Regional
Innovation and Entrepeneurship
Research Center

WORKING PAPER SERIES

2017-02

Does EU Framework Program participation affect regional innovation? The differentiating role of economic development

Attila Varga, Tamás Sebestyén
Regional Innovation and Entrepeneurship
Research Center

Regional Innovation and Entrepreneurship Research Center
Faculty of Business and Economics
University of Pécs

H-7622, Pécs Rákóczi str. 80.

Phone: +36-72-501-599/23121

www.webcím.hu

Does EU Framework Program participation affect regional innovation? The differentiating role of economic development

1. Introduction

The complexity of innovation necessitates firms to source significant parts of knowledge externally. As a result, innovation has become a collective process involving different actors like competing and related firms, supporting business services, private or public research organizations (Lundvall 2010). External knowledge is obtained via several channels, including (among others) formal collaborations, labor markets, technology licensing, or pure knowledge spillovers (Amin, Cohendet 2004). The geographic dimension of interactions in innovation has received a particular attention in the literature, the key role of spatial proximity being underlined in several studies (Varga, Horváth 2013). Geographical proximity is important in innovation for several reasons. Close location of actors is beneficial for establishing and maintaining social connections (Agrawal, Kapur, McHale 2008) which can facilitate quick and efficient flows of both tacit and codified knowledge. These connections are also advantageous for the development of trust and the establishment of common codes of communication, both essential for collaborative innovation (Koschatzky 2000). Additionally, some of the main facilitators of knowledge transfers such as spin-off firm formation (Klepper 2007) or labor mobility (Breschi, Lissoni 2009) also tend to operate within small geographical areas.

Despite the focal role of geography, some channels of innovation-related knowledge flows do not necessarily require the spatial proximity of actors. Collaborative research is one of those knowledge transfer mechanisms that operate even over large distances without requiring frequent personal interactions. The synergy between different types of proximities in knowledge transfers (Boschma 2005) and the fact that non-spatial forms of proximities (such as cognitive, social or institutional proximities) may efficiently compensate for geographical distance help understand why research collaboration is possible even over long distances. Cognitive proximity of scientists working in the same field ensures common understanding of the codes of scientific communication (Meder 2008) while social and relational proximities among researchers help build and maintain the necessary level of trust even without frequent interactions (Autant-Bernard, Billand, Massard 2007, Basile, Capello, Caragliu, 2012).

While there is ample evidence that research-related interactions among closely located actors increase innovation, contrary to expectations, the literature has not provided unequivocal evidence for the supposed positive impact of non-spatially mediated interregional research collaborations on innovation. Though Hoekman, Frenken and van Oort (2008) find a positive and significant relationship between research activity of scientific collaboration partners (measured by co-authorship) and patenting at the regional level for two technologies (biotechnology and semiconductors) comparable evidence is not reported in other papers. Maggioni, Nosvelli and Uberti (2007) study research networks supported by the Framework Programs (FP) which are the European Union’s major research funding instruments. At the NUTS 2 regional level they found no relationship between patenting and the number of collaborative projects funded by the Fifth Framework Program (FP5). In Varga, Pontikakis and Chorafakis (2014) there is also no direct effect of FP5 funded research collaboration on regional patenting. Sebestyén and Varga (2013a) dig deeper into the issue and found evidence that non-spatial interregional learning in patenting in Europe is mediated by co-patenting linkages and not by Fifth Framework Program participations. Extending the panel of European NUTS 2 regions including data on FP5, FP6 and FP7 programs Hazir and Autant-Bernard (2013) reinforce what is already reported in the papers surveyed before: interregional

R&D knowledge flows mediated by EU Framework Program participation are not related to patenting at the regional level[1].

Thus, while a positive association is observed between regional patenting and learning mediated by interregional co-publication networks, this relationship disappears for learning mediated by research collaborations funded by European Framework Programs. The difference in the results might arise from certain features of FP networks that have not been considered explicitly in the previous analyses. One of these specific features is the observed strong spatial regime effect of Framework Program participation in the production of new knowledge. The literature already shows very interesting regional patterns in this respect for different stages of innovation. With respect to Pasteur-type (pre-competitive) research it is found that EU Framework Program participation increases future publication activities but this positive impact is more prevalent for regions located in the periphery of Europe. According to Hoekman, Scherngell, Frenken and van Oort (2012) FP funding appears to be more efficient in promoting co-publications between previously poorly connected regions than strengthening already established co-publication ties. On the basis of this result the authors conclude that Framework Programs are successful in promoting co-publication activities of scientists located in the periphery of the European Union while the effect in the core is nonexistent or even negative.

A related finding in Sebestyén and Varga (2013c) is the geographically differentiated Framework Program effect on future publications. Their analysis shows that knowledge flows from FP5 partner regions increase the number of publications associated with any level of R&D expenditures in the region but this positive impact on the productivity of research is higher in peripherally located (Objective 1) regions than in the rest of the EU. This result has implications for Edison-type (competitive) research as well. Varga, Pontikakis and Chorafakis (2014) find evidence for a positive relationship between research productivity in publication and the inflow of R&D in subsequent time periods. Together with the spatial regime effect in R&D productivity and publication found in Sebestyén and Varga (2013c), this result suggests that participation in collaborative research funded by EU Framework Programs has a stronger influence on peripheral regions' future R&D, which (ceteris paribus) suggests a more pronounced indirect FP impact on patenting in lagging areas of Europe. Maggioni, Uberti and Nosvelli (2014) also show that CEE countries behave differently from other European regions in the production of new knowledge. While in CEE regions geographical spillovers play a limited role, FP6 contacts provide a one-way long-distance information channel for them.

Wouldn't it be the case that the generally missing evidence on a direct impact of FP participation mediated knowledge transfer on patenting masks important and regular spatial differences in Europe? Influenced by earlier findings in the literature, we assume in this paper

[1] An increasing network literature has emerged in the last decade in Europe analysing FP project participation. The line of this literature referred to in the main text studies the FP participation – regional innovation nexus. A related literature focuses on the formation and characteristics of networks. Maggioni and Uberti (2007) analyze the determinants of link formation in FP5 networks in the large EU countries under a gravity model approach. They find evidence for a limited role of geographical distance in forming these links compared to other types of knowledge linkages. Scherngell and Barber (2009) also investigate the determinants of interregional network tie formation on a wider sample of EU regions under FP5. They show that geographical factors are important, but the effects of technological proximity are stronger. Protogerou et al. (2011) analyze inter-organizational ties in FPs between 1995 and 2006 focusing on three ICT areas. Using network analytic techniques they show that these networks are highly connected, and some large-sized firms and prestigious universities constitute the core of the network. Scherngell and Barber (2011), using data on FP partnerships and an extended set of EU regions, show that technological proximity is the most important factor in both industrial and university collaboration while the role of geography is important for industrial but less so for public research cooperation. Autant-Bernard et al. (2013) provide a literature review of FP collaborations from a policy perspective.

that the direct impact of knowledge transfers between FP network partners on regional patenting follows different trends in core and peripheral regions in Europe. As there are no antecedents in the literature on the nature of these trends, we formulate two alternative hypotheses. According to the first one we assume that lagging areas, resulting from their low levels of absorptive capacities, are not yet equipped to utilize learning from FP research networks (Radosevic and Yoruk 2013) thus their patenting activity will not be affected by collaborations funded by Framework Programs contrary to core regions where strong innovation effects are expected. The alternative hypothesis (in the spirit of Hoekman, Scherngell, Frenken and van Oort 2012) states that since FP subsidies are only substitutes for other research funds in core EU regions they do not influence patenting significantly there, whereas in peripheral regions FP research support acts as a complementary resource and as such it becomes an important factor in innovation.

Thus we assume that the overall missing impact of EU Framework Program participation on regional patenting is related to a spatial regime effect. To this aim we separate EU regions into two sub-samples in the analysis: peripheral Objective 1 regions in Central and Eastern European (CEE) countries and regions in “old member states” together with non-Objective 1 regions of CEE countries. We then econometrically test the relationship between knowledge learned from FP participations and regional patenting in the two sub-samples separately. Our measure of knowledge accessed from research networks is the Ego Network Quality index (ENQ - Sebestyén and Varga 2013a, 2013b). This index has been developed to provide a summary measure of learning potential from a particular position in the network. With this index the aim is to overcome a frequent shortcoming of many previous studies in the geography of innovation field that focus exclusively on the effect of partners’ knowledge while important structural features of knowledge networks are not taken into account. Additionally, with the application of the ENQ index it is possible to explicitly account for dynamic changes in extra-regional knowledge networks contrary to the usual approach, which operates with fixed collaboration matrices (Hazir and Autant-Bernard 2013). To control for extra-regional knowledge flows mediated by geographical proximity, a systematic panel spatial econometric methodology is applied. Our data cover three subsequent Framework Programs: FP 5, FP 6 and FP 7 spanning over the time period of 1998-2009. Only a limited number of research fields can consistently be identified during the subsequent periods of EU Framework Programs. In this paper we selected information science and technology (IST) for study.

The subsequent section of the paper presents the empirical model and the methodologies applied in measuring localized and network mediated knowledge flows. Section 3 introduces the data followed by an exploratory analysis of the main variables in this study. In Section 4 we present our empirical results. Summary concludes the paper.

2. Empirical research methodology

2.1 The empirical model

Our empirical framework is built on the knowledge production function (KPF) introduced in Romer (1990) and then further developed by Jones (1995):

$$dA_i/dt = \delta H_{Ai} A_i \tag{1}$$

where dA_i/dt is the change in technological knowledge over time, H_{Ai} refers to human capital in research, A_i is the total stock of already existing scientific and technological knowledge (knowledge codified in publications, patents etc.) and i stands for the spatial unit. Therefore, technological change is associated with contemporary R&D efforts and previously accumulated knowledge. The same number of researchers can have a varying impact on technological change depending on the stock of already existing knowledge.

In order to empirically test our hypotheses on the role of external knowledge (mediated by FP research networks) in patenting we apply the following econometric specification. Using subscripts i to denote individual regions, the empirical counterpart of the Romerian KPF is specified as:

$$\log \mathrm{PAT_i} = \mathrm{a_0} + \mathrm{a_1} \log \mathrm{RD_i} + \mathrm{a_2} \log \mathrm{PAT\_STOCK_i} + \mathrm{Z_i} + \varepsilon_\mathrm{i} \qquad (2)$$

where PAT_i stands for new technological knowledge measured by patent applications, RD_i is expenditure on research and development and PAT_STOCK_i proxies technological knowledge accumulated over time in region i. In accordance with usual interpretations, a_1 reflects the influence of localized knowledge flows from R&D carried out by firms and public research institutions on regional patenting, while a_2 estimates the relation between patenting and accumulated knowledge. Besides regional controls, Z_i stands for variables measuring the two extra-regional knowledge sources: knowledge accessed via the participation of FP networks on the one hand and geographically proximate knowledge sources on the other. The following two sub-sections explain our measures of the two extra-regional knowledge sources one after another.

2.2 Measuring extra-regional knowledge accessed via research networks: The Ego Network Quality (ENQ) index

The theory of innovation emphasizes the role of interactions among different actors in innovation. These interactions follow a system and the characteristics of the system determine the efficiency of new knowledge production to a large extent (Lundvall 2010, Nelson 1993). An extensive survey-based empirical literature evidences that innovation is indeed a collective process where the knowledge and expertise of partners and the intensity of collaborations among them determine the production of new, economically useful knowledge (e.g., Diez 2002, Fischer and Varga 2002). Representing actors as nodes and their connections as ties, interactions of collaborating agents can be mapped as a network. On the basis of this representation the application of network analysis extends the frontiers of the study of knowledge interactions well beyond the possibilities of traditional innovation surveys.

In this paper we employ the previously developed Ego Network Quality (ENQ) index, which tries to capture the quality or value of knowledge, which can be accessed by a given region (represented as a node) in the network of knowledge flows. Behind the concept of ENQ there are three intuitions directly influenced by the theory of innovation. The first intuition is that the level of knowledge in an agent's network is in a positive relationship with the agent's productivity in knowledge creation. The second intuition is that the structure of connections in the agent's network can serve as an additional source of value (see e.g. Coleman, 1986; Burt, 1992). Following the third intuition we assume that partners in the ego network not only increase the amount of knowledge accessible, but also contribute to its diversity through building connections to different further groups not linked directly to the ego network.

According to these intuitions we structure ENQ around basically two dimensions, which are then augmented with a related third aspect. The two dimensions are: Knowledge Potential and Local Structure. Knowledge Potential (KP) measures knowledge accumulated in the direct neighbourhood and it is related to the number of partners and the knowledge of individual partners. Local Structure (LS) is associated with the structure of links among partners. The third aspect is called Global Embeddedness (GE) as it intends to capture the quality of distant parts of the network (beyond immediate partners). However, this aspect is implemented by applying the concepts of KP and LS for consecutive neighbourhoods of indirect partners in the network.[2] Here we give a brief summary of the ENQ index with the most important aspects. The reader is directed to Sebestyén and Varga (2013a, 2013b) for more detailed discussions.

The notation in the proceeding formulation is as follows. We represent the network under question by the adjacency matrix $\mathbf{A} = [a_{ij}]$, where the general element a_{ij} describes the connection between nodes i and j. The adjacency matrix defines the matrix of geodesic distances (lengths of shortest paths) between all pairs of nodes, which is denoted by $\mathbf{R} = [r_{ij}]$. In order to account for knowledge levels, we use $\mathbf{k} = [k_i]$ as the vector of knowledge at each specific node of the network.

Given the conceptual model presented above, we formalize ENQ as follows:

$$ENQ^i = \sum_{d=1}^{M-1} W_d LS_d^i \, KP_d^i = LS_1^i KP_1^i + GE^i \tag{3}$$

In this formula superscript i refers to the node for which ENQ is calculated and subscript d stands for distances measured in the network (geodesic distance). M is the size of the network, W_d is a weighting factor used for discounting values at different d distances from node i,[3] whereas KP_d^i and LS_d^i are the respective Knowledge Potential and Local Structure values evaluated for the neighbourhood at distance d from node i. The proposed formula for ENQ is a distance-weighted sum of Local Structure-weighted Knowledge Potentials evaluated for neighbourhoods at different distances in the network. The second equation in the above formula shows (using $W_1 = 1$ by definition) how the ENQ index can be divided into the three dimensions mentioned above: the Knowledge Potential and the Local Structure in the direct neighbourhood and Global Embeddedness which sums these aspects beyond the direct neighbourhood. In what follows, the two basic concepts, Knowledge Potential and Local Structure are introduced in more detail.

Knowledge Potential

The concept of KP relates to the amount of knowledge an agent's partners possess. Using the notation presented before, the concept of KP can be formulated in the following way:

$$KP_d^i = \sum_{j:r_{ij}=d} k_j \tag{4}$$

The Knowledge Potential, as perceived by node i, can thus be calculated for the neighbourhoods at different d distances from node i, and for all these distances it is the sum of knowledge possessed by nodes at these distances.

Local Structure

Following the theory of innovation we assume that the potentially accessible knowledge from immediate network partners depends not only on the partners' accumulated knowledge but also on new knowledge that potentially arises from mutual learning of the partners. The concept of Local Structure refers to the structure of connections in different neighbourhoods of a node. How one defines the 'good' structure, though, remains an open question. There is a concurrent debate in the literature of social capital and network position whether cohesive, tightly linked neighbourhoods provide a better position (Coleman, 1986) or structural holes, which puts weight on gatekeepers connecting different groups in the network (Burt, 1992). However, the formula for ENQ in (3) is specified in a way that LS can be filled with different

---

[2] By 'neighbourhood at distance *d*' we mean the nodes exactly at distance *d* from a specific node.

[3] In this paper we apply exponential weighting, where $W(d) = e^{1-d}$. Some analysis with respect to different formulations can be found in Sebestyén and Varga (2013b).

concepts. In this paper we use the cohesion approach, i.e. we attach higher weights to neighbourhoods in which more ties are present.[4]

As a consequence, Local Structure (LS) is associated with the number and strength of ties among partners. It is the sum of the edge weights present in a given neighbourhood, normalized by the size of this neighbourhood:

$$LS_d^i = \frac{1}{N_d^i}\left(\sum_{j:r_{ij}=d-1}\sum_{l:r_{il}=d} a_{jl} + \frac{\sum_{j:r_{ij}=d}\sum_{l:r_{il}=d} a_{jl}}{2}\right) \tag{5}$$

where N_d^i is the number of nodes laying exactly at distance d from node i. The expression in the parenthesis is made up of two parts. The first term counts the (weighted) ties between nodes at distance $d-1$ and d.[5] This reflects the intensity at which two adjacent neighbourhoods are linked together. The second term counts the (weighted) number of ties among nodes at distance d.[6] As a result, Local Structure following the cohesion approach captures the intensity with which the (possibly indirect) neighbours at distance d are linked together and linked to other neighbourhoods.

2.3 Modeling extra-regional localized knowledge flows: panel spatial econometric methodology

Increasing availability of spatial data collected over longer periods of time created the demand for econometric models accounting for spatial dependence in panel data. Methodological developments of models in this domain (Elhorst 2003, Anselin, Le Gallo, Jayet 2008, LeSage and Pace 2009) and the growing number of their applications in empirical research (Autant-Bernard 2012) are one of the most significant recent changes in spatial analysis.

In the subsequent econometric analyses we consider the following specification issues: identification of the network effect, identification of the effect of localized knowledge transfer and identification of the panel effects. Equations (6) to (11) provide the actual spatial panel representations of equation (2) used for estimation. In equations (6) to (8) ENQ enters the right hand side as a stand-alone variable. In these cases we measure the direct influence of interregional knowledge flows mediated by FP networks on patenting in a given region. On the other hand equations (9) to (11) represent an alternative specification when ENQ interacts with R&D. In this type of models the influence of network knowledge on patenting works through improved productivity of research. With regards to the impact of localized knowledge flows on regional patenting, three types of spatial models will be tested against each other: the spatial lag, the spatial error and the spatial Durbin models. In spatial lag models (equations 6 and 9) spatial dependence is modeled through the spatially lagged dependent variable. In spatial error models (equations 7 and 10) dependence is modeled in the error term. Alternatively, with the spatial Durbin model (equations 8 and 11) spatial dependence is modeled through both the dependent as well as the independent variables.

$$\log(PAT_{it}) = \delta\sum_{q=1}^{Q} W_{iq}\log(PAT)_{qt} + \alpha_0 + \alpha_1 log(RD_{it-2}) + \alpha_2 log(PATSTOCK_{it-2}) + \alpha_3 log(ENQ_{it-2}) + \alpha_4 log(HTEMP_{it-2}) + \mu_i + \lambda_t + \varepsilon_{it} \tag{6}$$

$$\log(PAT_{it}) = \alpha_0 + \alpha_1 log(RD_{it-2}) + \alpha_2 log(PATSTOCK_{it-2}) + \alpha_3 log(ENQ_{it-2}) + \alpha_4 log(HTEMP_{it-2}) + \mu_i + \lambda_t + \varphi_{it}\,,\ \varphi_{it} = \rho\sum_{q=1}^{Q} W_{iq}\varphi_{qt} + \varepsilon_{it} \tag{7}$$

[4] See Sebestyén and Varga (2013b) for an analysis with alternative specifications building on the structural holes concept.

[5] Distances are always measured from node i.

[6] Division by two is required because matrix **A** is symmetric, and thus we can avoid duplications in the counting.

$$\log(PAT_{it}) = \delta \sum_{q=1}^{Q} W_{iq} \log(PAT)_{qt} + \alpha_0 + \alpha_1 log(RD_{it-2}) + \alpha_2 log(PATSTOCK_{it-2}) + \alpha_3 log(ENQ_{it-2}) + \alpha_4 log(HTEMP_{it-2}) + \theta_1 \sum_{q=1}^{Q} W_{iq} log(RD_{qt-2}) + \theta_2 \sum_{q=1}^{Q} W_{iq} log(PATSTOCK_{qt-2}) + \theta_3 \sum_{q=1}^{Q} W_{iq} log(ENQ_{qt-2}) + \theta_4 \sum_{q=1}^{Q} W_{iq} log(HTEMP_{qt-2}) + \mu_i + \lambda_t + \varepsilon_{it} \quad (8)$$

$$\log(PAT_{it}) = \delta \sum_{q=1}^{Q} W_{iq} log(PAT_{qt}) + \alpha_0 + \alpha_1 log(ENQ_{it-2}) log(RD_{it-2}) + \alpha_2 log(PATSTOCK_{it-2}) + \alpha_3 log(HTEMP_{it-2}) + \mu_i + \lambda_t + \varepsilon_{it} \quad (9)$$

$$\log(PAT_{it}) = \alpha_0 + \alpha_1 log(ENQ_{it-2}) log(RD_{it-2}) + \alpha_2 log(PATSTOCK_{it-2}) + \alpha_4 log(HTEMP_{it-2}) + \mu_i + \lambda_t + \varphi_{it}, \ \varphi_{it} = \rho \sum_{q=1}^{Q} W_{iq} \varphi_{qt} + \varepsilon_{it} \quad (10)$$

$$\log(PAT_{it}) = \delta \sum_{q=1}^{Q} W_{iq} log(PAT_{qt}) + \alpha_0 + \alpha_1 log(ENQ_{it-2}) log(RD_{it-2}) + \alpha_2 log(PATSTOCK_{it-2}) + \alpha_3 log(HTEMP_{it-2}) + \theta_1 \sum_{q=1}^{Q} W_{iq} log(ENQ_{qt-2}) \, log(RD_{qt-2}) + \theta_2 \sum_{q=1}^{Q} W_{iq} log(PATSTOCK_{qt-2}) + \theta_3 \sum_{q=1}^{Q} W_{iq} log(HTEMP_{qt-2}) + \mu_i + \lambda_t + \varepsilon_{it} \quad (11)$$

There are some variables in equations (6) to (11) not yet introduced before. $HTEMP$ is employment in high technology industries. Its estimated parameter is considered as a proxy for the impact of the localized flows of non-research related industrial knowledge on patenting. μ_i and λ_t represent spatial and time-period (fixed or random) effects.

Selection among the spatial error, lag and Durbin models is guided by testing the so-called common factor hypothesis (Anselin 1988):

H_0: $\theta = 0$ and H_0: $\theta + \delta\alpha = 0$

where θ, just as α, is a Kx1 vector of parameters. The first hypothesis examines whether the spatial Durbin model can be simplified to the spatial lag model, and the second hypothesis whether it can be simplified to the spatial error model (Burridge, 1981). We applied the Wald test (Elhorst 2012) to empirically test the common factor hypothesis.

Regarding panel effect identification, we run LR tests on the joint significance of spatial fixed effects and time-period fixed effect, subsequently (Elhorst 2012). Hausman's specification test is used to test the random effects model against the fixed effects model (Lee and Yu 2010).

3. Data description and an exploratory analysis

The empirical analysis in this paper is based on a sample of 262 European NUTS2 regions. We use a panel database, covering the period between 2000 and 2009. As our main aim is to estimate the knowledge flow effects over a longer period of time, we need to join data from FP5, FP6 and FP7 running over this time. In order to have a consistent dataset, we need to restrict our analysis to those thematic areas which can be identified in all three FPs. Three such areas can be identified: “Quality of Life”, mainly covering life sciences, biological and medical research, “Information Society and Technology”, mainly covering information and communication technology, and “Euratom”, focusing on nuclear research (see also Hoekman et al., 2012). From these three areas we focus on the Information Society and technology (IST) thematic area in this paper. The specific thematic areas are: User Friendly Information Society in FP5, Information Society Technologies in FP6 and Information and Communication Technologies in FP7 – the same grouping is used by e.g. Hoekman et al., 2012. The dependent variable is patenting activity in the ICT sector at the regional level as proxied by patent applications to the EPO (PAT_{it}).[7] Although using patents as a proxy for technological innovation is far from a perfect solution, there are several reasons why it still remains one of the most widely used and accepted measures (see e.g. Griliches 1990, for a comprehensive study on the issue, or Acs, Anselin and Varga 2002, for an analysis on the links between patent and other innovation counts at the level of regions).

Following Romer (1990), the importance of knowledge stocks (or a 'standing on the shoulders of giants' effect) for knowledge production has been verified empirically (Furman, Porter and Stern, 2002; Zucker et al. 2007). In order to capture this effect we use proxies of regional knowledge stocks by calculating patent stocks for each region ($PATSTOCK_{it}$) according to the perpetual inventory method for the 1995–2009 period (see the details in Varga, Pontikakis and Chorafakis 2014).

Knowledge flows between regions are captured by FP cooperation networks in the information technology and society thematic areas (as discussed previously) over the period of 1998-2009. There are good reasons to expect that participation in the FP can be an appropriate proxy of the relational structure of interregional knowledge diffusion across Europe. The FPs were designed to support 'pre-competitive', collaborative research with no national bias as to the types of technologies promoted and the distribution of funds. The precompetitive character of supported research ensured that Community funding did not clash with the competition principles of the Common Market and did not function as a form of industrial subsidy; the collaborative character of research and the cost-sharing provisions were seen to guarantee the diffusion of technologies and the involvement of various types of actors from the whole technological knowledge creation spectrum, such as large and small firms, universities and public research institutes. One potential drawback of the FP as a data source is the fact that it is artificial; i.e. collaborating teams will not always coincide with naturally emerging networks of researchers. (Varga, Pontikakis and Chorafakis, 2014)

The regional information (address) of participants in FP projects together with the information of the date of cooperation (duration of FP programs) allows us to construct a simple network assigning to each FP project the regions where the partners are resident. Then, this two-mode network is converted into a one-mode network where the nodes are regions and the links between the regions refer to the cooperation between the regions. This conversion is done on the basis of the assumption that all partners listed for a given FP project are linked to each other. For example, if three actors, A, B and C cooperated in one project, and actors A and B belong to region 1 while actor C belongs to region 2, then we conclude that there is a link between regions 1 and 2. Furthermore, the links in this interregional network is weighted, the link weights corresponding to the number of projects in which organizations from the two regions are involved. This method is then iterated for each FP project and each year in the sample to obtain the annual adjacency matrices describing the network structure of knowledge flows. These matrices are then used to calculate the ENQ measures in this study.

Table 1. Variable description

Variable Name	Description	Source

[7] The database uses a fractional count for patents. If inventors from different regions invent a patent it is assigned to each region on a fractional basis.

PAT_{it}	Number of patent applications from the ICT sector to the European Patents office (EPO) by region of inventor (fractional counts)	Eurostat database
RD_{it}	Gross regional expenditures on R&D, in millions of Purchasing Power Standard (PPS) Euros, 1995 prices	Eurostat database
REG_FUND_{it}	Regional FP funding under the information technology and society thematic areas (User Friendly Information Society in FP5, Information Society Technologies in FP6 and Information and Communication Technologies in FP7), in millions of Purchasing Power Standard (PPS) Euros, 1995 prices	Authors' elaboration on FP5-6-7 administrative database, DG RTD, Dir A
$PATSTOCK_{it}$	Regional patent stock in the ICT sector	Authors' elaboration on Eurostat database
ENQ_DENS_{it},	Ego Network Quality – a comprehensive measure of the knowledge accessible from a network position. ENQ values are calculated for the interregional FP collaboration network in the information technology and society thematic areas (User Friendly Information Society in FP5, Information Society Technologies in FP6 and Information and Communication Technologies in FP7); DENS refers to the cohesion approach followed in the calculation of LS; KP is measured by regional FP funding	Authors' elaboration on FP5-6-7 administrative database, DG RTD, Dir A
$HTEMP_{it}$	Regional employment in the high tech sectors according to the Eurostat classification (high-tech manufacturing and high-tech knowledge-intensive services)	Eurostat database

The aggregation method we use also has its shortcomings. We assume that there is an 'individual' link between all project members and then interregional links are established according to the number of projects in which two participants from two regions cooperate. This method hides the possibly more refined structure of interrelations among partners and hence regions. Unfortunately, though, there is no information on the specific collaboration structure (e.g. internal groups and hierarchies) of the projects. With less project members the complete connectedness can be a reasonable proxy but at larger projects with many participants this method may overestimate the true intensity of collaboration among regions.

Although there is example in the literature to use different internal network structures for the projects (see e.g. Maggioni et al., 2012), we would argue that in these projects the possibility is given for all participants to communicate through project events and meetings. As a result, it is rather the strength of ties is important than their pure existence, however, there is no available information for this in our dataset.

Our data covers three subsequent Framework Programs: FP 5, FP 6 and FP 7 spanning over the time period of 2000-2009. We carry out the analysis with two European sub-samples: lagging EU regions, that is Central-Eastern European (CEE) Objective 1 regions (CEE Obj1 regions - 51 regions) and regions in old member states together with non-Objective 1 CEE regions (Rest of EU regions - 211 regions). Variable description is provided in Table 1, while descriptive statistics of the main variables are presented in Table 2.

Table 2. Variable descriptive statistics

	Total sample					
	PAT	RD	REG_FUND	PATSTOCK	ENQ	HTEMP
N	2,620	2,620	2,620	2,620	2,620	2,620
Mean	56.07	674.99	2.66	340.05	6,655.40	35.01
Std.dev.	137.21	1,166.34	5.56	856.23	7,055.57	41.52
Min	0.05	1.06	0.00	0.14	0.18	0.86
Max	1,926.59	13,269.56	70.07	7,582.23	25,653.63	474.77
	CEE OBJ1 regions					
	PAT	RD	REG_FUND	PATSTOCK	ENQ	HTEMP
N	510	510	510	510	510	510
Mean	2.14	123.91	0.62	9.03	2,945.60	23.12
Std.dev.	2.71	169.22	1.13	8.58	4,173.80	17.23
Min	0.06	4.16	0.00	0.70	0.18	5.47
Max	17.95	1,245.06	5.72	61.81	23,087.01	145.00
	Rest of EU regions					
	PAT	RD	REG_FUND	PATSTOCK	ENQ	HTEMP
N	2,110	2,110	2,110	2,110	2,110	2,110
Mean	69.11	808.19	3.15	420.06	7,552.08	37.88
Std.dev.	150.01	1,261.39	6.07	936.71	7,312.47	45.02
Min	0.05	1.06	0.00	0.14	0.18	0.86
Max	1,926.59	13,269.56	70.07	7,582.23	25,653.63	474.77

In what follows, some exploratory analysis is provided with respect to our basic variables. Figure 1 shows the evolution of patenting activity in CEE objective 1 regions and the rest of EU regions in the sample. First, it is evident form the figure that there is a magnitude difference between the two categories of regions in favor of rest of EU regions. On the other hand, we observe an increasing trend for CEE objective 1 regions while a decreasing one for the other regions, marking a catch-up process in the former. This is reinforced by the relative patenting activity (see the right axes), however the relative patenting intensity of CEE objective one regions is still only at 5-6% of that of the rest of EU regions.

Figure 1: Average and relative patenting activity in CEE objective 1 and rest of EU regions

Figure 2: Average FP funding in CEE objective 1 and rest of EU regions

Figure 2 shows average regional funding for CEE objective 1 and rest of EU regions in the sample as well as the relative position of CEE objective 1 regions compared to the rest of regions in the EU. It is also apparent that CEE objective 1 regions acquire far less funding through FP projects than other EU regions. However, they show an increasing trend in this respect resulting in a catch-up process through the period between 2000 and 2006. In 2006 these lagging regions acquired on average 25% of the FP funding realized in other regions. From 2006 to 2009, however, the relative position of the CEE objective 1 regions is worsening and rest of the EU regions acquire still almost 5 times more funding at the end of the observation period. The vertical bars mark the turning points between different FPs. During FP5 (although the period in the figure is truncated for this FP), we observe an increasing trend both for CEE objective 1 regions and rest of the EU regions. Through FP6, though, this trend breaks for the rest of EU regions and remains for CEE objective one regions while in FP7 funding stagnates (and even decreases slightly for CEE regions).

Turning to the ENQ index, Figure 3 shows how the average ENQ indices evolved over our sample period. Rest of EU regions step ahead of their CEE objective 1 partners with respect to their ENQ index over the whole period, while the difference in absolute terms increase in the middle of the period. The relative differences, although remain quite stable up to 2008 (slightly under 35%) there is a marked increase between 2004 and 2009 up to almost 50%. This shows that the relative position of CEE objective 1 regions in interregional knowledge networks improved significantly in the second half of the sample period, but still remains at half of the rest of EU regions. In addition, it is interesting to see the marked differences across different FPs. A heavily increasing trend in FP5 breaks under FP6 and there is a sharp drop under FP7 for both samples. However, this latter two periods lead to the catch up for CEE objective 1 regions as the drop there is less marked.

Figure 3: Average ENQ of CEE objective 1 and rest of EU regions

With respect the two subindices (Knowledge Potential and Local Structure, capturing the properties of the direct neighborhood of the regions in the sample), we can see that CEE objective 1 regions could increase their position significantly according to their Local Structure, from around 35% to over 50% at the end of the sample. In other words, these regions tend to reach more favorable positions in interregional knowledge networks with respect to the connectedness of their neighborhood: they are better connected in the sense that they are surrounded by more intensive collaboration structures, getting more similar in this respect to other EU regions in our sample. In the case of Knowledge Potential, we observe a maintained difference between CEE objective 1 and rest of EU regions over the sample period. This shows that the direct partners of CEE objective 1 regions in FP collaborations tend to possess less knowledge (proxied by FP funding). This can be explained by the typical network formation principle that nodes with some characteristics (in our case less knowledge) tend to connect to nodes with similar characteristics. On the other hand, we observe a relative increase in the Knowledge Potential scores of CEE regions, reaching 40-45% at the end of the sample. Overall, we can conclude that the relative catch up process of CEE regions in terms of their ENQ index can be traced back to the relative improvement in their Knowledge

Potential and Local Connectivity scores. In other words, their better position measured at the end of the sample relative to their initial positions stems from both more knowledge at their direct partners (which can be a result of either higher knowledge at already existing partners or forming connections to more knowledgeable ones) and a more intensive collaboration structure among the partners.

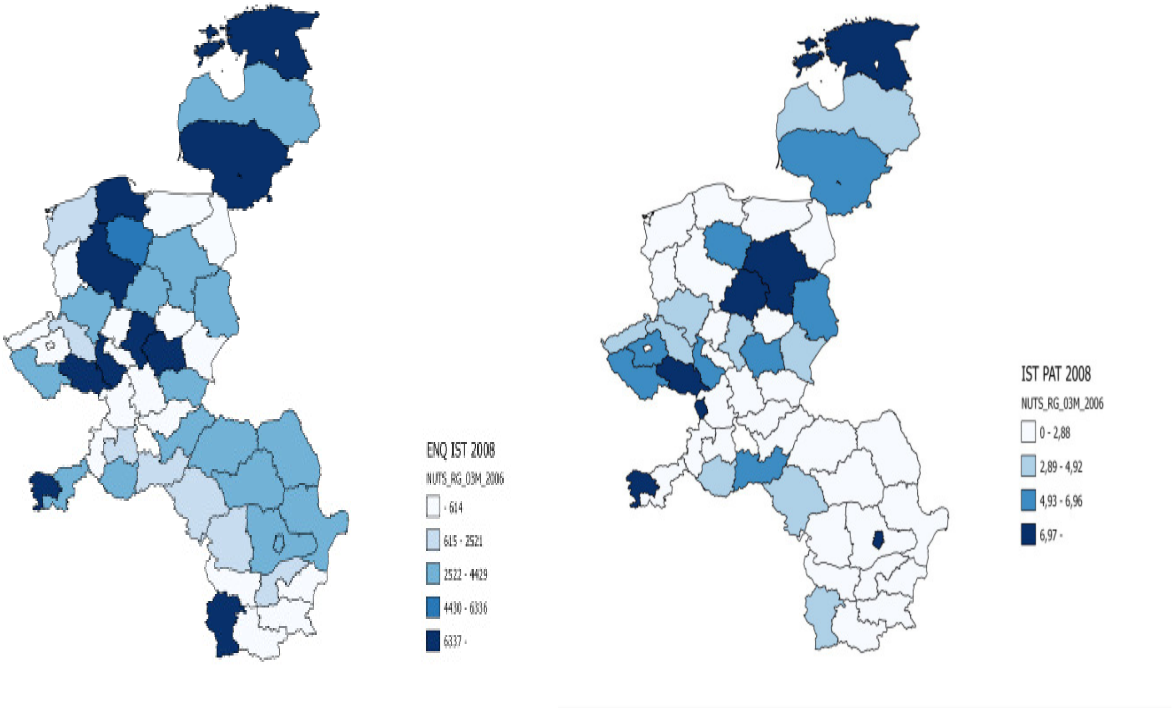

Figure 4: The spatial distribution of ENQ values and patent counts in CEE Obj 1 regions

Figure 4 shows the spatial distribution of regional patent counts and ENQ values for CEE Obj 1 regions calculated for 2008. Note that non-Obj 1 CEE regions (mostly the capital regions) are not depicted in the Figure. There are marked differences between the countries and also the regions. Poland, the Czech Republic and the Baltic countries show above average regional ENQ values and they are also over average in patenting. Overall, there seems to be a positive correlation between ENQ and patenting in these regions.

4. Empirical analysis

Previous studies reported that the impact of EU Framework Programs' research subsidies on scientific publication follow different patterns in peripheral regions of the European Union compared to the rest of the EU. We assume in this paper that the generally missing impact of EU Framework Program participation on regional patenting is also related to a spatial regime effect. To this aim we separated EU regions into two sub-samples: CEE Objective 1 regions and rest of EU regions, the latter containing non-CEE regions (including objective 1 regions there) and non-Objective 1 regions in CEE countries (practically the capital regions). As shown in the preceding section objective 1 regions in the recently joined CEE countries indeed follow different patterns in patenting and also in Framework Program participation.

Tables 3 and 4 present the results of the regression analysis for regions in the two sub-samples of the EU for the Information Science and Technology thematic area. We first study the regression outputs for the rest of EU regions then the results for CEE objective 1 regions. The usual two-year time lag between inputs to regional knowledge production and patenting is applied[8]. In Model (1) of Table 3 the two main variables of Equation (2) (R&D expenditures and stock of patents) appear with the expected positive sign and also with high significances. The fit of the regression is considerably high (adjusted R-square equals 0.89) especially taking into account the panel nature of the data. Models (2) to (4) document the results of our exploration of the role of extra-regional knowledge flows mediated by FP networks. The negative and significant coefficient of the ENQ variable in Model (2) is a consequence of the strong correlation between log(RD) and log(ENQ_DENS). An alternative specification is Model (3) where log(RD) interacts with log(ENQ_DENS). The negative and insignificant coefficient indicates that the productivity of R&D expenditures in patenting is not affected by FP participations. In Model (4) an alternative specification is followed: the interaction of Log(REG_FUND) (which is the funding received through FP projects in the region under the IST area) and log(ENQ_DENS), which is significant and positive. So far the results thus suggest that knowledge flows from FP networks positively influence the productivity of FP research subsidies in regional patenting. However it should be kept in mind that up to this point neither panel effects nor spatial dependence has been taken into consideration.

In Model (5) employment in high technology (HTEMP) enters the equation as an additional variable with a significant and positive coefficient. This model column shows spatial statistics as well. It is clear that both spatial lag and spatial error dependence are present no matter which spatial weight matrix is used in the tests. Since the strongest effect is observed with those 4 neighbors that locate closest to the region the 4-nearest-neighbors weight matrix will be used in spatial econometric estimations.

The significant LR tests (bottom part of the column of Model 5) support the extension of Model (5) with spatial and time period (two-way) fixed effects. On the other hand the significant Wald Lag and Wald Error test statistics at the bottom of Model (6) indicate that both the spatial lag and the spatial error model should be rejected in favor of the Spatial Durbin model. Thus after controlling for unmeasured regional and temporal characteristics as well as spatial dependence, Model (6) provides the final regression results. Though the size of the parameters of the R&D and patent stock variables decreased, these two parameters are still significant. One important change in Model (6) compared to Model (5) is the now insignificant parameter of the variable Log(REG_FUND)*Log(ENQ _DENS). This result is a strong indication that in rest of EU regions knowledge flows from FP networks do not play a meaningful role in regional patenting. Further essential results are the significant and positive parameters of the spatially lagged dependent variable and the spatially lagged R&D and high technology employment variables. These results together with the insignificant FP network effect indicate that regions in more developed regions tend to rely on localized knowledge inputs in patenting instead of extra-regional knowledge communicated via FP research networks.

Table 3. Regression Results for Log (PAT) for 211 Rest of EU NUTS 2 Regions and for the ICT sector, 2000-2009 (N=2110)

Model	(1) Pooled	(2) Pooled	(3) Pooled	(4) Pooled	(5) Pooled	(6) Spatial and time-period fixed effects

[8] Though the two-year time lag does not guarantee that the problem of potential endogeneity of some right hand side variables is perfectly cured in the model, taking also into consideration the fact that in both final models spatial Durbin estimates are applied we can reasonably argue that our estimations are superior compared with ignoring the potential problem of endogeneity (Fingleton, Le Gallo 2010).

Estimation	OLS	OLS	OLS	OLS	OLS	ML Spatial Durbin (4-nearest neigh)
Constant	-2.329*** (-39.45)	-2.407*** (-40.61)	-1.394*** (-35.35)	-2.305*** (-39.24)	-2.188*** (-36.62)	
W_Log(PAT)						0.148*** (4.83)
Log(RD(-2))	0.338*** (20.06)	0.368*** (21.47)				
LOG(RD(-2)-REG_FUND (-2))				0.326*** (19.25)	0.200*** (8.67)	0.105** (2.05)
LOG(ENQ_DENS(-2))		-0.021*** (-7.33)				
Log(RD_TOTAL (-2))*LOG(ENQ_DENS(-2))			-0.001 (-1.02)			
LOG(REG_FUND (-2))*LOG(ENQ_DENS(-2))				0.006*** (4.69)	0.005*** (3.96)	-0.001 (0.59)
LOG(PATSTOCK(-2)	0.712*** (53.31)	0.714*** (54.12)	0.940*** (103.76)	0.712*** (53.63)	0.685*** (50.55)	0.094** (2.40)
LOG(HTEMP(-2))					0.239*** (7.88)	0.073 (1.08)
W_LOG(RD(-2)-REG_FUND(-2))						0.329*** (3.50)
W_LOG(REG_FUND (-2))*LOG(ENQ_DENS(-2))						-0.002 (-0.63)
W_LOG(PATSTOCK(-2))						-0.006 (-0.09)
W_LOG(HTEMP(-2))						0.368*** (3.23)
R^2-adj	0.89	0.89	0.87	0.89	0.89	0.96
LIK	-2033.73	-2007.13	-2217.56	-2022.30	-1991.63	-967.01
LM-Err						
Neigh					23.04***	
INV2					21.99***	
4-nearest neighbours					48.71***	
LM-Lag						
Neigh					30.49***	
INV2					30.77***	
4-nearest neighbours					58.09***	
Wald-Lag (4-nearest neigh)						28.20***
Wald-Err (4-nearest neigh)						33.24***
LR-test joint significance spatial fixed effects					1783***	
LR-test joint significance time-period fixed effects					88.9***	
Hausman random effects test						160.2***

Notes: Estimated t-values are in parentheses; spatial weights matrices are row-standardized: Neigh is neighborhood contiguity matrix; INV2 is inverse distance squared matrix, 4-nearest neighbors is a weights matrix where those regions are considered as neighbors that are among the four most closely located ones; W_ denotes spatially lagged (dependent and independent) variables calculated with the weights matrix 4-nearest neighbours. *** indicates significance at $p < 0.01$; ** indicates significance at $p < 0.05$; * indicates $p < 0.1$.

Table 4 reports the regression results for CEE objective 1 regions. In Model 1 parameters of the two major variables are positive and significant, similar to what is observed for the rest of EU regions. However there are two important differences in the results of Model 1 in the periphery compared to the results of the same model for the rest of the EU. First, the estimated parameters of the R&D and patent stock variables are smaller, and second, regression fit is apparently lower (adjusted R-square is 0.44 in Table 4 compared to 0.89 in Table 3). The other important difference is the highly significant and positive ENQ parameter for CEE objective 1 regions in Model (2). The significant FP network impact remains unchanged after the introduction of the high technology employment variable in Model (3). It is also a meaningful difference between Model (3) in Table 4 and Model (5) in Table 3 that for CEE objective 1 regions the estimated parameter of the high technology employment variable is negative and insignificant suggesting limited roles of local industrial knowledge in patenting. The spatial statistics in Model (3) indicates the presence of both spatial lag and

Table 4. Regression Results for Log (PAT) for 51 CEE OBJ1 EU NUTS 2 Regions and for the ICT sector, 2000-2009 (N=510)

Model	(1) Pooled	(2) Pooled	(3) Pooled	(4) Pooled	(5) Random spatial effects, fixed time-period effects

Estimation	OLS	OLS	OLS	OLS	ML-Spatial Durbin (INV2)
Constant	-2.049*** (-14.89)	-1.939*** (-13.81)	-1.931*** (-9.88)	-1.921*** (-9.91)	
W_Log(PAT)					-0.190** (-1.93)
Log(RD-2))	0.294*** (8.03)	0.262*** (6.99)	0.265*** (4.53)	0.267*** (4.61)	0.215** (2.47)
LOG(ENQ_DENS(-2))		0.026*** (3.21)	0.027*** (3.20)	0.029*** (3.46)	0.024** (2.27)
LOG(PAT_STOCK(-2)	0.611*** (12.43)	0.576*** (11.56)	0.576*** (11.46)	0.528*** (10.10)	0.374*** (5.02)
LOG(HT_EMP(-2))			-0.006 (-0.06)	-0.012 (-0.12)	0.104 (0.68)
W_LOG(RD_TOTAL(-2)					0.411* (1.79)
W_LOG(ENQ_DENS(-2))					0.072* (1.90)
W_LOG(PAT_STOCK(-2)					0.352 (1.48)
W_LOG(HT_EMP(-2))					-1.260** (-2.57)
WEST_BORDER				0.277*** (3.07)	
R^2-adj	0.44	0.45	0.45	0.45	0.56
LIK	-641.74	-636.59	-636.58	-631.85	-1188.70
LM-Err (robust)					
Neigh			1.263		
INV2			7.737***		
4-nearest neighbours			0.803		
LM-Lag (robust)					
Neigh			1.239		
INV2			7.278***		
4-nearest neighbours			0.482		
Wald-Lag (INV2)					13.57***
Wald-Err (INV2)					11.69**
LR-test joint significance spatial fixed effects			196.1***		
LR-test joint significance time-period fixed effects			30.8***		
Hausman random effects test					1.573
ϕ					0.492*** (7.80)

Notes: Estimated t-values are in parentheses; spatial weights matrices are row-standardized: Neigh is neighborhood contiguity matrix; INV2 is inverse distance squared matrix, 4-nearest neighbors is a weights matrix where those regions are considered as neighbors that are among the four most closely located ones; W_ denotes spatially lagged (dependent and independent) variables calculated with the weights matrix 4-nearest neighbours. *** indicates significance at $p < 0.01$; ** indicates significance at $p < 0.05$; * indicates $p < 0.1$.

spatial error dependence while LR panel tests guide us to extend this model with spatial and time-period fixed effects.

The positive and significant parameter of the west border dummy in Model (4) clearly suggests that there are important unmeasured differences in Central and Eastern Europe. Regions neighboring old member states (ceteris paribus) appear to use local resources more efficiently than the rest of the CEE regions. Model (5) takes individual regional and time-period effects explicitly into account. The insignificant Hausman random effect test on the one hand and the significant Wald-Lag and Wald-Error tests point towards the Random spatial and Fixed time-period effect Spatial Durbin model.

Model (5) depicts regression outputs when unmeasured regional and time-period effects as well as spatial dependence are controlled for. The results document markedly different patterns in the absorption of local and network knowledge in the two areas of the European Union. Contrary to the missing FP network effect in regions of the old EU member states the significant and positive parameter for Log(ENQ_DENS) in the final model of Table 4 indicates that knowledge transferred from FP networks is an important element of regional patenting in CEE objective 1 regions. The significant effects of local R&D and patent stocks remain unchanged in the final model. An additional apparent difference between the results of the final models in Tables 4 and 3 is related to the role of localized knowledge transfers in regional patenting. The parameters of the spatially lagged dependent variable as well as that of the high technology employment variable are negative while significant. These results indicate a chessboard-like structure of regional knowledge production in CEE regions. Regions with relatively high levels of patenting are generally surrounded by low patent producing regions with small high technology sectors. Considering the marginally significant parameters of the spatially lagged R&D and ENQ variables only a weak evidence is found for the influence of geographically mediated extra-regional knowledge flows on patenting in CEE objective 1 regions.

5. Summary and conclusions

Framework Programs are the largest research support instruments of the European Union. These programs finance collaboration among research units located in different parts of Europe and as such they mediate the flow of a significant amount of knowledge across distantly located European regions. Therefore knowledge transferred via FP research networks can potentially serve as substantial inputs to regional innovation. Contrary to expectations though, no evidence has been found on the supposed positive regional innovation impact of FP participation. On the other hand, a related research on the role of FP mediated knowledge transfers in regional scientific publication activity indicates important differences between lagging and core regions of the European Union. These findings motivated us to assume that the missing overall impact of EU Framework Program participation on regional innovation masks important differences between core and peripheral regions in Europe.

Within the Romer knowledge production function framework we tested empirically if knowledge potentially accessed via FP network linkages has any relationship with regional patenting. We carried out the analysis on two sub-samples covering the years of 2000-2009: CEE objective 1 regions (51 regions) and regions in the rest of the EU (211 non-CEE regions and non-objective 1 CEE regions). The selected research area of study was information science and technology, as this area can be identified through three FPs (FP5, FP6 and FP7) in a relatively consistent manner. While studying the FP network impact on innovation we controlled for localized knowledge flows via a systematic panel spatial econometric methodology. We found that clear and marked differences exist between CEE objective 1 and rest of EU regions. While knowledge transferred via FP networks acts as a further important input to patenting in CEE objective 1 regions, this is not observed in rest of EU regions. On the other hand, it is clear that localized learning in patenting is extremely important for regions located in rest of EU regions, whereas knowledge flows from neighboring regions play only a marginal role in the innovation activity of CEE objective 1 regions.

Thus, our results suggest that FP research subsidies act as a substitute for funding from other (mainly national) sources in regions of old EU member states and capital regions in CEE countries. On the other hand, innovation tends to rely more on external knowledge transferred via FP funded research networks in CEE objective 1 regions, compensating for their less developed local knowledge infrastructures. Our findings are important as they suggest that strengthening research excellence and international scientific networking in relatively lagging regions (such as regions in CEE countries) could be a viable option to increase regional innovativeness, which in combination with other policies, could form a base for a systematic support of regional development (McCann, Ortega-Argiléz 2014).

References

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

Agrawal, A., Kapur, D., & McHale, J. (2008) How do spatial and social poximity influence knowledge flows. *Journal of Urban Economics*, 64 (2), 258-269.

Amin, A., Cohendet, P. (2004) *Architectures of knowledge: Firms, capabilities and communities (No. 196)*. Oxford University Press.

Anselin L 1988 *Spatial econometrics: methods and models*. Boston, Kluwer Academic Publishers.

Anselin, L., J. Le Gallo, and H. Jayet. 2008. Spatial panel econometrics. In L. Matyas and P. Sevestre (eds.) *The econometrics of panel data, fundamentals and recent developments in theory and practice*. Dordrecht, Kluwer, 627-662.

Autant-Bernard, C., Fadairo, M., Massard, N. (2013): Knowledge diffusion and innovation policies within the European regions: Challenges based on recent empirical evidence. *Research Policy* 42(1), pp. 196-210.

Autant-Bernard, C. (2012) Spatial Econometrics of Innovation: Recent Contributions and Research Perspectives. *Spatial Economic Analysis* 7 (4), 403-419.

Autant-Bernard, C., Billand, P., Massard N. (2007) Social distance versus spatial distance in R&D cooperation. Empirical evidence from European collaboration choices in micro and nanotechnologies. *Papers in Regional Science* 86, 495-519.

Basile, R., Capello, R., Caragliu, A. (2012) Technological interdependence and regional growth in Europe: Proximity and synergy in knowledge spillovers. *Papers in Regional Science* 91, 697-722.

Boschma R (2005) Proximity and innovation: a critical assessment. *Regional Studies* 39, 61–74.

Breschi, S., Lissoni, F. (2009) Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. *Journal of Economic Geo*graphy 9, 439-468.

Burridge, P. 1981. Testing for a common factor in a spatial autoregression model. *Environment and Planning A* 13, 795-400.

Burt, R.S. (1992) *Structural Holes*. Harvard University Press. Cambridge, MA.

Coleman, J.S. (1986) Social Theory, Social Research, and a Theory of Action. *American Journal of Sociology* 91,1309-1335.

Diez, R. (2002) Metropolitan Innovation Systems - A comparison between Barcelona, Stockholm, and Vienna. *International Regional Science Review* 25, 63-85.

Elhorst, J.P. (2003) Specification and estimation of spatial panel data models. *International Regional Science Review* 26(3), 244–68.

Elhorst, J.P. (2012) Matlab Software for Spatial Panels. *International Regional Science Review*, doi: 0160017612452429.

Fingleton, V. and Le Gallo, J (2010) Endogeneity in a Spatial Context: Properties of Estimators. In Páez, A., Le Gallo, J., Buliung, R. and Dall'erba, S. (Eds.) *Progress in Spatial Analysis. Methods and Applications*. Springer, Berlin Heidelberg, 58-73.

Fischer, M. and Varga, A. (2002) Technological innovation and interfirm cooperation. An exploratory analysis using survey data from manufacturing firms in the metropolitan region of Vienna. *International Journal of Technology Management* 24, 724-742.

Fratesi, U., Senn, L. (Eds.) (2009) *Growth and Innovation of Competitive Regions. The Role of Internal and External Connections*. Springer-Verlag, Berlin, Heidelberg.

Furman, J. L., Porter, M. E. and Stern, S. (2002) The determinants of national innovative capacity. *Research Policy* 31, 899-933.

Godsil, C., Royle, G.F. (2001) *Algebraic Graph Theory*. Springer, series: Graduate Texts in Mathematics..

Griliches Z. (1990) Patent statistics as economic indicators: a survey. *Journal of Economic Literature* 20, 1661-1707.

Hazir, C., Autant-Bernard, C. (2013) *The Effect of Spatio-Temporal Knowledge Flows on Regional Innovation Performance: the case of ICT patenting in Europe*. SEARCH working paper.

Hoekman, J., Frenken, K. and van Oort, F. (2008) *Collaboration networks as carriers of knowledge spillovers: Evidence from EU27 regions*. DIME Working paper 2008.3 in the series on "Dynamics of Knowledge Accumulation, Competitiveness, Regional Cohesion and Economic Policies".

Hoekman, J., Scherngell, T., Frenken, K., van Oort, F (2012) Acquisition of European research funds and its effect on international scientific collaboration. *Journal of Economic Geography*, doi:10.1093/jeg/lbs011.

Jensen. M., Johnson, B., Lorenz, E., Lundvall, B. (2007) Forms of knowledge and modes of innovation. *Research Policy* 36, 680-693.

Jones, C. (1995) R&D-based models of economic growth, *Journal of Political Economy 103*(4): 759-784.

Klepper, S. (2007) Disagreements, spinoffs, and the evolution of Detroit as the capital of the U.S. automobile industry. *Management Science* 53 616-631.

Koschatzky, K. (2000) *The regionalization of innovation policy in Germany – Theoretical foundations and recent evidence*. Working Papers Firms and Regions No. R1/2000, Fraunhofer Institute for Systems and Innovation Research (ISI), Department "Innovation Services and Regional Development".

Lee, L., Yu, J. (2010) Some recent developments in spatial panel data models. *Regional Science and Urban Economics* 40, 255-271.

LeSage, J., Pace, R. (2009) *Introduction to Spatial Econometrics*. Chapman and Hall/CRC Press, Taylor & Francis Group.

Lundvall, B. (Ed.) (2010) *National Systems of Innovation. Toward a Theory of Innovation and Interactive Learning*. Anthem Press, London.
Maggioni M.A., Uberti T.E., Nosvelli M. (2014) *Knowledge Flows and Regional Innovative Performance FP6 networks as paper trails?* CSCC Working Paper, 01/2014.

Maggioni, M., Uberti, E., Nosvelli, M. (2012) *Does intentional mean hierarchical? Knowledge flows and innovative performance of European regions*. Paper submitted to the international conference Geography of Innovation 2012, 26-28 January 2012, Saint Etienne – France.

Maggioni M, Uberti T (2011) Networks and geography in the economics of knowledge flows. *Quality and Quantity* 45,1031–1051.

Maggioni M.A., Uberti T.E. (2007) International networks of knowledge flows. In: Frenken, K. (ed): *Applied evolutionary economics and economic geography*. Edward Elgar Publishing, Cheltenham, 230-255.

Maggioni M.A., Nosvelli M., Uberti T.E., (2007) Space vs. networks in the geography of innovation: a European analysis. *Papers in Regional Science* 86, 471-493.

Malerba, F., Vonortas, N. (Eds.) (2009) *Innovation Networks in Industries*. Edward Elgar Publishers, Cheltenham, UK.

McCann, P. and Ortega-Argiléz, R. (2014) Smart Specialisation, Regional Growth and Applications to EU Cohesion Policy. *Regional Studies* (forthcoming).

Meder, A. (2008) *Technological and geographical patterns in the choice of cooperation partner*. Jena Economic Research Papers 2008-054.

Moreno, R., Paci, R., & Usai, S. (2005). Spatial spillovers and innovation activity in European regions. *Environment and Planning* A, 37 (10), 1793-1812.

Nelson, R.R. (Ed.) (1993) *National Innovation Systems: A Comparative Analysis*. Oxford University Press, Oxford.

Protogerou, A., Caloghirou, Y., Siokas, E. (2011): Heterogeneity of technological knowledge flows in EU-funded collaborative research networks. Paper to be presented at the DIME final Conference, 6-8 April 2011, Maastricht.

Radosevic, S., Yoruk, E. (2013) *Global shifts in world science base? A comparative analysis of Central and Eastern Europe with the world's regions*. GRINCOCH Working Paper, WP3, Task1.

Romer, P. M. (1990) Endogenous technological change, *Journal of Political Economy 5*(98): S71-S102.

Sebestyén, T., Varga, A. (2013a) Research productivity and the quality of interregional knowledge networks. *Annals of Regional Science*, 51(1) 155-189.

Sebestyén, T., Varga, A. (2013b) A novel comprehensive index of network position and node characteristics in knowledge networks: Ego Network Quality. In Scherngell, T. (Ed.) *The geography of networks and R&D collaborations*. Springer, New York, 71-97.

Sebestyén, T., Varga, A. (2013c) *Interregional Knowledge Network Quality and Research Performance: Do Objective 1 and EU 12 Border Regions Follow Different Patterns than the Rest of Europe?* SEARCH working paper 4.12.

Scherngell, T., Barber, M.J. (2011): Distinct spatial characteristics of industrial and public research collaborations: evidence from the fifth EU Framework Programme. *The Annals of regional Science* 46(2), pp. 247-266.

Scherngell, T., Barber, M.J. (2009): Spatial interaction modelling of cross-region R&D collaborations: Empirical evidence from the 5th EU framework programme. *Papers in Regional Science,* 88(3), 531-546.

Varga, A., Horváth, M. (2014) Regional knowledge production function analysis. In Anderson, M., Karlsson, C. (Eds.) *Handbook of Research Methods and Applications in Economic Geography*. Edward Elgar Publishers. (forthcoming).

Varga, A., Pontikakis, D. and 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 (doi:10.1093/jeg/lbs041).*

Wanzenböck, I., Scherngell, T., Brenner, T. (2013) *Embeddedness of regions in European knowledge networks. A comparative analysis of inter-regional R&D collaborations, co-patents and co-publications*. Marburg Geography Working Papers on Innovation and Space 07.13.

Wasserman, S., Faust, K. (1994) *Social Network Analysis – Methods and Application*. Cambridge University press, Cambridge, UK.

Zucker L.G. Darby, M.R.,Furner, J., Liu R.C. and Ma, H. (2007) Minerva unbound: Knowledge stocks, knowledge flows and new knowledge production, *Research Policy*, Vol. 36, No. 6, pp. 850-863.