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R&D networks and regional knowledge production in Europe: Evidence from a space-time model

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R&D networks and regional knowledge production in Europe.
Evidence from a space-time model

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ABSTRACT: In this paper we estimate space-time impacts of the embeddedness in R&D networks on regional knowledge production by means of a dynamic spatial panel data model with non-linear effects for a set of 229 European NUTS-2 regions in the period 1999-2009. Embeddedness refers to the positioning in networks where nodes represent regions that are linked by joint R&D endeavours in European Framework Programmes. We observe positive immediate impacts on regional knowledge production arising from increased embeddedness in EU funded R&D networks, in particular for regions with lower own knowledge endowments. However, long-term impacts of R&D network embeddedness are comparatively small.

1 Introduction

In the recent past, scientific research on the geographical dimension of R&D networks has attracted increasing interest. Such networks involve knowledge relations between a variety of actors coming from different sectors, industries and spatial scales. Research actors join together in R&D activities with the effect that specific skills or know-how of partners located further away in geographical space can be absorbed more easily. The regional science literature traditionally has devoted great emphasis on the spatial dimension of knowledge production, and in particular the spatial spread of knowledge diffusion; thus inter-regional R&D networks – defined as networks with nodes representing regions that are inter-linked by joint R&D endeavours – are of particular interest in the field (Autant-Bernard et al. 2007; Bergman 2009; Scherngell 2013). More recently, scholars increasingly apply a network analytic perspective by grasping the relations between organisations performing collaborative R&D as channels where knowledge can diffuse freely within and across regions (see, e.g. Wanzenböck et al. 2014a).

The study at hand follows this research stream, focusing on regional knowledge production and its relation to the embeddedness of regions in inter-regional R&D networks. By the notion of embeddedness we refer the structural positioning of regions in networks from a network analytic perspective. The theoretical discussion has been shaped by arguments highlighting the importance of so-called global pipelines, i.e. R&D networks that cross regional borders (Bathelt et al. 2004). As it is argued, the outward orientation of regions – or of distinct regional actors within a regional innovation system – provides important stimuli for regional knowledge generation and ensures knowledge-driven economic prosperity (Giuliani and Bell 2005; Breschi and Lenzi 2014). The inflow of novel ideas, knowledge and skills may enhance the ability or effectiveness of knowledge creation in regional sites, creates new impulses and mitigates the risk of being locked in narrow technology or sector specific thinking. However, recently also negative consequences have been put forward for regions that show a high degree of region external cooperation, for instance due to less developed region-internal interaction, knowledge exchange and learning processes (Graf 2011; Broekel et al. 2015). The questions that arise in this context are whether and in which way strong embeddedness in inter-regional R&D networks influences the ability of regions to produce new knowledge.

From an empirical perspective, systematic empirical evidence on the effects of R&D networks on regional knowledge and innovation performance, especially from a European perspective, is still scarce and inconclusive (see, e.g. Sebestyén and Varga 2013; Varga et al. 2014). This study proposes a new line of investigating the specific relationship of regional participation in inter-regional R&D networks, i.e. the embeddedness of regional organisations therein, to knowledge production activities at the regional level. The objective is to estimate space-time impacts of regional embeddedness in R&D networks on regional knowledge production in Europe. To address this objective, we implement a space-time approach and mainly consider the role of own region knowledge production endowments.

Our empirical application covers a set of 229 European NUTS-2 regions. Knowledge production is measured in terms of annual patent applications for the years 1999-2009; EU funded R&D networks are observed on the basis of collaborative R&D projects funded by the European Framework Programmes (FPs).

In this study we propose a comprehensive empirical approach that distinguishes itself from those applied in previous studies in at least three major aspects: *First*, effects of R&D networks on the generation of new knowledge are assumed to be moderated significantly by a region's endowment with own knowledge-generating factors. Thus, we specify an empirical knowledge production relationship that considers a region's embeddedness in R&D networks to be conditionally effective for increasing the knowledge output in regions. *Second,* a space-time perspective is implemented in order to show how effects of R&D network embeddedness unfold within and across European regions and over time. As space-time models producing spatial, temporal as well as spatio-temporal spillover effects are rather new to the field (Parent 2012), the current study will shed new light on the role of spatio-temporal spillover effects in a regional knowledge generation framework for the case of European regions. *Third,* we augment basic space-time impact measures (see Debarsy et al. 2012) by specifying an interacting effect in the set of regional knowledge production determinants. Investigating impacts of R&D network embeddedness in dependence of the own region knowledge endowments allows us to consider region-specific differences in the accessibility and absorbability of external knowledge via R&D network linkages, but also related to spillover effects over time and space.

The study is organised as follows. Section 2 deals with the theoretical background where we put forward our arguments for considering a conditional relationship between R&D networks and regional knowledge generation. Section 3 describes the empirical modelling approach, before Section 4 introduces the interaction term in our set of regional knowledge production determinants. Section 5 presents the approach to measure associated space-time impacts. In Section 6 we describe the data and the construction of the variables employed to reflect a region's embeddedness in R&D networks. Section 7 discusses the main findings, and in Section 8 we provide our conclusions and main pointers for future research.

2 Theoretical background

The increasing significance of inter-regional R&D networks has contributed to a reconceptualization of regional knowledge creation processes in the regional science and economic geography literature. In particular the work of Bathelt et al. (2004) has stimulated the debate on the complementarity character of the so-called 'local buzz' and 'global pipelines' when it regards the question of how new knowledge is generated. Here, 'global pipelines' refer to a specific type of knowledge relations that is

most often established over longer distances in geographical space and targeted specifically towards the exploitation of external knowledge sources, or specific skills not available in the local environment. Related literature suggests that such 'global pipelines' – in contrast to local-buzz types of knowledge relations (Storper and Venables 2004) – are tied more closely to certain purposes, and thus, are more often characterised by structured and formalized forms of interaction (see, for example, Giuliani and Bell 2005; Moodysson 2008; Graf 2011). Examples of such formal relations often mentioned in the context of R&D networks range from collaborative projects at the early or pre-competitive stages of the R&D process, to co-inventorship or co-publication (Scherngell and Barber 2009; Hoekman et al. 2010; Wanzenböck et al. 2014b, among others).

One of the fundamental assumptions in the regional science literature on R&D networks is that skills or competences are clustered spatially and concentrated regionally, and that specific pieces of knowledge can be accessed more easily by means of R&D collaboration (Autant-Bernard et al. 2007; Scherngell 2013). Partners share, exchange or pool knowledge and resources in their joint R&D endeavours, thus, are able to participate more actively in the specialised capabilities and tacit pieces of knowledge of others. Inspired by a network perspective, R&D linkages are often regarded in terms of channels that enable the flow of knowledge (Owen-Smith and Powell 2004). In cases where collaboration partners are located in different regional surroundings, strong R&D network relations facilitate the transfer of knowledge between different regions. Moreover, the expectations placed on the benefits of long distance R&D networks have considerably influenced policy measures at the regional, national or supranational level, so that promoting collaborative R&D has developed to one of the key concepts in current policy strategies (Breschi and Malerba 2009).

A number of studies have been produced so far investigating effects of cross-regional R&D relations of different spatial scales and in different geographical settings (see e.g. Ponds et al. 2010 for science-industry relations in the Netherlands; Broekel 2013 for cooperative R&D subsidies in Germany; or Sebestyén and Varga 2013; Varga et al. 2014 for EU Framework Programme projects across Europe). However, one aspect which has been widely disregarded in the empirical literature is the role played by a region's own resources in moderating the effects of networks. When it comes to the question of how embeddedness in inter-regional R&D network structures influences the knowledge performance of regions, we suggest placing higher emphasis on the conditional nature of how R&D networks are related to a region's knowledge production performance. In essence, we distinguish three main arguments supporting the idea of such a conditional relationship:

First, motives for engaging in R&D networks refer either to exchanging ideas, or they are directly related to aims of co-producing some kind of knowledge and absorbing specific know-how not available in own surroundings (Ozman 2009). Regional actors need to bring specific knowledge and skills into the collaborative endeavours, also for being recognized as valuable partners in present and future cross-regional R&D projects. The higher the quality of own regional knowledge endowments

the higher might be a region's embeddedness in inter-regional R&D settings. This could be even more the case when policy-funded R&D projects are concerned, where policy aims are not only related to the pooling of resources located in different regional environments but also to bringing knowledge production abilities of different regions closer to each other.

Second, while the economic geography literature generally assumes that R&D networks support and facilitate knowledge generation activities (see e.g. Bathelt et al. 2004; Huggins and Thompson 2014), the economics of networks literature deliver indications that gains of R&D network participation could also diminish. With increasing number of linkages, for instance, it is more likely that certain projects or collaboration partners are of low value while the costs of coordinating these linkages grow (see e.g. Goyal 2012). Collaborative projects – especially when region-external partners are involved – might constitute such a drain on resources that a sufficient amount of relational capacities is required for activating simultaneously and maintaining successfully a set of different R&D network linkages (Wanzenböck et al. 2014a). High outward orientation of regions could therefore hamper considerably the efficiency in generating new knowledge (Graf 2011; Broekel et al. 2015). Negative effects might be particularly severe if regions show high outward orientation and intensive interactions in cross-regional endeavours but lack the own capacities to process the knowledge absorbed by the R&D network linkages.

Third, and most important in the context of this study is the argument that positive effects of increasing embeddedness of regions in R&D networks might arise only if the regional actors have sufficient abilities to comprehend, integrate and process knowledge generated somewhere else. Both availability and quality of own knowledge-generating endowments determine the degree of absorbing non-regional knowledge and learning within regions. This point refers to the notion of absorptive capacity (Cohen and Levinthal 1990) suggesting that qualified individuals (e.g. researchers, scientists, engineers) or knowledge-intensive organisations (e.g. universities, firms, research organisations) are required to reap full benefits of R&D networks. Only in this case inter-regional R&D networks might truly leverage effectiveness or ability of creating new knowledge in regions. However, we can further expect that the marginal benefit of additional R&D relations is smaller for regions that are already equipped with high quality resources – thus also have high absorptive capacity – than for catching-up regions where own knowledge endowments are still limited.

Against the background of the main arguments presented above, we hypothesize that a region's own endowment with knowledge-generating factors significantly moderates the effects realised from cross-regional R&D linkages. However, the distinct relation between the embeddedness of regions in R&D networks and the own regional knowledge endowments is still to be explored in a regional knowledge production relationship. The next section introduces the modelling approach pursued to address this issue.

3 The space-time model

We employ a dynamic spatial panel data model to explore the relationship between the embeddedness of regions in R&D networks and regional knowledge production across European regions. The space-time model incorporates time-specific parameters in addition to spatial parameters, which enables us to capture jointly time and spatial dependence as well as space-time diffusion of regional knowledge production, and by this, trace the impact of the explanatory variables over time and space. Such space-time models are more complex in terms of estimation and interpretation of the model parameters, and thus, have been rarely applied in empirical research so far. Exceptions are the studies of Fischer and LeSage (2014) for regional convergence, Elhorst et al. (2013) for financial liberalisation and Vega and Elhorst (2014) analysing dynamics of labour market shocks, or Parent and LeSage (2010) for commuting flows. Moreover, the study of Parent (2012) is the first study that takes a space-time perspective in analysing knowledge production of US regions. The findings regarding significant temporal knowledge diffusion and higher regional interconnectivity in the long run are convincing theoretically, and opening up a new and highly relevant field of empirical applications for dynamic spatial panel data models. Our space-time approach to model regional knowledge production takes the form of a dynamic Spatial Durbin Model (SDM)[1] for a multiregional system with $i = 1, ..., N$ regions and $t = 2, ..., T$ periods, given by

$$y_t = \phi y_{t-1} + \rho W y_t + \theta W y_{t-1} + x_{t-1}\beta + W x_{t-1}\gamma + v_t \tag{1}$$

with

$$v_t = \mu + \tau_t \iota_N + \varepsilon_t \tag{2}$$

and

$$\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2 I_N) \tag{3}$$

where $y_t = (y_{1t}, ..., y_{Nt})$' is N x 1 containing observations of annual knowledge output in period t for every region in the sample, expressed in logarithms. Subscript t-1 is used for vectors containing serially lagged values. Vectors multiplied with W indicate spatially lagged values according to an N x N time-invariant, non-negative and row-normalized spatial weight matrix with w_{ij} elements describing the spatial connectivity structure between regions i and j. The elements of W are assumed as given

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[1] SDM specifications have gained growing interest in empirical research with focus on knowledge production or knowledge-based growth (see e.g. LeSage and Fischer 2008; Autant-Bernard 2012). LeSage and Pace (2009) provide important methodological motivation for preferring the SDM over other spatial model specifications such as the spatial autoregressive (SAR) model, especially in cases where *i)* important variables are likely to be omitted from the model, *ii)* these variables tend to be correlated with the explanatory variables included in the model, and *iii)* the disturbance process may be spatially correlated (LeSage and Pace 2009). All three points must be kept in mind when dealing with knowledge production phenomena where spatial correlations in the data have been widely confirmed, data availability is limited and omitted variable bias likely to arise.

with $w_{ij} > 0$ for $i \neq j$, if region i is assumed as being a neighbour to region j, and zero otherwise. Moreover, $w_{ii}=0$ for all i.

The scalars ϕ, ρ and θ are response parameters associated with y_{t-1}, denoting observations on regional knowledge production from the previous time period, Wy_t, the spatially weighted regional knowledge production, i.e. knowledge production of neighbouring regions in time period t, and Wy_{t-1}, regional knowledge production lagged in both space and time, respectively. The spatially lagged dependent variables, Wy_t and Wy_{t-1} imply that cross-regional knowledge diffusion effects are treated as endogenous. Hence, knowledge production of a particular region is determined by the knowledge production activities of that region in the previous year, as well as by knowledge produced in other regions in the same as well as in the previous year. The latter refers to regional diffusion effects of knowledge, depending on the specification of the spatial weight matrix W. W is specified according to the k nearest neighbours criterion, where positive values are assigned to the k=5 nearest neighbouring regions measured in terms of great circle distances[2]. $x_{t-1} = (x_{1t-1}, \ldots, x_{Nt-1})$' denotes an N x R matrix of explanatory variables, representing factors assumed to influence our knowledge production relationship. β and γ denote parameter vectors associated with these variables.

$v_t = (v_{1t}, \ldots, v_{Nt})$' is an N x 1 vector reflecting the disturbance specification at time t, with $\mu = (\mu_1, \ldots, \mu_N)$' being the N x 1 vector of region-specific fixed effects, and τ_t denoting time-specific fixed effects where ι_N is an N x 1 vector of ones, and $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{Nt})$' is an N x 1 vector of disturbances with zero mean and variance of $\sigma_\varepsilon^2 I_N$. We use a fixed-effects specification to control for time- and region-specific heterogeneities. The latter captures the effects arising from omitted factors in our knowledge production relationship which are specific to a distinct region in our sample, while the former controls for common effects that influence knowledge production activities among all regions in the sample. Elhorst et al. (2013) argues in favour of including time-specific effects in spatial panel data models in order to prevent potential upward bias of the spatial dependence parameter.

The parameters of the model are estimated using the bias corrected quasi maximum likelihood (ML) estimation procedures as put forward by Yu et al. (2008). It is worth noting that this approach does not specify the initial condition, but treat the data generation process as conditional on the first cross-section. The way of how to treat the initial period should, however, exert only little impact on the estimation when T is reasonably large (see e.g. Elhorst 2012; Parent and LeSage 2012 for a more rigorous discussion on this issue). Furthermore, Yu et al. (2008) show that the parameter estimates are consistent under the condition $\phi+\rho+\theta < 1$.

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[2] To check robustness against the specification of the spatial weight matrix, we run regressions for alternative spatial weight matrix specification from two to ten nearest neighbours. Results and main conclusions remain the same, and are available upon request.

4 Accounting for the moderating effect of a region's knowledge endowments

Based on our theoretical framework, we distinguish two different types of independent variables: *i*) knowledge-generating factors which are fundamental and required to produce some kind of knowledge output, and *ii*) facilitating factors that may affect the efficiency and in this way the output of the knowledge production process. In this study, the embeddedness in R&D networks is counted among the second type as involvement in R&D networks may be only conditionally effective to regional knowledge production; a fact which has been neglected in many studies focusing on knowledge production or innovation at the regional level.

Such nonlinearities in the explanatory variables can formally be best described by including an interaction term in the model (Greene 2008). Hence, we specify the determinants of knowledge production – the explanatory variables in the model – in the following form

$$x_{t-1} = [h_{t-1}, c_{t-1}, h_{t-1} \odot c_{t-1}, z_{t-1}] \tag{4}$$

where x_{t-1} is a N x R ($r = 1, ..., R = 5$) matrix involving a set of factors relevant for regional knowledge production at time t-1. h_{t-1} represents a region's endowment with knowledge production factors and c_{t-1} represent the embeddedness of the region in R&D networks, both constitute main terms in our model. Furthermore, we consider additional effects on regional knowledge production as given by z_{t-1} which denotes an N x O ($o=1, …, R$-2) matrix of additional control variables. In order to deal with possible endogeneity between the regressors and the dependent variable, we impose a time lag of one year for all explanatory variables in our knowledge production relationship. As it takes time that knowledge generating endowments can be transformed into new knowledge, assuming a time lag of one to several years' is commonly suggested in studies dealing with knowledge production (Griliches, 1995; Fischer and Varga 2003). However, in the case of dynamic models producing space-time diffusion processes and allowing us to trace impacts over several years, the time lag is assumed to be less important than it might be the case for cross-sectional models. Details on the definition of the explanatory variables are given in Sections 6.

Potential interaction effects of the two main variables h_{t-1} and c_{t-1} are reflected by $\odot$ denoting the Hadamard element-wise multiplication operator. This interaction term allows us to control for potential non-linearities in the knowledge production relationship. Specifically, based on this interaction term we are able to test whether the impact of R&D network embeddedness on knowledge production changes as a function of a region's level of own knowledge endowments. A significant coefficient would confirm our assumption of moderating effects arising from a region's own knowledge endowments, with a positive coefficient suggesting a relationship between knowledge resources and embeddedness in R&D networks that is generally reinforcing. A negative sign would

conversely suggest higher impacts in regions with low own endowments and a situation where lacking of own region endowments can be substituted effectively by higher R&D network embeddedness[3].

However, interpretation of the main terms is more complicated given the non-linearity of the interaction term. In spatial autoregressive models in general, LeSage and Pace (2009) show that the estimated slope parameters are not interpretable as compared to classical linear models. Additional complexity is moreover introduced via the interaction term (for details see the literature on interaction models, such as Jaccard and Turrisi 2003; or Balli and Sørensen 2013). They reflect a conditional relationship which is defined only for a distinct value of the other variable included in the interaction term[4]. One solution to receive more revealing interpretations from models with interaction terms in the variables is to calculate marginal effects consisting of the first partial derivative of the model (Balli and Sørensen 2013). We take this approach up in the next section demonstrating interacted variables are interpreted in the context of space-time impact measures.

5 Space-time impact measures

Endogenous regional diffusion effects in our space-time model imply that changes in the explanatory variables, i.e. knowledge inputs, of one region (at time t) will impact not only the contemporary and future knowledge outcome of the respective region (direct impact), but may also influence the knowledge outcome in all other regions (indirect impact). Thus, the model is able to characterise cases of temporal and inter-regional dependencies in knowledge production, where newly produced knowledge in one region may diffuse and in this way influence knowledge production also in other regions[5]. This section shows how such impacts over time (temporal spillovers) and space (spatial and spatio-temporal spillovers) associated with changes in R&D network centrality can be identified on the basis of the model parameters of the space-time model.

LeSage and Pace (2009) demonstrated in a cross-sectional context that specific impact measures are required in order to interpret the regression parameters of a spatial model with endogenous spillover effects correctly. Based on a partial derivative expression of the model they provide valuable measures

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[3] In this study we characterise a situation where R&D network centrality is the variable of interest, thus consider a region's own knowledge endowments as the factor that moderates the network effects on knowledge production. However, one might also be interested in the reverse case, i.e. whether the effects of own-region input factors increase with higher centrality in R&D networks. Note that both definition of the interaction model and statistical results of the analysis will remain the same, although interpretation of results might differ according to the distinct theoretical conceptualisation.

[4] For example, the regression coefficient for the R&D network embeddedness variable would reflect the influence of a region's network positioning when a region's own knowledge endowments equal zero. However, characterising the effects of R&D networks for situations where regions do not draw on own resources is not meaningful.

[5] Consider a situation where pieces of new knowledge developed in region a, and made available by the application of a patent, deliver the basis for other inventions and patents developed in the other regions (say b, c and d). Some of these ideas, in turn, may provide important input for additional inventions in region a. Such effects often referred to as feedback effects in the spatial econometric literature are highly relevant in the context of regional knowledge production. The specific character of the knowledge and innovation process, which is increasingly incremental than radical, as well as the public availability of distinct pieces of knowledge, for instance through patent documents, are assumed to additionally drive such inter-regional knowledge transmission processes.

for quantifying and drawing statistical inferences for direct and indirect (spillover) impacts in a multiregional system. Recently, several authors have taken up the basic reasoning and extended the approach to the case of space-time models (for an overview of the literature see Elhorst 2012).

For the space-time model as given in Eq. (1), we follow Debarsy et al. (2012) and define the impact on knowledge production at a particular point in time $t+s$ in terms of own- and cross-region partial derivatives with respect to the r-th explanatory variables at time t-1:

$$\frac{\partial y_{t+s}}{\partial x_{t-1}^{(r)'}} = D_s \, (I_N \, \beta_r + W \, \gamma_r) \tag{5}$$

with

$$D_s = (-1)^s \, (B^{-1} \, A)^s \, B^{-1} \ \text{ for } s = 0, \dots, S \tag{6}$$

where

$$A = -(\phi I_N + \theta W) \tag{7}$$

$$B = (I_N - \rho W) \tag{8}$$

D_s is a $N \times N$ space-time transformation matrix reflecting the temporal and spatial diffusion of impacts in the s-th period ahead, where A accounts for the diffusion of impacts over time and space (spatio-temporal spillovers) and B is referred to as the spatial diffusion parameter. In this model we are not able to trace separately the effects resulting from time dependence from those effects arising from spatial dependence or space-time diffusion (see Parent and LeSage 2010).

The diagonal elements of the $N \times N$ matrix of own and cross-partial derivatives resulting from Eq. (5) represent the direct effects in the different regions of the sample, and the off-diagonal elements are the indirect effects. To obtain a scalar summary measure for the direct impacts we follow the approach as first proposed by LeSage and Pace (2009), calculating the average over all regions, i.e. the main diagonal elements of the matrix. The scalar measure for the indirect impact is given by the average of the row sums (or column sums) of the off-diagonal elements. The total impact is the sum of the direct and indirect effects. In a similar way we are able to calculate the direct and indirect impacts at any time $t+s$ of a one unit change of the explanatory variable at time t-1.

In addition to these impact measures, we extent the basic impact expressions for space-time models to apply these measures also for empirical applications that contain non-linear terms in the variables, as in this study given by the interaction term $h_{t-1} \odot c_{t-1}$. Formally, the modifications are straightforward. We make use of marginal effect (i.e. partial derivative) interpretations of the model and define the space-time impacts with respect to changes in the R&D network centrality variable by

$$\frac{\partial y_{t+S}}{\partial x_{t-1}^{(c)'}} = D_s \left[I_N \, \beta_{(c)} + W \, \gamma_{(c)} + \text{diag}(x_{t-1}^{(h)}) \, \beta_{(h \odot c)} + W \, \text{diag}(x_{t-1}^{(h)}) \, \gamma_{(h \odot c)} \right] \tag{9}$$

where $D_s = (-1)^s (B^{-1} A)^s B^{-1}$. $x_{t-1}^{(c)}$ represents observations of the regional R&D network embeddedness at time t-1, $x_{t-1}^{(h)}$ represents regional knowledge endowments at time t-1, and $\beta_{(h \odot c)}$ and $\gamma_{(h \odot c)}$ are the coefficients associated with the (spatially lagged) interaction term. In analogy to Eq. (5), the direct (own region) knowledge production impacts of a one unit increase of the R&D network variable – but here adjusted by interaction relationship with the level of knowledge endowments of that region – are given by the main diagonal elements of the partial derivatives matrix in Eq. (9). Similarly, the indirect impacts reflecting the effects to all other regions depend on the level of knowledge endowments in the respective regions.

The cumulated impacts over the entire period from t to t+S which arise from changes in $x_{t-1}^{(c)}$ in the previous periods are derived by

$$\frac{\partial y_{t+S}}{\partial x_{t-1}^{(c)'}} = \sum_{s=0}^{S} D_s \left[I_N \, \beta_{(c)} + W \, \gamma_{(c)} + \text{diag}(x_{t-1}^{(h)}) \, \beta_{(h \odot c)} + W \, \text{diag}(x_{t-1}^{(h)}) \, \gamma_{(h \odot c)} \right] \tag{10}$$

where the sum of the main diagonal elements of the N x N matrices over the time period from t to t+S reflect the cumulative impacts within a region. The sum of the off-diagonal represents the indirect impacts in other regions resulting from the diffusion over space and time.

6 Geographical coverage, construction of variables and data

The geographical coverage in this study is given by a set of N = 229 NUTS-2 regions of the EU-25.[6] To proxy regional knowledge production activities, we use data on patent applications[7] assigned at the European Patent Office (EPO) or the World Intellectual Property Organisation (WIPO) over the period 1999-2009 (T = 11). Following the fractional counting approach, the study uses regional assignments of the annual patent applications according to the address of the inventor in order to trace the location of where new knowledge has been created. A three year average of the annual values is used to reduce the bias arising from yearly variations of patent applications and short-term disturbances.

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[6] NUTS (Nomenclature of Units for Territorial Statistics, Revision 2010) is a classification system referring to subdivisions of EU countries for statistical purposes. NUTS-2 regions have become increasingly important as policy units for regional research and innovation policies, and are widely used in empirical region-level studies (see, for example, LeSage and Fischer 2008 or Hoekman et al. 2013).

[7] Patents regarded as outcome of knowledge production processes indicate novel technological and commercially valuable knowledge. We are aware of the fact that patent provide only a partial picture of knowledge creation (for example, patents do not capture not patentable knowledge or new scientific findings). However, the public availability and the high level of standardisation are main advantages for using patent data in the empirical analyses of regional knowledge production (see Acs et al. 2002 for a discussion on patent data used as measure for economically useful new knowledge; or the studies of e.g. Ponds et al. 2010 or Varga et al. 2014).

EU funded R&D networks are observed on the basis of collaborative R&D projects implemented under the European Framework Programmes (FPs). FP projects can be characterised in terms of policy-induced R&D collaborations funded by the EU on a multi-year basis. They involve self-organised project consortia made up of individual researchers tied to particular organisations, such as industrial and commercial firms, universities or research organisations. The participating organisations spread over whole Europe, engaging jointly in basic and application-oriented research in a pre-competitive stage. Thus, FP projects create inter-regional networks of R&D collaboration of European scope. High participation in such a R&D network may constitute an important mean for regions to connect domestically located organisations and researchers to knowledge located somewhere else in geographical space (see Wanzenböck et al. 2014a).

Data for constructing the annual EU funded R&D networks are drawn from the EUPRO database. The database comprises information on research projects funded by the EU FPs (complete for FP1-FP7) and all participating organisations[8]. It contains systematic information on project name and participating organisations including the full name, the type of the organisation as well as the geographical location (full address) including assignment of each organisation to NUTS-2 regions of Europe[9].

To determine the positioning of regions in inter-regional R&D networks, we follow the approach proposed in Wanzenböck et al. (2014a), using a network representation at the organisation level to measure the network centrality of regions in the R&D network (see Wanzenböck et al. 2014a for more details and a formal presentation of the approach). We rely on this approach as information on intra- and inter-regional linkages contained in the organisational graph would be lost when defining a (weighted) R&D network directly at the aggregate level of regions. Table 1 presents some basic network statistics for the annual networks over the period of observation.

[Table 1 about here]

The embeddedness of regions in the R&D network is understood as the cumulative centralities of the organisations located in the respective region. Hence, high regional centrality in the R&D network of regions may be achieved due to a large number of different organisations involved in inter-regional FP projects but also due to only a few organisations ('key players') with high network centrality. We use

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a basic measure of network centrality (Wassermann and Faust 1994). The degree of region i is given by

$$c_i^{(d)} = \sum_{u \in u_i} \sum_{u'=1}^{U} a_{uu'} \tag{11}$$

where the element $a_{uu'}$ denotes the collaboration intensity between two organisations u and u' for $u \neq u'$. U is the total number of organisation in the network, and u_i indicates those organisations located in region i. A region's degree centrality is the sum of the degree centralities of the organisations located that region. Note that our measure of regional network centrality accounts for all organisational links irrespective if the links are inter-regional or intra-regional[10]. It corresponds to a local perspective on the R&D network, i.e. it does not take into account the entire network structure, such as for example eigenvector or betweenness centrality (see Wanzenböck et al. 2014a). Figure A.1 in Appendix A illustrates the spatial distribution of the degree centrality of regions in R&D networks across Europe.

With respect to the other explanatory variables in our knowledge production relationship, we use the share of population with tertiary education as a measure for a region's knowledge-generating endowments and its absorptive capacities[11]. Higher levels of education are often used as proxy for the human resources of a region (see e.g. Paci et al. 2014), as they reasonably approximate the people (scientists, engineers, researchers, etc.) that hold the necessary skills and (tacit) knowledge to generate new knowledge, on the one hand, and to comprehend and integrate external knowledge accessible via R&D collaborations, on the other hand. To characterise additional aspects of regional knowledge production processes, we include three further variables: *i*) the total regional R&D expenditures as a proxy for the financial resources devoted to R&D, *ii)* an industrial diversity index to control for different economic activities and the industrial structure in a region, and *iii*) the gross regional product (GRP) to account for regional size differences. Tables A.1 in Appendix A provides details on the definition and data sources of the variables, and Table A.2 reports some basic summary statistics.

7 Empirical results

This section focuses on the observed impacts of a region's embeddedness in inter-regional R&D networks on regional knowledge production. As discussed in Section 5, the partial derivatives of our

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[10] Model estimates and basic interpretation of impacts will not affected by our definition of regional degree centrality. Correlation to a definition which is based on inter-regional links of organisations amounts to 0.965.

[11] To test whether our results are robust with respect to the measurement of human resources, we estimated our model with two alternative measures: First, human resources in science and technology within a region, a measure provided by EUROSTAT and composed of individuals holding a university degree, as well as individuals engaged in fields of science and technology as professionals or technicians and associate professionals (Eurostat 2013), and second, the share of R&D employees in a region. Estimation results do not differ substantially.

model are non-linear and do not correspond with the model coefficients due to *i*) the space-time transformation matrix, and *ii*) the interaction term between the R&D network variable and the human resources variable. Hence, solid conclusions with respect to the knowledge production effects of R&D network embeddedness in regions are reported by the extended average direct and indirect impacts as given by Eq. (9) and (10). Before examining the estimates for the space-time impacts in detail, we pay some attention on the regression results of our dynamic spatial panel data model.

Table 2 reports the results of our space time model with spatial and time period fixed effects as given in Eqs. (1) - (3). Associated *t*-statistics are given in parentheses. At this point, focus is only on the space-time parameters and the direction of the interaction term since the remaining model coefficients are not interpretable directly as if they were marginal effects of changes in the explanatory variables. As indicated by the coefficients of the temporal and spatial dependence parameters as well as the space-time diffusion parameter, the stability condition of $\phi + \rho + \theta < 1$ is satisfied and significant, which guarantees that our model is not explosive and we obtain consistent parameter estimates. Moreover, all three parameters indicate significantly positive effects of knowledge diffusion, pointing to significant spillovers across regions and over time. These results are in line with the study of Parent (2012) revealing that knowledge generation is highly related inter-temporally and correlated over space. Our estimates further suggest that temporal as well as spatial knowledge diffusion processes have to be considered in the modelling of regional knowledge generation. Excluding one of these parameters from the model may lead to biased results and erroneous conclusions with respect to the remaining variables of the knowledge production relationship. However, it has to be noted that we are not able to parcel out the influences of time, i.e. the path dependency in regional knowledge production, independently from the influences arising from spatial diffusion across regions and over time. The restriction of $\theta = -\rho \phi$ discussed in Parent and LeSage (2010) is not satisfied.

[Table 2 about here]

The significant estimate of $\beta^{(h \circ c)}$ reflects the interaction of the R&D network centrality variable and the human resources of the respective regions. This confirms underlying assumptions on the role of R&D networks for regional knowledge creation, namely that R&D network embeddedness is – depending on the knowledge production endowments (i.e. human resources) in a region – conditional effective to regional knowledge production. The negative sign points to some kind of substitution effect between endowments with own knowledge capabilities and a region's linkages to external knowledge sources as provided by R&D networks.

In Table 3 we report the average direct, indirect and total impacts on knowledge production (measured in terms of patents) arising from one percent change of the R&D network variable in the initial period. They represent average responses over all regions but adjusted by the moderating effect of the region-specific levels of human resources (see Eq. 9 and 10). Both patent counts and the number of R&D network linkages are defined in logarithmic form which enables us to interpret our space-time impact estimates in terms of elasticities. Since we consider EU funded R&D networks, responses could be interpreted also in terms of an external (policy) stimulus that produces more intensive R&D collaborations across regions. Impact estimates for the remaining explanatory variables of the knowledge production relationship are reported in Appendix B.

[Table 3 about here]

Note that the explanatory variables are observed in the previous period t-1. Hence, we can indicate the response of knowledge production activity one year after the impulse (i.e. at time t) for the first time, and thereafter for any year. The first column of each panel in Table 3 refers to the years after the one-percent stimulus of the R&D network variable in the initial period. The mean indicates how knowledge production changes with respect to a one-time increase. The last columns in each sub table of Table 3 show the cumulative impacts according to Eq. (10) that – in contrast to such one-time stimuli – would arise when R&D network centrality is increased on a permanent basis. Due to the definition of our space-time transformation matrix, the one-year-ahead impacts include only own region (spatial) effects, while the two to ten year impacts result from time dependency as well as some spatio-temporal feedback effects. Significance of the impact estimates is evaluated on the basis of a 0.99 credible interval, with positive values for both the lower and upper 0.99 bound confirming a significant estimate at the 0.01 percent level.

With respect to the regional direct impacts we observe – on average – clear positive effects resulting from stronger embeddedness of regions in EU funded R&D networks. A one percent increase in own region R&D network centrality increases the knowledge production activity in this region by nearly half a percent in the following year. However, having the negative estimate for the interaction term in mind (see Table 2), we can further conclude that the positive impacts of changes in a region's network centrality decrease relatively to the level of human resources in this region. Possible explanations for this negative relationship could be related to potential costs associated with high centrality in R&D networks. While the marginal benefits of R&D network links are likely to decrease with higher levels of own resources (e.g. due to smaller learning effects), the marginal costs associated with additional R&D network linkages might increase, especially due to rising costs of coordination and the drain on own resources collaborative R&D might induce. Hence, regions with low levels of own knowledge-generating endowments show higher marginal benefits from inter-regional R&D networks, i.e. they

may be more efficient in exploiting the established linkages to other regions than those regions which are equipped with high own resources. New patents can be registered readily in these regions.

Although one-period ahead (immediate) effects are high, we find rapidly diminishing effects on knowledge production in subsequent years. The long-run effects of higher regional R&D network centrality – also interpretable as temporal spillovers within regions – are comparatively small. Hence, effects of a one-time stimulation of R&D network linkages are not of lasting nature within a region, indicating that the knowledge absorbed from R&D networks is exploited less likely for the generation of additional patents. From the cumulative own region impacts we further see that regional knowledge production activity will respond positively to ongoing increases in R&D network centrality over a period of up to five years. However, declining marginal impacts are also observable in this case. Since R&D network linkages are usually established not for one year but for a multi-year period, the increase in cumulative impacts which is observable for the first few years might partly reflect this fact. Therefore, it might be reasonable to regard the cumulative impacts for the first few, say five years, as short-term or immediate impacts that arise if regions (i.e. the regional actors) could increase and hold their centrality in the R&D network, while impacts in subsequent periods could be interpreted as the long-term effects that mainly result from temporal spillovers and feedback effects across regions.

For the average indirect effects we find positive and significance impacts for the first as well as for subsequent periods after the stimulus of R&D network centrality. Hence, regional knowledge production activity might be responsive to increasing R&D network centrality in neighbouring regions. More localized knowledge transmission, for example through channels of labour mobility or more intensive informal interactions across neighbouring regions (Breschi and Lissoni 2001), might deliver reasonable explanation for positive spatial spillover effects. From a temporal perspective, positive indirect impacts of increased R&D network centrality in neighbouring regions level off at a much slower path than it is the case for the direct effects; positive cross-region effects can be observed for more than five years (see also Figure 1)[12].

The average total effects reported in the last sub table of Table 3 combine both direct and indirect impacts. In our application, they characterise a situation where all regions simultaneously change their centrality in the R&D network, for example due to substantial increases in EU funded inter-regional R&D collaborations. Due to both positive direct and indirect effects, higher centrality in R&D networks is not competitive across the regions so that positive knowledge production effects could occur in all regions and overall knowledge production activity in the multi-regional system can be enhanced. From a temporal perspective, the evolution of total impacts is certainly in line with the results for direct and indirect impacts; i.e. also total impacts decrease sharply over time.

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[12] Concerning the magnitude of the spillovers, it has to be noted that the estimates sum up the indirect impacts over all regions. They are interpretable as if all neighbouring regions raise their R&D network centrality simultaneously. Hence, the indirect impacts arising from a single neighbouring region can only be approximated by dividing the mean impact estimates according to the k=5 first order neighbours, which leads to much smaller responses (LeSage and Pace 2009).

[Figure 1 about here]

Figure 1 illustrates these findings. The evolution of impacts is compared for the average own region impacts (left plot) and the average indirect (spillover) impacts (right plot). The direct effects diminish rapidly and die down to zero five years after the stimulus in R&D network centrality. In contrast, indirect effects of increased network centrality spilling over to neighbouring regions are observed for a longer period, reduce more smoothly and phase out gradually. Hence, long run effects on regional knowledge production arising from higher embeddedness of regions R&D networks may be to a large degree the result of spatio-temporal diffusion processes across regions. This indicates that positive knowledge production effects cannot be preserved but will level off in the longer run if the regions are not able to establish additional linkages in the R&D network. A one-time increase in R&D network centrality has only short time effects, and even if the R&D network linkages are held permanently at the increased level we can observe only small additional benefits in the long-run. From a network perspective, this implies that regions located at the periphery of the R&D network (with only a small number of network partners) can increase their knowledge production activity in a sustainable way only if they are able to establish additional links, thus gain higher centrality in the R&D network.

8 Discussion and conclusion

In this study we propose a novel empirical approach in perceiving the role of the embeddedness of regions in R&D networks in a regional knowledge production relationship. We analyse EU funded inter-regional R&D networks in their European dimension, as captured by collaborative R&D projects supported by the EU Framework Programmes (FPs) and observed for an extended set of European regions over the period from 1999 to 2009. A methodologically advanced measurement framework allows us to trace the evolution of impacts on knowledge output over time and across European regions.

This study has been drawn up with the aim of bringing forward new impulses to the research field of regional knowledge production in theoretical, methodological as well as empirical terms. Even though previous studies partly confirm positive effects of collaborative R&D on regional knowledge output (see e.g. Fornahl et al. 2011; Broekel 2013; Varga et al. 2014), the mechanisms of how such inter-regional R&D networks influence the generation of knowledge have remained mostly untouched in the empirical literature so far. In this study we emphasise the view that participation in R&D networks facilitates or supports the efforts of regional actors to generate new knowledge. Special attention is thus placed on the close and inevitable relation between the quality of own region knowledge resources and the ability of regional actors to exploit external knowledge sources accessible via R&D

network linkages. Methodologically, we use a dynamic spatial panel data model for modelling temporal and spatial dependence in the regional knowledge production relationship. Furthermore, we extend basic space-time impact measures based on partial derivatives expressions (Debarsy et al. 2012) by an interaction term that reflects the conditional relationship in our set of explanatory variables. By this, we propose a viable way for interpreting space-time impacts in relation with a region's embeddedness in inter-regional R&D networks, also in order to show how effects on regional knowledge output unfold within and across European regions in the short and long-run.

The results provide a range of interesting results. *First* and most importantly, our empirical findings provide strong evidence that the embeddedness in EU funded R&D networks indeed helps to increase a regions patenting activity when the moderating effects of region-specific endowments with knowledge-generating factors are considered. The estimates for the direct impact – on average over European regions – point to significant positive short-term responses of regional knowledge production. Hence, if we consider the fact that R&D networks are not productive on their own, but require research actors within regions to exploit and turn the skills and knowledge transmitted into new and economically valuable knowledge, we can observe clear positive impacts if regions increase their embeddedness in R&D networks.

Second, knowledge generation is stimulated particularly in regions with lower own region knowledge endowments. The significant negative interaction term provides indication that these regions – provided that they are able to increase their centrality in the R&D network – could achieve higher positive impacts on their patenting performance. However, such an impulse may not be sufficient enough to enhance regional knowledge production in a sustainable way. The cumulative direct impacts over a period of up to ten years show that temporal spillovers are comparatively small within regions, which might be interpreted as a sign that further use of knowledge and skills transferred via collaborative R&D is limited, at least as the generation of additional patents is concerned. This however does not mean that other and often indirect effects of learning from region-external partners will not occur.

Third, given the total impact measures considering both direct and spillover effects over all European regions, the study provides convincing evidence from a pan-European perspective that EU funded cross-regional R&D network linkages are highly valuable for the European research landscape. Stimulating effects arising from higher R&D network embeddedness are not only obtained for the respective regions but are observed to diffuse spatially to other regions. An increasing number of R&D network linkages across all European regions is likely to lead to higher average knowledge production activity in the multi-regional system.

Given some limitations of this study, pointers for further research efforts come into mind: *First*, applying the space-time modelling approach to distinct forms of collaborative R&D may constitute an

important extension of the current study. Differentiating between scientific or research oriented organisations and industrial firms in the construction of the R&D networks might shed new light on differences with respect to knowledge types. *Second*, a comparison of the space-time impacts in different technological fields with different rationales and intensities of inter-regional R&D collaboration might lead to interesting results on how the embeddedness of regions in inter-regional R&D networks translates into new knowledge at the regional level.

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TABLES AND FIGURES

Table 1: *Summary statistics of the annual European R&D networks*

Year	Number of vertices		Number of edges	Participations per organisation			Participating organisations per region		
	Org.	Proj.		Mean	Max	Vertices above mean*	Mean	Max	skewness
1999	12,241	8,950	40,355	3.297	248	0.297	53.45	613	3.861
2000	14,018	9,879	45,508	3.246	337	0.284	61.21	689	3.772
2001	15,789	10,615	50,250	3.183	364	0.274	68.95	795	3.884
2002	16,723	11,486	57,564	3.442	478	0.248	73.03	869	3.910
2003	16,111	10,058	55,621	3.452	493	0.260	70.35	823	3.834
2004	16,857	9,328	59,637	3.538	606	0.259	73.61	837	3.686
2005	16,065	8,202	56,232	3.500	647	0.250	70.15	762	3.515
2006	15,789	8,390	58,804	3.724	729	0.254	68.95	755	3.503
2007	15,611	7,881	56,917	3.646	698	0.250	68.17	732	3.441
2008	16,350	8,643	62,284	3.809	813	0.261	71.40	770	3.447

Notes: * Is the fraction of vertices with degree higher than the mean degree, and is a measure for the skewness of network vertices.

Table 2: Estimates of the space-time model with spatial and time period fixed effects

Variables	Coefficient	t-statistic
$\beta^{(c)}$ Degree centrality	0.289***	(5.428)
$\beta^{(h)}$ Human resources	0.436***	(5.045)
$\beta^{(rd)}$ RD expenditures	0.024	(1.150)
$\beta^{(id)}$ Industrial diversity	1.620***	(3.988)
$\beta^{(g)}$ GRP	0.302***	(3.788)
$\beta^{(h \circ c)}$ Interaction	-0.064***	(-3.831)
$\gamma^{(c)}$ W Degree centrality	0.019	(0.213)
$\gamma^{(h)}$ W Human resources	0.299	(1.705)
$\gamma^{(rd)}$ W RD expenditures	0.127***	(2.990)
$\gamma^{(id)}$ W Industrial diversity	-0.957	(-1.321)
$\gamma^{(g)}$ W GRP	0.082	(0.558)
$\gamma^{(h \circ c)}$ W Interaction	-0.007	(-0.124)
$\phi\, y_{t-1}$	0.312***	(-33.744)
$\rho\, W y_{t}$	0.163***	(4.928)
$\theta\, W y_{t-1}$	0.098***	(4.503)
Log-Lik	536.919	
σ_{ε}^{2}	0.033	

Notes: Dynamic spatial panel data model with spatial and time period fixed effects; $N = 229$, $T = 11$; estimates based on bias corrected quasi maximum likelihood estimators as in Yu et al. 2008, applying MATLAB codes taken from Elhorst et al. 2014; spatially weighted variables are estimated using a k-nearest neighbours matrix with $k = 5$; Wald Test of $\phi + \rho + \theta = 1$ is significant at the 0.01 level confirming stability of the model; ***significant at the 0.01 significance level, **significant at the 0.05 significance level, *significant at the 0.1 significance level.
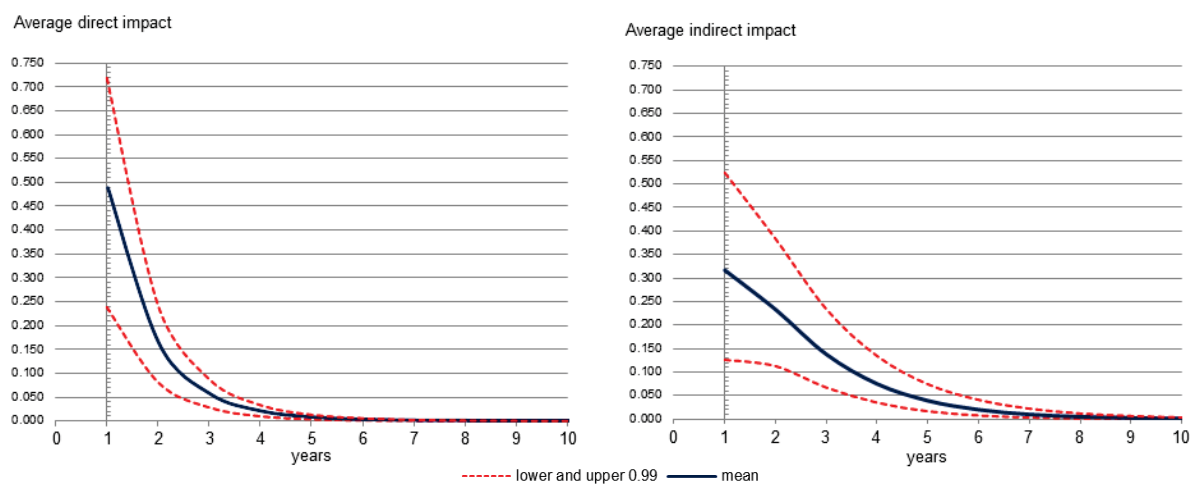
Table 3: Impact estimates for changes in R&D network centrality

Average direct impacts					Average indirect impacts			
years	Lower 0.99	mean	Upper 0.99	**Cumulative**	years	Lower 0.99	mean	Upper 0.99	**Cumulative**
1	0.239	0.491	0.719	**0.491**	1	0.126	0.317	0.524	**0.317**
2	0.081	0.163	0.242	**0.653**	2	0.113	0.233	0.383	**0.550**
3	0.029	0.056	0.088	**0.710**	3	0.067	0.138	0.234	**0.688**
4	0.010	0.021	0.033	**0.730**	4	0.035	0.075	0.134	**0.763**
5	0.004	0.008	0.013	**0.738**	5	0.017	0.039	0.074	**0.802**
10	0.000	0.000	0.000	**0.743**	10	0.000	0.001	0.004	**0.841**

Average total impacts				
years	Lower 0.99	mean	Upper 0.99	**Cumulative**
1	0.417	0.808	1.191	**0.808**
2	0.209	0.396	0.605	**1.203**
3	0.100	0.194	0.311	**1.397**
4	0.047	0.096	0.164	**1.493**
5	0.022	0.047	0.087	**1.540**
10	0.000	0.001	0.004	**1.585**

Notes: Average direct, indirect and total impacts estimated according to Eq. (9) and (10), with a $k=5$ nearest neighbours matrix and based on 1000 sampled raw parameter estimates.

Figure 1: Diffusion of R&D network centrality impacts over time

APPENDIX A:

Table A.1: Definition of the variables

Variable	Definition	Source
Patents	Log of annual patent application (3 year average), fractional counting, regional assignment according to inventors' address,	Eurostat Regional Statistics
Degree centrality	Sum of the degree centralities of organisations located that region (log); Annual networks based on collaborative Framework Programme (FPs) projects	EUPRO database
Human resources	Percentage share of population aged 25-65 with education attainment corresponding to levels 5 and 6 of the ISCED 1997 classification system (log)	Eurostat Regional Statistics
RD expenditures	Total expenditures on research and development (R&D) as a percentage share of GRP (log)	Eurostat Regional Statistics
Industrial diversity	Index of specialisation, based on the employment in the economic sectors of agriculture, construction, industry, financial, wholesale, non-market services. Defined as $z_t^{(ID)} = -\frac{1}{2}\sum_P \left| o_{ip} - \bar{o}_p \right|$ where o_{ip} is the region's i share of gross value added in a specific sector p and $\bar{o}_p$ is the mean of sector p for $N=229$ regions.	Cambridge Economic Data
GRP	Gross regional product at market prices, in millions	Eurostat Regional Statistics

Table A.2: Summary statistics

Variable	Min	Max	Mean	Median	Std. dev.
Patents	0	3,159.6	226.69	93.01	400.20
Degree centrality	0	4,804	237.19	114.50	376.06
Human resources	5.20	47.60	22.03	22.30	8.12
RD expenditures	0.04	13.73	1.52	1.13	1.24
Industrial diversity	0.02	0.45	0.11	0.10	0.06
GRP	789.79	575,842.00	44,499.06	31,221.22	51,993.20

Figure A.1: Embeddedness of European regions in the R&D network
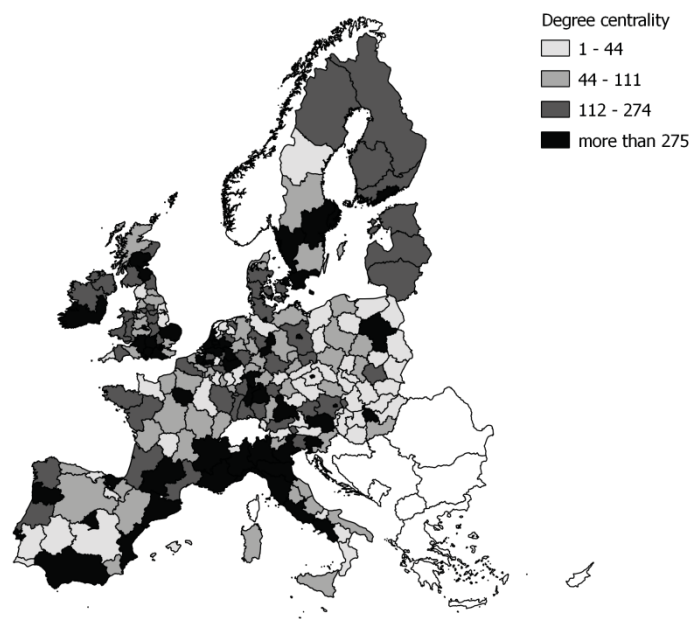
Notes: Average values of degree centrality for the period 1999 – 2008;
natural breaks are used to classifying data into four categories

APPENDIX B: Impact estimates

Human resources

Average direct impacts					Average indirect impacts				
years	Lower 0.99	mean	Upper 0.99	Cumulative	years	Lower 0.99	mean	Upper 0.99	Cumulative
1	0.290	0.544	0.791	0.544	1	0.231	0.458	0.707	0.458
2	0.099	0.182	0.265	0.727	2	0.168	0.309	0.476	0.766
3	0.035	0.064	0.095	0.791	3	0.093	0.177	0.281	0.943
4	0.013	0.024	0.037	0.814	4	0.046	0.095	0.159	1.038
5	0.005	0.009	0.015	0.824	5	0.021	0.049	0.087	1.087
10	0.000	0.000	0.000	0.830	10	0.000	0.002	0.004	1.136

R&D Expenditures

Average direct impacts					Average indirect impacts				
years	Lower 0.99	mean	Upper 0.99	Cumulative	years	Lower 0.99	mean	Upper 0.99	Cumulative
1	-0.006	0.009	0.024	0.009	1	0.011	0.047	0.085	0.047
2	-0.002	0.003	0.008	0.011	2	0.003	0.015	0.027	0.062
3	-0.001	0.001	0.002	0.012	3	0.001	0.005	0.009	0.066
4	0.000	0.000	0.001	0.012	4	0.000	0.001	0.003	0.068
5	0.000	0.000	0.000	0.012	5	0.000	0.000	0.001	0.068
10	0.000	0.000	0.000	0.012	10	0.000	0.000	0.000	0.068

Industrial Diversity

Average direct impacts					Average indirect impacts				
years	Lower 0.99	mean	Upper 0.99	Cumulative	years	Lower 0.99	mean	Upper 0.99	Cumulative
1	0.195	0.502	0.811	0.502	1	-0.837	-0.261	0.340	-0.261
2	0.060	0.157	0.254	0.659	2	-0.268	-0.082	0.107	-0.343
3	0.019	0.049	0.081	0.707	3	-0.086	-0.026	0.034	-0.368
4	0.006	0.015	0.026	0.723	4	-0.028	-0.008	0.011	-0.376
5	0.002	0.005	0.009	0.728	5	-0.009	-0.003	0.003	-0.379
10	0.000	0.000	0.000	0.730	10	0.000	0.000	0.000	-0.380

GRP

Average direct impacts					Average indirect impacts				
years	Lower 0.99	mean	Upper 0.99	Cumulative	years	Lower 0.99	mean	Upper 0.99	Cumulative
1	0.032	0.095	0.152	0.095	1	-0.036	0.047	0.132	0.047
2	0.010	0.030	0.048	0.125	2	-0.011	0.015	0.043	0.062
3	0.003	0.009	0.015	0.134	3	-0.003	0.005	0.014	0.066
4	0.001	0.003	0.005	0.137	4	-0.001	0.001	0.004	0.068
5	0.000	0.001	0.002	0.138	5	0.000	0.000	0.001	0.068
10	0.000	0.000	0.000	0.139	10	0.000	0.000	0.000	0.068

Notes: Average direct, indirect and total impacts estimated according to Eq. (5), (9) and (10), respectively, with a $k=5$ nearest neighbours matrix and based on 1000 sampled raw parameter estimates.

APPENDIX C: List of Regions (NUTS Classification 2010)

Austria:	Burgenland, Kärnten, Niederösterreich, Oberösterreich, Salzburg, Steiermark, Tirol, Vorarlberg, Wien
Belgium:	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
Czech Republic:	Jihovýchod, Jihozápad, Moravskoslezsko, Praha, Severovýchod, Severozápad, Střední Morava, Střední Čechy
Denmark:	Hovedstaden, Midtjylland, Nordjylland, Sjælland, Syddanmark
Estonia:	Eesti
Finland:	Åland, Etelä-Suomi, Helsinki-Uusimaa, Länsi-Suomi
France:	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
Germany:	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
Hungary:	Dél-Alföld, Dél-Dunántúl, Észak-Alföld, Észak-Magyarország, Közép-Dunántúl, Közép-Magyarország, Nyugat-Dunántúl
Ireland:	Border, Midland and Western; Southern and Eastern
Italy:	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
Latvia:	Latvija
Lithuania:	Lietuva
Luxembourg:	Luxembourg (Grand-Duché)
Netherlands:	Drenthe, Flevoland, Friesland, Gelderland, Groningen, Limburg (NL), Noord-Brabant, Noord-Holland, Overijssel, Utrecht, Zeeland, Zuid-Holland
Poland:	Dolnośląskie, Lubelskie, Lubuskie, Łódzkie, Mazowieckie, Małopolskie, Opolskie, Podkarpackie, Podlaskie, Pomorskie, Śląskie, Świętokrzyskie, Warmińsko-Mazurskie, Wielkopolskie, Zachodniopomorskie
Portugal:	Alentejo, Algarve, Centro (P), Lisboa, Norte
Slovakia:	Bratislavský kraj, Stredné Slovensko, Východné Slovensko, Západné Slovensko
Slovenia:	Vzhodna Slovenija, Zahodna Slovenija

Spain:	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
Sweden:	Mellersta Norrland, Norra Mellansverige, Småland med öarna, Stockholm, Sydsverige, Västsverige, Östra Mellansverige, Övre Norrland
United Kingdom:	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 & Warkwickshire; 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

Notes: 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. Also the Polish region of Kujawsko-Pomorskie was excluded from the sample because of lack of data.