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What determines the embeddedness of European regions in EU funded R&D networks? Evidence using graph theoretic approaches and spatial panel modeling techniques

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What determines the embeddedness of European regions in EU funded R&D networks? Evidence using graph theoretic approaches and spatial panel modeling techniques

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Abstract. This study shifts attention to the embeddedness of European regions in R&D networks, as captured by R&D joint ventures funded by the EU Framework Programmes (FPs) in the time period 1998-2006. By regional embeddedness we refer to a region's position in terms of different network analytic centrality measures, given aggregated region-by-region collaboration flows in the FP networks. Network embeddedness is measured by a region's betweenness centrality, a proxy for a region's ability to control knowledge flows, and eigenvector centrality, measuring a region's connectedness with central hubs. The objective is to estimate how different region-internal and region-external characteristics affect a region's embeddedness in the European network of R&D cooperation. We consider independent variables accounting for the knowledge production capacity of a region and the regional economic structure. In modelling regional network embeddedness, we make use of advanced spatial econometric techniques by means of panel spatial error models and panel spatial durbin error models with random effects. The results show that R&D expenditures, human capital and regional technological specialisation are the most important determinants for a region's network embeddedness. Further, the study provides evidence that spatial spillovers from neighbouring regions influence a region's FP network embeddedness.

JEL Classification: C02, C49, L14, O39, O52

Keywords: R&D cooperation, European Framework Program, large-scale networks, network embeddedness, panel spatial Durbin model

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1 Introduction

In the recent past, regional, national and supranational Science, Innovation and Technology (STI) policies have emphasized supporting interactions and networks between organisations of the innovation system. The reason for this policy focus has been mainly triggered by various considerations in theoretical and empirical literature of innovation economics and economic geography. Two arguments are essential in this respect: *First*, interactions, research collaborations and networks of actors are crucial for successful innovation (see, for instance, Fischer 2001, Powell and Grodal 2005), and, *second*, innovation and knowledge diffusion are the key vehicles for sustainable economic competitiveness (see, for instance, Romer 1990).

The key STI policy instrument of the EU in this context are the European Framework Programmes (FPs) that support pre-competitive R&D projects, creating a pan-European network of organisations performing joint R&D. Further, as regions are widely considered as essential sites of knowledge production and innovation (see, for instance, Lagendijk 2001), it is assumed that participation of organisations in networks enhances not only the organisational innovation capability, but has also – due to the existence of geographically localised knowledge spillovers – significant influence on the innovation capacity of the regional innovation system (see Cooke 2001 among others). Thus, we employ a regional perspective to analyse the embeddedness of European regions in the European network of R&D cooperation.

The focus of the study is on regional characteristics that affect a region's embeddedness in EU funded networks as captured by the participation in joint FP projects. By network embeddedness we refer to the notion of centrality in the sense of the Social Network Analysis (SNA) literature. In network theory, vertices that have a more prominent and central network position will more likely benefit from network advantages than actors that have a more distant, peripheral position in the network (see, for instance, Wasserman and Faust 1994). A higher network embeddedness of a region, i.e. of organisations located in that region, may increase information and knowledge access within the network, and may further create a competitive advantage when it comes to the formation and conditioning of new collaborations and alliances (see, for instance, Gilsing et al. 2008, Maggioni and Uberti 2005). From a regional policy perspective, it is therefore crucial to provide framework conditions that stimulate the participation intensity of organisations located in a specific region. A privileged access to information and knowledge access of these organisations may be beneficial for the region as a whole in the form of intra-regional knowledge flows and interactions with actors

throughout the regional innovation system, in particular local suppliers and smaller firms. In contrast, less central regions may lack sufficient access to external relevant information and knowledge, and, therefore, may not be able to benefit from inter- and intraregional knowledge spillovers.

The objective of this study is to investigate why some regions are able to obtain higher network embeddedness in the European network of R&D cooperation – constituted under the heading of the FPs – than other regions. For this reason, we aim to identify region-specific characteristics that influence a region's embeddedness, involving region-internal factors, such as knowledge production capacities, technology related conditions and economic structure. Further, we take into account region-external factors, considering the influence of the characteristics of neighbouring regions, referred to as inter-regional spatial spillovers (see, for instance, Fischer et al. 2009).

In order to address this question we employ a spatial econometric perspective that provides a useful toolbox to investigate the relationship between a region's network embeddedness and various region-internal and region-external characteristics. In our modelling approach we explicitly exploit the panel structure of our data, and at the same time consider spatial spillover effects. Thus, we combine panel econometrics with spatial econometric techniques as described by Elhorst (2003). The dependent variable is measured in terms of a region's centrality in the FP network for the years 1998-2006. We draw on data from the EUPRO database comprising systematic information on R&D projects funded by the FPs, including the assignment of participating organisation to a specific European region. To measure a region's centrality we rely on cross-region collaboration matrices as used by Scherngell and Barber (2009 and 2011) where individual cooperations are aggregated to the regional level leading to a network where the nodes are represented by regions and the edges by cross-region collaboration intensities. Using these matrices we are able to calculate a region's centrality relying on two different centrality concepts, that are betweenness- and eigenvector centrality (see, Wasserman and Faust 1994). The European coverage is achieved by using 241 NUTS-2 regions of the 25 pre-2007 EU-member states.

The study departs from previous research (see, for instance, Bergman and Maier 2009) by at least three major respects: *First*, we take into account region-external factors – in the form of spatial spillovers – that influence a region's embeddedness in the European network of R&D cooperation by employing a spatial Durbin Error modelling approach. *Second*, by focusing on an enlarged study area comprising 241 European NUTS-2 regions we are able to

comprehensively investigate the R&D network constituted under the FPs. *Third*, we consider the time dimension in our data on FP networks by using yearly collaboration patterns from 1998-2006. The study at hand opens up a new line of investigating the role of regions in the European network of R&D cooperation that is a central question in the actual policy debate on the development of the European Research Area (ERA) (see, for instance, CEC 2007). The results will enrich our understanding on determinants that discriminate core regions from less dominant regions in EU funded R&D networks. By this, the study is situated at the intersection of regional policy and STI policy.

The remainder of the study is organised as follows. Section 2 sets forth the theoretical background, embeds the current study in related literature and derives the main hypotheses for the empirical analysis. Section 3 operationalizes the concept of regional embeddedness in the European network of R&D collaboration, introduces the data set used and presents some exploratory analysis on the region's position in this network. Section 4 describes the spatial Durbin error with random effects that is used to estimate how different region-internal and region-external characteristics influence a region's network embeddedness, before Section 5 presents the estimation results. Section 6 concludes with a summary of the main results, some policy implications and some ideas for a future research agenda.

2 Theoretical background and main hypotheses

Today it is widely agreed that joint R&D activities, networks and collaborations are conducive to – even a sine-qua-non condition for – knowledge production and successful innovation (see, for instance, Powell and Grodal 2005). The motives and drivers for organisations to engage in R&D collaborations with firms, research organisations and universities are manifold; one of the most striking arguments is the increasing complexity of innovation processes, most notably in the context of converging and rapidly developing technologies (see, for instance, Pavitt 2005). Consequently, the absorption and integration of new knowledge from various sources as well as a permanent search for novel combination opportunities of complementary knowledge bases is the key to sustainable innovative capability.

One of the fundamental research issues in the investigation of R&D networks concerns their spatial structure. This is rooted in the 'geography of innovation' literature that shifts emphasis to the investigation of the geographical dimension of innovation attracting much interest in

the recent past (see, for instance, Audretsch and Feldman 1996). One of the crucial assumptions of this literature stream is that innovating actors are embedded in a regional innovation system benefiting from spatial proximity to other actors (see Asheim and Gertler 2005). Spatial proximity is considered to be of particular importance since knowledge is in part tacit; though the cost of transmitting codified knowledge may be invariant to distance, presumably the cost of transmitting non-codified knowledge across geographic space rises with geographic distance. In this context, the regional structure, its degree of urbanisation and agglomeration effects are considered to foster intra-regional knowledge flows and the establishment of local network structures. Thus, regions are widely recognized as essential sites of knowledge production and innovation due to the existence of localised knowledge flows and R&D network arrangements, facilitated by shared institutional and cultural values as well as a certain degree of homogeneity in terms of economic development (see, for example, Cooke 2001, Legendijk 2001).

However, innovating actors may not only benefit from these (often unintentional) localized knowledge flows, but also rely on additional mechanism of knowledge transmission (see, for example, Maggioni et al. 2007, Scherngell and Barber 2009 and 2011). One specific argument – particularly important for the motivation of the current study – is that key players of the regional innovation systems, such as universities and large knowledge-intensive firms do not only benefit from the local knowledge base, but increasingly are compelled to search for knowledge sources that are geographically located further away in order to keep pace in the global innovation competition. Such region-external knowledge sources are tapped via networking activities – for instance in the form of joint R&D project, joint assignment of patents or joint conduction of scientific publications – and/or labour mobility. Such region-external knowledge sources may be explicitly valuable for such organisations to gain contact with less familiar pieces of knowledge that may be important for their long-term development (see Maskell et al. 2006).

In this sense, a regions' innovative capability depends not only on its internal knowledge production and diffusion but also on its ability to identify and access region-external knowledge sources located further away. Consequently, the sustainable generation of localized knowledge spillovers makes an active participation in R&D collaborations essential, allowing for the acquisition of region-external knowledge acquired through network channels. However, a successful participation in networks cannot be taken for granted; instead it relies to a sufficient degree on the partners' technological and organisational capabilities to integrate

external information into the individual knowledge base, but also on their geographical, technological and cultural background (see, for example, Paier and Scherngell 2011, Maggioni and Uberti 2009, Autant-Bernard et al. 2007b).

At this point, it becomes evident that a network perspective is useful when analysing the innovative capability of regions. Distinct innovating actors are interconnected via R&D networks across regions, leading to inter-regional knowledge flows. Regions intensively involved in several collaborative arrangements are well interlinked with other regions, and therefore take up a central position within the whole network (see, for example, Bergman and Maier 2009). Highly embedded regions act as hubs for knowledge diffusion, spreading knowledge throughout several connected actors. Moreover, central players may be in a position to enable but also control knowledge flows between various de facto unconnected allies, acting as a ‘gatekeeper’ for information and knowledge running through them, and thus, exerting influence on the process of knowledge transmission throughout the entire network. From a regional perspective, a strategic advantageous position allows not only direct access and receipt of external knowledge through direct linkages, but also through indirect allies to relevant regions in the entire network.

The focus in this study is on the position of regions in the European network of R&D cooperation constituted under the heading of the EU Framework Programmes (FPs). The FPs support pre-competitive R&D projects, creating a pan-European network of actors performing joint R&D (see, for instance, Breschi and Malerba 2009, CEC 2007)¹. For a specific region, and, thus, for regional policy makers, the FPs may be an extremely promising instrument to connect the region to external knowledge bases. A strong embeddedness of a region in FP networks may ease the establishment of contacts to strategic important, region-external knowledge sources. Thus, from a regional policy perspective it may be highly desirable to foster the engagement in the FPs, to enhance regional attractiveness in such networks, and to

¹ Since their launch in 1984, the overall objectives of the FPs have been to strengthen the scientific and technological bases of the European scientific community and the European economy to foster international competitiveness, and the promotion of research activities in support of other EU policies (see *CORDIS* 2006). However, since FP5 a stronger focus on integrating national and regional research communities in different thematic fields across Europe is clearly noticeable. In the FPs, project proposals are to be submitted by self-organised consortia. Funding is open to all legal entities established in the Member States of the European Union – e.g. individuals, industrial and commercial firms, universities, research organisations, etc. – and can be submitted by at least two independent legal entities established in different EU Member States or in an EU Member State and an Associated State. Proposals to be funded are selected on the basis of criteria including scientific excellence, added value for the European Community, the potential contribution to furthering the economic and social objectives of the Community, the innovative nature, the prospects for disseminating and exploiting the results, and effective transnational cooperation.

reach a central position in the cross-region FP network. However, participating, or even more important, being central and becoming attractive in these networks requires a considerable degree of absorptive capacity (Cohen and Levinthal 1990), defined as the capability to identify and implement external knowledge from partner regions. Being able to exhaust new technological opportunities is, generally speaking, determined by the quality of the regional innovation environment, reflected in the interrelation of region-specific technological capabilities, economic structure and institutional background (see, for instance, Rodrigues-Pose and Storper 2006).

Based on these theoretical considerations, the question arises which specific regional characteristics and properties influence a region's network embeddedness in the FP network. In this sense, the study at hand aims to contribute to provide novel empirical evidence on this issue. In doing so, we consider the region's internal structure, most notably a region's endowment with knowledge-related production factors (see, for example, Broekel and Brenner 2011), and relational characteristics, such as connectivity to neighbouring regions, as most crucial factors for the active involvement, and a specific position in FP networks, leading to the following main hypotheses:

- i)* Regions with high knowledge production capacities in terms of endowment factors (see Broekel and Brenner 2011), resources and competences are more likely to explore, absorb and transfer knowledge from external sources, and thus, we argue, are more likely to gain a higher embeddedness and strategic position within R&D networks.
- ii)* Knowledge creation via R&D networks increasingly involves a combination of very specific pieces of knowledge, thus, we further argue, technological specialisation as well as the concentration on high-tech fields may have a positive effect on a region's embeddedness.
- iii)* We assume that urban regions are stronger embedded in FP networks due economies of scale and agglomeration externalities; the economic as well as cognitive power is particularly concentrated in urban regions hosting also the most important collaboration-intensive scientific organisations or multinational firms.
- iv)* Due to the presence of spatially discounted spillovers (see Fischer et al. 2009), we assume that also the characteristics from nearby regions in geographical space have an effect on a region's position in R&D networks.

3 Network embeddedness of European regions

Before we are able to identify region-internal and region-external characteristics affecting a region's embeddedness in the European FP network, we have to clarify the notion of network embeddedness as used in this study, and outline our measurement approach to empirically observe a region's network embeddedness. By network embeddedness we refer to a region's centrality in European R&D collaboration networks as captured by the participation in joint R&D projects funded by the EU FPs. We draw on data from the EUPRO database, which provides comprehensive information on funded research projects of the EU FPs and all participating organisations². For the study at hand, we rely on data on projects running between 1998 and 2006, and, thus, projects that were mostly funded in FP5 and FP6. However, we do not exclude projects from earlier FPs when they are still running in the time period under consideration.

The regional coverage is achieved by using a set of $n=241$ NUTS-2 regions (NUTS revision 2003)³; a detailed list of regions is given in Appendix A. By assigning all participating organisations in the FPs over the period 1998 to 2006 to a specific NUTS-2 region using a concordance scheme between cities and regions, we are able to aggregate the number of individual collaborative activities in time period t to the corresponding NUTS-2 level, and to construct n -by- n collaboration matrices of the type employed by Scherngell and Barber (2009 and 2011) containing the observed number of R&D collaborations between two regions i and j in time period t .

In terms of graph theory, the n -by- n collaboration matrix for a given year t may be considered as symmetric n -by- n adjacency matrix. We define

$$\mathbf{A}_t(i, j) = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nt} \end{pmatrix} \quad (1)$$

² EUPRO is constructed and maintained by AIT Austrian Institute of Technology. It contains systematic information on project objectives and achievements, project costs, project funding and contract type as well as on the participating organisations including the full name, the full address and the type of the organisation for FP1 to FP7 (see, for instance, Scherngell and Barber 2011).

³ Although substantial size differences and interregional disparities of some regions exist, these units are widely recognized to be an appropriate level for modelling and analysis purposes (see, for example, Fischer et al. 2006, LeSage et al. 2007).

constituting a weighted graph, where the element a_{ij} contains the collaboration intensity as measured in terms of joint FP projects between organisations located in region i and j . We define the unweighted, binary version of adjacency matrix (1) by

$$\mathbf{A}_t^{(bin)}(i, j) = \begin{cases} 0, & a_{ij} = 0 \\ 1, & a_{ij} > 0. \end{cases} \quad (2)$$

that is to be used for measuring specific types of centrality. Further we denote the number of edges incident on a vertex $i=1, \dots, n$ as the degree k_{it} in a given year t . A path is the alternating sequence of vertices and links, beginning and ending with a vertex, so that the shortest path or geodesic distance g_{ijt} between two regions i and j in time period t is defined as the number of vertices to be passed in the shortest possible path from one vertex to another (see Wassermann and Faust 1994 for further details).

Network embeddedness of region i is captured by two distinct centrality measures, namely betweenness and eigenvector centrality⁴. The betweenness concept intends to capture the centrality of a node (in our case region) in terms of its position for controlling the flow of information within the network by focusing on the number of shortest paths through this node (region) (see Freeman 1979). Thus, central regions benefit from gaining access to various knowledge sources, and, at the same time, take up – independent of their degree – a significant position in influencing the transfer of knowledge within the whole network. In other words, they act as ‘gatekeepers’ by exerting control over the knowledge flowing through them. We additionally use eigenvector centrality, according each region a centrality that depends both on the number and the quality of its connections by examining all regions in parallel and assigning centrality weights that correspond to the average degree of all linked regions (see Bonacich 1987)⁵.

We further explore these ideas by providing the mathematical specification of these concepts. For betweenness centrality we utilize the unweighted adjacency matrix $\mathbf{A}_t^{(bin)}$ for a given year

⁴ Further point centrality measures commonly used in SNA are degree and closeness centrality. Degree centrality focuses only on connections directly attached to a vertex and is therefore rather a measure for local centrality (see, for example, Wasserman and Faust 1994). In contrast, closeness centrality is based on the shortest distance to all other vertices in the network and indicates how close a distinct vertex is to all other vertices in the network.

⁵ Similar concepts focusing on the participation of organisations in European core networks, referred to as thematic backbones, have gained recent interest in FP evaluations and related literature (see, for instance, Heller-Schuh et al. 2011).

t^6 . Thus, in our case, betweenness centrality $y_{it}^{(b)}$ measures how often a region is situated between other, not directly interlinked, regions, in time period t , as defined by

$$y_{it}^{(b)} = \sum_{\substack{j=1 \\ j < q}}^n g_{jq}(i) / g_{jq} \quad (3)$$

where $g_{jq}(i)$ is the shortest path between region j and q going through region i at time t , for $i \neq j \neq q$.

Eigenvector centrality lays – as mentioned above – emphasis on the importance of direct linkages of a vertex in the network, but additionally takes the degree of all other connected vertices into account. Eigenvector centrality $y_{it}^{(ei)}$ of region i at time t is defined to be proportional to the sum of degrees of regions j to which it is connected, using the weighted adjacency matrix \mathbf{A}_t :

$$y_{it}^{(ei)} = \frac{1}{\lambda} \sum_{j=1}^n a_{ij} k_{jt} \quad (4)$$

where λ is the largest eigenvalue of \mathbf{A}_t ⁷.

Table 1 presents the top-10 central regional players according to their eigenvector and betweenness centrality for the years 1998 and 2006. Île-de-France has by far the highest value for eigenvector centrality in both years, indicating that the region has not only the highest number of interregional project participations but is also very well connected to other central regions. However, in terms of betweenness centrality Île-de-France only takes up the 6th rank. In general, it is noteworthy that the most central regions in terms of their betweenness have much lower ranks or are even not represented in the top-10 for eigenvector centrality. The explanatory analysis in the section that follows will provide some evidence whether these differences are related to distinct regional characteristics. Further, there are some considerable changes in the ranking observable between 1998 and 2006, especially for betweenness centrality (e.g. Catalonia improves from the 7th rank to the most central region in 2006, whereas Lombardia – the most central region in 1998 – is no more represented in the Top-10 in 2006). Furthermore, for eigenvector centrality the gap between Île-de-France and the other

⁶ We refrain using the weighted version of betweenness centrality, such as for instance defined by Newman (2001), since interpretation of shortest paths in terms of the weighted graphs that we use in this study, that is collaboration intensities between regions, is problematic.

⁷ A common notation used in this context is the eigenvector equation as given by $\lambda \mathbf{x} = \mathbf{A} \mathbf{x}$, where \mathbf{x} is a vector of centralities $\mathbf{x} = (x_1, x_2, \dots)$ denoting the eigenvector of the adjacency matrix \mathbf{A} with eigenvalue λ (see Bonacich 1987).

regions is remarkable for both years, particularly in view of the differences between the subsequent regions.

Table 1: Top-10 regions for betweenness and eigenvector centrality

Region	Eigenvector centrality	Region	Betweenness centrality
<i>1998</i>			
Île-de-France	1.000	Lombardia	369.434
Denmark	0.440	Île-de-France	344.095
Comunidad de Madrid	0.363	Inner London	342.143
Attiki	0.326	Attiki	300.148
Lombardia	0.321	Gelderland	294.756
Inner London	0.309	Emilia-Romagna	229.873
Zuid-Holland	0.278	Catalunya	222.749
Etelö-Suomi	0.271	Zuid-Holland	212.994
Oberbayern	0.246	Noord-Holland	212.820
Lazio	0.227	Lisboa	207.925
<i>2006</i>			
Île-de-France	1.000	Catalunya	172.681
Oberbayern	0.370	Attiki	172.534
Inner London	0.327	Pais Vasco	150.807
Comunidad de Madrid	0.314	Southern and Eastern	145.874
Denmark	0.306	Lazio	138.889
Lazio	0.297	Île-de-France	135.761
Lombardia	0.248	Stockholm	133.023
Attiki	0.244	Praha	132.395
Köln	0.234	Inner London	130.090
Region de Bruxelles	0.208	Comunidad de Madrid	127.767

Note: Eigenvector centrality is normalized between zero and one.

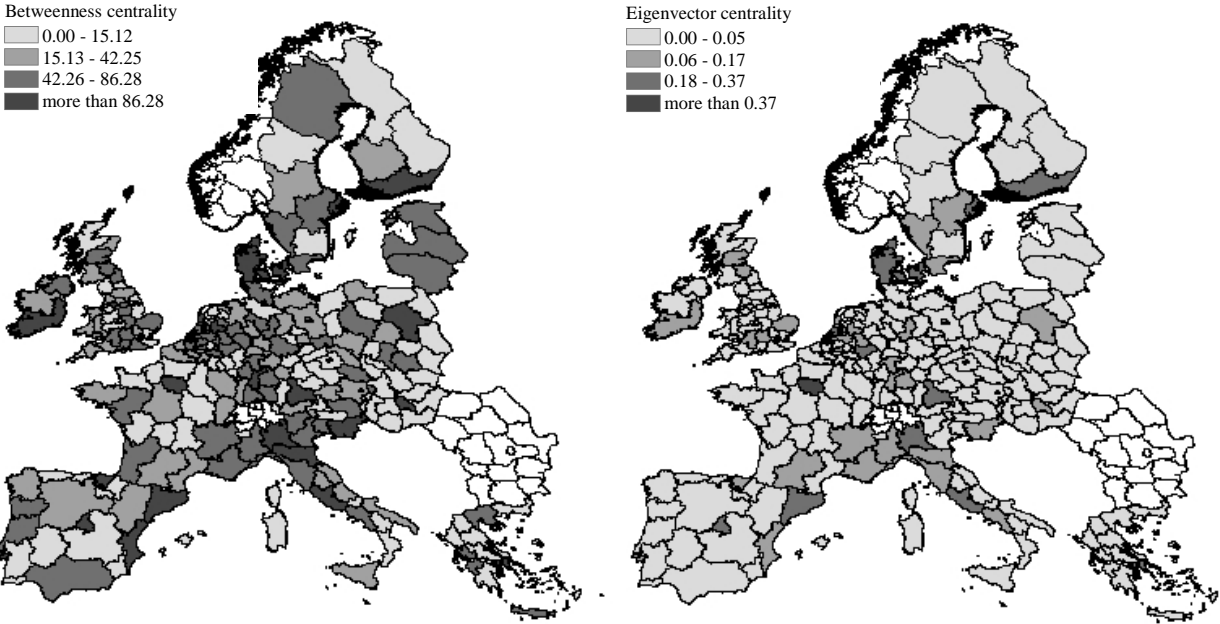
This is in line with the descriptive statistics given in Table 2 regarding the distribution of eigenvector and betweenness centrality, suggesting a highly right-skewed distribution, especially for eigenvector centrality. This finding points to the fact that there are just a few regions with high values for eigenvector centrality, while the distribution of betweenness centrality is more equally distributed. Further, it can be seen that skewness and kurtosis slightly increases between 1998 and 2006 for eigenvector centrality, while it decreases for betweenness centrality, i.e. concentration of high values on a few regions becomes higher for eigenvector centrality and lower for betweenness centrality. This may be related to the fact that new regions, in particular from Eastern European countries, increasingly participate in the FPs achieving a comparably high betweenness centrality, while they seem not to be connected to centrally positioned regions.

Table 2: Descriptive statistics for betweenness and eigenvector centrality

		Mean	Median	Standard deviation	Skewness	Kurtosis
Betweenness centrality	1998	55.410	27.320	69.584	1.874	6.891
	2006	37.580	26.01	37.464	1.234	4.140
Eigenvector centrality	1998	0.052	0.019	0.094	5.251	45.528
	2006	0.047	0.019	0.089	6.110	58.646

Figure 1 underlines these findings. It visualizes betweenness and eigenvector centrality for the year 2006 and reflects the spatial distribution of central regions in the EU funded R&D networks. It becomes obvious that especially Eastern European regions tend to catch-up in terms of betweenness centrality, while this is not the case for eigenvector centrality. However, it can be seen that a high eigenvector centrality is mainly subject to very central, mainly capital regions in Europe. Interestingly, the spatial distribution of regional eigenvector centralities shows remarkable similarities to the classical European core-periphery patterns often referred to as the European ‘blue banana’ (Brunet 2002) .

Figure 1: Regional betweenness and eigenvector centrality (2006)



Note: Natural breaks are used to classifying data into four categories.

4 Modelling regional network embeddedness

At this point, we seek to measure how different region-internal and region-external characteristics affect a region's embeddedness in the European FP network as observed in the previous section, given the two different concepts used to capture network embeddedness. Mathematically, the situation we are considering is one of observations y_{it} ($i, j=1, \dots, n=241$; $t=1, \dots, T=9$) on stochastic variables, say Y_{it} , corresponding to the centrality in the FP network of region i at time t , as measured by betweenness centrality $y_{it}^{(b)}$ or eigenvector centrality $y_{it}^{(ei)}$ defined by Equation (3) and Equation (4), respectively. Based on our theoretical framework, we assume an outcome of y_{it} to be determined by the 1-by- K row vector ($k=1, \dots, K$) of variables \mathbf{c} accounting for the *knowledge production capacity* of a region, and by the 1-by- M row vector ($m=1, \dots, M$) of variables \mathbf{z} accounting for the *regional economic structure and agglomeration effects*. From this perspective, we are interested in models of the type

$$Y_{it} = f(\mathbf{c}_{it}, \mathbf{z}_{it}) \quad i=1, \dots, n; t=1, \dots, T \quad (5)$$

that relates an endogenous random variable to our relevant exogenous determinants based on the theoretical considerations presented in Section 2. To derive an empirical model, we may in principle employ standard panel econometric techniques as given, for instance, by Baltagi (2008), leading to

$$y_{it} = \alpha + \mathbf{c}_{it}\boldsymbol{\beta}^{(c)} + \mathbf{z}_{it}\boldsymbol{\beta}^{(z)} + \mu_i + u_{it} \quad i=1, \dots, n; t=1, \dots, T \quad (6)$$

where α is a scalar parameter, $\boldsymbol{\beta}^{(c)}$ (K -by-1) and $\boldsymbol{\beta}^{(z)}$ (M -by-1) are associated parameter vectors estimating the influence of the regional knowledge production capacity \mathbf{c}_{it} , and effects of the regional economic structure and agglomeration \mathbf{z}_{it} for region i at time t . μ_i denotes the region-specific effect accounting for all space-specific time-invariant variables whose omission could bias the estimates, u_{it} is the disturbance term varying across i and t . We follow a random effects specification⁸ for balanced panel models assuming $\mu_i \sim N(0, \sigma_\mu^2)$ and independent of u_{it} .

⁸ We rely on a random effects model specification since in our case the units of observation for $n=241$ regions, in contrast to $t=9$, is relatively large, leading to a substantial loss of degrees of freedom, and thus, the spatial fixed effects could not be estimated consistently. Further, observations of certain independent variables are quite invariant in time, and could for this reason not have been included in our estimation (see, for example, Baltagi 2009). Further, the random effects specification of our empirical model is underlined by the significant Baltagi-Song-Koh-Test (Baltagi et al. 2007) pointing to random unobservable individual specific effects. The two-sided test points to the joint existence of time-series and spatial error correlation, providing statistical justification for our random effects spatial error model.

However, as we are dealing with a multiregional setting, we face a situation where interaction between our spatial units leading to spatial autocorrelation may violate the assumption of an identically distributed error term (see LeSage and Pace 2009). From spatial econometrics, two potential specifications come to mind, that is inclusion of a spatially lagged dependent variable or a spatial autoregressive process in u_{it} . In our case, we refrain including a spatial lag of y_{it} since such a model specification is usually motivated by means of significant spatial autocorrelation in the dependent variable. However, we cannot identify significant spatial autocorrelation in y_{it} ; the respective measures for spatial autocorrelation (Moran's I) for a given year t are statistically insignificant. Thus, we assume a spatial autoregressive process in u_{it} induced via spatially autocorrelated observed independent variables, which is in our case – given the independent variables introduced below – very likely. In this respect we define our error structure as given by

$$u_{it} = \rho \sum_{j=1}^n w_{ij} u_{jt} + \varepsilon_{it} \quad i=1, \dots, n; t=1, \dots, T \quad (7)$$

where w_{ij} is an element of the non-stochastic, time-invariant n -by- n spatial weights matrix \mathbf{W} describing the spatial arrangement of our set of n regions by defining $w_{ij} = 1$ if i and j are spatial neighbours in the form that they are sharing a common border, and zero otherwise, with $w_{ii} = 0$. ρ denotes the spatial autocorrelation coefficient to be estimated with $|\rho| < 1$, and ε_{it} being the IID error term. Model (6) with error specification (7) is called the panel spatial error model (SEM) with random effects. We use Maximum Likelihood estimation procedures to estimate the parameters (see Elhorst 2003 for details).

Further, from our theoretical background we assume that the characteristics from nearby regions in geographical space have an effect on y_{it} , i.e. modelling spatially discounted spillovers may add considerable value in terms of model interpretation. Thus, we extend model (6) by adding spatial lags for our independent variables, leading to

$$y_{it} = \alpha + \mathbf{c}_{it} \boldsymbol{\beta}^{(c)} + \sum_{j=1}^n w_{ij} \mathbf{c}_{jt} \boldsymbol{\gamma}^{(c)} + \mathbf{z}_{it} \boldsymbol{\beta}^{(z)} + \sum_{j=1}^n w_{ij} \mathbf{z}_{jt} \boldsymbol{\gamma}^{(z)} + \mu_i + u_{it} \quad i=1, \dots, n; t=1, \dots, T \quad (8)$$

that is referred to as the panel spatial durbin error model (SDEM) with random effects (see LeSage and Pace 2009), where $\boldsymbol{\gamma}^{(c)}$ is the K -by-1 parameter vector reflecting spatially weighted effects of the knowledge production capacity, and $\boldsymbol{\gamma}^{(z)}$ the M -by-1 parameter vector reflecting spatially weighted effects of economic structure and agglomeration. Thus, these parameters

capture spatial spillovers induced by neighbouring regions, directly interpretable as local multipliers (Le Sage and Pace 2009)⁹. Model estimation of the panel SDEM with random effects is the same as for the standard panel SEM with random effects (see Elhorst 2003).

The independent variables

As mentioned above, we consider – based on our theoretical framework presented in Section 2 – two different types of independent variables, namely a vector of variables c accounting for the *knowledge production capacity* of a region, and a vector of variables z accounting for the *regional economic structure and agglomeration effects*. We focus on $k=1, \dots, K=4$ variables accounting for a region's knowledge production capacity:

- i) $c_i^{(1)}$ captures total regional R&D expenditures, measured by the logarithmic share of public and private R&D expenditures as a percentage of GRP, used as a proxy for the degree of financial knowledge production inputs.
- ii) $c_i^{(2)}$ is the logarithmic share of population with tertiary education (corresponding to levels 5 and 6 of the ISIC 1997 classification system), serving as a measure for the regional endowment with human capital, and, in this context for the significance of knowledge for a region's economy and its absorptive capacity, which is one of the major necessities to collaborate and reap full benefits of joint R&D.
- iii) $c_i^{(3)}$ shifts attention on the region's R&D activities in high-tech sectors, and is measured in terms of number of high-tech patents¹⁰ per million employees, used in logarithmic form. We use this variable as a proxy for the existing knowledge base of the region, assuming that a high amount of high tech industry facilities is another proxy for absorptive capacity that is necessary to engage in joint R&D.
- iv) $c_i^{(4)}$ captures the degree of regional technological specialisation, using an index of specialisation measuring region's i share of patenting in each of the technological

⁹ We use the row standardized version of W allowing interpretation of the spatial lags of the independent variables being the weighted average impact on region i by their neighbouring regions. This is one specific advantage of the SDEM, namely the simplified and straightforward interpretation of both, direct and indirect effects, which are directly associated with the parameter estimates (see LeSage and Pace 2009, Sardadvar 2011). In contrast to spatial lag or spatial Durbin model specifications (see, for example, Le Sage and Fischer 2008, Fischer et al. 2009), which take global multipliers (induced by feedback loops between regions i and j) into account, the SEM and SDEM do not contain spatial lags of the dependent variable. Thus, interpretation of parameter estimates is less complicated since they directly reflect direct and indirect effects. Further, this implicates that common inference statistics such as the standard deviation and t -statistic can be used to examine significance of parameter estimates (LeSage and Pace 2009).

¹⁰ The classification of high-tech sectors is based on Eurostat.

subclasses of the International Patenting Classification (IPC)¹¹. The focus of a region's knowledge production process may range over a variation of different fields, or be very specific and specialised in a certain technology. As joint R&D means to pool, relate and assemble very different pieces of knowledge from different institutional backgrounds, a region's technological orientation may have considerable effects on a region's network embeddedness. High specialisation probably facilitates the development of a prominent and strategically advantageous position within a network, while technological diversification may reflect the possibility to engage in several networks and a better opportunity to exploit and combine inputs from different knowledge sources.

Then we include $m=1, \dots, M=3$ variables accounting for the regional economic structure and agglomeration effects.

- i) $z_{it}^{(1)}$ is the degree of industrial diversity within region i measured in terms of a industrial diversity index¹². A diverse economic structure may affect a region's attractiveness for joint R&D, given trends in increasing inter-sectoral production chains and interdependencies between different economic sectors.
- ii) $z_{it}^{(2)}$ is the logarithmic form of the gross regional product (GRP) per capita as a proxy for the general economic potential of a region that is assumed to be an impetus for the domestic R&D performance.
- iii) $z_{it}^{(3)}$ denotes the region's population density as measured by the number of inhabitants per square kilometre, used as proxy variable for the degree of urbanisation, and, in this context, for agglomeration effects.

Data have in most of the cases been drawn from the Eurostat regional database, containing information on a range of general macro-economic, education as well as science and technology related statistics at the NUTS-2 level. Furthermore, information on patents were

¹¹ The index is defined by $c_{it}^{(4)} = \frac{1}{2} \sum_Q |s_{ip} - \bar{s}_p|$ where s_{ip} is the region's i share of patents in a specific IPC class p and \bar{s}_p is the mean of IPC class p . Patents were taken into account at a three-digit level corresponding to the International Patent Classification (IPC).

¹² For the construction of the industrial diversity variable we include five different main economic sectors, namely agriculture, manufacturing, construction, private services and non-market service sector. Similar to technological specialisation, the index of specialisation to account for industrial diversity is defined as $z_{it}^{(1)} = \frac{1}{2} \sum_Q |o_{ip} - \bar{o}_p|$ where o_{ip} is the region's i share of gross value added in a specific sector p (indexed $p = 1, \dots, 5$) and \bar{o}_p is the mean of sector p for $n=241$ regions.

taken from the European Patent Office (EPO) database. Our sample comprises full data for 241 European NUTS-2 regions over the period 1998-2006.

5 Estimation Results

Table 3 presents the Maximum likelihood (ML) estimates for our regional network embeddedness models as specified in the previous section. Asymptotic standard errors are given in brackets. For our two types of network embeddedness under consideration, that is betweenness and eigenvector centrality as defined by Equations (3) and (4), we estimate a basic model version, using regional characteristics that are expected to be the most important factors based on our theoretical considerations, and an extended model version including all variables introduced in the previous section, leading to four different models versions when estimating the SEM as defined by Equation (6) and the SDEM as defined by Equation (8). In contrast to the SEM, the SDEM contains spatially lagged explanatory variables, accounting for spatial spillovers. Note that the SEM model versions are nested in the SDEM model versions. The bottom of Table 3 provides specification tests as well as various goodness-of-fit measures. From a methodological point of view it is worth noting that model performance of the SDEM compared to the SEM increases. The Bayesian information criterion (BIC) indicates that accounting for spatial interaction effects in the explanatory variables leads to better model fit. Further, for all model versions, the BSK-Test statistics underpins the joint significance of spatial error correlation and random regional effects, pointing to appropriate model specifications in terms of random vs. fixed effects and spatial error vs. spatial lag model, respectively.

This very first findings already point to a crucial result in the context of our research question related to hypothesis (iv): A region's R&D network embeddedness does not only depend on region-internal structural characteristics but is also substantially affected by indirect effects in the form of inter-regional spatial spillovers from neighbouring regions. Thus, geographical space does matter in explaining a region's embeddedness in the European FP network of R&D cooperation.

In general, parameter estimates for the different model versions are robust and significant, this holds true for direct effects exerted from region-specific characteristics, but in most cases also

for indirect impacts from neighbouring regions¹³. Concerning the influence of a region's knowledge production capacity (hypothesis *i*), all model specifications show that internal R&D expenditures, as given by the estimates for $\beta_1^{(c)}$, are indeed essential for the region's embeddedness in R&D networks, suggesting that the higher the importance of R&D in a region (proxied by the financial resources devoted to R&D) the more central is also a region's position in the FP networks, both in terms of betweenness and eigenvector centrality. Concerning eigenvector centrality, we find that R&D expenditures are the most important determinant (note that the parameters can be interpreted as elasticities), while for betweenness centrality the knowledge endowment related to human capital is more important than R&D expenditures, as given by the estimates for $\beta_2^{(c)}$. This leads to the conclusion that the region-internal knowledge endowment in the form of highly educated and specialised workers is particularly essential in order to gain access to numerous different collaborative R&D projects with partners located in different regions, reflecting the importance of absorptive capacity in that such human resources are crucial for the ability to absorb, assimilate and exploit external knowledge. However, in terms of eigenvector centrality, human capital seems to have no significant effect for the establishment of a high number of direct connections with central hubs in the European network of R&D cooperation.

Regarding technological specialisation effects (see estimates for $\beta_3^{(c)}$), the results show that a region's specialisation in only a few technological fields positively affects its R&D network embeddedness. The effects for the betweenness centrality models are higher than for the eigenvector centrality models, pointing to the fact that specialisation in a specific technological field is particularly relevant when a region aspires a central 'gatekeeper' position within the network. In contrast, when we shift attention from technological specialisation to the region's economic structure, we find that higher diversified regions in terms of industrial sectors are more likely to gain a better position in the FP network as evidenced by the estimates $\beta_1^{(z)}$.

Further, the results provide statistical evidence for the significant influence of a region's absorptive capacity, in this study measured by the number of high tech patents as proxy for the stage of development of a region's knowledge base. Although the effect is rather small, a

¹³ It is worth noting that similar results are conceived when controlling for EU15 member states. The coefficient for a EU15 dummy variable is insignificant and inclusion does not affect the estimators of the remaining variables, i.e. an Eastern European effect can be denied in explaining a region's R&D network centrality.

higher number of high-tech patents has a positive effect on a region's embeddedness in the European network of R&D cooperation, both in terms of eigenvector and betweenness centrality.

Table 3: ML estimation results for the SEM and the SDEM

	betweenness centrality				eigenvector centrality			
	SEM basic (1)	SEM extended (2)	SDEM basic (3)	SDEM extended (4)	SEM basic (5)	SEM extended (6)	SDEM basic (7)	SDEM extended (8)
<i>RD expenditures</i> [$\beta_1^{(e)}$]	0.642*** (0.156)	0.632*** (0.157)	0.527*** (0.157)	0.558*** (0.159)	0.598*** (0.075)	0.604*** (0.076)	0.557*** (0.077)	0.564*** (0.077)
<i>human capital</i> [$\beta_2^{(e)}$]	–	1.342*** (0.387)	–	1.981*** (0.043)	–	0.151 (0.204)	–	0.181 (0.209)
<i>Tech. Spec.</i> [$\beta_3^{(e)}$]	–	0.307*** (0.053)	–	0.311*** (0.053)	–	0.085*** (0.025)	–	0.098*** (0.025)
<i>High-tech pat.</i> [$\beta_4^{(e)}$]	–	0.058*** (0.011)	–	0.057*** (0.011)	–	0.028*** (0.005)	–	0.032*** (0.005)
<i>Ind. diversity</i> [$\beta_1^{(z)}$]	–	0.074*** (0.028)	–	0.064** (0.031)	–	0.042*** (0.014)	–	0.042*** (0.014)
<i>GRP p.c.</i> [$\beta_2^{(z)}$]	0.913*** (0.266)	0.280 (0.309)	0.861*** (0.277)	-0.593 (0.388)	0.732*** (0.158)	0.604*** (0.177)	0.712*** (0.163)	0.325 (0.200)
<i>Pop. density</i> [$\beta_3^{(z)}$]	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
<i>w. RD exp.</i> [$\gamma_1^{(e)}$]	–	–	0.028 (0.320)	0.051 (0.002)	–	–	0.058 (0.176)	0.132 (0.180)
<i>w. human capital</i> [$\gamma_2^{(e)}$]	–	–	–	-2.557*** (0.060)	–	–	–	-0.942*** (0.319)
<i>w. Tech. spec.</i> [$\gamma_3^{(e)}$]	–	–	–	0.020 (0.010)	–	–	–	0.017 (0.054)
<i>w. High-tech pat.</i> [$\gamma_4^{(e)}$]	–	–	–	0.066** (0.032)	–	–	–	0.090*** (0.007)
<i>w. Ind. diversity</i> [$\gamma_1^{(z)}$]	–	–	–	0.030*** (0.045)	–	–	–	0.053** (0.025)
<i>w. GRP p.c.</i> [$\gamma_2^{(z)}$]	–	–	0.185*** (0.004)	1.900*** (0.435)	–	–	0.092*** (0.022)	0.651*** (0.230)
<i>w. Pop. density</i> [$\gamma_3^{(z)}$]	–	–	-0.000 (0.000)	-0.001 (0.001)	–	–	-0.001** (0.000)	-0.001** (0.000)
SAR coefficient (ρ)	0.146*** (0.030)	0.143*** (0.030)	0.141*** (0.030)	0.123*** (0.031)	0.349*** (1.551)	0.339*** (0.026)	0.345*** (0.026)	0.339*** (0.026)
Constant (α)	-9.200*** (2.599)	-7.884*** (2.752)	-10.146*** (2.591)	-13.56*** (3.276)	-11.769*** (0.086)	-11.057*** (1.595)	12.211*** (1.541)	-13.393*** (1.954)
Log Likelihood	-4735.86	-4692.12	-4725.48	-4675.68	-3138.48	-3112.20	-3128.23	-3083.62
BIC	9517.83	9461.06	9520.11	9481.97	6323.06	6301.22	6325.61	6297.84
BSK-Test	3772.77***	3641.49***	3657.43***	3454.32***	4348.86***	4111.70***	4050.00***	3600.67***

Note: The independent variables are defined as given in the text. BIC denotes the Bayesian information Criterion, BSK-test is the Baltagi-Song-Koh Test as outlined by Baltagi et al. (2007). We checked variance inflation factors (VIFs) for the variables range inferring that there are no multicollinearity problems. ***significant at the 0.001 significance level, **significant at the 0.01 significance level, *significant at the 0.05 significance level.

The GRP per capita variable, as estimated by the coefficients $\beta_2^{(z)}$, is statistically significant for most of the basic model versions, suggesting that the general environment and economic conditions for a region's centrality in FP networks is crucial. However, the effect becomes insignificant for model (2), (4) and (8), i.e. other key factors, particularly those reflecting knowledge production capabilities, seem to some extent capture the effects attributed to the general region's economic development in the basic model versions. In contrast, the estimates $\beta_3^{(z)}$ for population density are significant for all model versions but exert only a marginal influence, providing evidence that central regions in terms of urbanisation (as proxied by population density) do only weakly affect 'relational' centrality in terms of network centrality.

Controlling for spatial spillovers in the respective models (see models (3), (4), (7) and (8)), the substantive results for region-internal characteristics remain unaffected, underlining robustness of the results. Interestingly, the estimates $y_2^{(c)}$ for the spatial lag of the human capital variable, are statistically significant and pointing to a negative effect, i.e. a high level of human capital in neighbouring regions has a negative effect on a region's network embeddedness. For a specific region this indicates that a certain concentration of highly educated workers in neighbouring regions leads to a decreasing potential for gaining a central position in FP networks, pointing to some kind of regional concentration effects and limited availability of human capital. However, when it comes to the knowledge endowment of neighbouring in the form of high-tech patents, we find a positive effects on a region's network embeddedness, as given by the estimates for $y_4^{(c)}$. The positive coefficient for the spatially lagged number of high-tech patents points to indirect effects from neighbouring regions, underscoring the significance of inter-regional knowledge spillovers in high-technology industries, as also found by Scherngell et al. (2008). Significant positive spatial spillover effects are also induced by the economic structure of neighbouring regions, reflected in the spatially lagged parameter estimates $y_1^{(z)}$ for industrial diversity and GRP per capita $y_2^{(z)}$.

6 Concluding remarks

One of the main research fields in Regional Science focuses on the 'geography of innovation'. This is to a large extent related to theoretical considerations assuming that innovation is the key driver for long-run economic growth, and to empirical studies providing evidence for innovative activity to be remarkably concentrated in geographical space. In the recent past,

the participation of regions in inter-regional R&D networks – based on considerations that such networks have become the norm rather than the exception in modern innovation processes. – has gained increasing interest, assuming that being part of such networks is an essential determinant for regional innovative capability, and, thus for regional competitiveness.

The focus of this study is on the embeddedness of European regions in R&D networks constituted under the heading of the European Framework Programmes (FPs). From a regional perspective, it is assumed that participation in such networks enhances the regional innovation capability due to existence of intra-regional knowledge spillovers enriched by inter-regional knowledge flows transmitted via such network channels. A strategic advantageous position in such networks allows not only direct access and receipt of external knowledge through direct linkages, but also through indirect allies to relevant regions in the entire network. The objective of this study was to estimate how different region-internal and region-external characteristics affect a region's embeddedness in the European network of R&D cooperation. Network embeddedness is captured in terms of a region's betweenness centrality, measuring a region's ability to control knowledge flows, and eigenvector centrality, measuring a region's connectedness with central hubs of the network. We consider independent variables accounting for the knowledge production capacity of a region and the regional economic structure, establishing the link between regional network embeddedness and the independent variables by means of panel spatial error models and panel spatial durbin error models with random effects.

The results are promising in the context of relevant scientific literature, but also imply significant policy implications, in particular from the perspective of regional policy makers. *First*, R&D expenditures are of crucial importance to boost a region's embeddedness in the European network of R&D cooperation, both in terms of betweenness centrality and eigenvector centrality. *Second*, the presence of highly educated workers has a higher positive effect than R&D expenditures for stimulating a region's betweenness centrality, i.e. its ability to control knowledge flows as 'gatekeeper', while it is less important for increasing a region's eigenvector centrality. *Third*, technologically specialised regions are in a position that fosters their network embeddedness, in particular when it comes to betweenness centrality, i.e. a high technological specialisation attracts a diverse set of network partners searching for specific pieces of knowledge. *Fourth*, the region's absorptive capacity has a positive effect on a region's embeddedness in the European network of R&D cooperation, both in terms of

eigenvectors and betweenness centrality. *Fifth*, the study provides evidence that spatial spillovers from neighbouring regions influence a region's FP network embeddedness in different ways.

In a policy context, it can be concluded that higher R&D expenditures and high level of education as well as the ability to attract highly educated workers is crucial to get access to inter-regional knowledge flows, in particular when a region aims to become a central 'gatekeeper' in the European network of R&D cooperation providing sustainable access to different pieces of knowledge. Concerning the results that technological specialisation is conducive gaining a central network position, while at the same time industrial diversity seems to have a – though small – positive effect, authorities may be encouraged to support specialisation in certain key technologies to be attractive in R&D networks, while such technologies may at the same time be used in different economic sectors leading to a diversified industrial structure. Further, the promotion to become a specialised player in specific technological fields or niches via specific funding programmes or other targeted measures such as regional cluster initiatives may be an appropriate way to bring the region in a position where its specialised knowledge can be tapped by region-external partners. Then, the outflow of highly educated people to neighbouring regions has to be avoided by providing respective framework conditions as a 'brain drain' in this direction will highly reduce a region's embeddedness in the European network of R&D cooperation. Finally, some ideas for a future research agenda come to mind: *First*, a dynamic analysis investigating the evolution of a region's network position would be of crucial interest to enrich our understanding in the context of European network dynamics as well as in a policy context regarding the realisation of an integrated and coherent European research area. *Second*, the study is limited to a very specific type of politically induced R&D networks, which are voluntary collaborations, and therefore restricted to very distinct types of arrangements. Thus, the additional investigation of other types of R&D networks may be a valuable extension to the current study.

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Appendix A: List of regions

NUTS is an acronym of the French for the “nomenclature of territorial units for statistics”, which is a hierarchical system of regions used by the statistical office of the European Community for the production of regional statistics. At the top of the hierarchy are NUTS-0 regions (countries) below which are NUTS-1 regions and then NUTS-2 regions. This study disaggregates Europe's territory into 255 NUTS-2 regions located in the EU-25 member states (except Cyprus and Malta) plus Norway and Switzerland. We exclude the Spanish North African territories of Ceuta y Melilla, the Portuguese non-continental territories Azores and Madeira, and the French Departments d'Outre-Mer Guadeloupe, Martinique, French Guayana and Reunion. Thus, we include the following NUTS 2 regions:

<i>Austria:</i>	Burgenland, Kärnten, Niederösterreich, Oberösterreich, Salzburg, Steiermark, Tirol, Vorarlberg, Wien
<i>Belgium:</i>	Prov. Antwerpen, Prov. Brabant-Wallon, Prov. Hainaut, Prov. Limburg (B), Prov. Liège, Prov. Luxembourg (B), Prov. Namur, Prov. Oost-Vlaanderen, Prov. Vlaams-Brabant, Prov. West-Vlaanderen, Région de Bruxelles-Capitale / Brussels Hoofdstedelijk Gewest
<i>Czech Republic:</i>	Jihovýchod, Jihozápad, Moravskoslezsko, Praha, Severovýchod, Severozápad, Střední Morava, Střední Čechy
<i>Denmark:</i>	Danmark
<i>Estonia:</i>	Eesti
<i>Finland:</i>	Åland, Etelä-Suomi, Itä-Suomi, Länsi-Suomi, Pohjois-Suomi
<i>France:</i>	Alsace, Aquitaine, Auvergne, Basse-Normandie, Bourgogne, Bretagne, Centre, Champagne-Ardenne, Corse, Franche-Comté, Haute-Normandie, Île de France, Languedoc-Roussillon, Limousin, Lorraine, Midi-Pyrénées, Nord - Pas-de-Calais, Pays de la Loire, Picardie, Poitou-Charentes, Provence-Alpes-Côte d'Azur, Rhône-Alpes
<i>Germany:</i>	Arnsberg, Berlin, Brandenburg, Braunschweig, Bremen, Chemnitz, Darmstadt, Dessau, Detmold, Dresden, Düsseldorf, Freiburg, Gießen, Halle, Hamburg, Hannover, Karlsruhe, Kassel, Koblenz, Köln, Leipzig, Lüneburg, Magdeburg, Mecklenburg-Vorpommern, Mittelfranken, Münster, Niederbayern, Oberbayern, Oberfranken, Oberpfalz, Rheinhessen-Pfalz, Saarland, Schleswig-Holstein, Schwaben, Stuttgart, Thüringen, Trier, Tübingen, Unterfranken, Weser-Ems
<i>Greece:</i>	Anatoliki Makedonia, Thraki; Attiki; Ipeiros; Voreio Aigaio; Dytiki Ellada; Dytiki Makedonia; Thessalia; Ionia Nisia; Kentriki Makedonia; Kriti; Notio Aigaio; Peloponnisos; Sterea Ellada
<i>Hungary:</i>	Dél-Alföld, Dél-Dunántúl, Észak-Alföld, Észak-Magyarország, Közép-Dunántúl, Közép-Magyarország, Nyugat-Dunántúl
<i>Ireland:</i>	Border, Midland and Western; Southern and Eastern
<i>Italy:</i>	Abruzzo, Basilicata, Calabria, Campania, Emilia-Romagna, Friuli-Venezia Giulia, Lazio, Liguria, Lombardia, Marche, Molise, Piemonte, Puglia, Sardegna, Sicilia, Toscana, Trentino-Alto Adige, Umbria, Valle d'Aosta/Vallée d'Aoste, Veneto
<i>Latvia:</i>	Latvija

<i>Lithuania:</i>	Lietuva
<i>Luxembourg:</i>	Luxembourg (Grand-Duché)
<i>Netherlands:</i>	Drenthe, Flevoland, Friesland, Gelderland, Groningen, Limburg (NL), Noord-Brabant, Noord-Holland, Overijssel, Utrecht, Zeeland, Zuid-Holland
<i>Poland:</i>	Dolnośląskie, Kujawsko-Pomorskie, Lubelskie, Lubuskie, Łódzkie, Mazowieckie, Małopolskie, Opolskie, Podkarpackie, Podlaskie, Pomorskie, Śląskie, Świętokrzyskie, Warmińsko-Mazurskie, Wielkopolskie, Zachodniopomorskie
<i>Portugal:</i>	Alentejo, Algarve, Centro (P), Lisboa, Norte
<i>Slovakia:</i>	Bratislavský kraj, Stredné Slovensko, Východné Slovensko, Západné Slovensko
<i>Slovenia:</i>	Slovenija
<i>Spain:</i>	Andalucía, Aragón, Cantabria, Castilla y León, Castilla-La Mancha, Cataluña, Comunidad Foral de Navarra, Comunidad Valenciana, Comunidad de Madrid, Extremadura, Galicia, Illes Balears, La Rioja, País Vasco, Principado de Asturias, Región de Murcia
<i>Sweden:</i>	Mellersta Norrland, Norra Mellansverige, Småland med öarna, Stockholm, Sydsverige, Västsverige, Östra Mellansverige, Övre Norrland
<i>United Kingdom:</i>	Bedfordshire & Hertfordshire; Berkshire, Buckinghamshire & Oxfordshire; Cheshire; Cornwall & Isles of Scilly; Cumbria; Derbyshire & Nottinghamshire; Devon; Dorset & Somerset; East Anglia; East Riding & North Lincolnshire; East Wales; Eastern Scotland; Essex; Gloucestershire, Wiltshire & North Somerset; Greater Manchester; Hampshire & Isle of Wight; Herefordshire, Worcestershire & Warwickshire; Highlands and Islands; Inner London; Kent; Lancashire; Leicestershire, Rutland and Northamptonshire; Lincolnshire; Merseyside; North Eastern Scotland; North Yorkshire; Northern Ireland; Northumberland and Tyne and Wear; Outer London; Shropshire & Staffordshire; South Western Scotland; South Yorkshire; Surrey, East & West Sussex; Tees Valley & Durham; West Midlands; West Wales & The Valleys; West Yorkshire