doi:10.1111/pirs.12236

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

Iris Wanzenböck[1], **Philipp Piribauer**[2]

[1] Austrian Institute of Technology (AIT), Innovation Systems Department and Vienna University of Economics and Business (WU), Institute for Economic Geography and GIScience, Austria (e-mail: iris.wanzenboeck@ait.ac.at)
[2] Vienna University of Economics and Business (WU), Institute for Macroeconomics, Austria (e-mail: philipp.piribauer@wu.ac.at)

Received: 4 March 2015 / Accepted: 17 March 2016

Abstract. In this study we estimate space-time impacts of the embeddedness in R&D networks on regional knowledge production using a dynamic spatial panel data model with non-linear effects for 229 European NUTS 2 regions in the period 1998–2010. Embeddedness refers to the positioning in networks where nodes represent regions that are linked by joint R&D projects funded by EU Framework Programmes. We find evidence that increasing embeddedness in EU funded R&D networks leads to positive immediate impacts on regional knowledge production, and that regions with lower levels of own knowledge endowments more likely exploit the positive effects. However, the long-term impacts of a region's embeddedness in these R&D networks are comparatively small.

JEL classification: C33, O31, R12

Key words: R&D networks, European Framework Programme, regional knowledge production, dynamic spatial panel data model, space-time impacts

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 placed great emphasis on the spatial dimension of knowledge production, and in particular the spatial spread of knowledge diffusion. Inter-regional R&D networks are gaining particular interest in this context, given that network arrangements are considered as essential for the successful creation of new knowledge (Autant-Bernard et al. 2007; Bergman 2009;

* The authors gratefully acknowledge the grant no. 16301 provided by the Anniversary Fund of the Oesterreichische Nationalbank (OeNB). Furthermore, we thank Thomas Scherngell and Manfred M. Fischer for many helpful suggestions and comments.

© 2016 The Author(s). Papers in Regional Science © 2016 RSAI

Scherngell 2013). Taking a regional perspective, R&D networks may be defined as systems of nodes representing regions that are inter-linked by joint R&D endeavours (see e.g., Wanzenböck et al. 2014). Under this umbrella, regional scientists increasingly apply a network-analytic perspective to capture structure and dynamics of inter-regional R&D network relations, viewed as channels where knowledge can diffuse within and across regions.

This study follows this research stream, focusing on regional knowledge production and its relation to the embeddedness of regions in inter-regional R&D networks. The theoretical discussion on the spatial scale of knowledge linkages has been shaped by arguments highlighting the importance for regions to have access to so-called global pipelines, namely, R&D networks that cross regional borders (Bathelt et al. 2004). 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 2015). 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 negative consequences have also been put forward for regions that show a high degree of region external co-operation, 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 the peculiar 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 an European perspective, is still scarce and inconclusive (see e.g., Sebestyén and Varga 2013; Varga et al. 2014). The objective of this study is to estimate space-time impacts of regional embeddedness in R&D networks on regional knowledge production in Europe. By the notion of regional embeddedness we refer to the structural positioning of regional organizations in R&D networks from a network analytic perspective. The structure of the R&D network is observed on the basis of collaborative R&D projects between organizations located in different regions and funded by the European Framework Programme (FP). To address the objective, we implement a space-time approach and consider the specific role played by own region knowledge endowments in this relation. Knowledge production is measured in terms of annual patent applications for the years 1998–2010, spatially distributed across 229 NUTS 2 regions.

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, we specify an empirical knowledge production relationship to measure the effects of R&D networks in dependence of a region's own endowments with knowledge-generating factors. Our modelling approach is based on the assumption that the embeddedness in R&D networks is only conditionally effective, that is, effects on regional knowledge output are moderated significantly by own region knowledge characteristics. 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 dynamic spatial panel data models are rather new to the field (see e.g., Autant-Bernard 2012; Parent 2012), the current study will shed new light on the role of spatio-temporal spillover effects between European regions in a regional knowledge generation framework. Third, we augment basic space-time impact measures (see Debarsy et al. 2012) by specifying an interaction effect in the set of knowledge production determinants. By this, we consider region-specific differences in the accessibility and absorbability of external knowledge via R&D network linkages, also related to spillover effects over time and space.

The remainder of the study is organized 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 dynamic spatial

panel modelling approach, before Section 4 introduces the interaction term in our set of regional knowledge production determinants, and Section 5 presents the associated space-time impact measures. 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' regarding the question of how new knowledge is generated. '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 characterized by structured and formalized forms of interaction (see e.g., Giuliani and Bell 2005; Graf 2011; Moodysson 2008). 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-inventorships or co-publications (Scherngell and Barber 2009; Hoekman et al. 2010; Wanzenböck et al. 2014, among others).

One of the fundamental assumptions in the regional science literature is that the location of skills or competences is distributed across geographical space. Specific pieces of knowledge, often concentrated in distinct regions, can be accessed more easily by means of R&D collaboration (Autant-Bernard et al. 2007; Scherngell 2013). Joint R&D endeavours are established in order to share, exchange or pool knowledge and resources which allows participating more actively in the specialized capabilities or tacit pieces of knowledge of others. Such R&D linkages are therefore often viewed as channels that enable the flow of knowledge (Owen-Smith and Powell 2004). In cases where collaboration partners are located in different regional surroundings, they are assumed to facilitate the transfer of knowledge, expertize and skills between different regions. High expectations placed on the mentioned benefits of long distance R&D networks have also considerably influenced the design of recent research and innovation policy measures. Promoting collaborative R&D has developed to one of the key concepts in current policy strategies at the regional, national and supranational level (Breschi and Malerba 2009).

A number of studies have investigated effects of inter-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 2015 for co-operative R&D subsidies in Germany; or Sebestyén and Varga 2013; Varga et al. 2014 for FP projects across Europe). However, one aspect which has been widely neglected in the empirical literature is the role of a region's own resources moderating the effects of embeddedness in inter-regional R&D networks. Thus, 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 two main arguments supporting the idea of such a conditional relationship:

First, motives for engaging in R&D networks are clearly related to specific aims (Ozman 2009), and these aims often refer to either co-producing some kind of knowledge or absorbing specific know-how not available in own surroundings. Regional actors need to bring specific knowledge and skills into the collaborative endeavours, for the sake of the current collaboration but also for being recognized as a valuable partner in present and future inter-regional R&D

projects. Furthermore, the study of Wanzenböck et al. (2015) identifies a positive relationship between human capital and R&D network embeddedness. Thus, we can assume that the higher the quality of own regional knowledge endowments, the higher might be the quality of the research activities in this region, which in turn positively influences a region's visibility in inter-regional R&D settings. This could even more be 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, positive knowledge production effects of increasing R&D network embeddedness might arise only if the regional actors have sufficient abilities to comprehend, integrate and process the knowledge generated somewhere else. Thus, both availability and quality of own knowledge-generating endowments (e.g., in form of qualified individuals such as researchers, scientists, engineers, as well as in form of knowledge-intensive organizations such as universities, firms, research organizations) 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) which at the level of regions suggests that a combination of both external R&D network relations and region-internal knowledge endowments is required to reap benefits of R&D networks (Abreu 2011).

For the reasons raised above, it may be relatively straightforward to assume that regional R&D network embeddedness is related with the knowledge endowments within a region. However, it is less clear-cut to hypothesize how this relationship materializes in terms of knowledge output. Thus, another question to be addressed empirically is whether R&D linkages to external knowledge sources substitute or complement a region's own knowledge capabilities in a knowledge production relationship.

The economic geography and regional science literature assumes at a more general level a supportive and facilitating role of inter-regional R&D networks for regional knowledge generation activities (see e.g., Bathelt et al. 2004; Huggins and Thompson 2014), while the economics of networks literature is less optimistic in this regard, delivering indications that R&D network participation not only facilitates but could also hamper knowledge production processes. With a higher number of linkages, for instance, it is more likely that certain projects or collaboration partners are of low value while the costs of co-ordinating these linkages increase (see e.g., Katz and Martin 1997; Goyal 2007). Collaborative projects – especially when region-external partners are involved – might constitute a considerable drain on resources as they involve high administrative efforts for managing the joint projects. In addition, the co-ordination of partners and their research might increase in joint R&D endeavours with high diversity of partners from different institutional backgrounds and research fields. In both cases, the productivity of the researchers involved in joint projects might be afflicted negatively. If this is the case, regions would require sufficiently high amounts of relational capacities to be able to activate and maintain at the same time a bundle of different R&D network linkages in an effective way.

Moreover, we can expect that regions that are already equipped with high quality resources show smaller learning effects from R&D collaborations, compared to catching-up regions where own knowledge endowments are still underdeveloped. In the latter case, the knowledge, skills or problem-solving capabilities acquired from inter-regional partners may contribute more substantially to the ability to generate new knowledge in these regions. In other words, the marginal benefit of external R&D relations might decrease with the level of own knowledge production capacities, and regions with higher own endowments will less likely exploit the knowledge benefits associated with inter-regional R&D networks.

Hence, it is reasonable to assume that two forces are at work; high outward orientation and R&D network embeddedness of regions is assumed to stimulate the regional knowledge production process, but at the same time it could also hamper the efficiency to generate new knowledge

with resources or knowledge inputs located within the region (Graf 2011; Broekel et al. 2015). Such negative effects may be related with the level of own region knowledge production factors. They might be particularly severe if regions show intensive interaction in cross-regional R&D endeavours but lack the own capacities to process the knowledge absorbed by the linkages.

The moderating effect arising from a region's level of own knowledge-generating factors has been widely neglected in empirical works so far. The distinct relation of how embeddedness of regions in R&D networks is related to own regional endowments is still to be explored empirically in a regional knowledge production relationship. Given the conditional nature, R&D network effects could, however, turn out less positive than generally assumed in region level studies. 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.[1] The study of Parent (2012) is the first 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)[2] for a multiregional system with $i=1, \ldots, N$ regions and $t=2, \ldots, T$ 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

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

where $y_t=(y_{1t}, \ldots, y_{Nt})'$ is $N\times 1$ containing observations of annual knowledge output in period t for region i 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 $N\times N$ time-

[1] Exceptions are the studies of Fischer and LeSage (2015) 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.

[2] 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 an 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. We test for our dynamic SDM specification using the general-to-specific principle as suggested, for example, by Elhorst (2012).

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 given 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, that is, 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 inter-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 period, as well as by knowledge produced in other regions in the same as well as in the previous period. 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.[3] $x_{t-1} = (x_{1t-1}, \ldots, x_{Nt-1})'$ denotes an $N \times R$ 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 $N \times 1$ vector reflecting the disturbance specification at time t, with $\mu = (\mu_1, \ldots, \mu_N)'$ being the $N \times 1$ vector of region-specific fixed effects, and τ_t denoting time-specific fixed effects where ι_N is an $N \times 1$ vector of ones, and $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{Nt})'$ is an $N \times 1$ 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 Lee and Yu (2010), applying a transformation based on group means to eliminate the region and time-specific effects. 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.[4] Furthermore, as shown in Yu et al. (2008) the parameter estimates are consistent under the condition $|\phi| + |\rho| + |\theta| < 1$.

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*) moderating 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. Such nonlinearities in the explanatory variables can formally be best described by including an interaction term in the model (Greene

[3] To check robustness against the specification of the spatial weight matrix, we run regressions for alternative spatial weight matrix using contiguity-based, inverse distance-based specifications as well as k-nearest neighbour matrices including two to ten nearest neighbours. Results and main conclusions remain basically the same for all specifications, and are available upon request.

[4] Treating the initial period of observation as endogenous, would add considerable complexity to the estimation framework. With $T = 13$, the number of time periods appears reasonably large, such that an exogenous treatment of the initial period should exhibit only minor impacts on the results.

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 an $N \times R$ ($r = 1, \ldots, R = 5$) 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 $N \times O$ ($o = 1, \ldots, R\text{-}2$) matrix of additional control variables. In order to deal with potential endogeneity between the regressors and the dependent variable, we impose a time lag of one year for all explanatory variables. Previous studies dealing with knowledge production – most often from a static perspective – commonly assume a time lag of one to several years' (see e.g., Griliches 1995; Fischer and Varga 2003). The main argument in this context is that it might take time that knowledge inputs fully materialize in some knowledge output like patent applications. However, our dynamic panel model tracing impacts over several periods allows us demarcating long-term from short-term responses. Thus, the time lag is assumed to be less important than it might be the case for static models. Details on the definition of the explanatory variables are given in Section 6 and Appendix A.

Potential interaction effects of the two main variables are reflected by $h_{t-1} \odot c_{t-1}$ with $\odot$ denoting the Hadamard element-wise multiplication operator. This interaction term allows us to control for potential non-linearities. Furthermore, 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, 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, pointing to a situation where regions which lack own-region endowments tend to exploit more likely positive knowledge and learning effects associated with inter-regional R&D networks. It is further noteworthy that we characterize 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 scenario, that is, whether the effects of own-region input factors increase with higher centrality in R&D networks. In this case, the interpretation of results might differ according to the distinct theoretical conceptualization, although the definition of the interaction effect as well as the statistical results of the analysis would remain the same.

Interpretation of the main variables, h_{t-1} and c_{t-1}, 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.[5] 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 how interacted variables are interpreted in the context of space-time impact measures.

[5] 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 Space-time impact measures

Endogenous regional diffusion effects in our space-time model imply that changes in the explanatory variables, namely, knowledge inputs, of one region (at time $t-1$) 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 characterize 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.[6] 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) demonstrate in a cross-sectional context that specific impact measures are required in order to interpret the parameters of a spatial model with endogenous spillover effects correctly. Based on a partial derivative expression of the model they provide valuable measures 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 Equation (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 rth 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

$$D_s = (-1)^s \left(B^{-1} A\right)^s B^{-1}, \quad s = 0, \ldots, S \tag{6}$$

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 sth period ahead, where A accounts for the diffusion of impacts over time and space (spatio-temporal spillovers) and B governs the contemporaneous spatial diffusion. 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 Equation (5) represent the direct effects in the different regions of the sample, and the off-diagonal elements are the indirect effects. Average direct effects are reminiscent of coefficient

[6] Consider a situation where pieces of new knowledge developed in region a at time t, 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 in later periods. 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.

interpretations in classical linear models and refer to the average response of a region's dependent variable when changing a covariate in the same region. Average spillover (or indirect) effects are defined as the average response of a region's dependent variable when changing an explanatory variable in all other regions (except in the own region). To obtain a scalar summary measure for the direct impacts we follow the approach proposed by LeSage and Pace (2009), calculating the average over all regions, namely, 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 average spillover effects thus capture the cumulative effects emanating from other regions. 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 extend 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:

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

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, respectively. In analogy to Equation (5), the direct (own region) knowledge production impacts of a one unit increase of the R&D network variable – but here adjusted by the interaction relationship with the level of knowledge endowments of that region – are given by the main diagonal elements of the partial derivatives matrix in Equation (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:

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

where the sum of the main diagonal elements of the $N \times N$ 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 countries.[7] To proxy regional knowledge production activities, we use data on patent applications[8] assigned at the European Patent Office (EPO) or the World Intellectual Property Organization (WIPO) over the period 1998–2010 ($T = 13$). The dependent variable is calculated using a three year moving window, with $y_{it} = (P_{it-1} + P_{it} + P_{it+1})/3$ where P_{it} is the annual number of patents applied for in region i. This transformation is required to reduce short-term

disturbances and bias arising from high yearly variations in the number of patent applications. The estimated annual direct and spillover impact estimates therefore reflect averaged responses of up to three years. 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. R&D networks are observed on the basis of collaborative R&D projects implemented under the European Framework Programme (FP) from 1998 to 2009.[9] FP projects are EU-funded R&D collaborations running over multiple years between organizations that spread over whole Europe. The project consortia are self-organized and typically made up of different types of organizations, such as industrial and commercial firms, universities or research organizations. Participating organizations engage jointly in basic and application-oriented research in a pre-competitive stage, although the composition and roles of project partners depend on the specific thematic field (see e.g., Heller-Schuh et al. 2011). Given their large geographical and thematic scope, FP projects are widely regarded as useful indicator for observing formal networks of inter-regional R&D collaboration (see also Autant-Bernard et al. 2007, Scherngell and Barber 2009, Balland 2012, Hoekman et al. 2013).[10] Important from the perspective of this study is that a high regional participation in the FP networks may constitute an important means for regions to connect domestically located organizations and researchers to knowledge located somewhere else in geographical space (see Wanzenböck et al. 2014).

Data for constructing the annual EU funded R&D networks are drawn from the EUPRO database.[11] The database comprises information on research projects funded by the EU FPs (complete for FP1–FP7) and all participating organizations. It contains systematic information on project name and participating organizations including the full name, the participating departments, the type of the organization as well as the geographical location (full address) including assignment of each organization/department to NUTS 2 regions of Europe. If available in the database, we use the most detailed information on the participating departments to trace back the location where R&D is carried out for each project. This is essential for relating FP participation to the regional level, and at the same time minimizing bias towards headquarters. Moreover, we count the projects for each year they are running based on the assumption that knowledge exchanges take place at different points in time during a project.

[7] 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 e.g. LeSage and Fischer 2008 or Hoekman et al. 2013).

[8] 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).

[9] The FPs were launched in 1984 with the aim of fostering international competitiveness of the European economy, strengthening the European scientific and technological base and increasing knowledge exchange between European R&D actors. These are important goals up to now (see e.g. Delanghe et al. 2009). The provision of funds for project applications is based on effective transnational co-operation between organisations located in the Member States or Associated States of the European Union, scientific excellence and innovative nature of the project, the prospects for exploiting the results, added value for the European Community and the potential to contribute to the economic and social objectives of the Community (see also Scherngell and Barber 2009).

[10] We test the correlation of our regional FP data with regional co-patent data drawn from the Regpat database and co-publication data from the ISI Web of Science (WoS) database and observe a significant and positive correlation between the regional participation intensities in FP networks and those in the co-patent and co-publication network. The results are available upon request. Hence, we assume that the 'core regions' in the EU-funded R&D network type may show also – due to their distinct knowledge production capabilities – high participations in unsubsidized forms of R&D collaborations. Nevertheless, we cannot fully exclude that other – for example of more informal – types of inter-regional R&D networks do not follow these structures.

[11] EUPRO is constructed and maintained by AIT (Austrian Institute of Technology).

To indicate inter-regional R&D network embeddededness of regions, we follow the approach proposed in Wanzenböck et al. (2015), using a network representation and measuring network centrality at the organization level (see Wanzenböck et al. 2015 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 organizational 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.

The embeddedness of regions in the R&D network is then understood as the cumulative centralities of the organizations 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 organizations involved in inter-regional FP projects but also due to only a few organizations ('key players') with high network centrality. We use a basic measure of network centrality (Wassermann and Faust 1994). The degree of region i is given by:

$$c_i^{(d)} = \sum_{u \in \mathscr{U}_i} \sum_{q=1}^{U} a_{uq}, \tag{11}$$

where the element a_{uq} denotes the collaboration intensity between two organizations u and q for $u \neq q$. U is the total number of organization in the network, and $\mathscr{U}_i$ indicates those organizations located in region i. A region's degree centrality is the sum of the degree centralities of the organizations located in that region as given by the participations of these organizations in FP projects. Note that our measure of regional network centrality accounts for all network linkages irrespective if they are inter-regional or intra-regional.[12] From a network analytical point of view, the degree centrality takes a local perspective on the R&D network focusing only on direct R&D collaborations. It does not take into account the entire network structure, such as for example eigenvector or betweenness centrality (see Wanzenböck et al. 2014).[13] Figure A1 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, we use the number of human resources in science and technology, a measure provided by Eurostat and composed of individuals holding

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

Year	Number of vertices		Number of edges	Participations per organization			Participating organizations per region		
	Org.	Proj.		Mean	Max	Vertices above mean[a]	Mean	Max	Skewness
1998	13,193	11,093	46,372	3.514	329	0.292	58.12	667	3.788
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
2009	15,356	8,453	58,620	3.817	794	0.257	67.35	713	3.404

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

a university degree, or professionals, technicians and associate professionals engaged in fields of science and technology. Highly-educated people engaged in science and technology-related fields are assumed to 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 control for other aspects of regional knowledge production processes, we include four additional 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; (*iii*) an index for regional specialization in high-tech patenting to account for specialization in sectors which are usually characterized by above average patenting intensities; and (*iv*) the gross regional product (GRP) to account for regional size differences.[14] All independent variables are observed over the period 1998–2009. Table A1 in Appendix A provides details on the definition and data sources of the variables, and Table A2 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 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 Equations (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 and associated *t*-statistics of our space-time model with spatial and time period fixed effects as given in Equations (1) to (3). 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. First, the stability condition of $|\phi|+|\rho|+|\theta|<1$ holds guaranteeing that our model is not explosive and we obtain consistent parameter estimates. Moreover, the temporal and spatial dependence as well as the space-time diffusion parameter point to significantly positive spillovers within and across regions 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. The significant estimates of the space, time and space-time parameters further suggest that temporal as well as spatial knowledge diffusion processes have to be considered in the modelling of regional knowledge

[12] We include intra-regional links in the definition of FP network centrality as they may constitute an important channel for diffusing externally acquired knowledge within the region. However, correlation to a definition which is based on merely inter-regional links of organisations is high and significant, amounting to 0.965. Thus, basic results and conclusions of our empirical analysis do not change compared to a definition at the aggregate level of regions.

[13] Global network measures considering the structural characteristics of networks from specific perspectives would introduce an additional dimension to our model, which would lead to more complex interpretations regarding the spatio-temporal evolution of R&D network effects in our model.

[14] We performed several robustness test: first, with respect to the measurement of human resources, we estimated our model with two alternative measures, due to data availability in a reduced temporal framework: (*i*) the share of population in tertiary education and (*ii*) the share of R&D employees in a region. Estimation results do not differ substantially. Second, with respect to the size of a region, we include regional population as additional variable, but do not observe a significant influence, Hence, economic size of a region seems to be more important for regional knowledge production than regional size in terms of population. All results are available upon request.

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

Variables	Coefficient	t-statistic
$\beta^{(c)}$ Degree centrality	0.238***	4.498
$\beta^{(h)}$ Human resources	0.218***	3.455
$\beta^{(rd)}$ RD expenditures	0.020	1.172
$\beta^{(id)}$ Industrial diversity	1.059***	3.031
$\beta^{(g)}$ GRP	0.271***	2.429
$\beta^{(ht)}$ High-tech specialization	0.059***	3.248
$\beta^{(h\odot c)}$ Interaction	–0.038***	–3.832
$\gamma^{(c)}$ *W* Degree centrality	0.022	0.136
$\gamma^{(h)}$ *W* Human resources	0.167	1.256
$\gamma^{(rd)}$ *W* RD expenditures	0.098***	2.809
$\gamma^{(id)}$ *W* Industrial diversity	0.171	0.535
$\gamma^{(g)}$ *W* GRP	0.254	1.493
$\gamma^{(ht)}$ *W* High-tech specialization	–0.075*	–1.895
$\gamma^{(h\odot c)}$ *W* Interaction	0.024	1.217
$\phi\, y_{t\text{-}1}$	0.357***	39.044
$\rho\, W y_t$	0.160***	5.269
$\theta\, W y_{t\text{-}1}$	0.130***	5.887
Log-Lik	546.027	
σ_ε^2	0.036	

Notes: Dynamic spatial panel data model with spatial and time period fixed effects; $N = 229$, $T = 13$; estimates based on bias corrected quasi maximum likelihood estimators as in Lee and Yu (2010), applying MATLAB codes taken from Elhorst et al. (2013); spatially weighted variables are estimated using a *k*-nearest neighbours matrix with $k = 5$; the two-sided Wald Test with H0: $|\phi| + |\rho| + |\theta| = 1$ confirming stability of the model. ***significant at the 0.01 significance level, **significant at the 0.05 significance level and *significant at the 0.1 significance level.

generation. Excluding one of these parameters from the model may induce biased and inconsistent results leading to erroneous conclusions with respect to the remaining variables. However, it has to be noted that we are not able to parcel out the influences of time, that is, 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.

The significant estimate of $\beta^{(h\odot c)}$ 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. Possible explanations for this negative relationship are the costs associated with R&D collaboration in general, and high centrality in EU funded R&D networks in particular. 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 due to rising costs of co-ordination and administration of joint projects and the associated drain on own resources collaborative R&D might induce.

In Table 3 we report the average direct, indirect and total impacts on knowledge production (measured in terms of patents) arising from one per cent 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 Equations (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 the European regions. Impact estimates for the remaining explanatory variables are reported in Appendix B.

The first column of each panel refers to the periods after the one-percent stimulus of the R&D network variable in the initial period. Note that the explanatory variables are observed in the previous period $t-1$, so that we can indicate the response of knowledge production activity at period t for the first time, and thereafter for any period. The mean estimates are associated with a one-time increase in the centrality in EU funded R&D networks. The cumulative means (the last columns in each sub table) report the effects arising when the higher level of R&D network centrality persists over future periods. Due to the definition of our space-time transformation matrix, the one-period-ahead impacts include only own region (spatial) effects, while the two to ten period 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 per cent 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 per cent increase in own region R&D network centrality increases the knowledge production activity in this region by more than half a percent in the following period. However, having the negative

Table 3. Impact estimates for changes in R&D network centrality

Period	Lower 0.99	Mean	Upper 0.99	Cumulative
		Average direct impacts		
1	0.170	0.519	0.892	0.519
2	0.064	0.198	0.343	0.717
3	0.025	0.080	0.138	0.797
4	0.010	0.034	0.060	0.832
5	0.005	0.015	0.028	0.847
10	0.000	0.001	0.001	0.861
		Average indirect impacts		
1	0.015	0.344	0.723	0.344
2	0.056	0.303	0.594	0.647
3	0.044	0.211	0.417	0.858
4	0.031	0.136	0.273	0.994
5	0.020	0.084	0.174	1.077
10	0.001	0.006	0.017	1.193
		Average total impacts		
1	0.196	0.863	1.574	0.863
2	0.120	0.501	0.924	1.364
3	0.071	0.292	0.548	1.655
4	0.042	0.170	0.332	1.825
5	0.025	0.099	0.200	1.924
10	0.001	0.007	0.018	2.054

Notes: Average direct, indirect and total impacts estimated according to Equations (9) and (10), with a $k = 5$ nearest neighbours matrix and based on 1,000 sampled raw parameter estimates.

estimate for the interaction term in mind (see Table 2), we have to consider that the positive impacts of changes in a region's network centrality decrease relatively to the level of human resources in this region. We can therefore conclude that regions with low levels of own knowledge-generating endowments show higher marginal benefits from EU funded R&D networks, namely, they may be more efficient in exploiting the increase in knowledge linkages to other regions than those regions which are already equipped with high own resources. New patents can be registered more readily (i.e., within one time period) in these regions.

Although one-period ahead (immediate) effects are high, we find rapidly diminishing effects on knowledge production in subsequent periods. The long-run effects of a higher regional R&D network centrality – also interpretable as temporal spillovers within regions – are comparatively small. Hence, the effects of a one-time stimulus of EU funded R&D networks do not last within a region, indicating that the knowledge absorbed from the established R&D linkages contributes less likely to the generation of additional patents in future periods. From the cumulative own region impacts we further see that regional knowledge production activity will respond positively to persistent increases in R&D network centrality, but with considerably declining marginal impacts. Since EU funded R&D projects, that is, the linkages in the R&D network, 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 periods might partly reflect this fact. Therefore, it might be reasonable to regard the cumulative impacts for the first few, say five periods, 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 significant 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 inter-region effects can be observed for more than five periods (see also Figure 1).[15]

The average total effects reported in the last sub table of Table 3 combine both direct and indirect impacts. In our application, they characterize 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; namely, total impacts decrease sharply over time.

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 peter out five periods 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

[15] Average spillover effects are defined as the average response of a region's dependent variable when changing an explanatory variable in all other regions. In contrast to the own-region direct effect estimates, the indirect effect estimates thus sum up the effects over all other regions. From this theoretical conception it is not surprising that spillover impacts are often much larger in magnitude as compared to direct impact estimates (see LeSage and Pace 2009).

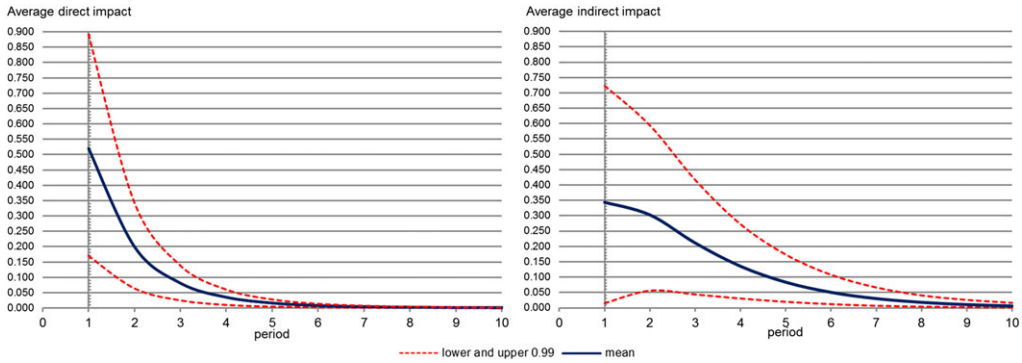

Fig. 1. Diffusion of R&D network centrality impacts over time

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.

Concerning the control variables, we find that industrial diversity seems to be – besides the centrality in R&D networks and human resources – the most important region-internal factor for regional knowledge production. Interestingly, we do not find significant (short-term) direct effects arising from changes in the own-region R&D expenditures or the domestic gross regional product (GRP) but can report significant indirect and total effects. Rising R&D specific and general economic capacities stimulate knowledge production in particular due to indirect impact mechanisms (details are given in Appendix B).[16] Given that our model includes temporal spillovers as well as region-specific (fixed) effects, financial and economic factors (in terms of R&D expenditures and GRP) seem to be less capable to explain annual variations in regional knowledge production. This is in contrast to factors that address more explicitly the availability and access to knowledge in terms of both of own-region endowments (in the form of human resources) and inter-regional linkages (in the form of R&D networks). Future research focusing on the distinct effects captured by the controls is of great relevance, given the importance of temporal effects and the interpretative power of space-time SDM relationships as used in this study.

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 over the period

[16] The results on the role of own-region financial resources seem to encounter former empirical findings in this research direction (see e.g. Ponds et al. 2010; Parent 2012). However, most studies either implement a static perspective or deal with a limited set of explanatory variables. Direct comparisons with these studies should thus be treated with caution. For example, the findings from a space-time perspective presented in this paper should not lead to the conclusion that region-internal R&D investments are not important for knowledge production; they might rather be regarded as precondition to establish knowledge production processes and participate in the inter-regional knowledge diffusion system. By this, our results provide empirical indication on how decisive it might be to address more explicitly the temporal dimension as it may considerably influence the explanatory power of certain parameters.

from 1998 to 2010. We specifically 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 229 European NUTS 2 regions. 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; Varga et al. 2014; Broekel et al. 2015), 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 emphasize 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 availability and 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 effect of region-specific endowments with knowledge-generating factors is 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 EU funded R&D networks.

Second, regions with lower own knowledge endowments more likely exploit the positive effects associated with EU funded R&D networks. The significant negative interaction term suggests that regions with a lower level of own human resources – provided that they are able to increase their centrality in the R&D network – could achieve higher positive impacts on their patenting performance. However, our results also indicate that such an impulse may not be sufficient enough to enhance regional knowledge production in a sustainable way. The evolution of cumulative direct impacts over ten periods shows that temporal spillovers of a one-time increase in R&D networking are comparatively small within regions. This observation could be interpreted as a sign that further use of knowledge and skills transferred via collaborative R&D in FP projects 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. We show that increasing inter-regional R&D networking across all European regions will 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 other forms of collaborative R&D may constitute an important extension of the current study, which is limited to inter-regional R&D network structures supported by the EU. Differentiating between scientific or research oriented organizations 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 and industrial sectors, characterized by different patenting intensities and different intensities and rationales for inter-regional R&D collaboration, will deliver crucial insights on how differently the embeddedness of regions in inter-regional R&D networks might translate into new knowledge. Such an approach might provide further reference for the design of specific research policy measures. Third, distinct results of this study gained by the estimates for the control variables, such as the role of R&D expenditures, technological specialization or industrial diversity, are an interesting issue for further in-depth explorations, in particular from a spatio-temporal perspective.

Appendix A

Table A1. 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 organizations located in a region (log); annual networks based on collaborative Framework Programme (FP) projects	EUPRO database
Human resources	Human Resources in Science and Technology (HRST) include individuals holding a university degree, and individuals engaged in fields of science and technology as professionals or technicians and associate professionals, in thousand (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 specialization, based on the employment in the economic sectors of agriculture, construction, industry, financial, wholesale, non-market services. Defined as $z_{it^{(id)}} = -\frac{1}{2}\sum_M \lvert o_{im} - \bar{o}_m \rvert$ where o_{im} is employment in region i in a specific sector m and $\bar{o}_m$ is the mean employment of sector m for $N = 229$ regions.	Cambridge Economic Data
GRP	Gross regional product at market prices, in millions (log)	Eurostat Regional Statistics
High-tech specialization	RTA index for regional specialization in high-tech based on patent data, defined as: $$z_{it^{(ht)}} = \frac{K_{iq} \Big/ \sum_{i=1}^{N} K_{iq}}{\sum_{q=1}^{Q} K_{iq} \Big/ \sum_{i=1}^{N}\sum_{q=1}^{Q} K_{iq}},$$ where K_{iq} denote patents applications in region i in high-tech q, Q denotes the number of all technological classes. We use a threshold value of 100 for the total number of patents. High-tech covers IPC classes in aviation, communication technology, computer and automated business equipment, lasers, micro-organism and genetic engineering and semiconductors.	Eurostat Regional Statistics

Table A2. Summary statistics

Variable	Min	Max	Mean	Median	Std. dev.
Patents	0	3,174	230.30	94.19	402.81
Degree centrality	0	4,804	235.87	113	376.10
Human resources	4	3,605	365.41	265	350.10
RD expenditures	0.01	13.73	1.52	1.14	1.24
Industrial diversity	0.02	0.45	0.11	0.10	0.06
GRP	0.84	509.95	45.25	31.66	52.32
High-tech specialization	0	3.258	0.46	0	0.63

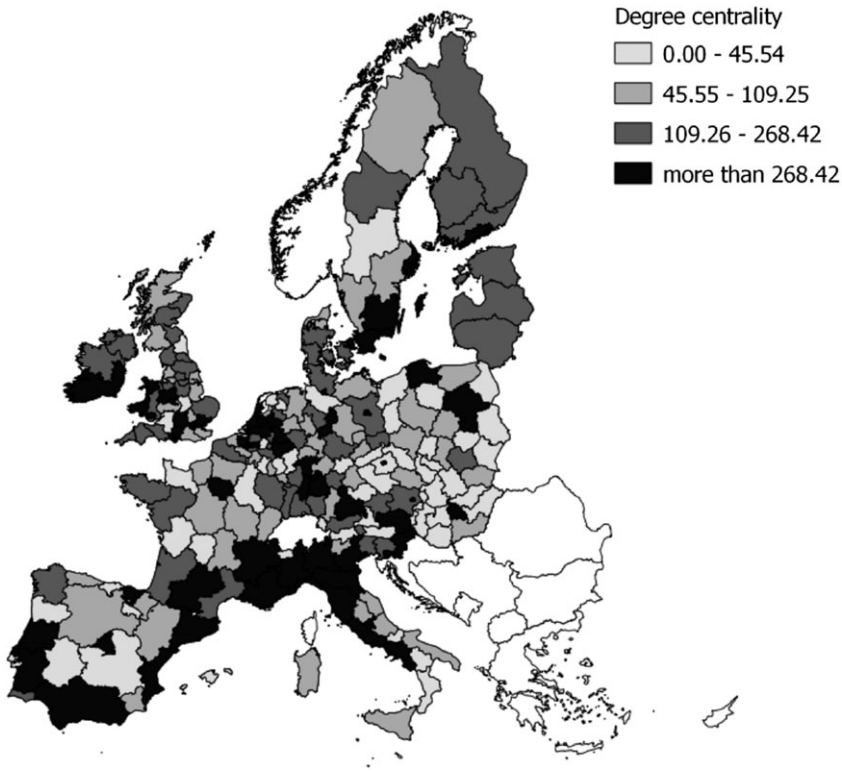

Fig. A1. Embeddedness of European regions in the R&D network

Appendix B

Table B1. Impact estimates for all variables

Period	Average direct impacts				Average indirect impacts				Average total impacts			
	Lower 0.99	Mean	Upper 0.99	Cumulative	Lower 0.99	Mean	Upper 0.99	Cumulative	Lower 0.99	Mean	Upper 0.99	Cumulative
R&D network centrality												
1	0.170	0.519	0.892	0.519	0.015	0.344	0.723	0.344	0.196	0.863	1.574	0.863
2	0.064	0.198	0.343	0.717	0.056	0.303	0.594	0.647	0.120	0.501	0.924	1.364
3	0.025	0.080	0.138	0.797	0.044	0.211	0.417	0.858	0.071	0.292	0.548	1.655
4	0.010	0.034	0.060	0.832	0.031	0.136	0.273	0.994	0.042	0.170	0.332	1.825
5	0.005	0.015	0.028	0.847	0.020	0.084	0.174	1.077	0.025	0.099	0.200	1.924
10	0.000	0.001	0.001	0.861	0.001	0.006	0.017	1.193	0.001	0.007	0.018	2.054
Human resources												
1	0.205	0.469	0.717	0.469	0.168	0.409	0.681	0.409	0.429	0.878	1.361	0.878
2	0.083	0.182	0.276	0.651	0.149	0.330	0.543	0.738	0.244	0.511	0.806	1.389
3	0.035	0.075	0.115	0.725	0.101	0.223	0.378	0.962	0.136	0.298	0.490	1.687
4	0.015	0.032	0.053	0.758	0.062	0.142	0.251	1.103	0.078	0.174	0.299	1.861
5	0.007	0.015	0.025	0.772	0.037	0.087	0.162	1.190	0.044	0.102	0.185	1.963
10	0.000	0.001	0.001	0.786	0.002	0.007	0.016	1.310	0.002	0.007	0.018	2.096
RD expenditures												
1	–0.007	0.008	0.022	0.008	0.007	0.042	0.081	0.042	0.013	0.050	0.091	0.050
2	–0.002	0.003	0.008	0.010	0.003	0.015	0.029	0.057	0.005	0.018	0.033	0.068
3	–0.001	0.001	0.003	0.011	0.001	0.005	0.010	0.063	0.002	0.006	0.012	0.074
4	0.000	0.000	0.001	0.012	0.000	0.002	0.004	0.065	0.001	0.002	0.004	0.076
5	0.000	0.000	0.000	0.012	0.000	0.001	0.001	0.065	0.000	0.001	0.002	0.077
10	0.000	0.000	0.000	0.012	0.000	0.000	0.000	0.066	0.000	0.000	0.000	0.078

(Continues)

Table B1. (Continued)

Period	Average direct impacts				Average indirect impacts				Average total impacts			
	Lower 0.99	Mean	Upper 0.99	Cumulative	Lower 0.99	Mean	Upper 0.99	Cumulative	Lower 0.99	Mean	Upper 0.99	Cumulative
Industrial diversity												
1	0.093	0.380	0.671	0.380	–0.388	0.134	0.623	0.134	–0.009	0.514	0.986	0.514
2	0.033	0.136	0.242	0.516	–0.139	0.048	0.221	0.182	–0.003	0.184	0.355	0.698
3	0.012	0.049	0.089	0.565	–0.052	0.017	0.078	0.199	–0.001	0.066	0.126	0.764
4	0.004	0.017	0.033	0.582	–0.019	0.006	0.028	0.205	0.000	0.024	0.046	0.787
5	0.001	0.006	0.012	0.588	–0.007	0.002	0.011	0.207	0.000	0.008	0.017	0.796
10	0.000	0.000	0.000	0.592	0.000	0.000	0.000	0.209	0.000	0.000	0.000	0.800
GRP												
1	–0.001	0.098	0.201	0.098	–0.023	0.126	0.286	0.126	0.099	0.225	0.366	0.225
2	–0.001	0.035	0.073	0.134	–0.008	0.045	0.103	0.171	0.036	0.080	0.132	0.305
3	0.000	0.013	0.026	0.146	–0.003	0.016	0.038	0.187	0.013	0.029	0.048	0.333
4	0.000	0.005	0.009	0.151	–0.001	0.006	0.014	0.193	0.005	0.010	0.017	0.344
5	0.000	0.002	0.004	0.152	0.000	0.002	0.005	0.195	0.002	0.004	0.006	0.347
10	0.000	0.000	0.000	0.153	0.000	0.000	0.000	0.196	0.000	0.000	0.000	0.350
High-tech specialization												
1	0.005	0.021	0.037	0.021	–0.067	–0.027	0.012	–0.027	–0.049	–0.007	0.035	–0.007
2	0.002	0.007	0.013	0.028	–0.024	–0.010	0.004	–0.037	–0.018	–0.002	0.013	–0.009
3	0.001	0.003	0.005	0.030	–0.009	–0.004	0.002	–0.040	–0.007	–0.001	0.005	–0.010
4	0.000	0.001	0.002	0.031	–0.003	–0.001	0.001	–0.041	–0.002	0.000	0.002	–0.010
5	0.000	0.000	0.001	0.032	–0.001	0.000	0.000	–0.042	–0.001	0.000	0.001	–0.010
10	0.000	0.000	0.000	0.032	0.000	0.000	0.000	–0.042	0.000	0.000	0.000	–0.010

Notes: Average direct, indirect and total impacts estimated according to Equations (5), (9) and (10), respectively, with a $k = 5$ nearest neighbours matrix and based on 1,000 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, Pohjois-ja Itä-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, Detmold, Dresden, Düsseldorf, Freiburg, Gießen, Hamburg, Hannover, Karlsruhe, Kassel, Koblenz, Köln, Leipzig, Lüneburg, Mecklenburg-Vorpommern, Mittelfranken, Münster, Niederbayern, Oberbayern, Oberfranken, Oberpfalz, Rheinhessen-Pfalz, Saarland, Sachsen-Anhalt, 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, Eastern Scotland, East Riding & North Lincolnshire, East Wales, East & West Sussex, Essex, Gloucestershire, Greater Manchester, Hampshire & Isle of Wight, Herefordshire, Highlands and Islands, Inner London, Kent, Lancashire, Leicestershire, Lincolnshire, Merseyside, North Eastern Scotland, North Yorkshire, Northern Ireland, Northumberland and Tyne and Wear, Outer London, Rutland and Northamptonshire, Shropshire & Staffordshire, South Western Scotland, South Yorkshire, Surrey, Tees Valley & Durham, West Midlands, West Wales & The Valleys, West Yorkshire, Wiltshire & North Somerset, Worcestershire & Warkwickshire

Notes: We exclude the Spanish North African territories of Ceuta and 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 is excluded from the sample because of lack of data.

References

Abreu M (2011) Absorptive capacity in a regional context. In: Cooke P, Asheim BT, Boschma R et al. (eds) *Handbook of regional innovation and growth*. Edward Elgar, Cheltenham

Acs ZJ, Anselin L, Varga A (2002) Patents and innovation counts as measures of regional production of new knowledge. *Research Policy* 31: 1069–1085

Autant-Bernard C (2012) Spatial econometrics of innovation: Recent contributions and research perspectives. *Spatial Economic Analysis* 7: 403–419

Autant-Bernard C, Mairesse J, Massard N (2007) Spatial knowledge diffusion through collaborative networks. *Papers in Regional Science* 86: 341–350

Balland PA (2012) Proximity and the evolution of collaboration networks: Evidence from research and development projects within the global navigation satellite system (GNSS) industry. *Regional Studies* 46: 741–756

Balli H, Sørensen B (2013) Interaction effects in econometrics. *Empirical Economics* 45: 583–603

Bathelt H, Malmberg A, Maskell P (2004) Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography* 28: 31–56

Bergman E (2009) Embedding network analysis in spatial studies of innovation. *The Annals of Regional Science* 43: 559–565

Breschi S, Lenzi C (2015) The role of external linkages and gatekeepers for the renewal and expansion of US cities knowledge base, 1990–2004. *Regional Studies* 49: 782–797

Breschi S, Lissoni F (2001) Knowledge spillovers and local innovation systems: A critical survey. *Industrial and Corporate Change* 10: 975–1005

Breschi S, Malerba F (2009) ERA and the role of networks. In: Delanghe H, Muldur U, Soete L (eds) *European science and technology policy: Towards integration or fragmentation?* Edward Elgar Publishing, Cheltenham

Broekel T (2015) Do cooperative research and development (R&D) subsidies stimulate regional innovation efficiency? Evidence from Germany. *Regional Studies* 49: 1087–1110

Broekel T, Brenner T, Buerger M (2015) An investigation of the relation between cooperation intensity and the innovative success of German regions. *Spatial Economic Analysis* 10: 52–78

Cohen WM, Levinthal DA (1990) Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly* 35: 128–152

Debarsy N, Ertur C, LeSage JP (2012) Interpreting dynamic space–time panel data models. *Statistical Methodology* 9: 158–171

Delanghe H, Muldur U, Soete L (2009) *European science and technology policy: Towards integration or fragmentation?* Edward Elgar Publishing, Cheltenham

Elhorst JP (2012) Dynamic spatial panels: Models, methods, and inferences. *Journal of Geographical Systems* 14: 5–28
Elhorst P, Zandberg E, Haan JD (2013) The impact of interaction effects among neighbouring countries on financial liberalization and reform: A dynamic spatial panel data approach. *Spatial Economic Analysis* 8: 293–313
Fischer MM, LeSage JP (2015) A Bayesian space-time approach to identifying and interpreting regional convergence clubs in Europe. *Papers in Regional Science* 94: 677–702
Fischer MM, Varga A (2003) Spatial knowledge spillovers and university research: Evidence from Austria. *The Annals of Regional Science* 37: 303–322
Fornahl D, Broekel T, Boschma R (2011) What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location. *Papers in Regional Science* 90: 395–418
Giuliani E, Bell M (2005) The micro-determinants of meso-level learning and innovation: Evidence from a Chilean wine cluster. *Research Policy* 34: 47–68
Goyal S (2007) *Connections: An introduction to the economics of networks*. Princeton University Press, Princeton
Graf H (2011) Gatekeepers in regional networks of innovators. *Cambridge Journal of Economics* 35: 173–198
Greene WH (2008) *Econometric analysis* (6th edn). Pearson/Prentice Hall, Upper Saddle River, NJ
Griliches Z (1995) R&D and productivity: Econometric results and measurement issues. In: Stoneman P (ed) *Handbook of the economics of innovation and technological change*. Wiley-Blackwell, Oxford
Heller-Schuh B, Barber M, Henriques L, Paier M, Pontikakis D, Scherngell T, Veltri GA, Weber M (2011) Analysis of networks in European Framework Programmes (1984–2006). JRC Scientific and Technical Reports, 24759 EN
Hoekman J, Frenken K, Tijssen RJW (2010) Research collaboration at a distance: Changing spatial patterns of scientific collaboration within Europe. *Research Policy* 39: 662–673
Hoekman J, Scherngell T, Frenken K, Tijssen R (2013) Acquisition of European research funds and its effect on international scientific collaboration. *Journal of Economic Geography* 13: 23–52
Huggins R, Thompson P (2014) A Network-based view of regional growth. *Journal of Economic Geography* 14: 511–545
Jaccard J, Turrisi R (2003) *Interaction effects in multiple regression*. Sage Publications, Thousand Oaks, CA
Katz JS, Martin BR (1997) What is research collaboration? *Research Policy* 26: 1–18
Lee L, Yu J (2010) A spatial dynamic panel data model with both time and individual fixed effects. *Econometric Theory* 26: 564–597
LeSage JP, Fischer MM (2008) Spatial growth regressions: Model specification, estimation and interpretation. *Spatial Economic Analysis* 3: 275–304
LeSage J, Pace RK (2009) *Introduction to spatial econometrics*. CRC Press, Boca Raton, FL
Moodysson J (2008) Principles and practices of knowledge creation: On the organization of 'buzz' and 'pipelines' in life science communities. *Economic Geography* 84: 449–469
Owen-Smith J, Powell WW (2004) Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. *Organization Science* 15: 5–21
Ozman M (2009) Inter-firm networks and innovation: a survey of literature. *Economics of Innovation and New Technology* 18: 39–67
Parent O (2012) A space-time analysis of knowledge production. *Journal of Geographical Systems* 14: 49–73
Parent O, LeSage JP (2010) A spatial dynamic panel model with random effects applied to commuting times. *Transportation Research Part B: Methodological* 44: 633–645
Ponds R, van Oort F, Frenken K (2010) Innovation, spillovers and university–industry collaboration: An extended knowledge production function approach. *Journal of Economic Geography* 10: 231–255
Scherngell T (ed) (2013) *The geography of networks and R&D collaborations*. Springer-Physica Verlag, Berlin
Scherngell T, Barber MJ (2009) Spatial interaction modelling of cross-region R&D collaborations: Empirical evidence from the 5th EU framework programme. *Papers in Regional Science* 88: 531–546
Sebestyén T, Varga A (2013) Research productivity and the quality of interregional knowledge networks. *The Annals of Regional Science* 51: 155–189
Storper M, Venables AJ (2004) Buzz: Face-to-face contact and the urban economy. *Journal of Economic Geography* 4: 351–370
Varga A, Pontikakis D, Chorafakis G (2014) Metropolitan Edison and cosmopolitan Pasteur? Agglomeration and interregional research network effects on European R&D productivity. *Journal of Economic Geography* 14: 229–263
Vega SH, Elhorst JP (2014) Modelling regional labour market dynamics in space and time. *Papers in Regional Science* 93: 819–841
Wanzenböck I, Scherngell T, Brenner T (2014) Embeddedness of regions in European knowledge networks. A comparative analysis of inter-regional R&D collaborations, co-patents and co-publications. *The Annals of Regional Science* 53: 337–368
Wanzenböck I, Scherngell T, Lata R (2015) Embeddedness of European regions in European Union-funded research and development (R&D) networks: A spatial econometric perspective. *Regional Studies* 49: 1685–1705
Wasserman S, Faust K (1994) *Social network analysis: Methods and applications*. Cambridge University Press, Cambridge
Yu J, de Jong R, Lee L (2008) Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large. *Journal of Econometrics* 146: 118–134

doi:10.1111/pirs.12236

Resumen. En este estudio se estiman los impactos espacio-temporales del arraigo en las redes de I+D en la producción de conocimiento regional utilizando un modelo dinámico espacial de datos de panel con efectos no lineales para 229 regiones europeas NUTS 2 en el período 1998–2010. El arraigo se refiere al posicionamiento en redes donde los nodos representan regiones que están vinculadas por proyectos conjuntos de I+D financiados por los Programas Marco de la UE. Se encontró evidencia de que el aumento del arraigo en las redes de I+D financiadas por la UE genera impactos inmediatos positivos en la producción de conocimiento regional, y que las regiones con niveles más bajos de dotación de conocimiento propio explotan más los efectos positivos. Sin embargo, los impactos a largo plazo del arraigo de una región en estas redes de I+D son comparativamente pequeños.

抄録: 本稿では、1998年から2010年までの欧州の第二種地域統計分類単位(NUTS2)に分類される229の地域の、非線形効果を用いたダイナミック空間パネルデータモデルを使用して、地域の知識生産に対する研究開発ネットワークにおける埋め込み(embeddedness)の時空間波及効果を推計する。埋め込み(embeddedness)とは、ノードがEUフレームワークプログラムの助成により行われた研究開発ジョイントプロジェクトにより繋がれた地域を表しているネットワーク上のポジショニングを指す。EUの助成による研究開発ネットワークが地域の知識生産に直接的な正の効果をもたらし、自己の知的資本(knowledge endowments)レベルがより低い地域には、その正の効果を上手く利用する傾向があることを示すエビデンスが認められた。しかし、研究開発ネットワークのひとつの地域の埋め込みが及ぼす長期的な波及効果は、比較的小さいものである。

© 2018 The Author(s). Papers in Regional Science © 2018 RSAI