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Does intentional mean hierarchical? Peering inside the black box of joint research networks

Mario A. Maggioni[1], Teodora E. Uberti[1], and Mario Nosvelli[1*]

[1] *DISEIS and CSCC, Universitá Cattolica del Sacro Cuore, Milano*
[*] *CERIS-CNR (Institute for Economic Research on Firms and Growth)*

CSCC
Centro di ricerca in Scienze Cognitive e della Comunicazione
Università Cattolica del Sacro Cuore
Via Necchi, 5 - 20123 - Milano ITALY

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

Abstract: The production of scientific and technical knowledge is mostly concentrated in specific locations (high-tech clusters, innovative industrial agglomerations, excellence centres, technologically advanced regions). Knowledge flows very easily within regions; however, scientific and technical knowledge does flow also between different regions. 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 patent application intensity – of regions. To achieve this aim, we estimate a regional knowledge production function and we test, 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 through the Fifth Framework Programme"). Furthermore we model the unobservable structure and link-value of actual knowledge flows within these joint research networks. Our research methodology shows that knowledge flows within inter-regional research networks along a non-symmetrical and hierarchical structure in which knowledge produced by network participants tend to be exploited by the coordinator.

Keywords: *Innovation, patents, networks, spatial econometrics, spillovers, knowledge flows*

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1. Introduction

Scientific and technical knowledge is mostly generated by specialized 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 geographical areas that can be named in different ways such as: 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 areas (and neighbouring ones) 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 spillovers. However, scientific and technical knowledge does flow also across different areas and some breakthrough technologies were indeed developed thanks to the joint efforts of scientists and technicians working in different geographical locations.

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 *et al*. 1993; Audretsch and Feldman 1996; Maurseth and Verspagen, 2002; Cowan and Jonard 2003; Paci and Usai 2000 and 2009; Breschi and Lissoni 2004 and 2009; Maggioni *et al*. 2007; Maggioni and Uberti 2007, 2009, 2011; Hoekman et al. 2009; Picci 2010; Cassi and Plunket, 2012; Maggioni *et al.* 2013); the second dealing with the use of spatial econometric techniques in order to take into account the existence of directly un-measurable (or unmeasured) spillovers effects (Audretsch and Feldman 1996; Acs *et al*. 2002; Fischer and Varga 2003; Bottazzi and Peri 2003; Greunz 2003; Bode 2004; Moreno *et al*. 2005, LeSage and Pace 2009; Autant-Bernard and LeSage 2010; Usai 2011; Varga *et al*. 2010).

In doing so we build on Maggioni *et al*. (2007) where we assumed that knowledge can be diffused and exchanged either through unintentional diffusive patterns based on spatial contiguity (Acs *et al*. 2002), or according to intentional relations based on a-spatial networks (Cowan and Jonard 2004).

According to the first pattern, the geographical selection process leading to a hierarchical structure of the location where innovative activities take place together with an increasing role of 'unintended' spatial knowledge spillovers that, from excellence centres, extend their positive effects to other agents (i.e. firms, universities, research centres) located in neighbouring areas. Hence relevant regions present both an 'attraction potential' and a 'diffusive capacity' (Hägerstrand, 1965 and 1967; Acs *et al*. 2002). Each innovative region extends its influence over neighbouring territories through a trickling down process of spatial diffusion (underlining the role of different forms of localised knowledge spillovers). In this view, space matters most and knowledge flows following almost pure 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). Technological and scientific knowledge, developed within the region, is in this case 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. Thus, in this second case, relational networks matter most and knowledge spreads following intentional patterns, which may have little correlation with geographical contiguity.

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

In a previous paper (Maggioni *et al.* 2007) – aimed at testing whether formal relationships based on a-spatial networks between geographically distant regions prevail over diffusive patterns based on spatial contiguity – spatial econometric techniques were adopted in order to measure the effects of different "spatial" weight matrices which referred to both geographical and relational "proximity". That analysis suffers from two main limitations: the first relates to the possibly inaccurate identification of inter-regional scientific relationships through the use of joint research networks financed under the European Union Fifth Framework Programme (henceforth 5FP) data; the second refers to possible misspecifications of the econometric model implied by the alternate use of "geographical" and "relational" weight matrices.

As far as the first limitation is concerned, the 5FP data record only the membership in a research network and (in most cases) the amount of funds and not the effective trails followed by knowledge flowing within the network.

As far as the second limitation is concerned, 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 econometric estimates.

In this paper, in addition to a larger sample of countries and regions[2], we take a novel route aimed at overcoming the above limitations firstly by taking into account both the geographical and the relational proximity effects in the same econometric specification, secondly by devising a series of tests aimed to identify the effective organisational structure of knowledge flows, connecting European regions, activated and financed through the 5FP.

The paper is organised as follows: in section 2 we discuss a number of empirical issues related to the use of geographical and relational weight matrices when performing spatial econometric analysis on patent data; in section 3 we present the research questions, in sections 4 and 5 we describe the estimated models and present the results. A final section 6 concludes the paper.

2. Some empirical issues related to the geography of innovation networks

In a standard empirical paper belonging to the "geography of innovation" stream of literature, this section, is customarily devoted to the presentation of the econometric model (based on different augmented versions of the knowledge production function) used to investigate the determinants of knowledge creation and diffusion within and across regions.

However, before performing the econometric analysis in order to investigate how scientific and technological networks is produced and, especially, diffused across European regions. we need to devise a method for peering inside the black box of joint research networks.

We are convinced that the regional level is a good choice for the empirical observation of innovative process since it allows the consideration of inter-agent spillovers which are missed when the analysis is performed at the individual agent (or institution level).

Regional innovative performance, as proxied by patents intensity, is determined by region-specific innovative inputs combined according to a knowledge production function and

[2] The initial sample of NUTS2 regions belonging to France, Germany, Italy, UK, and Spain considered in Maggioni *et al.* (2007), has been extended to the member of the EU-12, by adding NUTS2 regions belonging to Austria, Belgium, Greece, Luxembourg, the Netherland, Portugal and Sweden. For a full list of regions included in this paper see table A1 in Appendix.

influenced by the innovative performance of "neighbouring' regions" (where the definition of neighbourhood is both geographical and relational).

While the econometric analysis of spatial autocorrelation phenomena is well diffused in the innovation literature (as shown in the introduction) and the use of alternative measures of technological, institutional, social and organizational neighbourhood has also been deeply discussed (Torre and Gilly, 2000; Boschma, 2005; Cantner and Meder, 2007; Boschma and Frenken, 2009; Ponds *et al.*, 2007 and 2010; Marrocu *et al.*, 2013a), the innovative contribution of this paper consists in identifying an estimation method in which networks are not instrumentally used to compute alternative measure of proximity, but are considered as a research object *per se*. As thoroughly discussed in the section below, the variables of interest become the following: networks structure, reflecting how a FP5 contract is internally organised; links' weights, individuating the amount of knowledge flowing; and links' directions, identifying who the recipient and the sender of knowledge.

2.1. From "space vs. networks" to "space and networks"

In Maggioni *et al.* (2007) two distinct spatial econometric exercises (the first based on a geographical weight matrix, W^g; the second based on a relational 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). Since comparing the size of coefficients of two regressions based on different weight matrices is questionable, the 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 residual proximity definition included only "pure relational" connections established between geographically non-contiguous regions" (ibid., p.488). 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 adequately tackle the estimation problem. If the innovative performance of a region (which may be partly explained by an internal knowledge production function) is influenced both by its geographical and relational neighbouring regions, then any estimation based on a model specifying one definition of contiguity at a time (either relational or geographical) would result in a biased estimation, due to omitted variables specification.

This is the reason why, following Lacombe (2004), in this paper we estimate a SAR model with two different weight matrices to robustly detect the existence of "spatial" autocorrelation arising from both geographical and relational behaviours and dynamics. In doing so, following Marrocu *et al*. 2014) we apply specific econometric techniques in order to test different non-nested model specifications.

The main hypothesis behind the present econometric exercise is that innovative performance of a region is primarily determined by a region-specific knowledge production function and, secondly, influenced both by geographically contiguous and by relationally proximate regions. Thus, any estimate which does not take into account these three factors is misspecifies the data generation process, leading to biased and inconsistent estimates.

2.2 From membership to knowledge flows

As mentioned above, data on joint research networks funded by the EU under the 5FP – publicly available through the CORDIS website[3] – record only names and locations of the joining

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

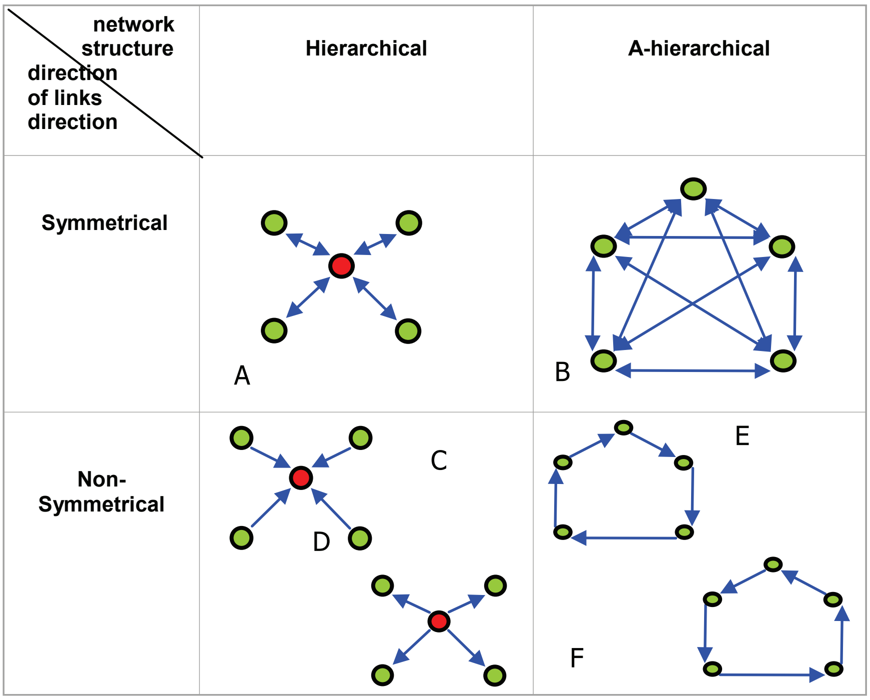
institutions, their status (either coordinators or participants) and, most of the times, the amount of granted funds.

The 5FP is a five years programme started in 1998 and concluded in 2002[4] with the official aim of integrating different research areas and developing a critical mass of European resources in Science and Technology. The total number of contracts financed within the 5FP is 16,085 with a total funding of about 12,000 million euros. Within this framework, we select only contracts with a network structure (mainly joint research projects) and base our analysis on 6,755 networks between institutions (42% of total 5FP contracts) with an average membership of 7 (1 coordinator plus 6 participants). The geographical scope of the analysis is limited to the 171 regions at NUTS2[5] part of EU 15 countries.

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

First, in order to define the structure of a research network, we use a simple taxonomy described in Maggioni and Uberti 2011, where two dimensions of knowledge flows (the direction of links and the structure of the network) and their combinations are considered (Figure 1).

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



Source: Maggioni and Uberti (2011)

In figure 1, for expositional purposes, we illustrate the case of a very small and simple research network composed by one coordinator and four participants. According to this taxonomy, knowledge may flow in 4 different ways within a network, hence 4 different relational structures may 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

[4] However, some research contracts were extended up to 2005.

[5] As in Table A1, few exceptions are Denmark and Luxemburg, for which data are available only at NUTS0 level, and Belgium and United Kingdom, for which data are available only at NUTS1 level.

coordinator and each participant (figure 1 panel A). 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 1 panel B). This structure reflects the absence of hierarchy within the network (indeed all indexes of centralization have values equal to zero) and the full potential of knowledge flowing among all actors. In addition no coordination and/or brokerage of knowledge and information is 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.

If knowledge flows involve an exclusive relation between the coordinator and each single participant, as in a star-like structure, but differently from figure 1 panel A, there is no mutual and balanced exchange of knowledge between them, two alternative structures can be considered: an inward structure (i.e. from participants to coordinator), as in figure 1 panel C; or an outward structure (i.e. from coordinator to participants), as in figure 1 panel D .

A final network structure can be characterised by no reciprocity of links and no hierarchy (figure 1 panels E and F): in this case every member exchanges knowledge locally and exclusively to his/her next neighbour (in clockwise or counter-clockwise direction), and a wheel-like structure of knowledge flows emerges, where all members are interchangeable and no most central node emerges. A wheel-like structure, by definition, achieves global transmission of knowledge only through multiple passages of local links. "Wheel" structures may provide micro-economic advantages, as shown by Jackson (2008); however, 5FP contracts are exactly meant to promote knowledge diffusion across all members. As wheel-like structures seem most unlikely to describe the effective knowledge flows within a 5FP research network and in section 4 these are excluded from the econometric analysis.

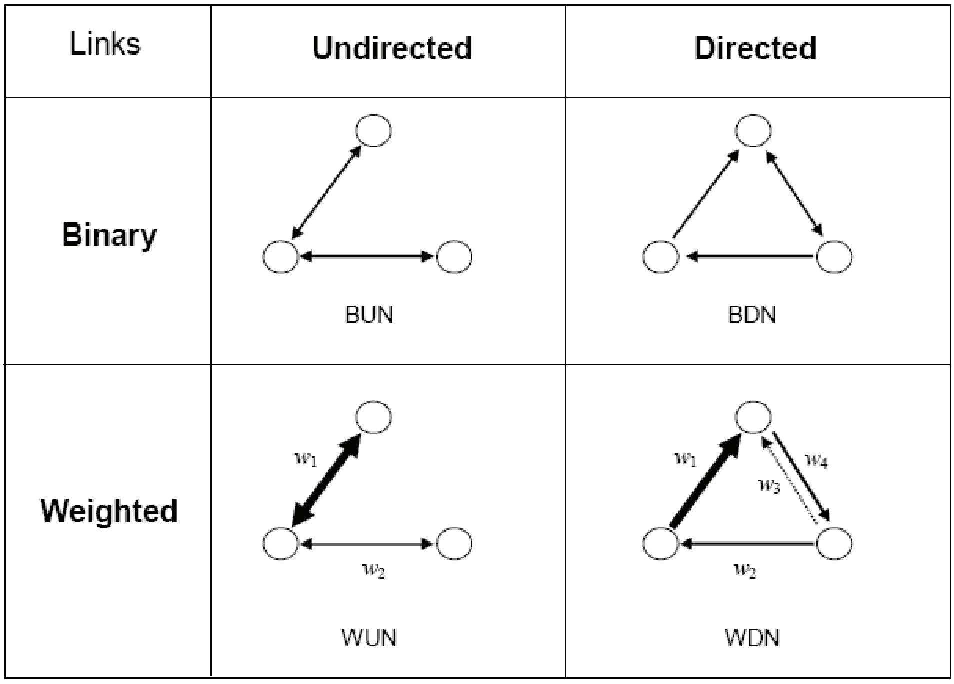
2.3. How to weight knowledge flows

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 (and/or transferred) within a network. This is part of a more general problem arising in Social Network Analysis (SNA) which has been recently addressed by the literature (Fagiolo *et al.,* 2007; Fagiolo, 2010; Opshal and Panzarasa 2009, Opshal *et al*. 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 different from 0; with respect to its direction, the link could be undirected (**U**) if there exists a symmetry of relation (as in figure 1 panels A and B), or directed (**D**), if the direction of the relation is relevant (as in figure 1 panels C and D).

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.

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



Source: Fagiolo et al. 2007

Looking for reasonable hypotheses on how we could use membership data contained in the CORDIS database in order to represent actual knowledge flows, we formulate the following 3 alternatives:

- We 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 the amount of knowledge exchanged and/or transferred within a larger network to be higher than in a smaller network and, indirectly that there are no "budget constraints" on the relational capacity of a node. We indicate such modality as **1**.
- We count as $1/N$ (where N is the total number of nodes in 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 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 non linearly depend on the number of nodes. We indicate such modality as **L**.

On the bases of the assumptions discussed above, it is possible to build 12 different knowledge flows layouts (4 structures, times 3 links weights) for each joint research network funded by the EU as in CORDIS database. However, since the paper focuses on the innovative performance at a regional level, we aggregate the joint research networks established among research institutions (and, less frequently, firms) and transform them into region-based networks.

This procedure follows a 3 steps procedure:

- firstly, we geo-localise (according to NUTS2 classification) each 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[6];
- thirdly, for each region we sum all contracts included in 5FP which involve institutions located there.

The final results[7], per each network layout (i.e. the combination of network structure and links weights), are squared matrices $\mathbf{Z}^{\mathbf{m}}$ (171 x 171) where a generic element Z^{m}_{ij} measures the extent of knowledge flows existing between region i and region j within a m generic network layout.

Since we want to take into account both the relational and the geographic dimension of knowledge flows, we use the above mentioned 12 $\mathbf{Z}^{\mathbf{m}}$ matrices, as relational weight matrices and the first order contiguity matrix as a geographic weight matrix, in the spatial econometric analysis of a regional knowledge production function performed in sections 4 and 5.

3. Research questions and hypotheses

The main hypothesis in the paper is that region *i*'s innovative output, as measured by patents, is explained by regional innovative inputs and structural characteristics, and by some "spatial" autocorrelation effects, which may arise from geographic knowledge spillovers and/or relational knowledge barter exchanges mediated by specific network layout and weight links and directions.

Through a series of spatial econometric exercises in sections 4 and 5 we test the existence and extent of this relational autocorrelation..

More generally the empirical analysis of this paper tests the following research questions (RQ):

RQ1: Is the inter-regional network structure obtained by the aggregation of individual joint research network contracts univocally determined by the theoretically imposed layout at the individual contract level?

The economic literature on European research networks financed under the EU Framework programs (Autant-Bernard *et al.*2007; Balland, 2012; Caloghirou *et al*. 2004; Breschi and Cusmano, 2004; Protogerou et al. 2010; Lata and Scherngell, 2010; Scherngell and Barber, 2009 and 2011), despite the high variance in databases, level of analysis and estimation methods, shows the existence of an oligopolistic structure in which a restricted number of institution localized in central and high-income regions plays a major role along a core-periphery pattern. Thus we may expect the interregional network structure to be also heavily influenced by the spatial distribution of members and coordinators in the different European regions. We tackle this research question in section 3.1.

RQ2: Do actual knowledge flows in 5FP joint research networks follow a hierarchical and a-symmetrical pattern?

The theoretical literature on network structure arising from the micro-based game-theoretical approach (recently surveyed in three books: Vega-Redondo, 2007; Jackson, 2008; Goyal, 2007) or from the heterogeneous agents, simulation and/or experimental approach *à la* Cowan and Jonard (2003 and 2004; Maggioni, 2004; Callander and Plott, 2005; Cassi and Zirulia, 2008;

[6] In most of the contracts financed within the 5FP there is only one institution per region, but this is not always the case. In such cases we recorded the presence of multiple institutions in the same region.

[7] 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.

Morone and Taylor, 2010; Goeree et al. 2009), as well as the copious literature on the effects of networks structure on the innovative performance of individual node (i.e. individual scientists, firms, regions), show evidence of advantages arising from different network structures. In particular while a small-world structure is signalled to be the most efficient layout for maximising the average content on a scientific network, it may well be unfit on the basis of equity reasons, thus being not preferred by voluntary aggregation of research institutions. Hub and spoke structure is surely an efficient layout and may be easily implemented when the balance of power between networks members are very unequal[8]. Since the high variance in this literature, in principle we do not have an *ex-ante* clear expectation of the prevailing structure. We address this research question in sections in section 5.

RQ3: Is there is a trade-off between the size of the scientific and technological network of a region and its effectiveness in influencing the innovative performance of the same region?

While it is self-evident that having a large network is an advantage in terms of the number of knowledge sources which can be accessed, there is theoretical evidence that the size of the network may be constrained by time and relations managed by networks members and the coordinator of the network itself and located in a hub position (Jackson and Wolinsky, 1996; Goyal and Joshi, 2003). If this intuition is right, then hierarchical network layout with decreasing return to the number of nodes (or, even better, links) should perform better in describing the effect of knowledge flows within regional joint research networks in innovative performance. We face this question in sections 5.

3.1 Network structures and flows directions

The whole procedure of passing from individual contract level to the regional level is crucially driven by two factors: the choice by the researcher of a particular layout for representing actual knowledge flows within a joint research network contract, and the actual spatial distribution of 5FP coordinators and participants across European regions as recorded in the Cordis database. Thus starting from a very hierarchical layout at the contract level, one may obtain a very egalitarian network structure at the regional level, if the distribution of coordinators is sufficiently equal across regions.

Table 1 and figures 3 and 4 formalise and extend the analysis by comparing the actual network structures of the entire 5FP at the regional level to ideal-typical representations of simulated networks with the same number of nodes for given layout (i.e. the actual network derived from the aggregation of contract along a C layout is compared to a star-shaped network of 171 nodes; while the actual network derived from the aggregation of contract along a B layout is compared to a complete network of 171 nodes).

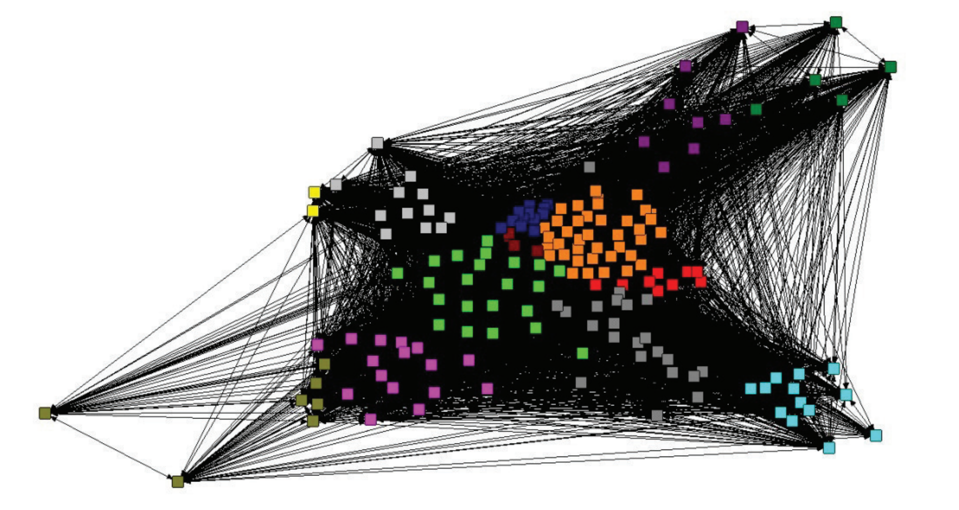
The similarity of the two networks (the actual and the simulated ones) is crucially dependent on the spatial distribution of institutions and organisation parts of joint research contracts financed by 5FP across the European regions. In particular, for the coincidence of the actual and the simulated networks, the C layout requires that coordinators of all contracts should be located only in one region; while B layout requires that every contract should involve one institution per each European regions therefore that contracts should be identically distributed across all regions.

Figure 3 shows, as examples, the resulting networks of knowledge flows between European regions embodied in the entire 5FP if a symmetrical and non-hierarchical layout (i.e. B_1) is assumed at the contract level and a non-symmetric and hierarchical inward oriented layout (i.e. C_1).

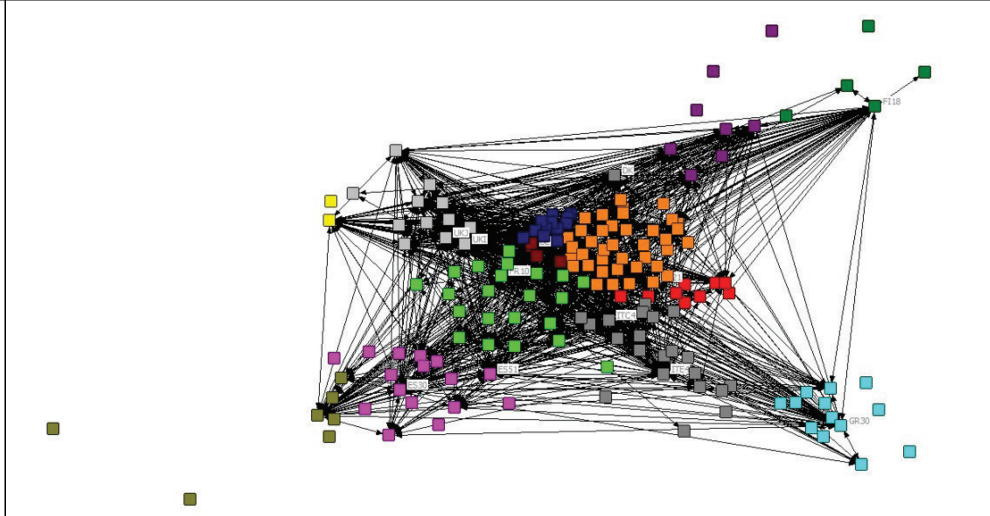
[8] Even if it may be subject to congestion when the arrival rate of new information exceed a given threshold (Arenas *et al.*, 2010).

Figure 3: 5FP research networks at the regional level (B_1 and C_1 layouts)

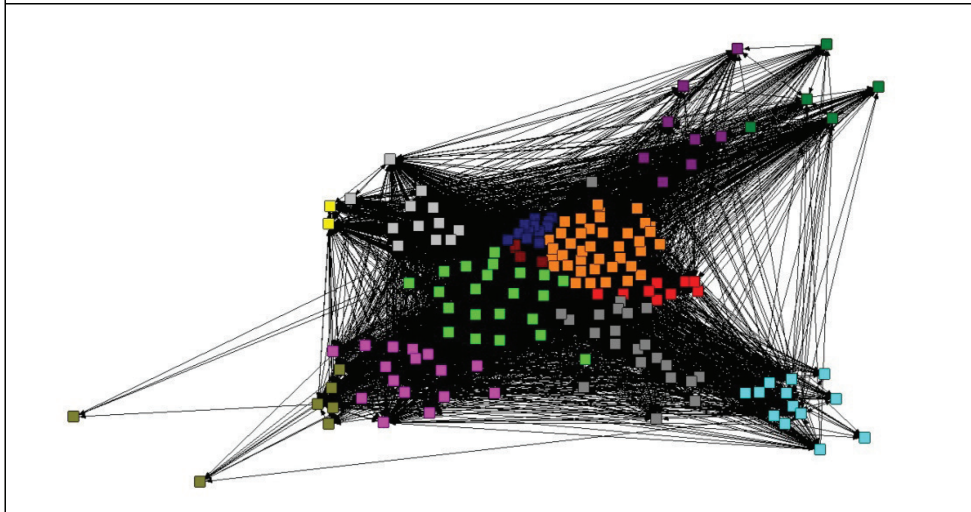
(B_1 layout threshold = 0)



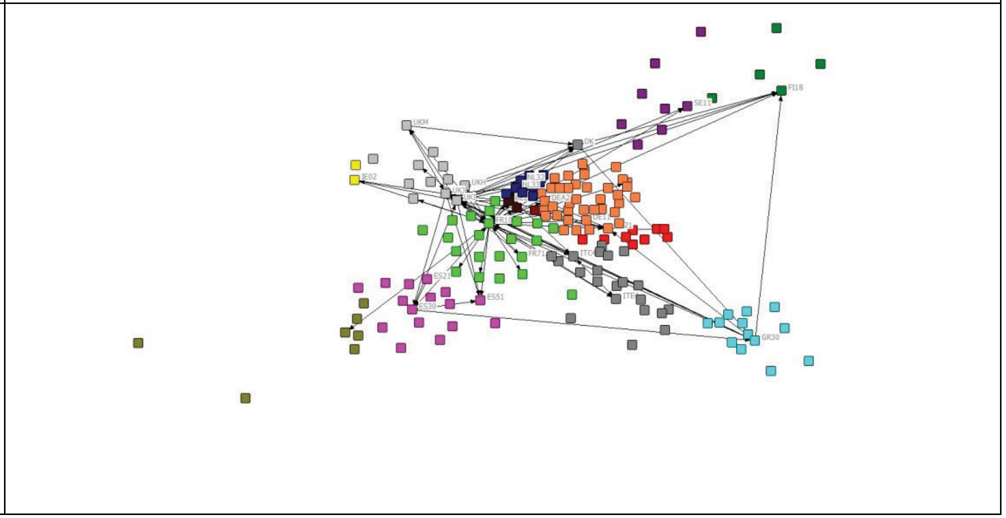
(B_1 threshold = 20)



(C_1 threshold = 0)



(C_1 threshold = 20)

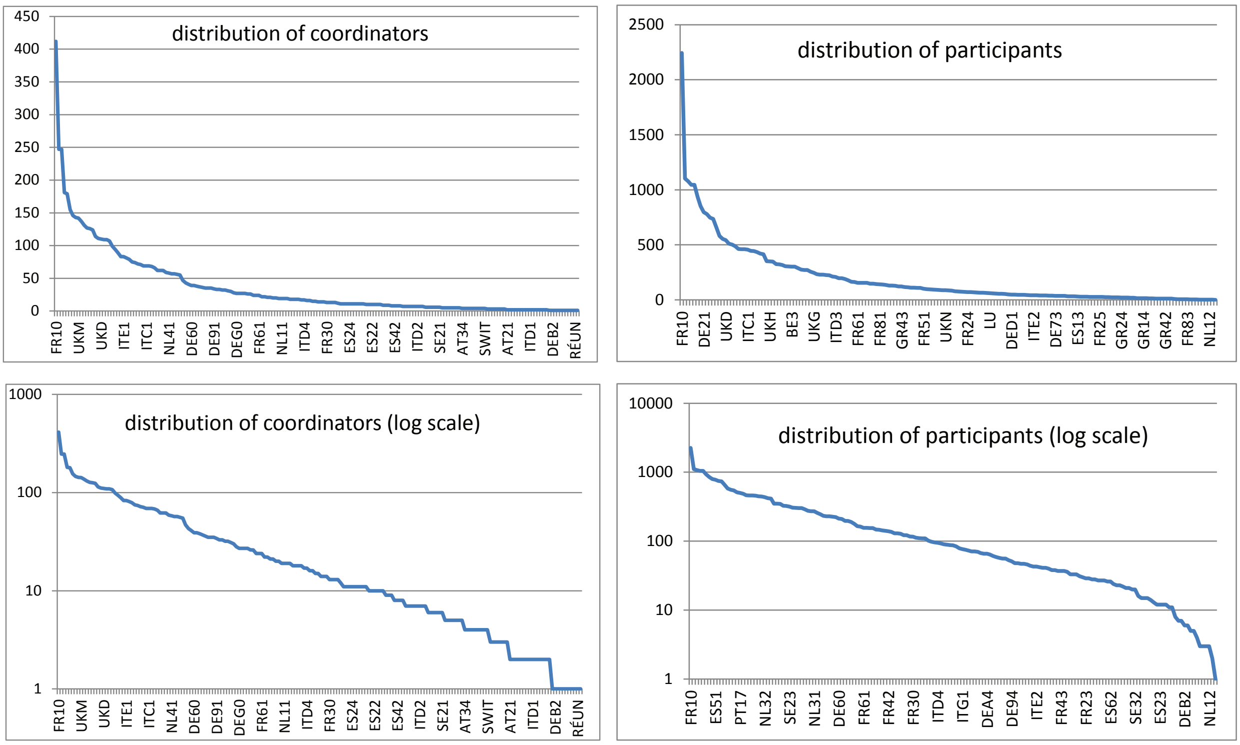


Panels on the left display a graphical representation of entire network when all links greater than 0 are shown while panel on the right show the same networks when higher (equal to 20) threshold values are chosen. The upper row of figure 3 shows that the choice of a symmetrical and a-hierarchical layout of knowledge flows at the individual contract level is reflected in a regional representation of the entire 5FP as a highly decentralised networks in which numerous regions in Europe play the same role in the continental network of knowledge flows.

The lower row of figure 3 shows that the choice of a hierarchical lay-out of knowledge flows at the individual contract level is reflected in a regional representation of the entire 5FP as a highly centralised networks in which few capital regions and some other central regions of individual countries play a major role as hubs of international knowledge flows.

Figure 4 describes the real spatial distribution of coordinators and participants across the 171 European regions as recorded in 5FP[9].

Figure 4:Distribution of 5FP research contracts at the regional level



In order to measure the similarity of actual regional networks based on different layouts with their respective ideal-types (i.e. star vs. complete networks), for each theoretical layout we simulate an ideal-type 171 nodes network and we compute some key network indexes – i.e. density, degree and betweenness centralization[10] – for both actual and simulated networks (see table 1).

[9] Table A1, in the Appendix, records the numbers of coordinators and participants per each region.
[10] Actual relational matrices are not binary, thus – for the sake of simplicity – we dichotomised each adjacency matrix according a threshold greater than 0 in order to evaluate the presence of knowledge flows among regions. This procedure therefore does not allow us to distinguish between different links weights within the same network topology.

Table 1: Simulated and actual networks statistics at the regional level

Network	Density	Level of significance	Degree Centralization		Betweenness Centralization
A simulated	***0.0117***		***1***		***1***
A actual	0.376	***	0.489		0.029
B simulated	***1***		***0***		***0***
B actual	0.636	***	0.332		0.007
C simulated	***0.006***		***0.00003*** *(out)*	***1*** *(in)*	***0***
C actual	0.270	***	0.536 (out)	0.453 (in)	***0.034***
D simulated	***0.006***		***1*** *(out)*	***0.00003*** *(in)*	***0***
D actual	0.270	***	0.453 (out)	0.536 (in)	***0.034***

Notes: *** significant at 1%

By using a procedure suggested in Snijders and Borgatti (1999) we are able to measure that actual networks display different (and statistically significant) densities respect to the simulated ones. In particular while actual networks derived from star-shaped layouts (A, C and D) record a higher number of links than their simulated version, actual B network displays a smaller value of the density index from the simulated complete network where all possible links are established. These results show that the actual regional distribution of coordinators and participants within 5FP contracts is such that coordinators are scattered in a small but consistent subset of central regions and participants are not identically distributed across Europe.

The values of degree and betweenness centralization actual networks for symmetric layouts (A and B), respect the ranking of simulated networks: actual A networks are more hierarchical than actual B networks. Results are mixed for asymmetric layouts (C and D).

4. The model and the estimation strategy

The empirical analysis consists in testing a knowledge production function (Grilliches, 1979) which describes the innovative output of a region as a function of different innovative inputs (i.e. different sources of R&D expenditure) and other variables characterising the innovative and productive structure of each region. The implicit form of the KPF is defined as follows:

$$PAT_i^t = f\left(BizRD_i^\tau, GovRD_i^\tau, UniRD_i^\tau, PROD_i^\tau, INN_i^\tau, ACCESS_i^\tau, BETW_i^\tau\right) \qquad (1)$$

where the dependent variable (PAT_i^t) is the number of EPO patent applications (whose geographical location is recorded according to inventors) per million labour force registered at time *t* in region *i* (source: OECD, 2010). This variable is the average value for period *t*, i.e. 2005 and 2006, for 171 European regions at different NUTS levels (see table A1).

Since we are interested in analysing how different sources of knowledge production affect patenting activity, we considered three different types of R&D intensity, expressed as share of regional GDP: business R&D ($BizRD_i^\tau$), government R&D and university R&D expenditure ($UniRD_i^\tau$) (source: Eurostat, 2010a).

Following Glaeser *et al*. (1992), in order to test whether specialisation, or differentiation, of the productive and the innovative structure of a region positively influence its innovative output, we included $PROD_i^\tau$ and INN_i^τ, i.e. location quotients calculated respectively for local units in high-tech sectors and for high-tech patents (source: Eurostat, 2010a, 2010b).

$ACCESS_i^\tau$ is the multimodal accessibility index, a measure of combined (in terms of air, road and rail) accessibility of a region. The index derives from the transformation of absolute values of each region so that the European value is 100 (source: Espon, 2010).

All regressors are computed for each region *i* at time τ, i.e. the average for the period 1999-2004. In this way we are able to take into account the time lag between R&D expenditure and patent applications and to cope with the relevant problem of missing values at the regional level.

In order to detect the relevance of the structural position of regions within FP5 research networks, we included $BETW_i^\tau$, the betweenness centrality[11] of each region *i*. This variable is a proxy of the power of a region to control, thanks to its bridging position, the diffusion of scientific and technical knowledge across research networks stretching across Europe[12].

As described in section 2, the innovative activity, as several other economic phenomena, is characterised by agglomeration and spillovers, hence simple OLS estimations could be biased and spatial econometric techniques should be applied.

In order to detect if spatial autocorrelation is relevant for this analysis, as preliminary investigation, we computed Moran's I on the dependent variable, i.e. patents PAT_i^t, with respect to a geographical (in this case first-order geographical contiguity, henceforth GEO[13]) matrix and different relational weight matrices[14].

Once detected the presence of positive and significant "spatial" autocorrelation (see table A3 for details and section 5 for further details), we proceeded in estimating a double-log specification of the explicit version of model (1) in order to estimate the autocorrelation.

Stemming from the seminal contribute by Anselin (1988), spatial econometric literature records several models dealing with the problem of spatial spillovers for cross sectional data[15]. A very general spatial autoregressive model including both a spatially autoregressive error term (indicated with the coefficient λ) and the spatial lag on the dependent variable (indicated with the coefficient ρ) is defined as follows:

$$y = \rho\, W_1 y + X\beta + u \text{ and } u = \lambda W_2 u + \varepsilon \quad (2)$$

where W_1 and W_2 are squared spatial weight matrices and could be also the same, and ε the error term. Imposing some restrictions on the weights of the previous model, i.e. W_1=0 or W_2=0, two different spatial autoregressive models could be tested, a spatial error model (SEM), if W_1=0:

$$y = X\beta + u \text{ and } u = \lambda W_2 u + \varepsilon \quad (3)$$

or the spatial autoregressive model[16] (SAR), if W_2=0:

$$y = \rho\, W_1 y + X\beta + u \quad (4)$$

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[11] Betweenness centrality, as defined in the SNA literature, is computed as the shares of times that a node *i* needs node *k* (whose centrality is being measured) in order to reach *j* via the shortest path (Borgatti, 2005, p. 60). The more times a node lies on the shortest path between two other nodes, the more control that the node has over the interaction between these two non-adjacent nodes (Wasserman and Faust, 1994). Betwennes assesses the degree to which a node lies on the shortest path between two other nodes, and is able to funnel the flow in the network. In so doing, a node can assert control over the flow (Opsahl *et al*. 2010).

[12] These values have been computed for any layout in order to distinguish different structural positions deriving from different contracts structures. Hence in any empirical specification we included the corresponding betweenness value.

[13] The existence of geographic autocorrelation has been measured with a contiguity and a distances matrix. Results are similar therefore in the paper we present results for the contiguity matrix only.

[14] As defined by the different layouts described in sections 2.2 and 2.3.

[15] LeSage and Pace (2009) and Ehlrost (2014) detail models both for cross sections and panel data.

[16] Initially these models were labelled mixed-regressive spatial autoregressive models, but now are simply named spatial autoregressive models (LeSage and Pace, 2009).

Since the spillovers effects could be attributed also to the explanatory variables, a Spatial Durbin Model (SDM) could be defined as follows:

$$y = \rho W_1 y + X\beta_1 + W_1 X\beta_2 + \varepsilon \qquad (5)$$

The selection of a model respect to another is a very complex and still open issue, however there are a number of appropriate econometric tests that, in conjunction with explicit theoretical assumptions on the transmission mechanisms of the knowledge spillovers, could help in selecting the most suitable model specification (Elhrost, 2010).

In this analysis spatial weight matrices (usually indicated with *W*) are, alternatively, the geographical matrix *GEO* and one of the different relational ones – derived form different layouts and links weights – as defined in sections 2.2. and 2.3.

Since the main point of this analysis is to "jointly" consider the presence of geographical and relational effects we estimated a two-weight SAR model, as described in Lacombe (2004) and LeSage and Pace (2009), which is defined as follows:

$$y = \rho_G W_G y + \rho_C W_C y + X\beta + \varepsilon \qquad (6)$$

where W_G and W_C are the geographical and the relational weights, and we can estimate both geographic lag (ρ_G) and relational lag (ρ_C) jointly.

5. Results

Once detected with a simple computation of Moran's I the presence of spatial autocorrelation in patenting activity (table A3), we need to individuate where this comes from and control for it. Table 2 includes values Moran's I on residuals of model 1 and displays some diagnostic tools, i.e. Lagrange Multiplier (LM) and robust LM, adopted in order to detect the presence of spatially autoregressive error term (and its coefficient λ) or the spatial lag on the dependent variable (and its coefficient ρ).

Following Florax *et al*. (2003) and adopting the "classical" approach, the LM test indicate the presence of spatial autocorrelation for the geographic weight matrix (*GEO*) and all *C* layouts, among all possible layouts with links weights and directions . In particular the classical approach for *C* and *GEO* suggested that the model to be estimated should include a spatial lag term, while for all the remaining relational weights matrices (*A*, *B*, and *D*), the LM tests do not detect any spatial dependence.

Thus according to this first econometric exercise, any research network layout at the individual contract level – other than the hierarchical and non-symmetrical structure label *C* – does not produce an autocorrelation effect on the innovative performance of a region.

Table 2: Moran's I calculated on residuals for different weight matrices and LM for lag and for error

Weight Matrix	Moran's I/DF		LM lag		LM robust lag		LM error		LM robust error
GEO	0.094	*	3.642	*	1.267		2.619		0.245
	(0.058)		(0.056)		(0.260)		(0.106)		(0.621)
A_1	0.008		0.465		0.300		0.180		0.015
	(0.279)		(0.495)		(0.584)		(0.672)		(0.903)
A_N	0.046		0.008		0.595		1.415		2.002
	(0.131)		(0.927)		(0.440)		(0.234)		(0.157)
A_L	0.024		1.249		0.291		1.057		0.099
	(0.105)		(0.264)		(0.590)		(0.304)		(0.754)
B_1	-0.002		0.147		0.625		0.021		0.500
	(0.356)		(0.702)		(0.429)		(0.884)		(0.480)
B_N	0.004		0.198		0.107		0.092		0.002
	(0.136)		(0.657)		(0.744)		(0.761)		(0.968)
B_L	0.016		0.373		0.011		0.552		0.190
	(0.180)		(0.541)		(0.917)		(0.458)		(0.663)
C_1	0.046	***	4.804	**	2.367		3.867	**	1.430
	(0.006)		(0.028)		(0.124)		(0.049)		(0.232)
C_N	0.051	***	5.861	**	2.980	*	4.221	**	1.339
	(0.006)		(0.015)		(0.084)		(0.040)		(0.247)
C_L	0.054	***	6.269	**	3.209	*	4.262	**	1.202
	(0.007)		(0.012)		(0.073)		(0.039)		(0.273)
D_1	0.002		0.002		0.003		0.011		0.012
	(0.566)		(0.966)		(0.954)		(0.917)		(0.911)
D_N	0.008		0.068		0.537		0.122		0.592
	(0.406)		(0.795)		(0.464)		(0.727)		(0.442)
D_L	0.005		0.102		0.424		0.042		0.364
	(0.543)		(0.749)		(0.515)		(0.838)		(0.546)

Probabilities reported in parenthesis. Significance level: *** 1%, ** 5%, * 10%.

By adopting a hybrid specification strategy, based on the robust LM values, we obtain very similar results: *C* layouts are the only weights matrices showing the presence of spatial autocorrelation (as a spatial lag specification). However, when using robust LM values, estimates adopting *GEO* weights matrix do not show any spatial dependence.

We decided to include *GEO* in the next following estimations since spatial autocorrelation is detected in the residuals (the ration of the Moran's I over the degrees of freedom is positive 0.094 and significant at a 10% l.o.s, while the same does not apply for *A*, *B* and *D*).

As highlighted above, these results suggests that research network layout at the individual contract is relevant in order to detect at the aggregate level the effects of knowledge flows on the innovative performance of a given region.

In particular if knowledge flows were described in terms of *A* (i.e. hierarchic structure with mutual exchange of knowledge), *B* (i.e. totally a-hierarchical structure with no core region) and *D* (i.e. a hierarchic structure with flows of knowledge stemming from the coordinator of the joint research contract toward the other members), it was not possible to detect any effect of the relational knowledge barter exchange phenomenon influencing the level of regional innovative activity.

Note also that, following Marrocu *et al.* (2013b, p. 1490) "we rule out the Spatial Durbin Model on substantive grounds, for this specification implies that the influence of neighbouring territories on the innovative performance of a certain region is mediated also by their R&D

investments, conditional on a given connectivity structure". This requires that neighbours' R&D investments are thoroughly productive across NUTS2 regions. As this assumption is hardly realistic in the European context we argue that it is more reasonable to assume that innovation spillovers work through the effective level of knowledge achieved by neighbouring regions, which is proxied by the level of patent intensity[17].

Therefore, throughout the empirical analysis we adopt the spatial autoregressive specification, described in general terms in equation 4 and applied to the problem at hand as follows:

$$PAT_i^t = \beta_0 + \beta_1 BizRD_i^\tau + \beta_2 GovRD_i^\tau + \beta_3 UniRD_i^\tau + \beta_4 PROD_i^\tau + \beta_5 INN_i^\tau + \\ + \beta_6 ACCESS_i^\tau + \beta_7 BETW_i^\tau + \rho_Z WPAT_i^t + \nu_i^\tau \qquad (7)$$

where ρ_Z is the coefficient of spatially lagged dependent variable patents which can be alternatively computed for 1 geographic (*GEO*) and 3 relational weight matrices arising from *C* layouts and 3 different links weights (C_1, C_N and C_L).

Table 3: Estimation results only 1 weight matrix at the time (SAR specification) (ML estimations)

Dependent variable: PAT^t_i, log of patents applications per million labour force, double log specification

	GEO		C_1		C_N		C_L	
Constant	3.899	***	2.512	*	2.384	*	2.367	*
	(2.933)		(1.754)		(1.687)		(1.689)	
BizRD	0.962	***	1.044	***	1.039	***	1.037	***
	(10.811)		(13.404)		(13.382)		(13.370)	
GovRD	-0.075		-0.093		-0.096		-0.096	
	(-1.032)		(-1.293)		(-1.343)		(-1.336)	
UniRD	0.003		0.007		0.008		0.008	
	(0.037)		(0.106)		(0.113)		(0.123)	
PROD	1.003	***	0.994	***	0.991	***	0.992	***
	(13.243)		(13.059)		(13.093)		(13.127)	
INN	0.054	*	0.061	**	0.062	**	0.063	**
	(1.732)		(1.980)		(2.020)		(2.034)	
ACCESS	0.189		0.412		0.410		0.409	
	(0.644)		(1.432)		(1.433)		(1.432)	
BETW	-0.048	*	-0.108	***	-0.113	***	-0.114	***
	(-1.892)		(-3.268)		(-3.496)		(-3.577)	
ρWPAT	0.177	***	0.280	***	0.308	***	0.314	***
	(2.656)		(2.672)		(3.018)		(3.152)	
Obs.	*171*		*171*		*171*		*171*	
LIK	-280.498		-280.052		-279.344		-279.059	
AIC	578.997		578.105		576.688		576.117	

z-value are reported in parenthesis. Significance level: *** 1%, ** 5%, * 10%.

[17] For a robustness check, we estimate the model also along a Spatial Durbin specification. The results showed clearly no spatial autocorrelation for all independent variables, while the spillover effect on the dependent variable was still significant. In a similar context, Marrocu *et al.* (2014) explain such a result in a very convincing way "This result may be due to the intrinsic characteristics of the SDM specification, which entails a very complex externalities structure, and puts too strong a requirement on the data, especially at the territorial level considered in this study (NUTS 2 regions) (Marrocu *et al.*, 2014).

Looking at the coefficients of the independent variables showed in table 3 it is evident that the only positive and significant R&D is related to business activity, BizRD. The coefficients for GovRD and UniRD are not significantly different from zero, most probably because these two sources of financing are mainly devoted to basic research, not directly patentable or because institutional difficulties, raised by the different national legislations for individual scientists – working in public university and/or institutions – willing to patent an innovation.

The coefficient of the ACCESS variable is never significant, thus showing that the relevant "centrality" in European networks has probably more to do with socio-economic factors than with mere logistics. The coefficients of PROD and INN (which measure the specialisation of the regional production and innovation system in high-tech) are also positive and significant thus hinting at a role for specialization rather than differentiation as a source of innovation advantages along the lines indirectly suggested by Glaeser *et al*. (1992).

BETW of any region in any joint research networks according to *C* layout of knowledge flows displays a negative and significant coefficient in all models, using *GEO* and *C* weight matrices. This apparently puzzling results may be explained by considering this variables as a signal – as suggested by Leydesdorff (2007) for the bibliometric context, – of the "degree of inter-disciplinarity" of the regional scientific and technological population (these being universities, research institutions, firms, etc.)[18]. This result confirms that the innovative performance of a region depends on the specialization of its scientific and technological base.

Finally table 3 shows that both geographical spillovers and relational barter exchange, i.e. the ρ_Z coefficients of the spatially lagged dependent variables for all weight matrices included, are significantly and positively influencing the innovative activity of a given region.
Having tested that these effects are at work at the regional level in Europe, since the innovative performance of a region is influenced by its geographical and relational neighbouring regions, we moved a step forward by testing the joint effect of these two weight matrices given that any estimation based on a model specifying exclusively one definition of contiguity only (i.e. relational or geographical) would result in a biased estimation, due to omitted variables specification.

Hence we estimate a SAR model including both weight matrices as follows:

$$\begin{aligned} PAT_i^t &= \beta_0 + \beta_1 BizRD_i^\tau + \beta_2 GovRD_i^\tau + \beta_3 UniRD_i^\tau + \beta_4 PROD_i^\tau + \beta_5 INN_i^\tau + \\ &+ \beta_6 ACCESS_i^\tau + \beta_7 BETW_i^\tau + \rho_C W_{REL} PAT_i^t + \rho_G W_{GEO} PAT_i^t + \varepsilon_i^\tau \end{aligned} \tag{8}$$

where variables $\rho_C W_{REL} PAT^t_i$ and $\rho_G W_{GEO} PAT^t_i$ represent respectively the spatial lags of the dependent variable both for relational and geographical weight matrices.

Despite the fact that the main aim of the paper is to investigate the actual internal structure of scientific and technological knowledge flows within the regional networks activated in Europe by the 5FP and thus the focus of the econometric exercises is on the autocorrelation coefficients, it is worth looking at the sign and significance of coefficients of the covariates, presented in table 4. They are similar to those obtained in table 3: BizRD is the only research input influencing positively the regional innovative activity; PROD and INN coefficients are positive and significant; BETW is negative and significant.

[18] If one further considers that a in regional network derived by the aggregation of individual contracts - in which knowledge flows according to a hierarchical and a-symmetrical layout (as it is the case for layout *C*) – a high value of the betweenness centrality index implies the contemporary presence in the regions of both coordinators and members of different research networks, the result is further enforced.

Table 4: Estimation results 2 weight matrices jointly considered (SAR specification) (ML estimations)

Dependent variable: PAT^t_i, log of patents applications per million labour force, double log specification

	C_I-GEO		C_N-GEO		C_L-GEO	
CONSTANT	2.753	**	2.608	**	2.577	**
	(2.092)		(1.989)		(1.968)	
BizRD	0.965	***	0.964	***	0.963	***
	(12.640)		(12.671)		(12.674)	
GovRD	-0.074		-0.077		-0.077	
	(-1.040)		(-1.091)		(-1.087)	
UniRD	0.001		0.002		0.002	
	(0.017)		(0.025)		(0.034)	
PROD	0.988	***	0.986	***	0.986	***
	(13.182)		(13.198)		(13.219)	
INN	0.055	*	0.056	*	0.057	*
	(1.809)		(1.850)		(1.864)	
ACCESS	0.262		0.269		0.270	
	(0.923)		(0.948)		(0.953)	
BETWC	-0.093	***	-0.100	***	-0.101	***
	(-3.747)		(-4.013)		(-4.089)	
$\rho_{CI}W_{REL}PAT$	0.225	*				
	(1.903)					
$\rho_{CN}W_{REL}PAT$			0.256	**		
			(2.201)			
$\rho_{CL}W_{REL}PAT$					0.264	**
					(2.322)	
$\rho_{G}W_{GEO}PAT$	0.135	*	0.129		0.127	
	(1.660)		(1.588)		(1.574)	
BizRD						
Direct effect	0.968	***	0.969	***	0.964	***
Indirect effect	0.620	*	0.659	*	0.681	*
Total effect	1.587	***	1.628	***	1.645	***
PROD						
Direct effect	0.988	***	0.984	***	0.987	***
Indirect effect	0.632	*	0.668	*	0.698	*
Total effect	1.620	***	1.653	***	1.685	***
INN						
Direct effect	0.056	*	0.056	*	0.055	*
Indirect effect	0.036		0.039		0.038	
Total effect	0.092		0.095	*	0.093	
BETWC						
Direct effect	-0.095	***	-0.100	***	-0.101	***
Indirect effect	-0.061		-0.068		-0.072	*
Total effect	-0.157	**	-0.168	**	-0.173	**
Obs	*171*		*171*		*171*	
LIK	-473.974		-473.351		-473.087	
AIC	967.948		966.702		966.174	

Asymptot t-stat value are reported in parenthesis. Significance level: *** 1%, ** 5%, * 10%.

Table 4 includes also direct, indirect and total effects for all significant variables of model 8[19]. As one may expect, direct effects are always larger than indirect. In particular the only positive and significant indirect effects are those associated with BizRD and PROD. This means that the innovative performance of a region (as measured by patent intensity) is mainly explained by its own R&D investment of the business sector, and by the specialization of both its production and innovation system in high-tech sectors; but is also positively influenced by the innovative performance and by the high-tech specialisation of the neighbouring regions, where by neighbours we intend both the geographic and the relational ones

Far more interesting in this paper are the values of the spatially lagged dependent variables, ρ. In the first model C_1-*GEO* – where the relational weight matrix at the regional level is built on the basis of individual contract in which each link has the same weight (equal to 1) – both ρ_C and ρ_G are positive and significant, i.e. both mechanisms of transmission of knowledge are at place.
When we model the structure of individual contract with links weights structure which reflect the opportunity cost for a coordinator in establishing a new link (as in the models C_N-*GEO*, in which each link is inversely related to the number of nodes in the network, and C_L-*GEO*, in which each link is valued is inversely related to the number of links in the networks), geographical contiguity becomes insignificant, while the relational proximity is still at place.

In order to compare the different ρ values (recorded in tables 3 and 4) and computed in different non-nested models, following Burnham and Anderson (2002), we compute Akaike weights, $prob_j$, as follows:

$$prob_j = \frac{\exp\left[-\frac{1}{2}\left(AIC_{C\,j} - AIC_{C\,MIN}\right)\right]}{\sum_{r=1}^{R}\exp\left[-\frac{1}{2}\left(AIC_{C\,r} - AIC_{C\,MIN}\right)\right]}$$

where j is the model, R is the number of models and AIC_C is the bias-adjusted AIC value.

These results are presented in table 5, in which the main diagonal displays the estimated spatial lag coefficients for SAR specification (7) with only one weight matrix, while the off-diagonal values are the estimated spatial lag coefficients for SAR model (8) in which a couple of geographic and relational matrix is jointly considered in the analysis. The last column (weighted average) allows the comparison of ρ across different matrices.

Table 5: Spatial lags coefficients (a weighted average comparison)

	GEO	**C_1**	**C_N**	**C_L**	**Weighted average**
GEO	0.177	0.135	0.129	0.127	***0.020***
C_1	0.225	0.280			***0.052***
C_N	0.256		0.308		***0.144***
C_L	0.264			0.314	***0.174***

Values on the main diagonal are the estimated rho coefficients in table 3, a SAR model with one weight matrix. Off-diagonal values are the estimated rho coefficients in table 4, a SAR model with two weight matrices.
Weighted averages are computed on the basis of AIC values for each model in tables 3 an 4.

[19] As in LeSage and Pace (2009) we computed these effects using a Markov Chain Monte Carlo (MCMC) estimation method and we computed posterior estimates.

These results shows that relational effects are stronger than geographical proximity: C_I is 2,5 times larger than *GEO*, C_N more than double the previous effect, and finally C_L has the highest value, that is more than 8 times bigger than the geographical one, thus hinting at a more relevant role of intended knowledge barter exchange over unintended geographical spillovers across European regions, as suggested by Breschi and Lissoni (2001).

Further, the higher values of the weighted average of ρ associated with relational matrices suggest that the positive net effects, in terms of knowledge flows exchange that the coordinator is enjoying from any new member included in a research networks are counterbalanced by coordination costs and, more generally, by the budget constrain in terms of time and relational activity (along the line of the co-authorship model in Jackson and Wolinsky, 1996).

6. Conclusion

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

In this paper we modelled geographic proximity, in terms of contiguity, as a measure of unintended knowledge spillovers; and relational proximity, in terms of 5FP research contracts, as a measure of inter-regional intentional knowledge exchange among research institutions.

We did not limit to the detection of the presence of relational autocorrelation, but we also designed a research methodology aimed at looking inside the black box of joint research contracts, able to identify which structures of knowledge flows more effectively affect the relational autocorrelation of innovative performance at the regional level.

In addition in this paper we adopted a spatial econometric specification able to 'jointly' consider the effects of geographical and relational autocorrelation (Lacombe, 2004; LeSage and Pace (2009) and a statistical procedure, which enable us to compare ρ across non-nested models, Burnham and Anderson (2002).

Firstly our results confirm that the relational autocorrelation is at work in influencing the innovative performance of European NUTS2 regions.

Secondly, although relational autocorrelation may theoretically apply for all hypothesised layouts, only one typology of contract structure (i.e. the hierarchical non-symmetrical layout, *C*) is relevant in influencing the patenting activity of a relationally defined neighbour region.

This result suggests, on the one hand, that knowledge intentional exchanges mainly follow hierarchical network structures, probably for efficiency reasons; but, on the other, they may hint that research framework programmes may be good policy instruments to sustain the innovative performance of certain regions but not to foster regional cohesion, since most coordinators are located in core regions.

When geography is also included in the model in order to capture the spatial autocorrelation in influencing innovative activity, all standard results on this issue apply. As far as the estimated knowledge production function is concerned, innovative activity, as proxied by patent intensity, is mainly supported by private sector (BizRD) as well as by the specialisation of the production (PROD) and the innovative (INN) structure in high-tech sectors.

Thirdly, when we jointly computed the effects of spatial and relational autocorrelation, we were able to show that – for a hierarchical and a-symmetrical layout (i.e. *C*) at the individual contract level –a relational proximity effect at the regional level is at place. In addition we were also able to prove that – when more realistic links (i.e. C_N and C_L), which include the opportunity costs of enlarging the size of a research network – the pure geographical effect (deriving from pure unintended spillovers) loose its significance.

Finally, more generally, our results showed that, on average, the role played by relational effects (which relate to intended knowledge barter exchange) is more than 8 times larger than the role played by geographical ones (which relate to the unintended exchange).

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Appendix

Table A1: List of regions, number of coordinated contracts, number of participation in contracts and ranking

Region	NUTS code	NUTS level	number of coordinated contracts	rank of coordinated contracts	number of partecipants	rank of participated contracts
Burgenland (A)	AT11	2	0	161	3	166
Niederösterreich	AT12	2	20	74	66	96
Wien	AT13	2	69	29	462	19
Kärnten	AT21	2	2	144	21	142
Steiermark	AT22	2	37	49	163	56
Oberösterreich	AT31	2	24	67	110	76
Salzburg	AT32	2	5	125	33	124
Tirol	AT33	2	9	107	84	87
Vorarlberg	AT34	2	4	132	16	146
Région De Bruxelles-Capitale / Brussels Hoofdstedelijk Gewest	BE1	1	109	16	461	20
Vlaams Gewest	BE2	1	137	10	660	12
Région Wallonne	BE3	1	55	42	303	36
Stuttgart	DE11	2	111	14	421	26
Karlsruhe	DE12	2	57	39	348	30
Freiburg	DE13	2	35	51	155	59
Tübingen	DE14	2	32	57	155	59
Oberbayern	DE21	2	155	6	797	8
Niederbayern	DE22	2	1	153	1	171
Oberpfalz	DE23	2	6	120	38	118
Oberfranken	DE24	2	0	161	28	131
Mittelfranken	DE25	2	9	107	112	74
Unterfranken	DE26	2	4	132	42	114
Schwaben	DE27	2	5	125	26	136
Berlin	DE30	2	56	41	415	27
Brandenburg - Nordost	DE41	2	7	113	24	138
Brandenburg - Südwest	DE42	2	28	61	93	82
Bremen	DE50	2	62	34	197	51
Hamburg	DE60	2	39	46	213	49
Darmstadt	DE71	2	31	59	276	39
Gießen	DE72	2	11	93	40	117
Kassel	DE73	2	10	102	37	120
Mecklenburg-Vorpommern	DE80	2	16	85	56	102
Braunschweig	DE91	2	34	54	147	62
Hannover	DE92	2	14	86	128	69
Lüneburg	DE93	2	10	102	30	128
Weser-Ems	DE94	2	17	83	51	105
Düsseldorf	DEA1	2	33	55	197	51
Köln	DEA2	2	94	20	510	16
Münster	DEA3	2	6	120	56	102
Detmold	DEA4	2	6	120	66	96
Arnsberg	DEA5	2	18	80	130	67
Koblenz	DEB1	2	4	132	12	152
Trier	DEB2	2	1	153	6	161

Rheinhessen-Pfalz	DEB3	2	35	51	148	61
Saarland	DEC0	2	14	86	47	108
Chemnitz	DED1	2	9	107	48	106
Dresden	DED2	2	18	80	98	79
Leipzig	DED3	2	11	93	46	110
Sachsen-Anhalt	DEE0	2	18	80	87	86
Schleswig-Holstein	DEF0	2	24	67	111	75
Thüringen	DEG0	2	27	62	117	72
Danmark	DK	0	179	5	1046	4
Galicia	ES11	2	11	93	90	83
Principado De Asturias	ES12	2	3	139	23	139
Cantabria	ES13	2	3	139	31	127
País Vasco	ES21	2	83	22	323	32
Comunidad Foral De Navarra	ES22	2	10	102	38	118
La Rioja	ES23	2	7	113	12	152
Aragón	ES24	2	11	93	75	90
Comunidad De Madrid	ES30	2	143	8	852	7
Castilla Y León	ES41	2	11	93	59	100
Castilla-La Mancha	ES42	2	8	110	33	124
Extremadura	ES43	2	8	110	8	158
Cataluña	ES51	2	109	16	779	9
Comunidad Valenciana	ES52	2	68	32	272	40
Illes Balears	ES53	2	7	113	27	133
Andalucía	ES61	2	39	46	230	45
Región De Murcia	ES62	2	6	120	26	136
Itä-Suomi	FI13	2	8	110	57	101
Etelä-Suomi	FI18	2	107	18	735	11
Länsi-Suomi	FI19	2	5	125	122	70
Pohjois-Suomi	FI1A	2	14	86	67	95
Åland	FI20	2	0	161	2	170
Île De France	FR10	2	412	1	2244	1
Champagne-Ardenne	FR21	2	1	153	12	152
Picardie	FR22	2	12	92	43	112
Haute-Normandie	FR23	2	2	144	29	129
Centre	FR24	2	21	72	71	92
Basse-Normandie	FR25	2	5	125	27	133
Bourgogne	FR26	2	2	144	33	124
Nord - Pas-De-Calais	FR30	2	13	89	116	73
Lorraine	FR41	2	10	102	64	98
Alsace	FR42	2	22	70	139	65
Franche-Comté	FR43	2	4	132	37	120
Pays De La Loire	FR51	2	19	76	102	78
Bretagne	FR52	2	13	89	137	66
Poitou-Charentes	FR53	2	3	139	41	115
Aquitaine	FR61	2	24	67	156	57
Midi-Pyrénées	FR62	2	57	39	305	35
Limousin	FR63	2	1	153	11	156
Rhône-Alpes	FR71	2	114	13	581	13
Auvergne	FR72	2	7	113	37	120
Languedoc-Roussillon	FR81	2	26	66	141	64
Provence-Alpes-Côte D'azur	FR82	2	66	33	326	31
Corse	FR83	2	0	161	6	161

Anatoliki Makedonia, Thraki	GR11	2	2	144	15	147
Kentriki Makedonia	GR12	2	30	60	224	48
Dytiki Makedonia	GR13	2	1	153	7	159
Thessalia	GR14	2	0	161	15	147
Ipeiros	GR21	2	4	132	27	133
Ionia Nisia	GR22	2	0	161	3	166
Dytiki Ellada	GR23	2	20	74	96	80
Sterea Ellada	GR24	2	2	144	22	141
Peloponnisos	GR25	2	1	153	4	165
Attiki	GR30	2	181	4	1103	2
Voreio Aigaio	GR41	2	5	125	20	144
Notio Aigaio	GR42	2	0	161	12	152
Kriti	GR43	2	27	62	122	70
Border, Midland And Western	IE01	2	11	93	71	92
Southern And Eastern	IE02	2	79	25	460	21
Piemonte	ITC1	2	69	29	457	22
Valle D'aosta/Vallée D'aoste	ITC2	2	0	161	5	163
Liguria	ITC3	2	41	45	233	44
Lombardia	ITC4	2	146	7	937	6
Provincia Autonoma Bolzano/Bozen	ITD1	2	2	144	11	156
Provincia Autonoma Trento	ITD2	2	7	113	53	104
Veneto	ITD3	2	62	34	209	50
Friuli-Venezia Giulia	ITD4	2	17	83	95	81
Emilia-Romagna	ITD5	2	69	29	351	28
Toscana	ITE1	2	83	22	443	24
Umbria	ITE2	2	7	113	43	112
Marche	ITE3	2	10	102	48	106
Lazio	ITE4	2	124	12	748	10
Abruzzo	ITF1	2	3	139	28	131
Molise	ITF2	2	0	161	3	166
Campania	ITF3	2	22	70	165	55
Puglia	ITF4	2	11	93	73	91
Basilicata	ITF5	2	1	153	15	147
Calabria	ITF6	2	5	125	21	142
Sicilia	ITG1	2	13	89	77	89
Sardegna	ITG2	2	11	93	47	108
Luxembourg (Grand-Duché)	LU	0	11	93	61	99
Groningen	NL11	2	19	76	70	94
Friesland (NL)	NL12	2	4	132	3	166
Drenthe	NL13	2	4	132	7	159
Overijssel	NL21	2	36	50	156	57
Gelderland	NL22	2	89	21	289	38
Flevoland	NL23	2	2	144	36	123
Utrecht	NL31	2	47	43	271	41
Noord-Holland	NL32	2	99	19	434	25
Zuid-Holland	NL33	2	127	11	555	14
Zeeland	NL34	2	5	125	13	151
Noord-Brabant	NL41	2	58	38	226	47
Limburg (NL)	NL42	2	27	62	89	84
Norte	PT11	2	19	76	229	46
Algarve	PT15	2	2	144	23	139

Centro (P)	PT16	2	21	72	110	76
Lisboa	PT17	2	43	44	502	17
Alentejo	PT18	2	2	144	29	129
Região Autónoma Dos Açores	PT20	2	0	161	5	163
Região Autónoma Da Madeira	PT30	2	0	161	14	150
Stockholm	SE11	2	72	27	487	18
Östra Mellansverige	SE12	2	27	62	257	42
Småland Med Öarna	SE21	2	6	120	44	111
Sydsverige	SE22	2	35	51	190	53
Västsverige	SE23	2	32	57	317	33
Norra Mellansverige	SE31	2	3	139	41	115
Mellersta Norrland	SE32	2	1	153	20	144
Övre Norrland	SE33	2	7	113	79	88
North East (England)	UKC	1	33	55	130	67
North West (England)	UKD	1	110	15	543	15
Yorkshire And The Humber	UKE	1	75	26	178	54
East Midlands (England)	UKF	1	59	37	306	34
West Midlands (England)	UKG	1	62	34	247	43
East Of England	UKH	1	81	24	350	29
London	UKI	1	247	2	1077	3
South East (England)	UKJ	1	247	2	1046	4
South West (England)	UKK	1	71	28	303	36
Wales	UKL	1	38	48	143	63
Scotland	UKM	1	142	9	446	23
Northern Ireland	UKN	1	19	76	88	85

Table A2: Descriptive statistics for 12 layouts

layout	min	max	sum	average value	sd	quota of 0's
A_1	0.0	124.0	49,182.0	1.7	5.2	62.4%
A_N	0.0	17.2	6,727.9	0.2	0.7	62.4%
A_L	0.0	21.3	8,756.0	0.3	0.9	62.4%
B_1	0.0	399.0	197,504.0	6.8	17.8	36.4%
B_N	0.0	45.0	19,716.2	0.7	1.9	36.4%
B_L	0.0	16.6	7,591.3	0.3	0.7	36.4%
C_1	0.0	64.0	24,591.0	0.8	2.7	73.0%
C_N	0.0	8.7	3,363.9	0.1	0.4	73.0%
C_L	0.0	10.7	4,378.0	0.2	0.5	73.0%
D_1	0.0	64.0	24,591.0	0.8	2.7	73.0%
D_N	0.0	8.7	3,363.9	0.1	0.4	73.0%
D_L	0.0	10.7	4,378.0	0.2	0.5	73.0%

Table A3: Moran's I calculated on the dependent variable: PAT_i^t

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)

Values in parenthesis indicates probability