to geographical contiguity or on relational proximity based on EU 5th FP data – aimed at testing whether formal relationships based on a-spatial networks between geographically distant regions prevail over diffusive patterns based on spatial contiguity.

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[1] For an exhaustive survey see Rosenthal, Strange (2004), Henderson (2003); Ottaviano Thisse (2004); Duranton, Puga (2004).

However the analysis developed in that paper contained two main limitations: the first relates to the correct identification of the existence of inter-regional scientific relationships though the use of FP data; the second refers to a possible misspecification of the econometric model implied by the alternative use of the “geographical” or the “relational” weight matrix.

EU FP data contain only the membership of each specific research network and (in most cases) the amount of funds and not the effective trails followed by knowledge flowing within the network; secondly, if the data generation process (i.e. the influence of other regions innovative activity on each region innovative performance) has both a geographical and a relational component, then any attempt to measure either one of the components without taking into account the other one, may lead to biased and inefficient estimates.

In this paper we aim at overcoming this limitation firstly by taking into account in the same econometric specification both the geographical and the relational contiguity effects, secondly by devising a series of tests aimed to identify the effective structure of knowledge flows within joint research networks.

In this respect this paper encompasses two different streams of literature: the first dealing with the identification and study of network structure within innovative process (Jaffe A.B., Henderson R., Trajtenberg M., 1993; Audretsch, Feldman, 1996; Cowan and Jonard, 1999; Paci and Usai, 2000; Breschi and Lissoni, 2004 and 2009; Maggioni and Uberti, 2005 and 2008, Maggioni, Nosvelli and Uberti, 2007; Le Sage and Pace, 2008; Picci, 2010; Maggioni, Uberti and Usai 2011); the second dealing with the use of spatial econometric techniques in order to take into account the existence of directly unmeasurable (or unmeasured) spillover effects (Acs, Anselin and Varga, 2002; Fischer and Varga, 2003; Bottazzi and Peri, 2003, Greunz, 2003; Bode E., 2004; Moreno, Paci and Usai, 2005, Autant-Bernard and LeSage, 2009; Usai, 2010; Varga et al. 2010)

The paper is organised as follows: after this introduction, in section 2 we discuss the issue of how to deal with geographical and relational weight matrices when performing spatial econometric exercise on patent data; in section 3 we present the treatment methods we applied to original FP data and the estimation strategy we devised in order to disentangle the actual structure of knowledge flows from membership data; in section 4 we describe the estimated models and we present the results. A final section which highlights some policy implication and sketch a future research agenda concludes the paper.

2. From “space vs. networks” to “space and networks”

In Maggioni et al. (2007) two distinct spatial econometric exercises (the first based on a geographical “spatial weight matrix”, W^g; the second based on a relational “spatial weight matrix”, W^r) were performed in order to “verify whether or not hierarchical relationships, based on a-spatial networks between geographically distant excellence centres, prevail over diffusive patterns, based on spatial contiguity” (Maggioni et al, 2007 p. 472). However since one cannot compare the size of the coefficients of two regressions based on two different weight matrices, the mentioned analysis was complemented by a third exercise based on a third spatial’ weight matrix, $W^{r\text{-}g}$, obtained as difference between W^r and W^g. In other words we subtracted an index of geographical contiguity to an index of relational contiguity, so that the surviving neighbourhood definition included only “pure relational" connections established between geographically non-contiguous regions[2]" (ibid.). The results confirmed the existence of a pure relational component of the autocorrelation phenomenon which acts, together with the already known geographical component, in order to determine the innovative performance of a region.

However all the above does not properly tackle the estimation problem. If the innovative performance of a region (which may be partly explained by an internal knowledge production function) is also influenced both by its geographical and relational neighbouring regions, then any estimation based on a model specifying only one out of the two possible definitions of contiguity (relational or geographical) would result in a biased estimation, due to omitted variables specification.

This is the reason why, following Hoekman et al. (2009) in section 4 we present an estimation method (based on the construction of an "artificial" lagged dependent variable) which should be able to robustly estimate the existence of spatial autocorrelation arising from both geographical and relational behaviours and dynamics.

3. From membership to knowledge flows

As mentioned above, data on joint research networks funded by the EU under the 5th Framework programme (henceforth 5FP) – publicly available through the CORDIS website[3] – records only the names and locations of the joining institutions, their status (either coordinators or mere participants) and, most of the time[4], the amount of funds granted by the EU.

The 5FP is a five years programme started in 1998 and concluded in 2002[5] with the official aim of integrating different research areas and developing a critical mass of European resources in S&T. The total number of contracts financed within the 5FP is 16,085 with a total funding of about 12,000 millions euros [6]. Within this framework, we select contracts with a network structure (mainly joint research projects) and based our analysis on 6,755 networks between institutions (42% of total 5FP contracts): average membership is equal to 7 (6 participants plus 1 coordinator). The geographical scope of the analysis was limited to 171 regions at NUTS 2[7] part of EU 15 countries.

Since we are interested in the structure of knowledge flows within these collaborative research networks, then different and specific hypotheses on how knowledge effectively flows within the networks must be defined and then tested.

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2 Which may be used as a proxy for the 'intentional' knowledge barter exchange phenomenon. Hence, a generic entry in the "spatial weight matrix $w_{ij}^{r\text{-}g}$ is equal to 1 if region i and j are relationally contiguous but not geographically contiguous, and 0 otherwise. In the same paper an alternative exercise was conducted by dividing the original relational matrix by the distance matrix to obtain a new spatial weight matrix which takes somehow into account both the geographic and the relational dimensions of the autocorrelation.

3 The official web site is available at cordis.europa.eu/home_en.html (European Commission-CORDIS, 2010).

4 More precisely, it has been possible to obtain the funding data for most of the cases, 90%. In the analysis performed in section 4, we therefore selected 6,755 network contracts out of 16,085 research contracts that includes data on funding.

5 However, since some research contracts were funded in subsequent years, due to administrative delays, they were granted an extended end date up to 2005.

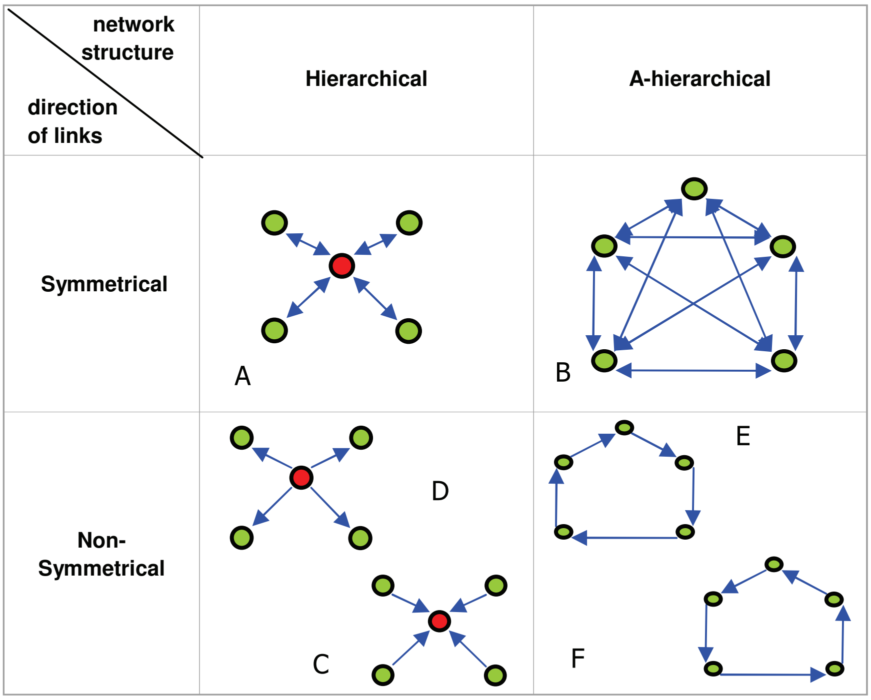
6 We described the details of 5FP in Maggioni et al. (2007).

7 Except for Denmark and Luxemburg, for which data are available only at NUTS0, Belgium, Ireland and United Kingdom at level 1. For a full list of regions see table A1.

3.1. Network structures and flows directions

The first issue is relative to the definition of the structure of a research network. We could start with the definition of a simple taxonomy (described in Maggioni and Uberti 2011) where two dimensions (the direction of links and the structure of the network) and their combinations, are considered (see figure 1).

Figure 1: A taxonomy of knowledge flows within collaborative research networks



Source: Maggioni and Uberti (2011)

According to this taxonomy – where, for expositional purposes, we illustrate the case of a very small and simple research network composed by one coordinator and four participants – knowledge may flow in 4 different ways within the same network, hence 4 different relational structures could emerge. Firstly links (i.e. knowledge flows) could be reciprocal and the underlying network structure could be hierarchical if there exist mutual, egalitarian but exclusive ties between coordinator and each participant (figure 1A). In this case the network structure is star-like, with a very high centralization value, but symmetry of relations guarantees a mutual exchange of knowledge, that is filtered by the pivotal player.

Differently knowledge could easily flow within the set of agents irrespective of any structural position (figure 1B). This structure reflects two facts: the absence of hierarchy within the network (indeed all indexes of centralization have values equal to zero) and no limitations to knowledge flows among all actors. In addition no coordination a/o brokerage of knowledge and information are at play and all agents have equal status of “member”.

The assumption of reciprocity of ties could be easily relaxed if we suppose the existence of different levels of knowledge stock between coordinator and participants in terms of emission of knowledge and absorptive capacity, and two structures could emerge according to the existence of hierarchy within the network.

A bottom-up structure (i.e. from participants to coordinator), as in figure 1C, or a top-down structure (i.e. from coordinator to participants), as in figure 1D could be considered if knowledge flows involve an exclusive relation between the coordinator and each single participant as in a star-like structure, but differently from figure 1A, there is no mutual and balanced exchange of knowledge between them.

A final network structure, characterised by no reciprocity of links and no hierarchy (figure 1E and 1F): in this case every member exchanges knowledge locally and exclusively to his/her next neighbour (in clockwise or couinter-clockwise direction), and a weel-like structure of knowledge flows emerges, where all members are interchangeable and no most central node emerges.

In section 4 we tested the existence of relational autocorrelation between the innovative activities of European regions based on four out of six of the abovementioned structures[8].

3.2. How to weight a knowledge flow

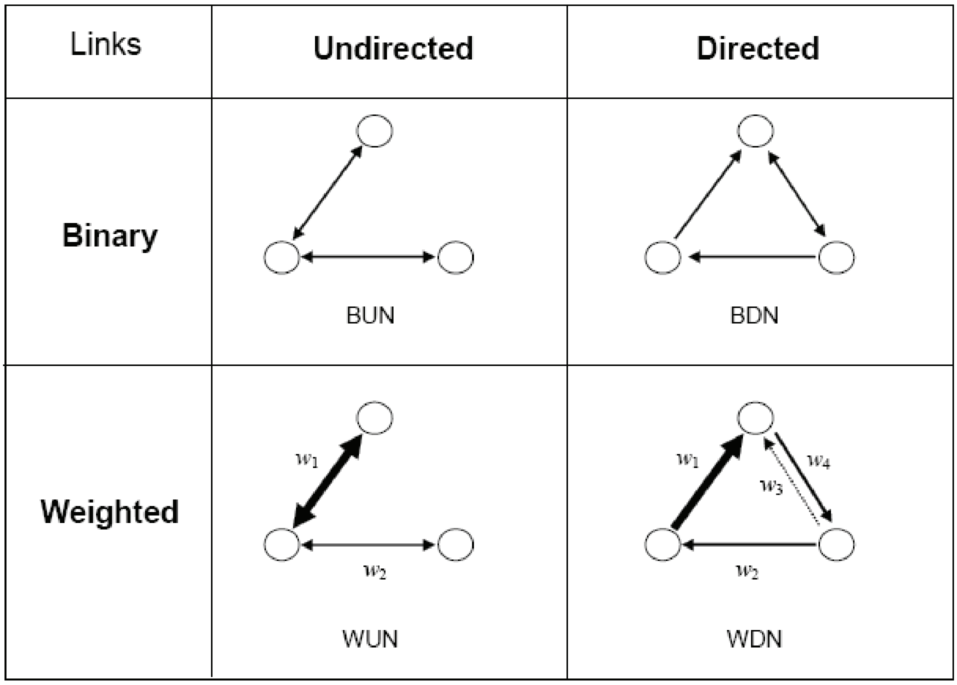
The second issue concerns the values of links within a research network and the use of binary vs. weighted networks to measure the existence and amount of knowledge exchanged (a/o transferred) within a network. This is part of a more general problem arising in SNA (Social Network Analysis) which has been recently addressed by the literature (Fagiolo *et al.,* 2007; Fagiolo, 2010; Opshal et al. 2009 and 2010; Barigozzi et al., 2010)

In figure 2 (derived from Fagiolo et al., 2007) we represent a taxonomy of links typology: a link value could be binary (B), reflecting the presence or absence of a relation, or weighted (W), if the link presents a value greater than 0; with respect to its direction, the link could be undirected (U) if there exist a symmetry of relation, or directed (D), if the direction of the relation is relevant.

These 4 typologies of network structures (N) could be ranked in ascending order of analytical difficulty of treatments as follows: BUN; BDN, WUN and WDN. While most of the relevant economic applications of SNA should be treated as WDN, most of the analyses performed by researchers are based on BUN, through dichotomisation and symmetrisation procedures which are far from being neutral.

[8] Since these wheel-like structure seems most unlikely to be the structure of knowledge flows within a research network, in section 4 they will be excluded from the hypotheses being tested.

Figure 2: A taxonomy of networks based on weights and direction of links



Source: Fagiolo et al. 2009

Looking for reasonable hypotheses on how we could use the membership data contained in the 5FP-CORDIS database in order to represent actual knowledge flows, we formulate the following 5 alternatives:

- We could count as 1 each and every link described by the chosen network structure irrespective to the number of nodes in the networks. In this way we assume that the amount of knowledge exchanged a/o transferred within a larger network to be higher than that in a smaller network and, indirectly that there are no "budget constrains" on the relational capacity of a node. We indicate such modality as **1**.
- We could count as $1/N$ (where N is the total number of node of a given network) each and every link described by the chosen network structure so to take into the account the limited relational capacity of a node within a network. We indicate such modality as **N**.
- We could go further on such consideration and count as $1/L$ (where L is the number of links of a given network) each and every link described by the chosen network structure so to take into account the limited relational capacity of a network which may depend non linearly on the number of nodes. We indicate such modality as **L**.
- Alternatively we could count as F/N (where F is the amount of funds received from the EU and N is the total number of node of a given network) each and every link described by the chosen network structure so to take into account both the different financial "size" of different networks and the limited relational capacity of a node within a network. We indicate such modality as **SF**[9].
- Finally we could modify the previous modality by allowing the sharing of funds to be a-symmetrical in order to consider that the coordinators take a larger slice of the cake (in our

[9] Which stands for symmetric funding.

simple simulation each participant count as 1 in the funds division, while the coordinator count as 2). We indicate such modality as **AF**[10].

Therefore in a 5 nodes network as that represented in figure 1, each link counts respectively as: 1 (if we choose alternative **1**); 1/5 (if we choose alternative **N**); 1/10 or 1/4 (if we choose alternative **L**[11]; F/5 (if we choose alternative **SF**); 2/7 of total funding to the coordinator and 1/7 of total funding to each participating if we choose alternative **AF**).

3.3. From institutional to regional networks of knowledge flow

All the issues discussed in sections 3.1 and 3.2 allowed us to build 20 different layouts (4 structures * 5 links weights) for every research network funded by the EU and recorded in the 5FP CORDIS database. However, since the paper focuses on the regional innovative performance we had to transform all these research networks established among research institutions (and, less frequently, firms) into region-based networks.

This has been done, following Maggioni et al. (2007), through a 3 steps procedure:

- Firstly, we geo-localised (according to NUTS2 classification) each single actor involved in the selected network contracts, distinguishing between coordinators and participants within each contract;
- secondly, we re-coded the data of each contract on a regional basis[12] ;
- thirdly we summed up, for each region, all contracts involving institutions located there.

The final results[13] are, per each network specification (i.e. couplet of network structure and link weights), an asymmetric[14] squared matrix $\mathbf{Z^m}$ (171 * 171) which in a generic cell Z^m_{ij} contains a measure of the scientific relationship established between region *i* and region *j*.

For each of these 19[15] $\mathbf{Z^m}$ matrices, which measures in a different way the scientific relationship existing between regions, we can therefore apply an econometric procedure[16] (described in details in section 4) whose aim is to identify which of the specifications shows a significant relational autocorrelation.

Thus, we are indirectly testing the following hypotheses:

Hyp. 1: Not every network structure, theoretically consistent with the contract membership, is actually conductive of knowledge flows, as measured by relational autocorrelation between regional patents intensity.

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[10] Which stands for a-symmetric funding since the coordinator gets a share of **2F/(N+2)** and each participant gets a share of **F/(N+2)**,

[11] 1/10 for a complete directed network; 1/4 for a star shaped undirected one.

[12] In most of the contracts financed within the 5FP there is only one institution per region, but this is not always the case.

[13] This procedure has been developed with an ad-hoc software application developed by M. Ruberl within the framework of agreement existing between Eggsyst and CSCC.

[14] Since some of the network structures involve directed links.

[15] There are 19 network specifications instead of 20 (and therefore 19 $\mathbf{Z^m}$ weights matrices), since asymmetrical funding is not logically consistent with a "B" network structure. In other words, matrix B_{AF} does not exist.

[16] These matrices will be used as weight matrices in the econometric exercise to define the relational proximity/distance, together with the geographical matrix defined using the rook contiguity among regions.

Hyp. 2: The actual amount of knowledge flowing through each link within a network is inversely dependent on the network size.

Hyp. 3: Intentional knowledge barter exchange (i.e. relational autocorrelation) implies a hierarchic non-symmetrical network structure (as in structure C and D in figure 1).

Hyp. 3.1: If 3 is verified, then the direction of knowledge flows is more likely to be inward oriented, from participants to the coordinator (as in network C) than to be outward oriented, from the coordinator to participants (as in network D).

Therefore, if data shows the existence of relational autocorrelation, 3 possible results may be obtained with such a procedure:

- if there is positive and significant relational autocorrelation (and coefficient are almost equal) for all network specification, then the entire exercise of the paper is useless;
- if there is positive and significant relational autocorrelation (and coefficient are different) for every network specification, then case studies or field experiments are needed in order to understand why and when a given layout produces certain results;
- if there is positive and significant relational autocorrelation only for a restricted set of network specification, then we may assume that we have identified a possible way knowledge may flow within the research networks (at least at the aggregate regional level).

4. The model and the estimation strategy

The empirical analysis consists in testing a traditional knowledge production function which describes the innovative output of a region as a function of the traditional innovative inputs (Private and public R&D), and some other variables describing the innovative and productive structure of the region:

$$PAT^{t} = f\left(BizRD^{t-\tau}, GovRD^{t-\tau}, INN^{t-\tau}, PROD^{t-\tau}, ACCESS^{t-\tau}, COORD^{t-\tau}, BETW^{t-\tau}\right) \qquad (1)$$

where the dependent variable (*PAT*) is the number of patent applications per million labour force. We take the yearly average value of patent applications to the European Patent OFFICE (for the period 2005 and 2006) registered by inventors located in our 171 European regions (Eurostat, 2010a).

Since we are interested in analyzing the creation of potential "marketable" knowledge leading to an active patenting activity, we selected business R&D expenditure (*BizRD*) and government R&D expenditure (*GovRD*) expressed as percentage of the regional GDP (Eurostat, 2010a)[17].

The variables *INN* and *PROD* are the location quotients calculated for high-tech patents and for local units in high-tech sectors defined as in Maggioni et al. (2007). The former is used to verify the specialisation of the innovation system, the latter is used to test the specialisation of the production system. Both indexes are calculated considering the average of values 1999-2004 (Eurostat, 2010a, 2010b).

[17] For the independents variables we computed a yearly average over a 5 year period to cope with missing values.

ACCESS is the multimodal index of accessibility, a relative measure, based on the European average, of the easiness/difficulty of accessing with different means of transport (roads, railway, vessels and aircraft) a certain region from every other site in Europe (Espon, 2010).

COORD measures the number of contracts coordinated regional institutions and indicates the relative centrality of a certain region within the European research networks funded under the 5FP (European Commission CORDIS, 2005).

BETW is the betweenness centrality of each region *i* and defines the centrality of a region as the degree to which it falls in the shortest path connecting all other regions in the network. In this framework it can be considered as a proxy of the power of each region to control for the diffusion of scientific and technical knowledge across Europe.

Since the innovative activity, as several other economic phenomena, is characterised by agglomeration, a simple OLS estimations could be biased. Hence the estimation procedure should take into consideration this and applying appropriate spatial econometric techniques.

The first empirical investigation is devoted to the testing of hypothesis 1, i.e. the test of the existence of spatial autocorrelation of the dependent variable *PAT*, both in a geographical and a relational way. Traditionally the empirical index to test it is the Moran's I calculated on the phenomenon under investigation, i.e. patents.

The values of Moran's I indexes, calculated for all weight matrices, are positive and significant (see Table 1) indicating the presence of "spatial autocorrelation". In other term neighbouring regions (both defined in a geographical or in a relational way) show similar values of innovative activity.

Table 1: Moran's I calculated on the dependent variable: patent (2005-06)

Weights \ Structures	GEO	A	B	C	D
GEO	0.170 (0.002)				
1		0.059 (0.000)	0.063 (0.000)	0.070 (0.000)	0.058 (0.000)
N		0.084 (0.014)	0.069 (0.000)	0.074 (0.000)	0.057 (0.002)
L		0.061 (0.001)	0.069 (0.000)	0.076 (0.001)	0.056 (0.005)
SF		0.043 (0.010)	0.054 (0.000)	0.074 (0.000)	0.041 (0.039)
AF		0.043 (0.009)		0.074 (0.000)	0.041 (0.036)

Values in parenthesis indicates probability

The results in table 1 show the existence of both geographical and spatial autocorrelation in the patent intensity at the regional level confirming the first hypothesis. Apparently it seems that there is no difference in the relevance of network structure and weights, as supposed in hypothesis 2, but to detect this we will run an appropriate estimation. However this autocorrelation must be detected through the appropriate econometric procedures based on a double-log specification of the explicit form of equation 1.

Once the existence of the spatial and relational autocorrelation has been verified, we correct it by introducing two operators, i.e. the spatial lag defined on the dependent variable, and the spatial error defined on the error term, both tested with ML procedures (Florax et al., 2003).

The values of Lagrange Mutiplier and Robust LM computed on errors and on lags showed that for some weights matrices (A, D, B_1 and B_{SF}) the model strategy should stop at the OLS estimations, since the errors were not affected by any bias and the estimations were BLUE (see table 1).

These estimations refine hypothesis 1, suggesting that the structure of research network is relevant in order to enable knowledge flows.

Table 2: Moran's I calculated on the residuals from a regression (as in model 2)

Weight Matrix	Moran's I/DF	Probability	Model specification
GEO	0.1009	0.051	LAG
B_1	-0.0001	0.233	No autocorrelation
B_N	0.0088	0.049	LAG
B_L	0.0225	0.091	ERROR
B_{SF}	-0.0037	0.678	No autocorrelation
C_1	0.0464	0.007	LAG
C_N	0.0512	0.007	LAG
C_L	0.0541	0.009	LAG
C_{SF}	0.0475	0.011	LAG
C_{AF}	0.0472	0.011	LAG
A_1	0.0110	0.220	No autocorrelation
D_1	0.0002	0.673	No autocorrelation

The results of this first empirical test enable to select the research contracts structures (i.e. weight matrices in spatial econometrics terms) that are more relevant in order to identify correctly how relations impact innovation activity. Hence according to these results, A and D network structures do not allow for any relational spillovers to be detected.

For the B_L weight matrices the procedure suggested to select a spatial autoregressive error model (SEM), while for all other relational matrices (B_N, C_1, C_N, C_L, C_{SF}, C_{AF}) and for the geographical matrix (GEO) the procedure suggested the specification that included the spatial autoregressive term, i.e. spatial autoregressive model (SAR) as follows:

$$\begin{aligned} PAT_{it} &= \rho_1 WPAT_{it} + \beta_0 + \beta_1 BizRD_i^{t-n} + \beta_2 GovRD_i^{t-n} + \beta_3 INN_i^{t-n} + \\ &+ \beta_4 PROD_i^{t-n} + \beta_5 ACCESS_i^{t-n} + \beta_6 COORD_i^{t-n} + \beta_6 BETW_i^{t-n} + v_i^{t-n} \end{aligned} \tag{2}$$

Table 3: Regression results: Testing for the existence of geographical or relational autocorrelation: OLS and ML estimations

		Geo Prox	Relational Proximity						
	OLS	*contiguity*	B_N	B_L	C_1	C_N	C_L	C_{SF}	C_{AF}
Variables									
CONSTANT	5.653***	4.726***	3.464**	5.796***	3.568***	3.428***	3.463***	3.691***	3.710***
BizRD	1.091***	0.966***	1.060***	1.084***	1.073***	1.068***	1.065***	1.073***	1.074***
GovRD	-0.102	-0.072	-0.096	-0.121*	-0.083	-0.089	-0.089	-0.073	-0.073
ACCESS	0.001	2.716E-04	0.001	0.001	0.001	0.001	0.001	0.001	0.001
PROD	1.038***	1.021***	1.023***	1.025***	1.039***	1.038***	1.039***	1.041***	1.041***
INN	0.066**	0.054*	0.054*	0.080**	0.061**	0.062**	0.063**	0.058**	0.058**
COORD	-0.055**	-0.055**	-0.052**	-0.056**	-0.188***	0.195***	-0.193***	-0.181***	-0.180***
ρ_1PAT		0.196**	0.408*		0.510***	0.540***	0.533***	0.479***	0.475***
λPAT				0.485**					
Obs.	171	171	171	171	171	171	171	171	171
LIK	-283.53	-280.31	-282.90	-282.54	-277.32	-276.17	-275.90	-278.07	-278.14
AIC	581.07	576.62	581.81	579.09	570.63	568.33	567.81	572.13	572.29

*Note: * significant at 10%. ** significant at 5%. *** significant at 1%*

Table 3 reports the results of the SEM and SAR specification of the regression. The results show that government R&D is never significant for innovative and patentable activity, probably because government R&D is mostly devoted to basic research that is not directly patentable. Business R&D and PROD are mostly responsible for patenting activity with coefficient values (that can be interpreted as elasticities) higher than 1.

Hence hypothesis 3 seems to be partially confirmed since a star like structure (i.e. C structure) is relevant, while D is excluded, but full structure, like B, is still at work. The hypothesis 3.1 is certainly confirmed.

Interestingly COORD values are negative and significant showing that being the coordinator of a European research contract does not pay in terms of being more innovative. Probably this could be related to the extremely high organisation costs that affect a coordinator in such contracts.

The "spatial" lag operator on patents is positive and significant and shows the relevance of geographical and relational spillovers in determining the innovative activity of a region.

The procedure described in table 3 is taking into account and correcting either the relational or the geographical autocorrelation. However, as already explained in the introduction, if the innovative performance of a region is also influenced both by its geographical and relational neighbouring regions, then any estimation based on a model specifying only one out of the two possible definitions of contiguity (relational or geographical) would result in a biased estimation, due to omitted variables specification. Therefore we build a model that include, in the same specification, both geographically lagged and relationally lagged variables. In particular we computed an artificial lagged dependent variable on the base of the contiguity matrix (WGEOPAT) and another one based on the relational weight matrices (WRELPAT^{m}[18]). Hence we performed the spatial econometrics procedure to select the correct model specification, i.e. SEM or SAR following Florax et al. (2003).

The models we tested are based on equation 1 with the inclusion of the artificially lagged variables combining alternatively the artificial geographical variable (WGEOPAT) with the relational lagged operator (defined by ρ_2), as follows:

$$PAT_{it} = \rho_2 WRELPAT_i^{t-n,m} + \beta_0 + \beta_1 BizRD_i^{t-n} + \beta_2 GovRD_i^{t-n} + \beta_3 INN_i^{t-n} \\ + \beta_4 PROD_i^{t-n} + \beta_5 PERIPH_i^{t-n} + \beta_6 COORD_i^{t-n} + \beta_7 BETWC_i^{t-n} + WGEOPAT_i + v_i^{t-n} \quad (3)$$

and the artificial relational variable (WRELPAT^{m}) with the geographical lagged operator (defined by ρ_3), as follows:

$$PAT_i^t = \rho_3 WGEOPAT_i + \beta_0 + \beta_1 BizRD_i^{t-\tau} + \beta_2 GovRD_i^{t-\tau} + \beta_3 INN_i^{t-\tau} \\ + \beta_4 PROD_i^{t-\tau} + \beta_5 PERIPH_i^{t-\tau} + \beta_6 COORD_i^{t-\tau} + \beta_7 BETWC_i^{t-\tau} + WRELPAT_i^{t-n,m} + \mu_i^{t-\tau} \quad (4)$$

The results on the presence of spatial autocorrelation on residuals are reported in table 4 which is applied to the only "surviving" network structures, B and C (but for the whole set of links weights).

According to this procedure now we are able to exclude the presence of relational autocorrelation in a symmetrical and non-hierarchical network structure (as structure B in figure 1). In fact the results suggest that the model strategy should be based on a OLS estimation since no autocorrelation is detected on the residuals (see the column relative to the Moran's I value on table 4). Hence these results seem to show that a research contract, whose structure is similar to a completely full network (like in a B structure in figure 1) without any hierarchy being at place, has no relational spillovers in the innovation activity, when the geography is taken into account simultaneously.

This confirms hypothesis 3, rejecting the possibility of a structure like B to be at work in the relational spillovers effects of research joint networks.

Table 4: Testing for the existence of geographic and relational autocorrelation. Moran's I calculated on the residuals from a regression (as in models 3 and 4)

Lagged variable	Coefficient	Probability	Weight matrix	Moran's I/DF	Probability	Model specification
WGEOPAT	0.246	0.008	B_1	-0.0046	0.656	OLS
WGEOPAT	0.246	0.008	B_N	0.0026	0.191	OLS
WGEOPAT	0.246	0.008	B_L	0.0162	0.167	OLS
WGEOPAT	0.246	0.008	B_{SF}	-0.0079	0.860	OLS
WGEOPAT	0.246	0.008	C_L	0.0391	0.017	LAG
WGEOPAT	0.246	0.008	C_N	0.0443	0.015	LAG
WGEOPAT	0.246	0.008	C_L	0.0477	0.017	LAG
WGEOPAT	0.246	0.008	C_{SF}	0.0391	0.028	LAG
WGEOPAT	0.246	0.008	C_{FA}	0.0388	0.029	LAG
WRELPAT B_1	0.499	0.344	GEO	0.094	0.065	OLS
W RELPAT B_N	0.401	0.362	GEO	0.096	0.059	OLS
W RELPAT B_L	0.258	0.326	GEO	0.099	0.053	OLS
W RELPAT B_{SF}	0.579	0.276	GEO	0.098	0.055	OLS
W RELPAT C_1	0.534	0.001	GEO	0.084	0.093	LAG
W RELPAT C_N	0.566	0.000	GEO	0.083	0.095	LAG
W RELPAT C_L	0.556	0.000	GEO	0.085	0.089	LAG

[18] We should remind that m stands for the each network structure and the relative weight.

W RELPAT C_{FS}	0.499	0.001	GEO	0.083	0.097	LAG
W RELPAT C_{FA}	0.495	0.001	GEO	0.083	0.096	LAG

Therefore the final model to be tested according to equations 3 and 4 takes into account, together with the geographical autocorrelation, the inward oriented hub and spoke network structure defined as structure C in figure 1.

Table 5: Testing for the existence of geographical and relational autocorrelation: ML estimations

Structures / Variables	C_1	C_N	C_L	C_{SF}	C_{AF}	GEO	GEO	GEO	GEO	GEO
CONSTANT	2.990***	2.867***	2.886***	3.073***	3.089***	3.055***	2.92***	2.951***	3.157***	3.175***
BizRD	2.990***	0.954***	0.951***	0.949***	0.949***	0.984***	0.982***	0.979***	0.980***	0.980***
GovRD	-0.057	-0.063	-0.063	-0.047	-0.048	-0.063	-0.069	-0.068	-0.052	-0.053
ACCESS	0.0009	0.0005	0.0005	0.0004	0.0004	0.0006	0.0006	0.0006	0.000	0.000
INN	1.022***	1.022***	1.022***	1.023***	1.023***	1.026***	1.026***	1.026***	1.028***	1.028***
PROD	0.048*	0.049*	0.050*	0.045	0.045	0.051*	0.052*	0.053*	0.048*	0.048*
COORD	-0.172***	-0.181***	-0.179***	-0.164***	-0.163***	-0.181***	-0.190***	-0.186***	-0.172**	-0.170**
BETWC	0.005	0.005	0.004	0.004	0.004	0.003	0.003	0.002	0.001	0.001
WGEOPAT	0.191**	0.183**	0.183**	0.199**	0.199**					
$WRELPAT_{C_1}$						0.471***				
$WRELPAT_{C_N}$							0.507***			
$WRELPAT_{C_L}$								0.500***		
$WRELPAT_{C_{SF}}$									0.438***	
$WRELPAT_{C_{AF}}$										0.433***
ρ2 WRELPAT	0.4313***	0.467***	0.463***	0.400***	0.3965***					
ρ3 WGEOPAT						0.142**	0.136**	0.137**	0.148**	0.149**
Obs	171	171	171	171	171	171	171	171	171	171
R^2	0.851	0.853	0.8540	0.8511	0.8509	0.8510	0.8529	0.8533	0.8498	0.8497
Log-Likelihood	-275.023	-274.021	-273.743	-275.571	-275.639	-275.394	-274.312	-274.042	-276.021	-276.096
Akaike info criterion	570.045	568.042	567.486	571.142	571.278	570.787	568.624	568.084	572.042	572.193

*Notes: * significant at 10%. ** significant at 5%. *** significant at 1%*

Table 5 shows the usual values of coefficient for both private and public R&D and for the innovative and productive specialisation of the region. The hypothesis 3.1 is certainly tested.

The results of the econometric specification, which uses together the "spatial" lag operator and the artificially lagged dependent variable, are robust as shown by the similarity of the geographical coefficient (whose values are always around 0.2) and the relational coefficients (whose values are always above 0.4) computed in both ways.

The value of COORD is again negative and significant, thus confirming that a region whose institutions are often coordinating a high number of research contracts does not enhance its innovative activity[19]. Coordinating the "right" networks is definitively a better strategy to increase the innovative output.

Different link values make the difference for symmetrical and non-hierarchical network structures (as in table 3). Here for a non symmetrical and hierarchical network structure (as structure C in figure 1) there is not a great difference between the number of nodes and the number of links. Thus coefficients for different links weights are almost identical.

Finally geography is less relevant than relations in determining the innovative activity of a region, thus suggesting that the intentional exchange of knowledge within these European research networks are more relevant than the simple unintended and mechanistic spillover phenomenon.

5. Conclusion

Regional innovation activity is a complex phenomenon with several forces at play. A production function which relates regional innovative inputs to regional output must take into account the effect of both geographical and relational proximity.

In this paper, following Maggioni et al. (2007) we modelled geographical proximity as a measure of unintended knowledge spillovers; and relational proximity as a measure of inter-regional intentional knowledge exchange between research institutions and we overcome two main limitations of the previous analysis. Firstly we considered, in the same spatial econometric specification, both the effect of geographical and relational autocorrelation. Secondly we designed a research methodology in order to identify the actual structure of knowledge flows within the joint research networks financed by the 5FP.

In this way we were able to show that relational exchange prevails over geographical spillovers as determinants of regional innovative output and to model the unobservable structure and link value of actual knowledge flows within joint research networks.

Our research methodology showed that knowledge flows within inter-regional research networks along a non symmetrical hierarchical structure in which knowledge produced by network participants is exploited by the coordinator.

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[19] This result may be more easily interpreted by referring to the fact that, in our database we list all research network in any scientific fields. The number of coordinated network may be inversely related to the patenting opportunity of the different scientific and technological fields.

While on the one hand these results suggest that knowledge intentional exchanges mainly follows hierarchical network structures, probably for efficiency reasons; on the other they may hint that Framework programmes may be good policy instruments to sustain the knowledge economy but not to foster regional cohesion if most coordinators are located in core regions.

Finally, according to our results, coordinating a lot of joint research networks has not a positive effect on the regional innovative activity. Being connected with other advanced regions is a definitely more effective way to increase the innovation output of a region..

Further research can complement and re-enforce these results along different lines.

It would be interesting to develop a theoretical model of the emergence and stability of research networks by encompassing Jackson and Wolinsky (1996), with Cowan and Jonard (2004) in order to take into account more realistic hypotheses on the nature of knowledge and on the informational asymmetries.

One could also use behavioural experiments (as in Callander and Plott, 2005 and Goeree et al. 2009) to see how “real” people behave when they have to establish relations in order to solve complex problems requiring collaboration.

Finally, some field experiments and primary data collections on the behaviour of single researchers involved in a large scale joint research network could shed some lights on the mechanics and dynamics of knowledge flows.

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Appendix

Table A1: List of regions

Region	**NUTScode**
Burgenland (A)	AT11
Niederösterreich	AT12
Wien	AT13
Kärnten	AT21
Steiermark	AT22
Oberösterreich	AT31
Salzburg	AT32
Tirol	AT33
Vorarlberg	AT34
Région De Bruxelles-Capitale / Brussels Hoofdstedelijk Gewest	BE1
Vlaams Gewest	BE2
Région Wallonne	BE3
Stuttgart	DE11
Karlsruhe	DE12
Freiburg	DE13
Tübingen	DE14
Oberbayern	DE21
Niederbayern	DE22
Oberpfalz	DE23
Oberfranken	DE24
Mittelfranken	DE25
Unterfranken	DE26
Schwaben	DE27
Berlin	DE30
Brandenburg - Nordost	DE41
Brandenburg - Südwest	DE42
Bremen	DE50
Hamburg	DE60
Darmstadt	DE71
Gießen	DE72
Kassel	DE73
Mecklenburg-Vorpommern	DE80
Braunschweig	DE91
Hannover	DE92
Lüneburg	DE93
Weser-Ems	DE94
Düsseldorf	DEA1
Köln	DEA2
Münster	DEA3
Detmold	DEA4
Arnsberg	DEA5
Koblenz	DEB1
Trier	DEB2
Rheinhessen-Pfalz	DEB3
Saarland	DEC0
Chemnitz	DED1
Dresden	DED2
Leipzig	DED3

Sachsen-Anhalt	DEE0
Schleswig-Holstein	DEF0
Thüringen	DEG0
Danmark	DK
Galicia	ES11
Principado De Asturias	ES12
Cantabria	ES13
País Vasco	ES21
Comunidad Foral De Navarra	ES22
La Rioja	ES23
Aragón	ES24
Comunidad De Madrid	ES30
Castilla Y León	ES41
Castilla-La Mancha	ES42
Extremadura	ES43
Cataluña	ES51
Comunidad Valenciana	ES52
Illes Balears	ES53
Andalucía	ES61
Región De Murcia	ES62
Itä-Suomi	FI13
Etelä-Suomi	FI18
Länsi-Suomi	FI19
Pohjois-Suomi	FI1A
Åland	FI20
Île De France	FR10
Champagne-Ardenne	FR21
Picardie	FR22
Haute-Normandie	FR23
Centre	FR24
Basse-Normandie	FR25
Bourgogne	FR26
Nord - Pas-De-Calais	FR30
Lorraine	FR41
Alsace	FR42
Franche-Comté	FR43
Pays De La Loire	FR51
Bretagne	FR52
Poitou-Charentes	FR53
Aquitaine	FR61
Midi-Pyrénées	FR62
Limousin	FR63
Rhône-Alpes	FR71
Auvergne	FR72
Languedoc-Roussillon	FR81
Provence-Alpes-Côte D'azur	FR82
Corse	FR83
Anatoliki Makedonia, Thraki	GR11
Kentriki Makedonia	GR12
Dytiki Makedonia	GR13
Thessalia	GR14
Ipeiros	GR21
Ionia Nisia	GR22

Dytiki Ellada	GR23
Sterea Ellada	GR24
Peloponnisos	GR25
Attiki	GR30
Voreio Aigaio	GR41
Notio Aigaio	GR42
Kriti	GR43
Border, Midland And Western	IE01
Southern And Eastern	IE02
Piemonte	ITC1
Valle D'aosta/Vallée D'aoste	ITC2
Liguria	ITC3
Lombardia	ITC4
Provincia Autonoma Bolzano/Bozen	ITD1
Provincia Autonoma Trento	ITD2
Veneto	ITD3
Friuli-Venezia Giulia	ITD4
Emilia-Romagna	ITD5
Toscana	ITE1
Umbria	ITE2
Marche	ITE3
Lazio	ITE4
Abruzzo	ITF1
Molise	ITF2
Campania	ITF3
Puglia	ITF4
Basilicata	ITF5
Calabria	ITF6
Sicilia	ITG1
Sardegna	ITG2
Luxembourg (Grand-Duché)	LU
Groningen	NL11
Friesland (NL)	NL12
Drenthe	NL13
Overijssel	NL21
Gelderland	NL22
Flevoland	NL23
Utrecht	NL31
Noord-Holland	NL32
Zuid-Holland	NL33
Zeeland	NL34
Noord-Brabant	NL41
Limburg (NL)	NL42
Norte	PT11
Algarve	PT15
Centro (P)	PT16
Lisboa	PT17
Alentejo	PT18
Região Autónoma Dos Açores	PT20
Região Autónoma Da Madeira	PT30
Stockholm	SE11
Östra Mellansverige	SE12
Småland Med Öarna	SE21

Sydsverige	SE22
Västsverige	SE23
Norra Mellansverige	SE31
Mellersta Norrland	SE32
Övre Norrland	SE33
North East (England)	UKC
North West (England)	UKD
Yorkshire And The Humber	UKE
East Midlands (England)	UKF
West Midlands (England)	UKG
East Of England	UKH
London	UKI
South East (England)	UKJ
South West (England)	UKK
Wales	UKL
Scotland	UKM
Northern Ireland	UKN