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EU Framework Program participation and innovation: The role of regional development

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**EU Framework Program participation and innovation:
The role of regional development**

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Abstract
This paper investigates the influence of regional development on the extent to which knowledge transfers mediated by European Framework Program participations affect regional patenting. The selected time span is 1998-2009 while the research area in this study is information science and technology (IST). We found that with respect to the role of localized knowledge flows and FP network learning in patenting clear and marked differences exist between lagging regions located in Central and Eastern Europe and the rest of the European Union. While knowledge transferred from FP networks acts as an additional source of patenting in CEE-Objective 1 regions, network knowledge is not related significantly to patenting in regions of the old member states. On the other hand it is clear that while localized learning in patenting is important for regions located in the EU 15 knowledge flows from neighboring regions play only a marginal role in CEE Objective 1 regions' innovation.

EU Framework Program participation and innovation: The role of regional development

1. Introduction

The complexity of innovation necessitates firms to source significant parts of knowledge externally. As a result, in the overwhelming majority of cases innovation becomes a collective process involving different actors like competing and related firms, supporting business services, private or public research organizations (Lundvall 2010). Knowledge external to firms is channeled to innovation via several routes, which, among others, include formal collaborations, labor markets, technology licensing, or pure knowledge spillovers (Amin, Cohendet 2004).

Recent research gives substantial evidence that the actual distribution of knowledge in space is a key determinant of innovation both at the regional and macro levels (Varga, Horváth 2013). Agglomeration of knowledge sources is beneficial for innovation for several reasons. Proximity helps build and maintain social connections, which have been identified as major channels of knowledge flows (Agrawal, Kapur, McHale 2008). Also, physically proximate locations provide the opportunities for frequent personal interactions. These interactions could facilitate the transfer of tacit knowledge, though they are also instrumental for quick and efficient flows of both tacit and codified knowledge. Frequent interactions are also advantageous for the development of trust or the establishment of the common codes of communication which are both essential in collaborative innovation (Koschatzky 2000). Additionally, some of the important carriers of knowledge transfers such as spin-off firm formation (Klepper 2007) or labor movements between firms (Breschi, Lissoni 2009) tend to work most frequently within small geographical areas.

Positive agglomeration effects arising from the proximity of external knowledge act as centripetal forces attracting further knowledge-related activities that reinforce a cumulative regional growth process over time (Fujita, Thisse 2002, Varga, Pontikakis, Chorafakis 2013). As a result this process works towards widening the gap between innovative and less innovative regions. Are there mechanisms that can potentially counteract this agglomerative process by helping regions with less developed local knowledge infrastructures to source from distant places those complementary knowledge elements that are not available locally? In theoretical discussions it is suggested that agglomeration and interregional knowledge networks may act as substitutes in regional knowledge creation (Johansson, Quigley 2004).

Indeed certain channels of knowledge flows do not seem to necessarily require the spatial proximity of actors. The synergistic nature of different types of proximities in knowledge transfers and especially that other types of proximities may efficiently compensate for geographical distance provide the conceptual base for understanding long-distance knowledge flows (Boschma 2005). Collaborative research is one of such knowledge transfer mechanisms, which can be conducted even over large distances without frequent personal interactions. Long distance exchange of codified knowledge (a type of knowledge that can be transported in space without significant difficulties) is made possible partly by the cognitive proximity of researchers that ensures common understanding of the codes of communication without frequent interactions (Meder 2008), and partly by social and relational proximities that help build and maintain the necessary level of trust between scientists even if they contact personally only on an infrequent basis (Autant-Bernard, Billand, Massard 2007, Basile, Capello, Caragliu, 2012).

However, the literature has not provided unequivocal evidence as to the supposed positive role of interregional research collaboration in innovation. Though Hoekman, Frenken and van Oort (2008) find a positive and significant relationship between publication activity of co-authors located in other NUTS 3 regions and regional patenting for two technologies (biotechnology and semiconductors), which is an indication of knowledge transfers mediated by research network linkages, this finding is not repeated 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 (2013) there is no direct relation between research productivity in patenting and R&D conducted by FP5 project partners located in other regions. However, their interesting result is that there is a strong indirect connection between EU Framework Program participation and patenting. According to their findings R&D expenditures of network partners located in other regions are positively related to productivity in scientific publication, which then increases the chances of attracting additional R&D in the future to the region. Sebestyén and Varga (2013a) dig deeper into the issue and found that non-spatial interregional learning in patenting in Europe is not mediated by Framework Program participations but by co-patenting linkages instead. Extending the panel of European NUTS 2 regions including data on FP5, FP6 and FP7 programs Hazir and Autant-Bernard (2013) reinforces 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 observed at the regional level.

Thus, while a positive relationship between knowledge flows mediated by interregional R&D networks and patenting has been detected when co-publication networks are examined, this relationship disappears when knowledge flows through European Framework Program participation are considered. This difference in the results might arise from some not yet explored differences in the nature of the two networks, the specificities of the data set in the Hoekman, Frenken and van Oort (2008) study (e.g., industry focus, publication as a proxy for regional knowledge inputs), but it could also be the case that there are still some important features of FP networks that has not yet been explicitly considered in analysis.

One of those features is the strong spatial regime effect in Framework Program participation. The literature already shows very interesting regional patterns in this respect for Europe and 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 involving scientists located in the periphery of the European Union while the effects in the core is nonexistent or even negative in this respect. It is thus suggested by these findings that FP funding acts as a substitute for other research funds in core regions of Europe whereas in the periphery FP financed subsidies turn out to be efficient complementary resources for research.

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 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 finding has implications for Edison-type (competitive) research as well. In Varga, Pontikakis and Chorafakis (2013) a positive relationship between research productivity in publication and the change of R&D in subsequent time periods is evidenced. This finding together with the spatial regime effect in R&D productivity in publication in Sebestyén and Varga (2013c) implies that participation in collaborative research funded by EU Framework Programs has a stronger influence on peripheral regions' future R&D, which (ceteris paribus) implies a more pronounced indirect FP impact on patenting in lagging areas of Europe.

The research question of this paper is much related to existing findings in the literature, which have already discovered several aspects of spatial regime effects in regional knowledge production. Wouldn't it be the case that the missing evidence on a direct knowledge transfer impact on patenting mediated by FP participations masks important and regular spatial differences in Europe? Influenced by earlier findings in the literature in this paper we hypothesize 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 to the nature of the expected differences in the trends there are no antecedents in the literature that could guide us to formulate one single hypothesis. Consequently, the hypothesis that lagging areas are not yet equipped to utilize learning from FP research networks in patenting because of their low levels of absorptive capacities (Radosevic and Yoruk 2013) can be raised with a chance similar to that of the other, which states (in the spirit of Hoekman, Scherngell, Frenken and van Oort 2012) that FP subsidies are only substitutes for other research funds in core EU regions and as such do not influence patenting.

Interregional knowledge flows mediated by FP network participation is measured in this paper by the index of Ego Network Quality (ENQ - Sebestyén and Varga 2013a, 2013b). With this measure the aim is to overcome a frequent shortcoming of 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 temporarily 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. We carry out the analysis with two European sub-samples: Central-Eastern European (CEE) Objective 1 regions (51 regions) and non-CEE regions (211 regions) in the old member states of the European Union. The selected research area of study is information science and technology (IST).

The subsequent section 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):

$$dA_i/dt = \delta H_{Ai} A_i \qquad (1)$$

where dA_i/dt is the temporal change in technological knowledge, 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:

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

where $\mathrm{PAT_i}$ stands for new technological knowledge measured by patent applications, $\mathrm{RD_i}$ is expenditure on research and development and $\mathrm{PAT\_STOCK_i}$ proxies technological knowledge accumulated over time in region i. In accordance with usual interpretations $\mathrm{a_1}$ reflects the influence of localized knowledge flows from R&D carried out by firms and public research institutions on regional patenting while $\mathrm{a_2}$ proxies the relation of patenting with accumulated knowledge. Besides regional controls, $\mathrm{Z_i}$ 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 as well as the intensity of collaborations among them largely 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.

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 agents' productivity in new knowledge generation. The second intuition is that the structure of connections in the agents' 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.

Therefore 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 LC for consecutive neighbourhoods of indirect partners in the network.[1] 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 discussion.

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 we denote 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 can formalize ENQ as follows:

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

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,[2] 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 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.

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

[2] 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).

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

The concept of Local Structure refers to the structure of connections in different neighbourhoods of a node. However, the formula for ENQ in (3) is specified in a way that LS can be filled with different concepts. In this paper we introduce two specific ways to fill LS with content, namely Local Connectivity and Connected Components. The two alternative specifications are linked to the concepts of cohesion and structural holes familiar from the theory of social capital. Cohesion, as defined by Coleman (1986) emphasizes the role of cohesion, while the notion of structural holes (Burt, 1992) puts weight on gatekeepers or information brokers connecting different groups in the network.

<u>Local Connectivity</u>

Local Connectivity (LC), referring to the cohesion concept, is associated with the strength of ties and the intensity of interactions among partners. It is the sum of the tie weights present in a given neighbourhood, normalized by the size of this neighbourhood:

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

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.[3] 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.[4] As a result, Local Connectivity captures the intensity with which the (possibly indirect) neighbours at distance d are linked together and linked to other neighbourhoods. Using the LC approach, the ENQ index is formulated as follows:

$$ENQ^i = \sum_d W_d Q_d^i = \sum_d W_d KP_d^i LC_d^i \tag{6}$$

<u>Connected Components</u>

Connected Components (CC) integrates the concept of structural holes into the ENQ index through LS. Here we propose a simple approach to capture the basic intuition behind the concept: we introduce CC_d^i which counts the number of connected components (unconnected

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[3] Distances are always measured from node i.

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

groups of nodes) in different neighbourhoods.[5] Using the CC approach, the ENQ index is formulated as follows:

$$ENQ^i = \sum_d W_d Q_d^i = \sum_d W_d KP_d^i CC_d^i \tag{7}$$

<u>A mixed version</u>

Although intuitive, both Local Connectivity and Connected Components take a very strict view and measurement of the phenomena they intend to capture. However, by combining the two approaches, ENQ can reflect a more refined picture about the structure of local neighbourhoods. Let's redefine ENQ with the product of Local Connectivity and Connected Components as the weighting factor of Knowledge Potentials (the Local Structure component, defined before):

$$ENQ^i = \sum_d W_d Q_d^i = \sum_d W_d KP_d^i CC_d^i LC_d^i \tag{8}$$

This formulation refines the two extreme cases by providing a natural way to combine the two effects as the multiplication of Connected Components and Local Connectivity attach higher weights to structures which lay in between neighborhoods with extreme structural holes and extreme connectivity.

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

Increasing availability of spatial data collected over longer time periods 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 the following specification issues will be considered: network effect identification, localized knowledge transfer impact identification and panel effect identification. Equations (9) to (11) represent those models where ENQ enters the patent equation as a stand-alone variable. In cases when this specification is selected interregional knowledge flows mediated by FP networks directly affect patenting in the region. On the other hand equations (12) to (14) 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. Turning 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 9 and 12) spatial dependence is modeled through the spatially lagged dependent variable. In spatial error models (equations 10 and 13) dependence is modeled in the error term. Alternatively, with the spatial Durbin model (equations 11 and 14) spatial dependence is modeled through both the dependent as well as the independent variables.

$$\log(PAT_{rt}) = \delta \sum_{q=1}^{Q} W_{rq} \log PAT_{qt} + \alpha_0 + \alpha_1 log\ RD_{rt-2} + \alpha_2 log\ PATSTOCK_{rt-2} + \alpha_3 log\ ENQ_{rt-2} + \alpha_4 log\ HTEMP_{rt-2} + \mu_r + \lambda_t + \varepsilon_{rt} \tag{9}$$

[5] The number of connected components in a neighbourhood is given by the multiplicity of the zero eigenvalues of the Laplacian matrix of the subgraph spanned by the nodes at a specific distance from the node in question (see e.g. Godsil and Royle, 2001).

$$\log(PAT_{rt}) = \alpha_0 + \alpha_1 log\ RD_{rt-2} + \alpha_2 log\ PATSTOCK_{rt-2} + \alpha_3 log\ ENQ_{rt-2} + \alpha_4 log\ HTEMP_{rt-2} + \mu_r + \lambda_t + \varphi_{rt}\ ,\ \varphi_{rt} = \rho \sum_{q=1}^{Q} W_{rq}\varphi_{qt} + \varepsilon_{rt} \quad (10)$$

$$\log(PAT_{rt}) = \delta \sum_{q=1}^{Q} W_{rq} \log PAT_{qt} + \alpha_0 + \alpha_1 log\ RD_{rt-2} + \alpha_2 log\ PATSTOCK_{rt-2} + \alpha_3 log\ ENQ_{rt-2} + \alpha_4 log\ HTEMP_{rt-2} + \theta_1 \sum_{q=1}^{Q} W_{rq} log\ RD_{qt-2} + \theta_2 \sum_{q=1}^{Q} W_{rq} log\ PATSTOCK_{qt-2} + \theta_3 \sum_{q=1}^{Q} W_{rq} log\ ENQ_{qt-2} + \theta_4 \sum_{q=1}^{Q} W_{rq} log\ HTEMP_{qt-2} + \mu_r + \lambda_t + \varepsilon_{rt} \quad (11)$$

$$\log(PAT_{rt}) = \delta \sum_{q=1}^{Q} W_{rq} log(PAT_{qt}) + \alpha_0 + \alpha_1 log\ ENQ_{rt-2}\ log\ RD_{rt-2} + \alpha_2 log\ PATSTOCK_{rt-2} + \alpha_3 log\ HTEMP_{rt-2} + \mu_r + \lambda_t + \varepsilon_{rt} \quad (12)$$

$$\log(PAT_{rt}) = \alpha_0 + \alpha_1 log\ ENQ_{rt-2}\ log\ RD_{rt-2} + \alpha_2 log\ PATSTOCK_{rt-2} + \alpha_4 log\ HTEMP_{rt-2} + \mu_r + \lambda_t + \varphi_{rt}\ ,\ \varphi_{rt} = \rho \sum_{q=1}^{Q} W_{rq}\ \varphi_{qt} + \varepsilon_{rt} \quad (13)$$

$$\log(PAT_{rt}) = \delta \sum_{q=1}^{Q} W_{rq} log(PAT_{qt}) + \alpha_0 + \alpha_1 log\ ENQ_{rt-2}\ log\ RD_{rt-2} + \alpha_2 log\ PATSTOCK_{rt-2} + \alpha_3 log\ HTEMP_{rt-2} + \theta_1 \sum_{q=1}^{Q} W_{rq} log\ ENQ_{qt-2}\ log\ RD_{qt-2} + \theta_2 \sum_{q=1}^{Q} W_{rq} log\ PATSTOCK_{qt-2} + \theta_3 \sum_{q=1}^{Q} W_{rq} log\ HTEMP_{qt-2} + \mu_r + \lambda_t + \varepsilon_{rt} \quad (14)$$

There are some variables in equations (9) to (14) 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_r *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) in empirically testing the Common factor hypothesis.

Regarding panel effect identification, which is the third specification issue 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). Paul Elhorst's MATLAB routines are run for the spatial panel estimations (Elhorst 2012).

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 1998 and 2009. As made possible by the thematic diversification of our FP database, the sample is restricted to those projects and the respective participants which fall under the broad thematic area of information technologies and society (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 ($Patents\_IST_{i,t}$). 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 ($IST\_PAT\_STOCK_{i,t}$) according to the perpetual inventory method for the 1995–2009 period (see the details in Varga, Pontikakis and Chorafakis 2013).

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, 2013)

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 where to each FP project we assign 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 actor-actor contacts between the regions. In the previous example, we count two links between regions 1 and 2, one for the link between actors A and C and one for the link between actors B and C. This method is then iterated for each FP project and each year in the sample to obtain the adjacency matrices describing the network structure of knowledge flows. These matrices are then used to calculate the ENQ measures in this study.

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

Table 1. Variable description

Variable Name	Description	Source
$PAT_{i,t}$	Number of patent applications from the ICT sector to the European Patents office (EPO) by region of inventor (fractional counts)	Eurostat database
$RD_{i,t}$	Gross regional expenditures on R&D, in millions of Purchasing Power Standard (PPS) Euros, 1995 prices	Eurostat database
$REG\_FUND_{i,t}$	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
$PATSTOCK_{i,t}$	Regional patent stock in the ICT sector	Authors' elaboration on Eurostat database
$ENQ\_DENS_{i,t}$, $ENQ\_STRH_{i,t}$ $ENQ\_MIXD_{i,t}$, $KP_{i,t}$, $LS\_DENS_{i,t}$, $LS\_STRH_{i,t}$, $GE_{i,t}$	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, STRH to the structural holes and MIXD to the mixed approach of calculating the Local Structure component of ENQ. KP is the Knowledge Potential component, LS is the Local Structure component, LS is the Global Embeddedness component	Authors' elaboration on FP5-6-7 administrative database, DG RTD, Dir A
$HTEMP_{i,t}$	Regional employment in the high tech sectors according to the Eurostat classification (high-tech manufacturing and high-tech knowledge-intensive services)	Eurostat database

Table 2. Variable descriptive statistics

	PAT	RD	REG_FUND	PATSTOCK	ENQ_DENS	HTEMP
Total sample						
N	2620	2620	2620	2620	2620	2620
Mean	56,07	674,99	2,90	340,05	6655,36	35,01
Std.dev.	137,22	1166,34	5,75	856,23	7055,61	41,52
Min	0	1,06	0,00013	0	0	0,86
Max	1926,59	13269,56	70,07	7582,23	25653,63	474,77
CEE regions						
N	510	510	510	510	510	510
Mean	2,14	123,91	0,74	9,03	2945,53	23,12
Std.dev.	2,71	169,22	1,20	8,58	4173,85	17,23
Min	0,06	4,16	0,00193	0,7	0	5,47
Max	17,95	1245,06	5,72	61,81	23087,01	145
Non CEE regions						
N	2110	2110	2110	2110	2110	2110
Mean	69,11	808,19	3,37	420,06	7552,05	37,88
Std.dev.	150,01	1261,39	6,21	936,71	7312,51	45,02
Min	0	1,06	0,00013	0	0	0,86
Max	1926,59	13269,56	70,07	7582,23	25653,63	474,77

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.

Variable description is provided in Table 1, while descriptive statistics of the main variables are presented in Table 2.

In what follows, some exploratory analysis is provided with respect to our basic variables. Figure 1 shows the evolution of patenting activity in CEE regions and the rest of the regions in the sample regions. What is evident form the figure is that there is a magnitude difference between the two categories of regions in favor of non-CEE regions. However, we observe a decreasing trend for non-CEE regions while an increasing one for the CEE regions, which sign a catching up process in the latter ones.

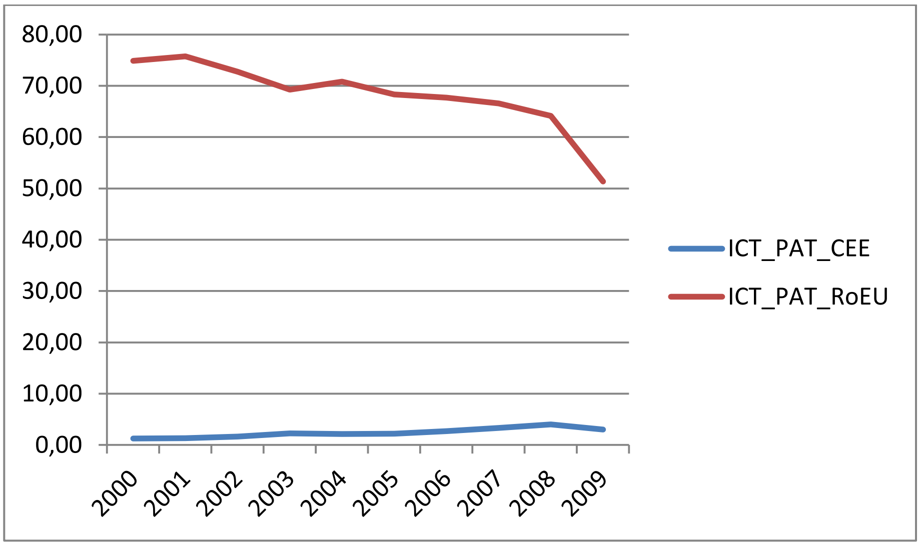

Figure 1: Average patenting activity in CEE and non-CEE regions

Figure 2 shows the average regional funding for CEE and non-CEE regions in the sample. It is also apparent that CEE regions acquire far less funding through FP projects than non-CEE ones. However, they show an increasing trend in this respect while no trend is detected for non-CEE regions.

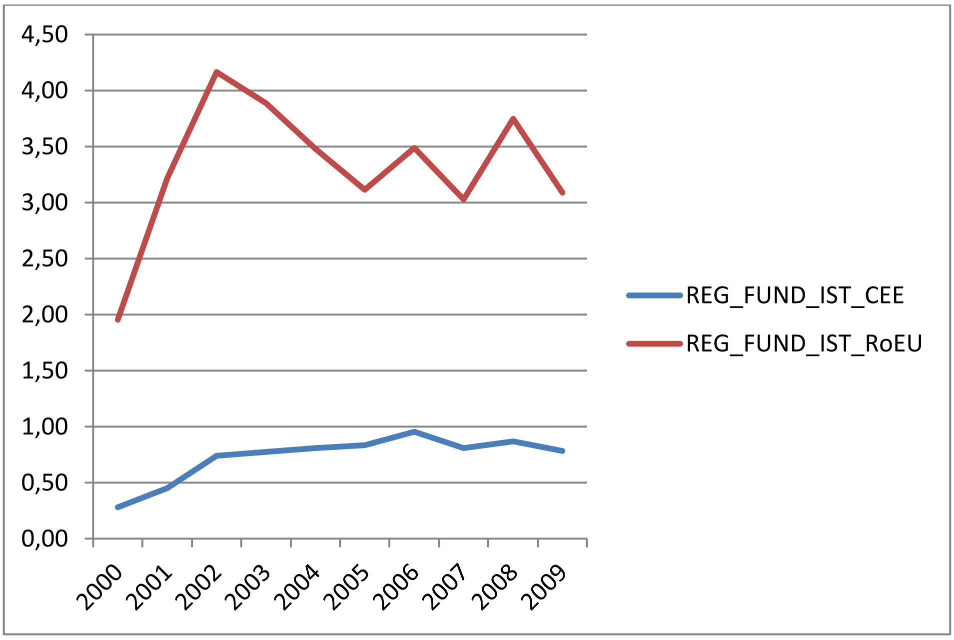

Figure 2: Average FP funding in CEE and non-CEE regions (information technologies and society)

If we look at the relative funding, the catch up process of CEE regions is apparent, although it clearly breaks for the final years of our sample and together with the catch up, the average FP funding of CEE regions (in the information technologies and society areas) just reaches 25% of the funding intensity of non-CEE regions.

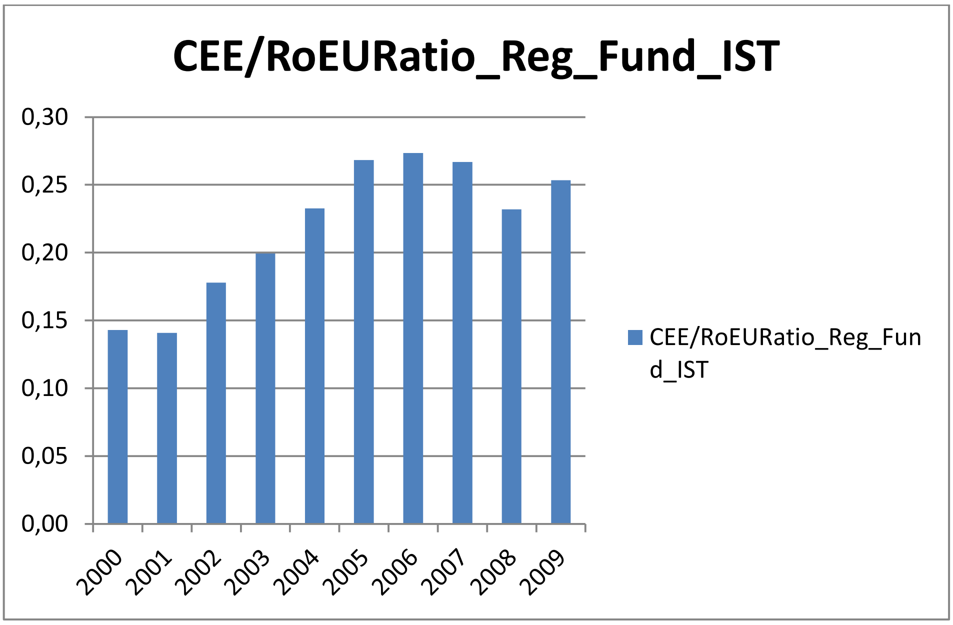

Figure 3: Relative FP funding of CEE and non-CEE regions

Turning to the ENQ index, Figure 4 shows how the average ENQ indices[6] evolved over our sample period. Figures 5 and 6 show the evolution of two subindices, namely the Knowledge Potential and the Local Connectivity indices, which capture the properties of the direct neighborhood of the regions in the sample (average values are indicated on the figure). Figures 7-9 show the respective relative figures.

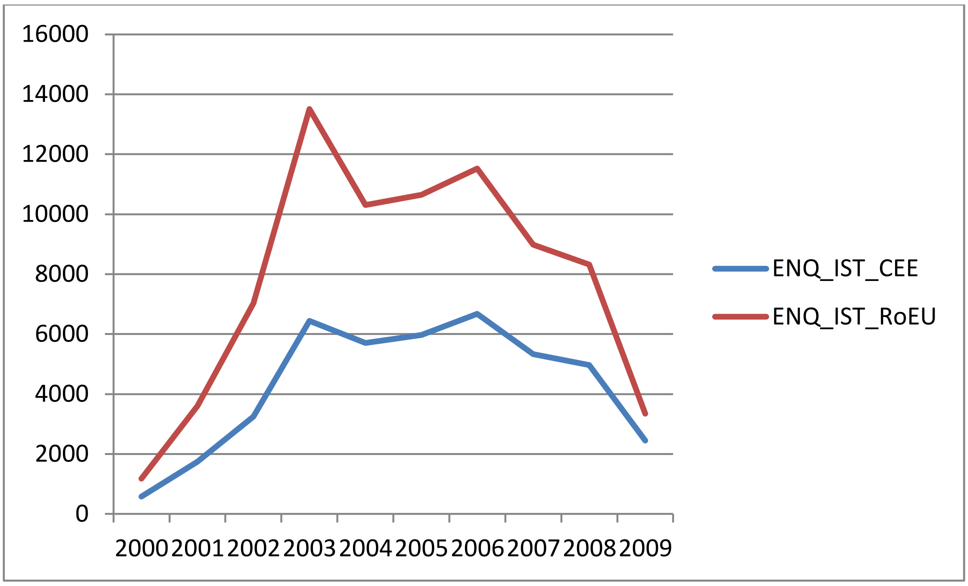

Figure 4: Average ENQ of CEE and non-CEE regions

[6] ENQ indices shown in the figures are calculated with Local Connectivity used as the underlying concept of the Local Structure subindex in ENQ.

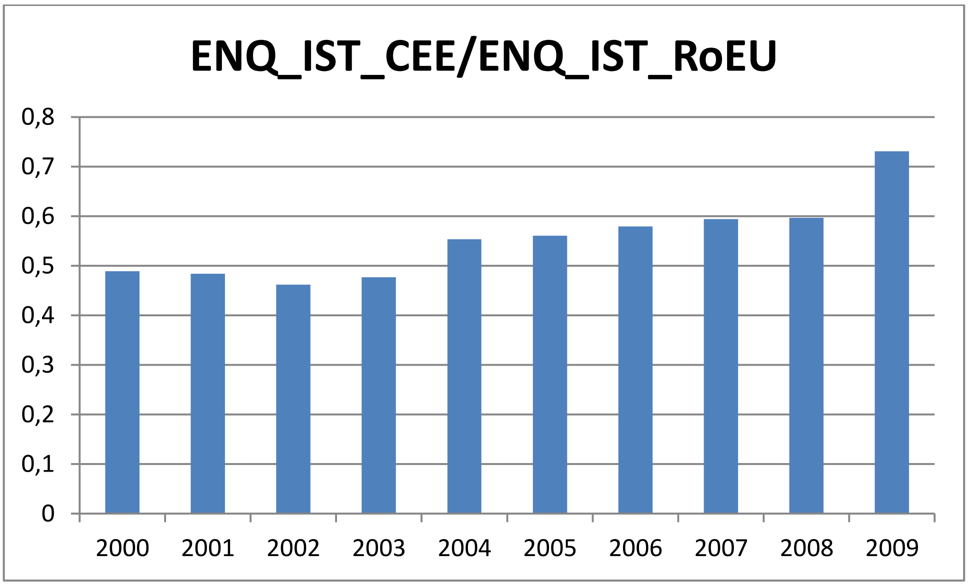

Figure 5: Relative ENQ indices of CEE and non-CEE regions

Figure 4 shows that non-CEE regions step ahead of their CEE 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 60%) there is a marked increase in the last year. This shows that the position of CEE regions in interregional knowledge networks improved a bit at the end of the sample, but still remains at 70% of the non-CEE regions.

If we look at the two subindices, it is apparent that CEE regions slightly increase their position with respect to Local Connectivity, from around 50% to over 60% at the end of the sample. In other words, CEE 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 more intensive collaboration structures surround them, getting more similar in this respect to non-CEE regions.

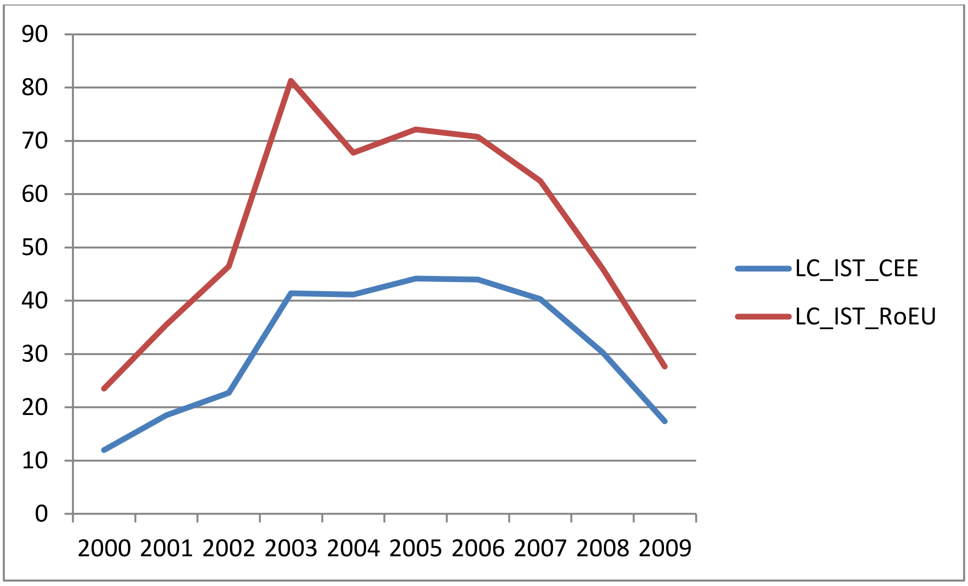

Figure 6: Average Local Connectivity values of CEE and non-CEE regions

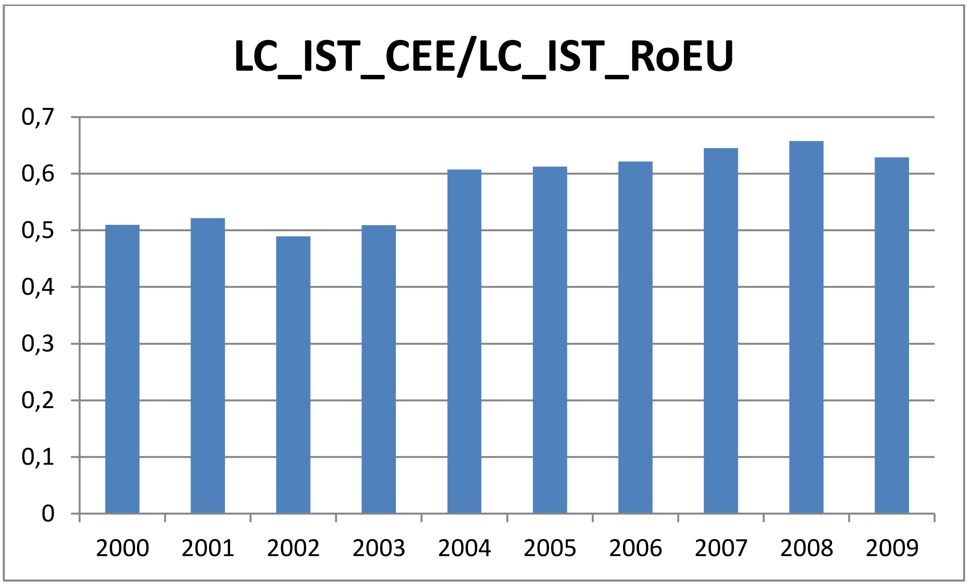

Figure 7: Relative Local Connectivity values of CEE and non-CEE regions

With respect to Knowledge Potential, we observe a maintained difference between CEE and non-CEE regions over the sample period. This shows that the direct partners of CEE 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 60% at the end of the sample.

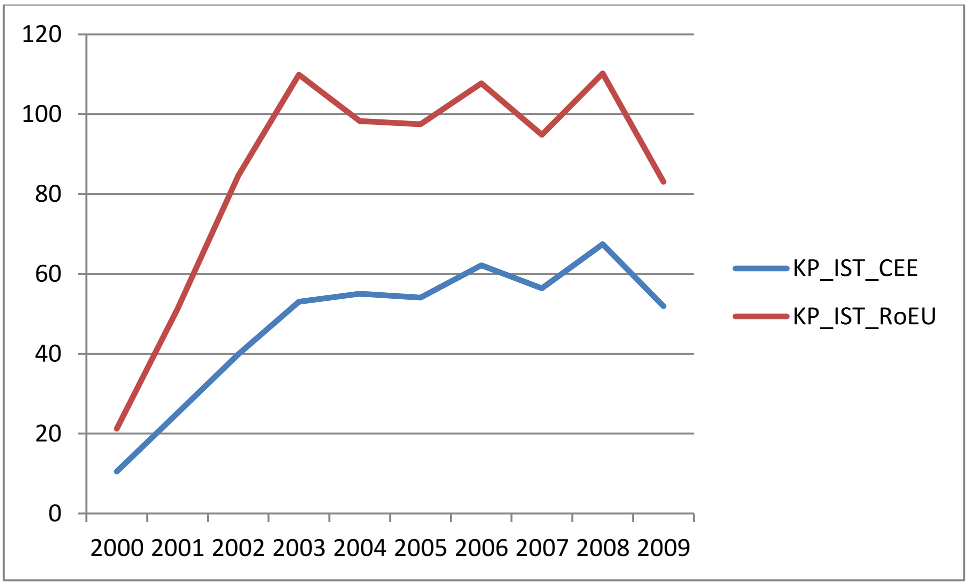

Figure 8: Average Knowledge Potential values of CEE and non-CEE regions

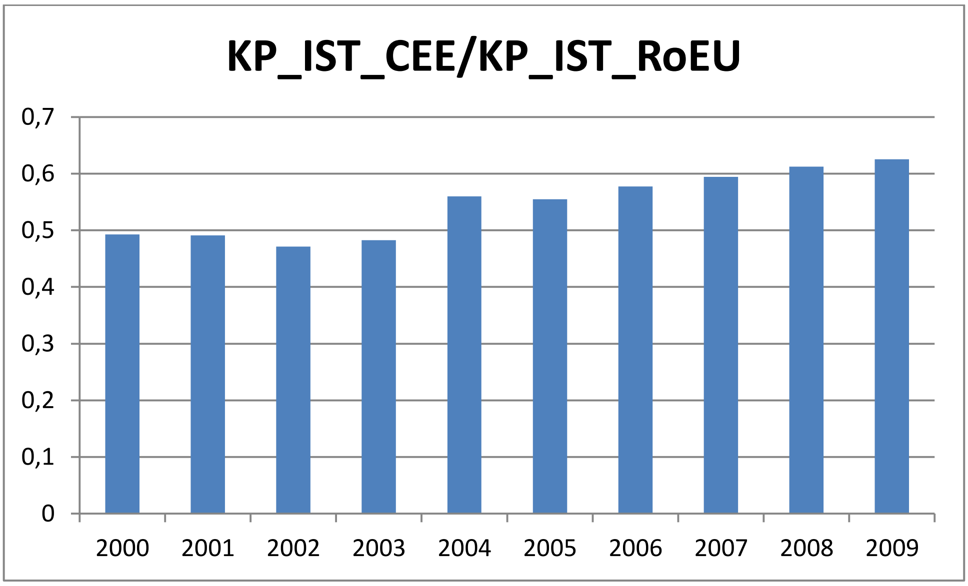

Figure 9: Relative Knowledge Potential values of CEE and non-CEE regions

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 the 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.

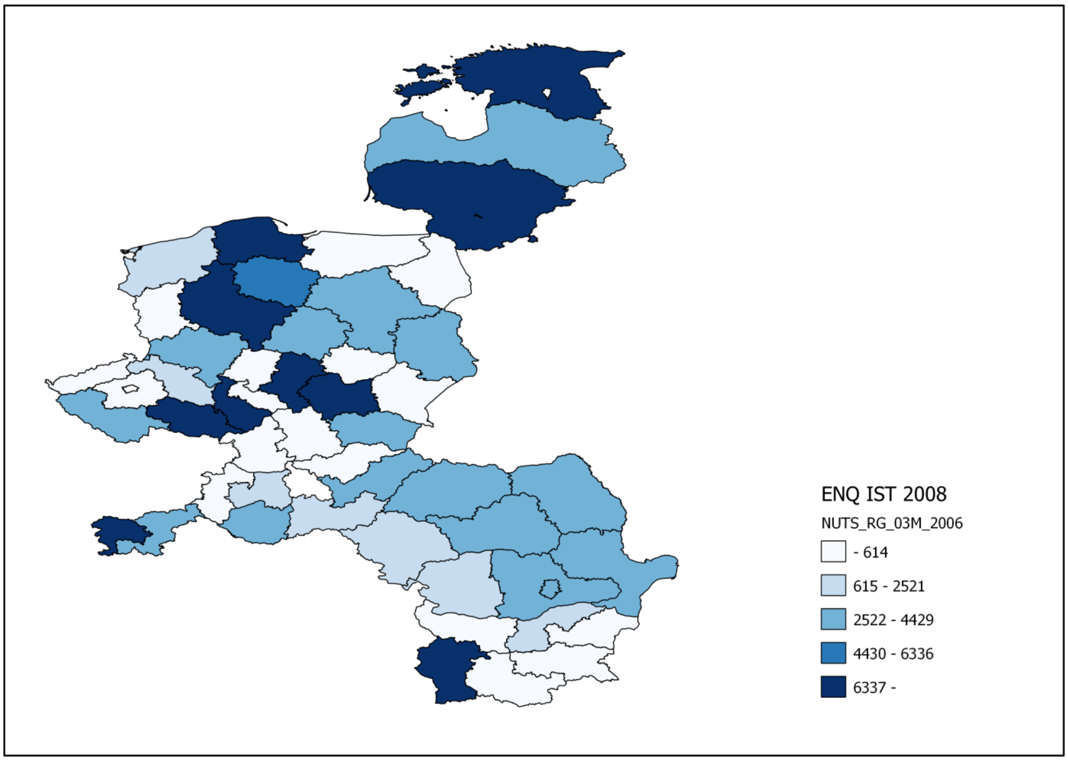

Figure 10: Spatial distribution of ENQ values in CEE regions

Figure 10 shows the spatial distribution of regional ENQ values calculated for 2008. 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.

4. Empirical analysis

In earlier studies it was 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 non-CEE regions. As shown in the preceding section Objective 1 regions of the EU in the recently joined Central and Eastern European 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 sector. We first study the regression outputs for Non-CEE 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. 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 (adjusted R-square equals 0.89) is considerably high especially taking into account the panel nature of the data. Models (2) to (4) document the results of our exploration for 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 weights 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 weights matrix will be used in spatial econometric estimations.

Models (6) to (9) provide details on the network effect. Gatekeeper position (Model 9), when the Local Structure is measured by the presence of structural holes in the neighborhoods, seems to increase research productivity most intensively. However, the interesting result is that the ENQ impact does not change whether this gatekeeper position is taken into account (Model 6) or not (Model 5).

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

Table 3. Regression Results for Log (PAT) for 211 Non-CEE EU NUTS2 Regions and for the ICT sector, 2000-2009 (N=2110)

Model	(1) Pooled	(2) Pooled	(3) Pooled	(4) Pooled	(5) Pooled	(6) Pooled	(7) Pooled	(8) Pooled	(9) Pooled	(10) Spatial and time-period fixed effects
Estimation	OLS	OLS	OLS	OLS	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)	-2.187*** (-36.59)	-2.332*** (-37.60)	-2.298*** (-37.62)	-2.399*** (-37.19)	
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)	0.200*** (8.66)	0.216*** (9.41)	0.212*** (9.23)	0.225*** (9.78)	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(REG_FUND (-2))*LOG(ENQ_MIXD(-2))						0.005*** (3.96)				
LOG(REG_FUND (-2))*LOG(KP(-2))							0.007*** (7.15)			
LOG(REG_FUND (-2))*LOG(LS_DENS(-2))								0.009*** (6.68)		
LOG(REG_FUND(-2))*LOG(LS_STRH(-2))									0.012*** (7.70)	
LOG(PATSTOCK(-2)	0.712*** (53.31)	0.714*** (54.12)	0.940*** (103.76)	0.712*** (53.63)	0.685*** (50.55)	0.685*** (50.55)	0.687*** (51.13)	0.687*** (51.03)	0.687*** (51.23)	0.094** (2.40)
LOG(HTEMP(-2))					0.239*** (7.88)	0.239*** (7.88)	0.240*** (7.99)	0.238*** (7.93)	0.247*** (8.24)	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	0.89	0.89	0.89	0.89	0.96
LIK	-2033.73	-2007.13	-2217.56	-2022.30	-1991.63	-1991.62	-1974.16	-1977.34	-1970.12	-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. Regression Results for Log (PAT) for 51 CEE OBJ1 EU NUTS2 Regions and for the ICT sector, 2000-2009 (N=510)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Random spatial effects, fixed time-period effects
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	ML-Spatial Durbin (INV2)
Constant	-2.049***	-1.939***	-1.931***	-1.929***	-1.807***	-1.839***	-1.742***	-1.970***	-1.921***	
	(-14.89)	(-13.81)	(-9.88)	(-9.88)	(-8.83)	(-9.13)	(-7.98)	(-10.20)	(-9.91)	
W_Log(PAT)										-0.190**
										(-1.93)
Log(RD-2))	0.294***	0.262***	0.265***	0.264***	0.255***	0.252***	0.268***	0.269***	0.267***	0.215**
	(8.03)	(6.99)	(4.53)	(4.52)	(4.35)	(4.29)	(4.60)	(4.61)	(4.61)	(2.47)
LOG(ENQ_DENS(-2))		0.026***	0.027***						0.029***	0.024**
		(3.21)	(3.20)						(3.46)	(2.27)
LOG(ENQ_MIXD(-2))				0.027***						
				(3.28)						
LOG(KP(-2))					0.041***					
					(3.52)					
LOG(LS_DENS(-2))						0.052***				
						(3.52)				
LOG(LS_STRH(-2))							0.110***			
							(3.12)			
LOG(GE_DENS(-2))								0.031***		
								(3.18)		
LOG(PAT_STOCK(-2)	0.611***	0.576***	0.576***	0.575***	0.573***	0.574***	0.582***	0.582***	0.528***	0.374***
	(12.43)	(11.56)	(11.46)	(11.45)	(11.42)	(11.48)	(11.64)	(11.65)	(10.10)	(5.02)
LOG(HT_EMP(-2))			-0.006	-0.007	-0.0003	0.004	-0.007	-0.004	-0.012	0.104
			(-0.06)	(-0.06)	(-0.03)	(0.039)	-(0.07)	(-0.03)	(-0.12)	(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	0.45	0.45	0.44	0.45	0.45	0.56
LIK	-641.74	-636.59	-636.58	-636.35	-635.53	-635.53	-636.83	-636.67	-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 $p < 0.1$.

significant Wald Lag and Wald Error test statistics at the bottom of Model (10) 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 (10) 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 (10) 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 Non-CEE regions in Europe knowledge flows from FP networks do not play a meaningful role in regional patenting. The other essential result is 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 old EU member states tend to rely on localized knowledge inputs in patenting instead of extra-regional knowledge communicated via FP research networks.

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

Models (4) to (8) in Table 4 provide additional details as to the individual impact of the ENQ components on regional patenting. Outstanding role of structural holes gets evidenced again. Similar to what is found for Non-CEE regions incorporating the gatekeeper position to ENQ does not change the size and significance of the respective estimated parameter in Table 4 either. The positive and significant parameter of the west border dummy in Model (9) 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 (10) takes individual regional and time-period effects explicitly into account. The significant 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 (10) 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 high technology employment 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

In the introduction of this paper we raised the question whether knowledge transferred from long distances via research networks can somehow compensate lagging regions for their low levels of locally agglomerated knowledge. To empirically investigate this problem, we chose research networks subsidized by the European Framework Programs as potential channels for knowledge transfer. Though projects supported by these programs are selected on the basis of scientific excellence and not on the base of equity principles, excellent research groups may be in a position to transfer such knowledge to the region that could later contribute to regional innovation. Earlier research on FP participation and future publication activity found that while this impact is considerable for lagging regions it is non-existent or even negative for core regions. Building on this literature we hypothesized in this paper that knowledge transported via FP networks bears different impacts on innovation depending on regional development.

Within the frame of the Romerian knowledge production function we tested if the quality of regions' individual FP networks has any relationship with regional patenting. We carried out the analysis with two sub-samples covering the years 1998-2009: CEE-Objective 1 regions (51 regions) and non-CEE regions (211 regions). The selected research area of study was information science and technology (IST). While analyzing the FP network impact we controlled for localized knowledge flows via a systematic panel spatial econometric methodology. We found that with respect to the role of localized knowledge flows and FP network learning in patenting clear and marked differences exist between CEE-Obj 1 and non-CEE regions. While knowledge transferred from FP networks acts as an additional source of patenting in CEE-Obj 1 regions, network knowledge is not a significant input in patenting in regions of the old member states. On the other hand it is clear that while localized learning in patenting is extremely important for regions located in the EU 15, knowledge flows from neighboring regions play only a marginal role in CEE Objective 1 regions' innovation.

Thus, our results suggest that while for regions in old EU member states FP research subsidies seem to act as a substitute for funding from other sources, innovation in CEE Objective 1 regions tends to rely more on external knowledge transferred from FP funded research networks to compensate for their less developed local knowledge infrastructure. Our findings are important as they suggest that strengthening research excellence and international scientific networking in relatively lagging regions (such as regions in CEE and ENP 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).

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