

Scherngell, Thomas; Lata, Rafael

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Integration in the European Research Area by means of the European Framework Programmes Findings from Eigenvector filtered spatial interaction models

Thomas Scherngell¹ and Rafael Lata¹

¹Foresight and Policy Development Department,
Austrian Institute of Technology (AIT)
Vienna, Austria

Abstract. One of the main goals of the European Research Area (ERA) concept is to improve coherence and integration across the European research landscape by removing barriers for collaborative knowledge production in a European system of innovation. The cornerstone of policy instruments in this context is the European Framework Programme (FP) that supports pre-competitive collaborative R&D projects, creating a pan-European network of actors performing joint R&D. However, we know only little about the contribution of the FPs to the realisation of ERA. The objective of this study is to monitor progress towards ERA by identifying the evolution of separation effects, such as spatial, institutional, cultural or technological barriers, which influence cross-region R&D collaboration intensities between 255 European NUTS-2 regions in the FPs over the time period 1999-2006. By this, the study builds on recent work by Scherngell and Barber (2009) that addresses this question from a static perspective. We employ Poisson spatial interaction models taking into account spatial autocorrelation among residual flows by using Eigenvector spatial filtering methods. The results show that geographical distance and country border effects gradually decrease over time when correcting for spatial autocorrelation among flows. Thus, the study provides evidence for the contribution of the FPs to the realisation of ERA.

JEL Classification: O38, L14, R15

Keywords: R&D networks, European Framework Programme, large-scale networks, Spatial interaction modelling, Eigenvector spatial filtering

1 Introduction

The notion of the so-called “fifth freedom” in the concept of the *European Research Area* (ERA) refers to the objective to enable and facilitate “free circulation of researchers, knowledge and technology” across the countries of the European Union (see CEU 2008, p. 6). This policy goal is to be addressed by improving coherence of the European research landscape, removing barriers and obstacles for knowledge diffusion, and stimulating R&D networks and collaborative knowledge production in a European system of innovation (see CEC 2007, Frenken et al. 2007). By this, ERA has become the main pillar of the well known ‘Lisbon Agenda’ that outlines the strategic European policy goal to become “... the most competitive and dynamic knowledge based economy in the world ...” (European Council 2000, p. 2), formulated back in the year 2000.

This European policy focus has been triggered by various scientific considerations in the 1990s. Two arguments – that are widely accepted nowadays – are essential in this respect: *First*, interactions, research collaborations and networks of actors are crucial for successful innovation (see, for instance, Powell and Grodal 2005)¹, and, *second*, innovation and knowledge diffusion are the key vehicles for sustainable economic competitiveness (see, for instance, Romer 1990). From this perspective, it seems natural that modern STI policies shift emphasis on stimulating R&D networks and interactions between innovating actors. They focus on supporting free and expansive knowledge diffusion between relevant actors in a system of innovation. In fact, the establishment and support of R&D networks has become a major concern of recent STI policy initiatives on a national as well as supranational scale (for a discussion of major international examples, see Caloghirou et al. 2002).

The cornerstone of policy instruments explicitly designed to address the ERA objectives are the European Framework Programmes (FPs) for Research and Technological Development (RTD). The FPs support pre-competitive R&D projects, creating a pan-European network of actors performing joint R&D. From its inception, different thematic aspects and issues of the

¹ Theoretical and empirical literature emphasises that R&D networks – defined as a set of firms, universities and research institutions connected with each other via various kinds of interactions and interdependencies in research and development processes – play a crucial role in developing and integrating new knowledge in the innovation process (see Powell and Grodal 2005). This is explained by considerations that innovation nowadays takes place in an environment characterized by uncertainty, increasing complexity and rapidly changing demand patterns in a globalised economy. Participation in R&D networks may reduce the degree of uncertainty and provides fast access to different kinds of knowledge, in particular tacit knowledge (see, for example, Kogut 1988).

European scientific landscape have been addressed by the FPs, though the main emphasis has been shifted more and more towards the establishment of ERA (see Breschi and Malerba 2009). In this sense, the FPs aim to promote scientific excellence and technological competitiveness while at the same time it is meant to foster cohesion (see Peterson and Sharp 1998, Begg 2010). However, the observation that knowledge flows are geographically bounded since important parts of new knowledge have some degree of tacitness (see Krugman 1991) may favour core regions instead of fostering integration of peripheral regions. In Europe these forces may be arguably particularly strong, as distinct national and regional systems still persist and countries maintain their own strategies next to the European-wide Lisbon Agenda (Crescenzi et al. 2007). This is also reflected by the current distribution of R&D capabilities across Europe (see, for instance, Hoekman et al. 2010 for the case of scientific knowledge production as captured by publications).

R&D networks constituted under the heading of the FPs have recently attracted a number of empirical studies, most of them employing a social network analysis perspective (see, for instance, Breschi and Cusmano 2004). However, there are relatively few empirical studies investigating the contribution of the FPs to the ERA goal of an integrated European research landscape by focusing on their geographical dimension. The studies of Scherngell and Barber (2009 and 2010) are notable recent exceptions in this respect. Their work discloses spatial collaboration patterns of the fifth FP by estimating various separation effects – such as different types of geographical barriers and technological distance – that influence collaboration intensities in FP5 at a regional level using a Poisson spatial interaction modelling framework. In a European STI policy context, their results point to mixed policy outcomes. The FPs seem to have a positive effect on lowering institutional barriers in the form of country borders as well as geographical barriers in the public research sector, while in the industry sector these barriers still play an important role.

However, one important shortcoming of Scherngell and Barber (2009 and 2010) is that they just provide a static picture by using cross-Section data from FP5. This is where the current study is intended to connect up. The objective is to estimate the progress towards more integration of ERA by identifying the evolution of separation effects over the time period 1999-2006 that influence the probability of cross-region collaboration activities in the European network of cooperation in the FPs. Separation effects involve geographical, technological, economic, cultural and institutional barriers. We follow previous empirical

work and employ a Poisson spatial interaction modelling perspective. We take into account spatial autocorrelation in network data that has been recently referred to as a critical issue in spatial interaction data (see, for instance, LeSage and Pace 2008, Fischer and Griffith 2008). Thus, the current study departs from previous literature by at least two major respects: *First*, by employing a dynamic perspective in the analysis of the spatial dimension of R&D collaborations in the FPs, and, *second*, methodologically by specifying Eigenfunction spatial filters to address spatial network autocorrelation problems in the parameter estimation of the Poisson spatial interaction models.

The remainder of the study is organised as follows. Section 2 sets forth in more detail the conceptual and theoretical background of the study by describing the FPs as main instrument for the realisation of the ERA goals, and by embedding the current study in relevant empirical and theoretical literature. Section 3 introduces the spatial interaction modelling framework that is used to identify the evolution of separation effects influencing the probability of cross-region collaborations in the FPs. Section 4 describes the empirical setting, introduces the data used, and specifies the dependent and independent variables, before Section 5 outlines the Eigenfunction spatial filtering specification of the spatial interaction models for taking into account spatial autocorrelation issues in spatial interaction data. Section 6 presents the modelling results while Section 7 closes with a summary of the main results and some conclusions in a European policy context.

2 Theoretical background

The concept of the European Research Area (ERA) has become the key reference for the European STI policy. ERA addresses the establishment of an ‘internal market’ for research across Europe, where researchers, technology and knowledge are supposed to circulate freely (see Delanghe et al. 2009). According to the ERA green paper (CEC 2007), the future European science and research landscape should be characterized by an adequate flow of competent researchers with high levels of mobility between institutions, by integrated and networked research infrastructures and effective knowledge sharing, notably between public research and industry. This requires the removal of barriers – such as geographical, cultural, institutional and technological impediments – for knowledge flows, knowledge diffusion and researcher mobility by a European-wide coordination of national and regional research

activities and policy programmes, including a considerable amount of jointly-programmed public research investment (see Delanghe et al. 2009).

The main underlying assumption of the strategic policy goal reflected by ERA is that the emergence of an integrated European system of innovation – as characterized by effective network structures and system-wide knowledge diffusion – is the key to sustainable technological, and, thus, economic competitiveness. This is related to the widely accepted assumption that networks and collaborative knowledge production are crucial for successful innovation (see OECD 1992, Granstrand 1998, Cowan 2004, Pavitt 2005, among others)². Based on these considerations, the support of collaborative knowledge production has become the main pillar of STI policies in Europe. The main instrument in this context are the Framework Programmes (FPs) on Research and Technological Development (RTD), that have funded thousands of pre-competitive collaborative R&D projects to support transnational cooperation and researcher mobility for training purposes, creating a network of actors distributed across Europe performing joint R&D (see Breschi and Cusmano 2004).

In spite of their different scopes, the fundamental rationale of the FPs has remained unchanged since their launch in 1984 (see Barker and Cameron 2004)³. The overall objectives of the FPs have been to strengthen the scientific and technological bases of the European scientific community and the European economy to foster international competitiveness, and the promotion of research activities in support of other EU policies (see CORDIS 2006). However, public funding has increased tremendously in the late 1990s. By this, the main emphasis of the FPs has been shifted more and more towards the establishment of an integrated European Research Area, in particular since the fifth and the sixth FP that show a stronger focus on research integration (see Breschi and Malerba 2009)⁴. In the FPs, project

² Pavitt (2005) notes that the growing complexity of technology and the existence of converging technologies are key reasons for this development. In particular, firms have expanded their knowledge bases into a wider range of technologies (Granstrand 1998), which increases the need for more different types of knowledge, so firms must learn how to integrate new knowledge into existing products or production processes (Cowan 2004). The fundamental importance of interactions and networks for innovations is also reflected in the various systems of innovation concepts (see Lundvall 1992, among others). In this conception, the sources of innovation are often established between firms, universities, suppliers and customers.

³ Implementation of the EU FPs began in 1984; the current seventh programme has begun in 2007 and will run until 2013. See Roediger-Schluga and Barber (2006) for a detailed discussion on the history and different scopes of the EU FPs since 1984.

⁴ In particular in FP6 new instruments were introduced aiming at the creation of progressive and lasting integration of existing and emerging research initiatives: The Integrated Projects (IPs) that are large multi-partner projects were intended to obtain results with direct impact on the European industrial competitiveness, while the Networks of Excellence (NoEs)

proposals are to be submitted by self-organised consortia. Funding is open to all legal entities established in the Member States of the European Union – e.g. individuals, industrial and commercial firms, universities, research organisations, etc. – and can be submitted by at least two independent legal entities established in different EU Member States or in an EU Member State and an Associated State. Proposals to be funded are selected on the basis of criteria including scientific excellence, added value for the European Community, the potential contribution to furthering the economic and social objectives of the Community, the innovative nature, the prospects for disseminating and exploiting the results, and effective transnational cooperation (European Council 1998).

So far, progress toward an integrated ERA by means of the FPs has been assessed empirically mainly in terms of the policy actions taken at different levels (see Delanghe et al. 2009). There are a few studies that investigate structural properties of the arising FP networks by using social network analysis techniques, such as the contributions of Breschi and Cusmano (2004) or Roediger-Schluga and Barber (2008). They show that integration between collaborating organisations has increased over time and conclude that these findings point towards a more integrated European Research Area. However, there have been relatively few empirical studies that investigate the contribution of the FPs to the realisation of an integrated ERA by focusing on the geographical dimension of FP networks. Notable recent contributions involve the studies of Scherngell and Barber (2009 and 2010). They focus on spatial collaboration patterns of the fifth FP by estimating how geographical, institutional, cultural and technological barriers influence the probability of cross-region FP5 collaboration activities. Their results point to mixed policy outcomes as the FPs seem to have a positive effect on lowering institutional barriers in the form of country borders as well as geographical barriers in the public research sector, while in the industry sector these barriers still play an important role. Furthermore, the contribution of Constantelou et al. (2004) investigates inter-country linkages in EU FPs and unveils a picture of significant collaborative activity among clusters of neighbouring countries. Maggioni and Uberti (2007) model cross-region collaboration in FP5 programs for five large EU countries with gravity equations estimated by using standard OLS estimation procedures, also finding that geographical distance exerts a significant, though a rather small negative effect on collaboration probabilities in FP5.

are large multi-partner projects aimed at reinforcing European scientific and technological excellence (Breschi and Cusmano 2009).

However, these few empirical studies dealing with the geographical dimension of the FPs all adopt a static perspective by focusing at one point in time. Thus, they are not able to provide insight into the evolution of these separation effects over time. The study at hand aims to fill this important research gap, as just a dynamic perspective is able to shed some light on how the FPs contribute to the realisation of the ERA goals. Further, we methodologically improve previous studies using spatial interaction models for the analysis of the geography of FP collaborations by taking spatial network autocorrelation issues into account. Neglecting spatial network autocorrelation may lead to biased estimates, in particular an underestimation of geographical distance effects (see Fischer and Griffith 2008) may produce misleading interpretations in the context of estimating progress towards spatial integration of ERA.

3 The Model

In our study we use a spatial interaction modelling perspective to estimate how specific separation effects influence the variation of R&D networks in Europe over time. As noted by Fischer and LeSage (2010) and many others, spatial interaction models constitute sustainable methods for modelling origin-destination flow data and were used to explain different kinds of flows across geographic space.

The common spatial interaction model depends on three types of functions that explain the variation of interaction: (i) the origin function O_i which characterizes the origin i of the interaction, (ii) the destination function D_j which describes the destination j of the interaction, and (iii) the distance-deterrence function S_{ij} which measures the spatial separation or distance between an origin region i and a destination region j and represents the main focus of spatial interaction models. Driven by our research questions we take a longitudinal perspective so that our basic model takes the form

$$Y_{ijt} | y_{ijt} = X_{ijt} + \varepsilon_{ijt} \quad (1)$$

with

$$X_{ijt} = O_{it} D_{jt} S_{ijt} \quad i, j = 1, \dots, n; \quad t = 1, \dots, T \quad (2)$$

where ij is an index for the cross-sectional dimension (spatial units), with $i, j = 1, \dots, n$, and t describes an index for the time dimension (time periods), with $t = 1, \dots, T$. Y_{ijt} is a stochastic dependent variable that corresponds to observed R&D collaborations y_{ijt} between region i and j in time period t with the property $E[Y_{ijt}|y_{ijt}] = X_{ijt}$. X_{ijt} is a function that captures the stochastic relationship to other random variables sampled from a specified probability distribution dependent upon some mean, say μ_{ijt} . In our model, $\mu_{ijt} = X_{ijt}$ is specified as a function of covariates measuring the characteristics of origin regions, destination regions and their separation. ε_{ijt} is a disturbance term with the property $E[\varepsilon_{ijt} | y_{ijt}] = 0$. We specify $O_{it} = O(o_{it}, \alpha_{1t}) = o_{it}^{\alpha_{1t}}$ and, $D_{jt} = D(d_{jt}, \alpha_{2t}) = d_{jt}^{\alpha_{2t}}$, where α_{1t} and α_{2t} denote parameters to be estimated. o_{it} and d_{jt} are the origin and destination variables. The main emphasis lies on the distance-deterrence function and the definition of an adequate set of separation measures that can be included as explanatory variables.

We employ the distance-deterrence function in a multivariate exponential form and define:

$$S_{ijt} = \exp \left[\sum_{k=1}^K \beta_{kt} s_{ijt}^{(k)} \right] \quad i, j = 1, \dots, n; \quad t = 1, \dots, T \quad (3)$$

where $s_{ijt}^{(k)}$ is a multivariate measure of spatial separation that varies across all origin-destination pairs with K separation measures and β_{kt} ($k = 1, \dots, K$) are parameters to be estimated. We use $K = 6$ separation measures such as geographical distance or technological distance between regions i and j (see Section 3 for the definition of the separation variables).

Incorporating O_{it} , D_{jt} and S_{ijt} in (1) yields

$$y_{ijt} = o_{it}^{\alpha_{1t}} d_{jt}^{\alpha_{2t}} \exp \left[\sum_{k=1}^K \beta_{kt} s_{ijt}^{(k)} \right] + \varepsilon_{ijt} \quad (4)$$

Note that we estimate the parameters α_{1t} , α_{2t} and β_{kt} for each time period t separately. Thus, our parameters vary over time but are estimated independently from each other.

The discrete nature of our dependent variable and the presence of zero flows revoke the use of least-squares parameter estimation due to the fact that zero flows invalidate the normality

assumption $\varepsilon_{ijt} \sim N(0, \sigma^2)$. A reasonable and approved procedure to overcome this deficiency is a Poisson model specification. However, this specification may suffer from unobserved heterogeneity between the region pairs and, thus, leads to biased estimates (see Cameron and Trivedi 1998). The introduction of a stochastic heterogeneity parameter $\exp(\xi_{ijt})$ overcomes this problem leading to

$$\Pr(Y_{ijt} = y_{ijt} | X_{ijt}^*) = \exp(-\mu_{ijt}^{\exp(\xi_{ijt})}) \mu_{ijt}^{y_{ijt}} / y_{ijt}! \quad i, j = 1, \dots, n; t = 1, \dots, T \quad (5)$$

with

$$X_{ijt}^* = \exp \left[\alpha_{0t} + \alpha_{1t} \log(o_{it}) + \alpha_{2t} \log(d_{jt}) + \sum_{k=1}^K \beta_{kt} s_{ijt}^{(k)} + \xi_{ijt} \right] \quad (6)$$

and

$$\exp(\xi_{ijt}) \sim \Gamma(\gamma) \quad (7)$$

where overdispersion is modelled by an additional model parameter γ and $\Gamma(\cdot)$ describes the gamma function (see Long and Freese 2001). Integrating (ξ_{ijt}) out of Equation (5) leads to a Negative Binomial density distribution of y_{ijt} . Thus, our Negative Binomial spatial interaction model is defined as

$$\Pr(Y_{ijt} = y_{ijt} | X_{ijt}^*) = \frac{\Gamma(y_{ijt} + \gamma^{-1})}{[y_{ijt}! \Gamma(\gamma^{-1})]} \theta_{ijt}^{1/\gamma} (1 - \theta_{ijt})^{y_{ijt}} \quad i, j = 1, \dots, n; t = 1, \dots, T \quad (8)$$

with

$$\theta = \gamma^{-1} / (\gamma^{-1} + \mu_{ijt}) \quad (9)$$

4 Data and variables

This Section focuses on our empirical setting and the construction of the dependent and independent variables. Our study area is composed of $i, j = 1, \dots, n = 255$ NUTS-2 regions

(NUTS revision 2003) of the 25 pre-2007 EU member-states, as well as Norway and Switzerland (the detailed list of regions is given in Appendix A).

The dependent variable and its properties

For the construction of the dependent variable, which describes the region-region collaboration matrix Y , we use data from the EUPRO database, including information on more than 60,000 collaborative research projects of the FP1-FP6 and more than 60,000 participating organisations, including systematic information on the geographical location and the organisation type. We extract n -by- n collaboration matrices for each time period $t = 1, \dots, T$ by aggregating the number of individual collaborative activities in time period t to the regional level which leads to the observed number of R&D collaborations y_{ijt} between two regions i and j in time period t . The resulting regional collaboration matrix Y for a given year t contains the collaboration intensities between all (i, j) -region pairs, given the $i = 1, \dots, n = 255$ regions in the rows and the $j = 1, \dots, n = 255$ regions in the columns. We follow previous work and construct our regional collaboration matrix Y using the full counting procedure; for a project with e.g. three different participating organisations a, b and c , which are located in three different regions, we count three links (from a to b , from b to c and from a to c).

Table 1 presents some descriptive statistics on observed R&D collaborations among the 255 (i, j) -region pairs for the years 1999 to 2006. They provide some interesting preliminary insights into the evolution of FP collaboration patterns over the observed time period. *First*, regarding the overall collaboration intensity (top of Table 1), it can be seen that the sum and mean of cross-region collaboration activities increases from 1999 to 2004, i.e. the European network of R&D cooperation is becoming denser. The slight decrease after 2004 is related to the fact that the EUPRO database does not record complete data for 2005 and 2006 yet. *Second*, concerning positive links that refer to (i, j) -region pairs that show at least one FP project collaboration we can also identify a considerable growth from 1999 (34,828 positive links) to 2006 (43,113). This means that new regions pairs that collaborate arise over the observed time period indicating that the FPs are becoming not subject to a European core group of regions only. This is also reflected by a spatial visualisation of the cross-region R&D collaboration in Europe as given by Figure 1. In this spatial network map the nodes correspond to one region; the size of the nodes are proportional to the number of regional project participation, the lines with the number joint projects between two regions. The

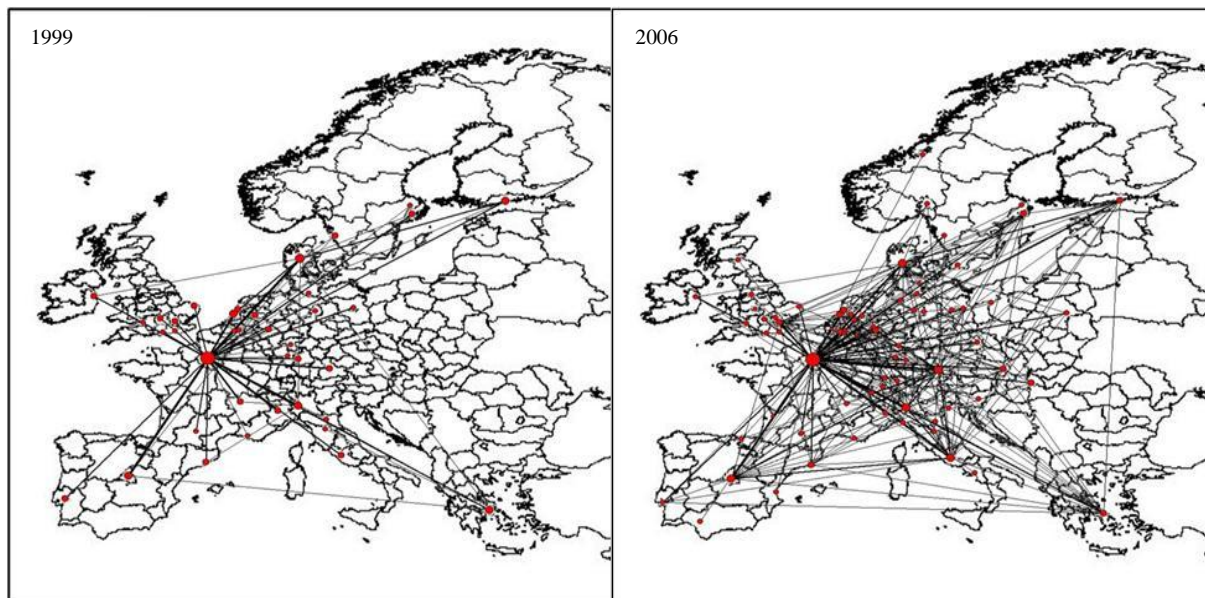
increasing density as well as the spread of the network to Eastern European countries is clearly evident from these maps.

Table 1. Descriptive statistics on R&D collaborations (1999-2006)

All links	1999	2000	2001	2002	2003	2004	2005	2006
Matrix elements	65,025	65,025	65,025	65,025	65,025	65,025	65,025	65,025
Sum	399,017	485,142	591,300	711,928	722,841	913,751	891,192	778,682
Mean	6.14	7.46	9.09	10.95	11.12	14.05	13.71	11.98
Standard deviation	20.32	25.19	30.25	37.36	37.18	46.57	46.42	40.72
Min	0	0	0	0	0	0	0	0
Max	1,238	1,677	2,104	2,906	2,907	3,324	3,205	2,212
Positive links								
Matrix elements	34,828	37,668	40,758	42,656	43,146	45,057	44,781	43,113
Sum	399,017	485,142	591,300	711,928	722,841	913,751	891,192	778,682
Mean	11.46	12.88	14.51	16.69	16.75	20.28	19.90	18.06
Standard deviation	26.64	32.03	37.17	45.07	44.60	54.81	54.83	48.90
Min	1	1	1	1	1	1	1	1
Max	1,238	1,677	2,104	2,906	2,907	3,324	3,205	2,212
Intraregional links								
Matrix elements	255.00	255.00	255.00	255.00	255.00	255.00	255.00	255.00
Sum	9,105	10,780	12,342	15,602	15,081	17,093	15,596	12,848
Mean	35.71	42.28	48.40	61.02	59.14	67.03	61.16	50.38
Standard deviation	97.27	125.84	153.00	206.21	203.27	230.44	219.26	159.87
Min	0	0	0	0	0	0	0	0
Max	1,238	1,677	2,104	2,906	2,907	3,324	3,205	2,212
Interregional links								
Matrix elements	64,770	64,770	64,770	64,770	64,770	64,770	64,770	64,770
Sum	389,912	474,362	578,958	696,368	707,760	896,658	875,596	765,834
Mean	6.02	7.32	8.94	10.75	10.93	13.84	13.52	11.82
Standard deviation	19.33	23.87	28.65	34.99	34.87	44.24	44.33	39.48
Min	0	0	0	0	0	0	0	0
Max	648.00	946.00	1,099	1,572	1,536	1,998	2,110	1,718

From the descriptive statistics presented in Table 1 we can also conclude that the European network of R&D cooperation is highly skewed. The standard deviation is always much higher than the mean, i.e. there are a few regions that show a very high participation intensity, while the large majority of regions show a low or no participation. We can further see that intraregional collaborations are much more frequent than mean cross-region collaboration intensities. Figure B.1 in Appendix underlines this finding when plotting the frequency of cross-region R&D collaborations for each time period.

Figure 1. Spatial patterns of European FP networks (1999 and 2006)



Note: Only observations with more than 200 R&D collaboration links between any two regions are displayed

The independent variables

The independent variables consist of one origin measure, one destination measure and $K = 6$ separation measures. The origin variable is simply measured in terms of the number of organizations participating in joint FP projects in region i in time period t , while the destination variable denotes the number of organizations participating in joint FP projects in region j in time period t . Note that the values for the origin and destination variable are the same, but their interpretation in the spatial interaction modelling estimation is different.

The separation variables are the focus of interest in the context of our research questions. As we are seeking to observe progress towards an integrated European research area, we focus on barriers that may hamper cross-region collaboration probability, and, thus, progress towards integration. In a policy context, often mentioned barriers for European integration in research collaboration refer to spatial effects, cultural and institutional hurdles and economic or technological barriers (see, for instance, Frenken 2007, LeSage et al. 2007, Hoekman et al. 2009 and 2010, Scherngell and Barber 2009 and 2010). According to these types of barriers, we focus on $K = 6$ separation measures that can be grouped into three categories:

- (i) Variables accounting for *spatial effects*: First, $s_{ij}^{(1)}$ measures the geographical distance between the economic centres of two regions i and j in time period t , by using the great circle distance. Second, we introduce two dummy variables that account for spatial

localization effects at the level of regions and countries: $s_{ijt}^{(2)}$ is a neighbouring region dummy variable that takes a value of one if the regions i and j in time period t are direct neighbours, and zero otherwise. $s_{ijt}^{(3)}$ is a neighbouring country dummy variable that takes a value of one if the regions i and j in time period t are located in neighbouring countries, and zero otherwise.

(ii) Variables accounting for *institutional and cultural effects*: $s_{ijt}^{(4)}$ is a country dummy variable that we use as a proxy for institutional barriers. The variable takes a value of zero if two regions i and j in time period t are located in the same country, and one otherwise. $s_{ijt}^{(5)}$ is a language dummy variable – accounting for cultural barriers – that takes a value of zero if two regions i and j in time period t are located in the same language area, and one otherwise.

(iii) Variables accounting for *technological effects*: $s_{ijt}^{(6)}$ captures technological distance by using regional patent data from the European Patent Office (EPO). The application date is used to extract the data for each year of our time frame. The variable measures region i 's share of patenting in each of the technological subclasses of the International Patent Classification (IPC). Technological subclasses correspond to the third-digit level of the IPC systems (see Moreno, Paci and Usai 2005).

5 Model specification using the eigenvector filtering approach

At this point we seek to estimate the parameters α_{1t} , α_{2t} and β_{kt} for each time period t using Maximum Likelihood estimation techniques. However, Maximum likelihood estimation of the Negative Binomial regression model given by Equation (8) assumes that all observations, in our case cross-region R&D collaborations, are mutually independent. As recently demonstrated by Chun (2008) and Griffith (2009), a violation of this assumption may be in particular induced by spatial network autocorrelation leading to misspecified models and incorrect inferences. In the current case, it is reasonable to assume that our observed cross-region collaboration flows are not independent from each other.

We shortly introduce the notion of spatial network autocorrelation as it is not as common as the notion of spatial autocorrelation in the context of attribute data. Spatial autocorrelation of flows is, for example, when flows from a particular origin may be correlated with other flows that have the same origin and, similarly, flows into a particular destination may be correlated with other flows that have the same destination. This is also referred to as origin-to-destination dependence (Chun 2008). In our case, this means that the intensity of R&D collaborations from an origin region i to a destination region j may be correlated with the intensity of R&D collaborations from the same origin i to *another* destination j , or vice versa the intensity of R&D collaborations from an origin region i to a destination region j may be correlated with the intensity of R&D collaborations from *another* origin i to the same destination j . Given the descriptive statistics in Table 1 and the spatial network maps from Figure 1, we can conclude that spatial network autocorrelation may be an issue in our empirical setting.

Taking the problem of spatial network autocorrelation into account, we follow Griffith (2009) and construct origin- and destination-specific filters which cover and isolate spatial dependencies of R&D collaboration flows between our (i, j) -region pairs at time t . We prefer the spatial filtering method over specifying a spatial autoregressive model as we are dealing with a Poisson spatial interaction context. The key benefit of the spatial filtering approach is that it does not depend on a normality assumption and is therefore easily applied to our Negative Binominal specification (see Fischer and Griffith 2008). The essence of the spatial filtering approach is to introduce a set of spatial proxy variables that are added as control variables to the model specification. These proxy variables are extracted as n eigenvectors that we label E_n from a modified spatial weights matrix W^* of the form

$$W^* = (I - \mathbf{1}\mathbf{1}^T/n) W (I - \mathbf{1}\mathbf{1}^T/n) \quad (10)$$

with I denoting the n -by- n identity matrix, $\mathbf{1}$ is an n -by-1 vector of ones, and W the n -by- n spatial weights matrix, with elements

$$w_{ij} = \begin{cases} 1 & \text{if } s_{ij}^{(1)} \leq s_{ig(i)}^{(1)} \\ 0 & \text{otherwise.} \end{cases} \quad (11)$$

where $w_{ij} = w_{ji}$, and $s_{ij}^{(1)}$ measures the geographical distance, as defined in the previous Section, between two regions i and j , and $g_{(i)}$ denotes the g -nearest neighbour of i . We define $g = 5$, as used in various empirical studies dealing with European regions (see, for example, LeSage and Pace 2008).

As shown by Tiefelsdorf and Boots (1995), each extracted Eigenvector E_i relates to a distinct map pattern that has a certain degree of spatial autocorrelation for a specific set of numerical values, i.e. when we extract our E_n Eigenvectors of the modified spatial weights matrix given by Equation (10), the E_n eigenvectors describe the full range of all possible mutually orthogonal and uncorrelated map patterns (see, for example, Grimpe and Patuelli 2008). Thus, they can be interpreted as synthetic map variables that represent specific natures and degrees of potential spatial autocorrelation. When we add them to our model specification they will serve as spatial surrogates to isolate the spatial signal in the error term from the remaining uncorrelated part. Note that the modified form of the spatial weights matrix as given by Equation (10) ensures that the first extracted eigenvector E_1 is the one showing the highest degree of positive spatial correlation as given by the Moran Coefficient (MI) that can be achieved by any spatial recombination; the second eigenvector E_2 has the largest achievable degree of spatial autocorrelation by any set that is uncorrelated with E_1 until the last extracted eigenvector E_n will maximize negative spatial autocorrelation (Griffith 2003).

As noted by Fischer and Griffith (2008), it is not reasonable to add the full set of E_n eigenvectors as spatial proxy variables to the model specification. They should be bounded to a set of distinguished eigenvectors (e.g. this can be done on the basis of their MI values). In the current study we follow Fischer and Griffith (2008) and extract an adequate set of eigenvectors from the full set E_n by employing a critical value of $MI/MI_{\max} > 0,25$, where MI_{\max} indicates the maximum MI value. Further, as we are dealing with flow data in the form of R&D collaborations between regions i and j , an adaption of the selected eigenvectors E_m to a spatial interaction framework is necessary (see, for example, Griffith 2009). This link is done by means of the Kronecker product, where the origin candidate eigenvectors are obtained from $I \otimes E_m$ and the destination candidate eigenvectors are drawn from $E_m \otimes I$, where \otimes denotes the Kronecker product (see Fischer and Griffith 2008). Adding the selected origin and destination filters as regressors to our negative binomial spatial interaction, leads to the spatially filtered negative binomial spatial interaction model

$$X_{ijt}^{*st} = \exp \left[\alpha_{0t} + \sum_{q=1}^Q E_{qt} \psi_{qt} + \alpha_{1t} \log(o_{it}) + \sum_{r=1}^R E_{rt} \varphi_{rt} + \alpha_{2t} \log(d_{jt}) + \sum_{k=1}^K \beta_{kt} s_{ijt}^{(k)} + \xi_{ijt} \right] \quad (12)$$

where o_{it} , d_{jt} and s_{ijt} are specified as given in the previous Section, E_{qt} describes the selected subsets of eigenvectors that characterize the origin variable and E_{rt} denotes the selected subsets of the eigenvectors that describe the destination variable. The coefficients for the spatial filters are ψ_{qt} and φ_{rt} . Model estimation is done by standard maximum likelihood estimation procedures.

6 Modelling results

Table 2 presents the estimation results of the standard negative binomial interaction model at the top of the table and spatial filter specification model at the bottom. The respective columns give the results for each year. Standard errors are given in brackets, and parameters are estimated by maximum likelihood procedures. The estimations for the Negative Binomial interaction models as well as the Negative Binomial spatial filter specification models are mostly significant and robust. The significant estimates for the dispersion parameter γ indicate that the Negative Binomial specification is appropriate in order to control for unobserved heterogeneity between the (i, j) -region pairs leading to overdispersion.

The results are promising, both methodologically and in a European policy context in that they provide novel insights into the dynamic mechanisms of collaboration networks in the FPs. Methodologically, it is notable that the application of eigenvector spatial filters leads to a better model performance. This is reflected by a Likelihood Ratio test that compares the goodness-of-fit of the spatially filtered against the unfiltered model versions (see bottom of Table 2). The test statistic is significant for all models under consideration. It is worth noting that the magnitudes of the parameters change considerably between the two model specifications. Particularly the estimator for geographical distance effects is underestimated, when spatial flow autocorrelation is not taken into account.

Table 2. Estimation results

Negative Binomial Spatial Interaction Models								
	1999	2000	2001	2002	2003	2004	2005	2006
<i>Origin and Destination variable</i> [α_1] = [α_2]	0.959*** (0.003)	0.965*** (0.002)	0.967*** (0.005)	0.968*** (0.002)	0.972*** (0.002)	0.976*** (0.002)	0.977*** (0.002)	0.978*** (0.002)
<i>Geographical distance</i> [β_1]	-0.209*** (0.006)	-0.181*** (0.005)	-0.159*** (0.005)	-0.151*** (0.005)	-0.144*** (0.004)	-0.118*** (0.004)	-0.112*** (0.004)	-0.100*** (0.004)
<i>Neighbouring region</i> [β_2]	0.456*** (0.023)	0.423*** (0.022)	0.361*** (0.020)	0.319*** (0.181)	0.335*** (0.019)	0.333*** (0.018)	0.292*** (0.018)	0.270*** (0.763)
<i>Neighbouring country</i> [β_3]	-0.003 (0.010)	0.004 (0.009)	0.019* (0.008)	0.014 (0.008)	0.014 (0.009)	0.013 (0.007)	0.024** (0.007)	0.027 (0.008)
<i>Country border effects</i> [β_4]	-0.105*** (0.018)	-0.088*** (0.017)	-0.048** (0.016)	-0.031* (0.015)	-0.020 (0.015)	-0.011 (0.014)	-0.023 (0.014)	-0.024 (0.014)
<i>Language area effects</i> [β_5]	-0.225*** (0.016)	-0.238*** (0.015)	-0.198*** (0.014)	-0.171*** (0.013)	-0.168*** (0.013)	-0.163*** (0.012)	-0.147*** (0.019)	-0.153*** (0.013)
<i>Technological Distance</i> [β_6]	-0.765*** (0.082)	-0.652*** (0.075)	-0.469*** (0.066)	-0.422*** (0.063)	-0.354*** (0.061)	-0.311*** (0.059)	-0.315*** (0.060)	-0.340*** (0.061)
<i>Constant</i> [α_0]	-10.070*** (0.092)	-10.607*** (0.086)	-11.163*** (0.076)	-11.453*** (0.071)	-11.635*** (0.545)	-12.098*** (0.069)	-12.143*** (0.070)	-12.088*** (0.071)
<i>Dispersion</i> (γ)	3.916*** (0.060)	4.393*** (0.064)	5.517*** (0.081)	5.902*** (0.083)	6.218*** (0.088)	6.194*** (0.084)	6.302*** (0.086)	6.366*** (0.094)
Log Likelihood	-217,282.23	-231,895.05	-248,731.40	-261,892.51	-264,208.46	-286,688.18	-282,816.69	-269,961.74
Spatially Filtered Negative Binomial Spatial Interaction Models								
	1999	2000	2001	2002	2003	2004	2005	2006
<i>Origin and Destination variable</i> [α_1] = [α_2]	0.970*** (0.003)	0.977*** (0.003)	0.977*** (0.002)	0.976*** (0.002)	0.979*** (0.002)	0.980*** (0.002)	0.980*** (0.002)	0.980*** (0.002)
<i>Geographical distance</i> [β_1]	-0.320*** (0.006)	-0.275*** (0.006)	-0.239*** (0.005)	-0.218*** (0.005)	-0.210*** (0.005)	-0.176*** (0.048)	-0.160*** (0.005)	-0.146*** (0.005)
<i>Neighbouring region</i> [β_2]	0.325*** (0.023)	0.307*** (0.022)	0.267*** (0.020)	0.236*** (0.019)	0.251*** (0.019)	0.257*** (0.018)	0.229*** (0.018)	0.210*** (0.019)
<i>Neighbouring country</i> [β_3]	0.004 (0.010)	0.005 (0.009)	0.019* (0.008)	0.010 (0.008)	0.013 (0.008)	0.010 (0.007)	0.019* (0.007)	0.027*** (0.008)
<i>Country border effects</i> [β_4]	-0.176*** (0.018)	-0.150*** (0.017)	-0.114*** (0.016)	-0.079*** (0.015)	-0.064*** (0.015)	-0.036* (0.014)	-0.025 (0.014)	-0.012 (0.015)
<i>Language area effects</i> [β_5]	-0.200*** (0.034)	-0.224*** (0.015)	-0.193*** (0.014)	-0.163*** (0.013)	-0.161*** (0.013)	-0.165*** (0.012)	-0.156*** (0.013)	-0.160*** (0.013)
<i>Technological Distance</i> [β_6]	-0.683*** (0.083)	-0.622*** (0.077)	-0.452*** (0.068)	-0.400*** (0.065)	-0.295*** (0.063)	-0.303*** (0.061)	-0.342*** (0.062)	-0.341*** (0.062)
<i>Number of origin filters</i> Q	19	19	19	20	19	20	18	15
<i>Number of destination filters</i> R	18	19	21	20	19	19	15	14
<i>Constant</i> [α_0]	-9.596*** (0.093)	-10.213*** (0.088)	-10.820*** (0.078)	-11.171*** (0.075)	-11.387*** (0.073)	-11.819*** (0.071)	-11.844*** (0.072)	-11.819*** (0.073)
<i>Dispersion</i> (γ)	4.149*** (0.065)	4.628*** (0.068)	5.814*** (0.087)	6.193*** (0.088)	6.519*** (0.093)	6.436*** (0.088)	6.494*** (0.089)	6.529*** (0.097)
Log Likelihood	-215,933.28	-230,571.75	-247,491.04	-260,764.37	-263,125.21	-285,703.82	-282,021.01	-269,352.88
Likelihood Ratio Test	256.241***	281.032***	185.548***	106.303***	82.454***	87.159***	105.668***	67.575***

Note: The dependent variable in the models is the cross-region collaboration intensity between two regions i and j in period t . The independent variables are defined as given in the text. The Likelihood Ratio test compares model fit of the spatially filtered against the unfiltered model versions. *** significant at the 0.001 significance level, ** significant at the 0.01 significance level, * significant at the 0.05 significance level.

Therefore, in our interpretation of the results we focus on the negative binomial spatial filter models. Geographical distance as evidenced by the estimate β_1 has – in accordance with previous studies (see Scherngell and Barber 2009 and 2010) – a significantly negative effect on the likelihood of R&D collaborations across European regions during the observed period. However, the most important aspect is that the effect gradually declines over time. i.e. the likelihood for long-distance collaborations has increased during the observed time period. The magnitude of β_1 decreases by 54% between the first observation in the year 1999 and the most recent observation in the year 2006. In 1999 the estimate ($\beta_1 = -0.320$) indicates that for each additional 100 km between two organizations, the collaboration probability decreases by 38.3%, while for 2006 ($\beta_1 = -0.146$) for each additional 100 km probability for collaboration decreases only by 18.7%. A quite similar result is found for the estimate of β_2 reflecting that the probability for the localization of cross-region R&D collaborations in neighbouring regions considerably decreases between 1999 and 2006. However, the localization effect of $\beta_2 = 0.222$ in 2006 is still remarkable, indicating that the probability for collaboration increases by 1.24% when the organizations are located in regions that are direct neighbours.

Concerning country border effects, the results clearly point to positive outcomes in a policy context. The estimate β_4 for country border effects decreases between 1999 and 2004, and becomes insignificant for 2005 and 2006. This indicates that a country border between two regions does not influence their collaboration intensity in the FPs, i.e. the policy goal of ERA to abolish barriers for research collaborations constituted by country borders has been met for the case of the FPs.

With respect to language area effects that we use as a proxy for ‘cultural distance’ we find mixed results in a policy context. Though negative language area effects decrease between 2000 and 2003 as evidenced by β_5 , the estimate remains relatively stable between 2003 and 2006. For 2006 the estimate $\beta_5 = -0.160$ is still significant, indicating that organizations located in the same language area have a significantly higher probability to collaborate.

As indicated by the estimate of β_6 , technological distance is – as also found by other studies for the case of the FPs (see Scherngell and Barber 2009 and 2010), and in studies using other indicators for collaborations (see, for instance, LeSage et al. 2007, Scherngell and Hu 2010) – the most important determinant of cross-region R&D collaborations. However, also the

negative effect of technological distance decreases during the observed period, indicating that interdisciplinary research – also fostered by the FPs – becomes more important.

6 Concluding remarks

In the recent past the empirical literature in economic geography and economics of innovation puts emphasis on the relevance of R&D networks. In particular, the geographical and temporal analysis of such networks is of primary interest, both in a scientific and a European policy context. The objective of the study at hand was to identify the evolution of separation effects over the time period 1999-2006 that influence the probability of cross-region collaborations in the European network of cooperation in the FPs. We used negative binomial spatial interaction models with a spatial filter specification to estimate the evolution of separation effects over the time period under consideration.

The analysis has produced interesting results in the context of the relevant empirical and theoretical literature, and in particular in a European policy context: While geographical distance between two regions still exerts a negative effect on their collaboration probability, the effect significantly decreases between 1999 and 2006, i.e. in a policy context one may conclude that the FPs indeed help to increase the probability for large distance collaborations and, thus, contribute to geographically integrate European research systems. The same result was found for neighbouring region effects, i.e. European research collaborations extent further in geographical terms which is one explicit ERA goal. Furthermore, the FPs significantly contributed to abolishing barriers for research collaborations within the FPs constituted by country borders, another important European policy goal. Concerning ‘cultural barriers’ – as captured by language area effects – we find mixed results in a policy context, as negative language area effects seem to be reduced in general, but relatively slowly.

Methodologically, the study follows former similar empirical studies by employing Negative Binomial spatial interaction modelling techniques to describe patterns of R&D networks, but expands previous work by taking spatial autocorrelation among residual flows using Eigenvector origin and destination spatial filters into account. The results provide evidence for the importance of considering spatial autocorrelation in an interaction context as shown by the higher model performance of the model specification using spatial filters.

Concerning a research agenda for the future at least three points come to mind: *First*, the examination of dynamic effects within our spatial interaction modelling framework using techniques from panel econometrics may be a worth extension of the cross-Section models in the current study. *Second*, the integration of further separation variables, in particular accounting for scientific, technological and economic structures may improve the significance of the models. *Third*, disaggregating results obtained for the total FPs by different thematic areas may be another promising extension, in particular in the context of the future design of specific subprograms.

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Appendix A

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

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

<i>Italy:</i>	Abruzzo, Basilicata, Calabria, Campania, Emilia-Romagna, Friuli-Venezia Giulia, Lazio, Liguria, Lombardia, Marche, Molise, Piemonte, Puglia, Sardegna, Sicilia, Toscana, Trentino-Alto Adige, Umbria, Valle d'Aosta/Vallée d'Aoste, Veneto
<i>Latvia:</i>	Latvija
<i>Lithuania:</i>	Lietuva
<i>Luxembourg:</i>	Luxembourg (Grand-Duché)
<i>Netherlands:</i>	Drenthe, Flevoland, Friesland, Gelderland, Groningen, Limburg (NL), Noord-Brabant, Noord-Holland, Overijssel, Utrecht, Zeeland, Zuid-Holland <i>Norway:</i> Agder og Rogaland, Hedmark og Oppland, Nord-Norge, Oslo og Akershus, Sør-Østlandet, Trøndelag, Vestlandet
<i>Poland:</i>	Dolnośląskie, Kujawsko-Pomorskie, Lubelskie, Lubuskie, Łódzkie, Mazowieckie, Małopolskie, Opolskie, Podkarpackie, Podlaskie, Pomorskie, Śląskie, Świętokrzyskie, Warmińsko-Mazurskie, Wielkopolskie, Zachodniopomorskie
<i>Portugal:</i>	Alentejo, Algarve, Centro (P), Lisboa, Norte
<i>Slovakia:</i>	Bratislavský kraj, Stredné Slovensko, Východné Slovensko, Západné Slovensko
<i>Slovenia:</i>	Slovenija
<i>Spain:</i>	Andalucía, Aragón, Cantabria, Castilla y León, Castilla-La Mancha, Cataluña, Comunidad Foral de Navarra, Comunidad Valenciana, Comunidad de Madrid, Extremadura, Galicia, Illes Balears, La Rioja, País Vasco, Principado de Asturias, Región de Murcia
<i>Sweden:</i>	Mellersta Norrland, Norra Mellansverige, Småland med öarna, Stockholm, Sydsverige, Västsverige, Östra Mellansverige, Övre Norrland
<i>Switzerland:</i>	Espace Mittelland, Nordwestschweiz, Ostschweiz, Région lémanique, Ticino, Zentralschweiz, Zürich
<i>United Kingdom:</i>	Bedfordshire & Hertfordshire; Berkshire, Buckinghamshire & Oxfordshire; Cheshire; Cornwall & Isles of Scilly; Cumbria; Derbyshire & Nottinghamshire; Devon; Dorset & Somerset; East Anglia; East Riding & North Lincolnshire; East Wales; Eastern Scotland; Essex; Gloucestershire, Wiltshire & North Somerset; Greater Manchester; Hampshire & Isle of Wight; Herefordshire, Worcestershire & Warwickshire; Highlands and Islands; Inner London; Kent; Lancashire; Leicestershire, Rutland and Northamptonshire; Lincolnshire; Merseyside; North Eastern Scotland; North Yorkshire; Northern Ireland; Northumberland and Tyne and Wear; Outer London; Shropshire & Staffordshire; South Western Scotland; South Yorkshire; Surrey, East & West Sussex; Tees Valley & Durham; West Midlands; West Wales & The Valleys; West Yorkshire

Appendix B

Figure B.1. Frequency of cross-region R&D collaborations for each time period

