Innovation in Central and Eastern European Regions: Does EU Framework Program participation lead to better innovative performance?

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Abstract: In this paper we raise the question whether knowledge transferred from long distances via research networks can somehow compensate lagging regions in Central and Eastern Europe for their low levels of locally agglomerated knowledge. To empirically investigate this problem we choose research networks subsidized by the European Framework Programs. Within the frame of the Romerian knowledge production function we test 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 the broad area of quality of life (QOL). We measure extra-regional knowledge accessible via FP research networks by the index of Ego Network Quality. We also control for localized knowledge flows via a systematic panel spatial econometric methodology. We found that important differences exist between CEE-Objective 1 and non-CEE regions with respect to FP network learning in patenting. While knowledge transferred from FP networks positively influences the impact of FP research subsidies on regional innovation in CEE-Objective 1 regions, network knowledge does not turn out to be a significant input in patenting in regions of the old member states.

1. Introduction

Central and Eastern European countries, accessed to the European Union in 2004 and 2007, have gone through a development path which is markedly different from that of the old member states of the EU. These countries also share some characteristics due to their common starting point of a relatively fast transition to a market economy in parallel with the political independency from the former Soviet Union. A vast literature is devoted to the questions of transition and catching up with Western countries (see e.g. Mervelede (2000) for a review of the literature or Grinberg et al. (2008) or Havlik et al. (2012) for an overview on structural change and productivity growth).

In addition to the relatively broad attention to transition economies at the national level, there is less research done on the regional aspects of these processes. Petrakos (2001) analyses regional disparities during the transition, emphasizing the fact that in CEE countries metropolitan and border regions are favored under the transition process. Tondl and Vuksic (2003) and Varga and Schalk (2004) show that foreign direct investment plays a crucial role in regional growth and reinforce that capital and border regions outperform others. Gorzelak (1998) emphasizes the role of accessibility to markets in Western Europe, while Kallioras and Petrakos (2010) draw attention to the role of initial structural and geographical conditions in the catching up process.

Innovation follows different patterns in CEE countries compared to the rest of Europe. Von Tunzelmann and Nassehi (2004) argue that EU innovation policies are suitable for the core countries but are ineffective in CEE countries. Although it is clear that economic growth in these countries has not been based on innovation during the past decades (Varblane et al., 2007), there still remains the issue of the huge difference between Western and CEE countries in terms of innovative output (EC, 2009). According to Radosevic and Yoruk (2013) CEE countries show an increasing trend in publication and citations compared to other regions, but there is still a gap from North America, the rest of EU and Pacific Asia. This raises the question of the existence and functioning of regional innovation systems in CEE regions, a field where even less research has been done so far.

Gorzelak (1996) calls attention to the fact that the socialist regime created significant dependence of regions on the capitals. As a result, economic development in the post-socialist period was concentrated mainly in capital regions. This tendency then leads to innovation systems, which are also concentrated into capital regions (Radosevic 2002). Inzelt (2004) emphasizes that R&D capacities (including available private and public resources) have been strongly destructed during the first years of transition from the soviet era to the market economy. As a result, innovation systems in CEE countries are largely dependent on the presence of foreign capital and R&D activities located there by multinational corporations. Systems of innovation in CEE countries thus typically emerge in close proximity to foreign firms and domestic business groups (Radosevic 1999). Though interfirm cooperation is still low (Inzelt and Szerb 2006) and the links between industry and universities are still week in general (Inzelt 2004) there is also some evidence that universities and state-controlled services were able to maintain their role in the innovation systems in lagging regions (Lengyel and Leydesdorff 2011).

Capello and Perucca (2013) add to the picture the role of extra-regional linkages in innovation concluding that in general 'global regions' which have decent connections with the rest of the world (even outside Europe) and are specialized in growing sectors have led the growth process in their countries. With respect to linkages connecting actors of innovation in CEE countries with the extra-regional world our knowledge is still in infancy. Radosevic (2011) stresses that interactions between foreign owned and domestic companies located in CEE regions are still week to which Lengyel et al. (2006) add that individual cooperation of university professors in international projects has insignificant local effects. On the other hand Lengyel et al. (2013) emphasizes that US patenting in CEE countries is inherently linked to international collaborations however granted US patents are rarely found with inventors exclusively from these countries.

In this paper we investigate the role of extra-regional knowledge transfers in regional innovation in Central and Eastern European countries from a specific angle, namely that of their participation in European Framework Programs (FP) funded research partnerships and its effect on regional patenting activity. To the best of our knowledge this is the first such attempt in the literature. The role of knowledge transfers mediated by FP participations in regional innovation has been studied quite intensively in previous papers (i.e., Maggioni, Nosvelli and Uberti 2007, Hazir and Autant-Bernard 2013, Varga, Pontikakis and Chorafakis 2013, Sebestyén and Varga 2013a) but without the focus on Central and Eastern European regions.

Extra-regional knowledge linkages could potentially help lagging regions in their development (Johansson, Quigley 2004). As it was highlighted previously in this introduction capital regions in Central and Eastern European countries generally follow distinctive patterns, as these regions show higher levels of advancement comparable to decently developed regions in the rest of the EU. However, capital regions are exceptional and as such do not represent general trends in Central and Eastern Europe. For this purpose our study focuses on lagging (Objective 1) regions in CEE countries. This paper also follows a marked comparative perspective in order to highlight specific characteristics of innovation in CEE countries. Patterns of regional innovation in CEE Objective 1 regions are thus systematically compared to those of regions in the rest of Europe.

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 Quality of Life (QOL) corresponding to the broad thematic areas of the FP programs.

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

We apply an empirical framework built on the knowledge production function (KPF) introduced by 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 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.

We apply the following econometric specification to empirically test our hypotheses on the role of external knowledge mediated by FP research networks in patenting. Using subscripts *i* to denote individual regions, the empirical counterpart of the Romerian KPF (1) 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 $\mathrm{PAT_i}$ 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

In the following empirical analyses we employ the Ego network Quality index developed and introduced by Sebestyén and Varga (2013a, 2013b), in order to capture the amount of knowledge available by a region through its interregional knowledge connections. The concept of ENQ builds on three intuitions directly influenced by the theory of innovation. First, that the level of knowledge in an agent's network is in a positive relationship with the agents' productivity in generating new knowledge. Second, that the structure of connections in the agents' network can serve as an additional source of value (see e.g. Coleman 1986; Burt 1992). Third, that partners in the ego network contribute to diversity through building connections to different further groups not linked directly to the agent.

The ENQ index is structured around two dimensions, which are then augmented with a related third aspect. The two dimensions are: (i) Knowledge Potential, which measures knowledge accumulated in the direct neighbourhood and it is related to the number of partners and the knowledge of individual partners, and (ii) Local Structure, what is associated with the structure of links among partners. The third aspect is Global Embeddedness (GE) and captures 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 network under consideration is represented 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.

We formalize the conceptual model of ENQ presented above in the following way:

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

where 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 can be interpreted as calculating the Knowledge Potentials for neighbourhoods at different distances from node i, weighted by the Local Structure value of the same neighbourhood. Then, these results for the different neighbourhoods are weighted by a distance-decay factor and summed over distances. 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 of 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

Using the notation presented before, the concept of KP can be formulated in the following way:

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

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. What one means by structure, though, is a matter of question here. 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

[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).

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.

Local Connectivity

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:

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

where N_d^i is the number of nodes laying exactly at distance d from node i. The first term in the parenthesis counts the (possibly 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 (possibly weighted) number of ties among nodes at distance d.[4] As a result, Local Connectivity can be defined as 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:

$$ENQ^i = \sum_d W_d Q_d^i = \sum_d W_d KP_d^i LC_d^i \quad (6)$$

Connected Components

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

$$ENQ^i = \sum_d W_d Q_d^i = \sum_d W_d KP_d^i CC_d^i \quad (7)$$

A mixed version

Although both intuitive, 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):

$$ENQ^i = \sum_d W_d Q_d^i = \sum_d W_d KP_d^i CC_d^i LC_d^i \quad (8)$$

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

As the availability of spatial data collected over longer periods of time increased, the demand for accounting for spatial dependence in panel data econometric models has also been raised. Two of the most significant recent changes in spatial analysis are the methodological developments of

[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.

[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).

models (Elhorst 2003, Anselin, Le Gallo, Jayet 2008, LeSage and Pace 2009) and the growing number of applications in empirical research (Autant-Bernard 2012) in this domain.

We are going to consider the following specification issues in the subsequent econometric analyses: identification of network effects, identification of the impact of localized knowledge transfer and identification of panel effects. Equations (9) to (11) provide those settings where the ENQ index enters the regression equation as a stand-alone variable. In these interregional knowledge flows mediated by FP networks is assumed to 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 knowledge from FP networks on patenting is assumed to work through the improved productivity of research. With regards the estimation of 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.

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

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

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

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

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

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

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 test 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

3.1. The database

The empirical analysis in this paper is based on a sample of 262 European NUTS2 regions, 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 called 'Quality of Life'. (the specific thematic areas are: Quality of Life in FP5, Life Sciences, Genomics and Biotechnology for Health in FP6 and Health in FP7 – the same grouping is used by e.g. Hoekman et al. 2012). The dependent variable is patenting activity under the QOL area (see the specification of patents corresponding to this area later) at the regional level as proxied by patent applications to the EPO ($PAT_{i,t}$). 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 innovation counts at the level of regions).

Romer (1990) emphasizes the importance of knowledge stocks (or a 'standing on the shoulders of giants' effect) for knowledge production, which concept has been verified empirically (Furman, Porter and Stern 2002; Zucker et al. 2007). In order to capture this effect, we apply patent stocks as proxies of regional knowledge stocks in the empirical analysis. These patent stocks ($PATSTOCK_{i,t}$) are calculated according to the perpetual inventory method for the 1995–2009 period (for details see Varga, Pontikakis and Chorafakis 2013).

We capture knowledge flows between regions by FP cooperation networks in the quality of life 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)

Table 1. Variable description

Variable Name	Description	Source
$PAT_{i,t}$	Number of patent applications under the category 'QOL – Quality of Life' corresponding to the broad thematic areas of the FP programmes (see the description for the details).	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 'quality of life' thematic areas (Quality of Life in FP5, Life Sciences, Genomics and Biotechnology for Health in FP6 and Health 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 under the category 'QOL – Quality of Life' corresponding to the broad thematic areas of the FP programs (see the description for the details).	Authors' elaboration on Eurostat database
$ENQ\_DENS_{i,t}$, $ENQ\_STRH_{i,t}$ $ENQ\_MIXD_{i,t}$, $KP_{i,t}$, $LS\_DENS_{i,t}$, $LS\_STRH_{i,t}$,	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 quality of life thematic areas (Quality of Life in FP5, Life Sciences, Genomics and Biotechnology for Health in FP6 and Health 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	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

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 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.

Table 1 contains the description of the empirical variables employed in our analysis.

3.2. Concordance between the FP thematic area 'QOL' and patent counts

In this analysis we focus on a specific thematic area of FP projects, called 'quality of life' (QOL). The choice of this area is based on the fact that using aggregate data on FP collaborations would lead to an overcrowded landscape of connections due to the many projects. Focusing on one area, in contrast, allows for a more refined picture of cooperation networks and a more clear interpretation of the results. On the other hand, due to the changing nature of thematic areas over the different FPs, there are few areas which can be consistently analyzed through FP5, FP6 and FP7. On possible choice, according to Hoekman et al. (2012) is the QOL, which is also used here.

Table 2. Correspondence between FP scientific fields and patent sub-categories

FP scientific fields *Hoekman et al. (2012)*	**Patent sub-categories*** *Glänzel and Meyer (2003)*	**USPC patent classes** *Hall et al. (2001)*
Biomedical sciences	Drugs (31) Surgery & Medical Instruments (32) Miscellaneous-Drugs & Medical (39)	424, 514 128, 600, 601, 602, 604, 606, 607 351, 433, 623
Basic life sciences	Biotechnology (33) Drugs (31)	435, 800 424, 514
Biological sciences	Biotechnology (33)	435, 800
Clinical medicine	Drugs (31) Surgery & Medical Instruments (32) Biotechnology (33) Miscellaneous-Drugs & Medical (39)	424, 514 128, 600, 601, 602, 604, 606, 607 435, 800 351, 433, 623

** Codes of the category in Hall et al. (2001) are in parenthesis*

Once the thematic areas of FP projects are narrowed down, we have to assign patents to this area to consistently fit into the regression equations[6]. As a result of the broad categorization of FP projects, this is not straightforward though. We take the approach of Hoekman et al. (2012) as a starting point who present a correspondence between the broad thematic areas of FPs and scientific fields. They report weights for different scientific fields showing how relevant they are for the different thematic FP areas (for this they use information retrieved from the acknowledgements of scientific publications in journals belonging to these scientific fields. The weights show the relevance of a field to the thematic areas. If the weight is greater than one, the given scientific field contributes more to the thematic area than expected (according to a uniform distribution). For the QOL area their identification shows 5 scientific fields which have a weight close to or greater than one, which are: 'biomedical sciences', 'basic life sciences', 'biological sciences', 'chemistry and chemical engineering' and finally 'clinical medicine'. These scientific fields are then assigned to patent sub-categories according to Hall et al. (2001).

Glänzel and Meyer (2003) report a weighted correspondence between scientific fields and these patent sub-categories. First, however, a matching is required between the scientific fields used by Hoekman et al. (2012) and those used by Glänzel and Meyer (2003). While 'biomedical sciences', 'biological sciences' and 'clinical medicine' can be identified by the name of the categories, the identification of the field under the name of 'basic life sciences' is not obvious. Hoekman et al. (2012) cites NOTW (Nederlands Observatorium van Wetenschap en Technologie) which reports Science and Technology Indicators. The reports refer to CTWS (Centre for Science and Technology Studies, Leiden University, the Netherlands) as a basis of scientific category breakdown. Rinia et al. (2002), one of the most cited (based on Google Scholar) article of the research faculty of this institution clarifies the contents of the category of 'basic life sciences' which is comparable with 'biosciences' and 'neurosciences & behavior' subcategories detailed in Glänzel and Schubert (2003). This correspondence coincides with the definition of the basic life sciences domain on the website of the University College London (UCL 2013). Table 2 contains the correspondence from the scientific fields used by Hoekman et al. (2012) to patent sub-categories as in Glänzel and Meyer (2003) and their USPC codes.

As a consequence of the above-described correspondences on the basis of Glänzel and Meyer (2003) empirical study, we can assign patent categories to the QOL thematic area. Since Glänzel and Meyer (2003) applied the patent sub-categories from Hall et al. (2001) which specifies the exact United States Patent Classification (USPC) codes, that codes can be linked directly with the QOL area. The USPC patent sub-classes can then be converted into IPC categories (USPTO 2013), and consequently the QOL thematic area of the FP projects can be linked with IPC codes. This assignment, though, is not perfect because the USPTO concordance tables specify 7 or 8-digit precision USPC subclasses assigned to 8-digit IPC codes, but the Eurostat publishes patent counts only on 3-digit IPC categories. Thus we assign a 3-digit IPC subclass to a 3-digit USPC class if any of the subclasses of this USPC class corresponds to a 8-digit group of the IPC subclass. Table 3 contains the concordance between USPC and IPC codes.

As a result, we have a list of IPC classes, which corresponds to the QOL thematic field of the FP projects. This list, consisting of the IPC codes presented in the right-hand-side column of Table 3, was finally used to extract patent counts specific to the QOL area from the Eurostat database.

[6] The concordance tables were developed by Márton Horváth. For more details on the procedure see Horváth (2013).

Table 3. Concordance between 3-digit USPC and IPC codes in "Quality of life" sciences

3-digit USPC Classes	3-digit IPC Subclasses
424	A61, A01, C11, B01, D21, A23
514	A01, A61, C07, C12
128	A61, B05, A62, F24, B63, G08, B65, H05, F16, G05, F23, F15
600	A61, B64, H04, B65
601	A61
602	A61
604	A61
606	A61
607	A61, A63
435	A01, C12, G01, A23, C07, C02, A62, B09, D06, C14, A61, C11, C08, C13, D21, D01, C10
800	G01, C12, A01
351	G02, A61
433	A61
623	A61

3.3. Exploratory analysis

In this section we provide a brief exploratory analysis of our dataset. Table 4 contains some descriptive statistics, from which it is apparent that CEE regions show a significantly worse performance in all aspects exhibited here (number of patents, patent stock, regional FP funding, R&D, ENQ and high tech employment).

Table 4. Variable descriptive statistics

	PAT	RD	REG_FUND	PATSTOCK	ENQ	HTEMP
			Total sample			
N	2620	2620	2620	2620	2620	2620
Mean	106,64	674,99	1,69	347,17	73261,51	35,01
Std.dev.	198,19	1166,34	2,99	858,97	40080,02	41,52
Min	0	1,06	0,0008	0	0	0,86
Max	1746,97	13269,56	30,46	7582,23	151744,7	474,77
			CEE regions			
	PAT	RD	REG_FUND	PATSTOCK	ENQ	HTEMP
N	510	510	510	510	510	510
Mean	5,21	123,91	0,47	15,99	55415,89	23,12
Std.dev.	7,29	169,22	0,57	78,18	39268,99	17,23
Min	0,04	4,16	0,0008	0,70	0,00	5,47
Max	59,40	1245,06	3,19	1565,20	141346,20	145,00
			Non CEE regions			
	PAT	RD	REG_FUND	PATSTOCK	ENQ	HTEMP
N	2110	2110	2110	2110	2110	2110
Mean	131,15	808,19	1,90	427,21	76357,84	37,88
Std.dev.	213,71	1261,39	3,19	939,02	39404,70	45,02
Min	0,00	1,06	0,0007	0,00	0,00	0,86
Max	1746,97	13269,56	30,46	7582,23	151744,70	474,77

In what follows, some dynamic 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. 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.

Figure 1. Average patenting activity in CEE and non CEE regions

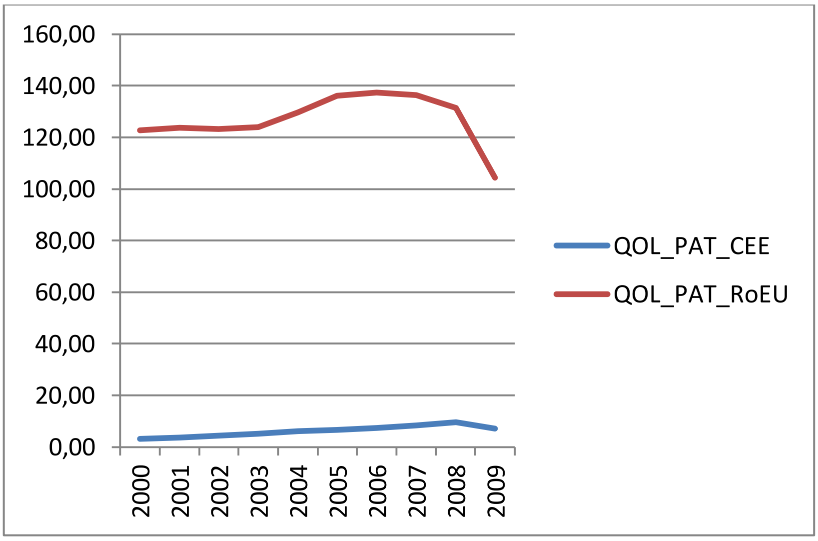
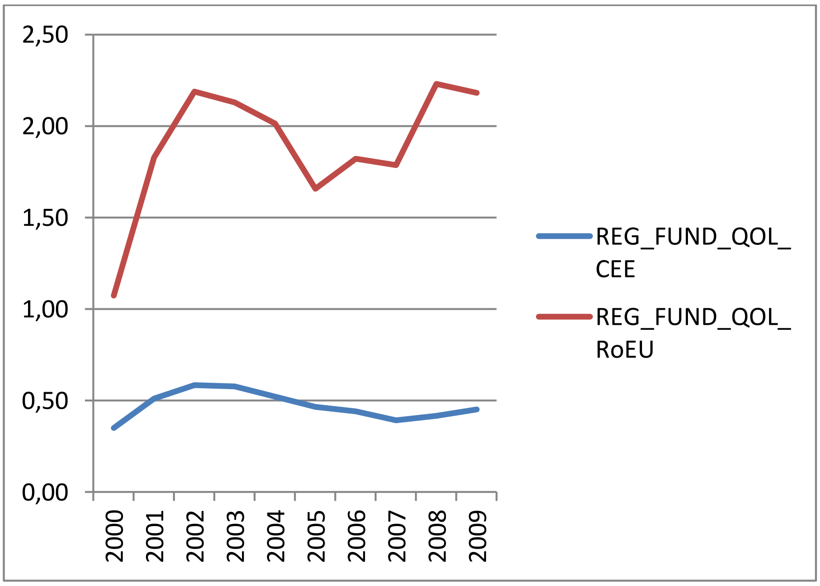


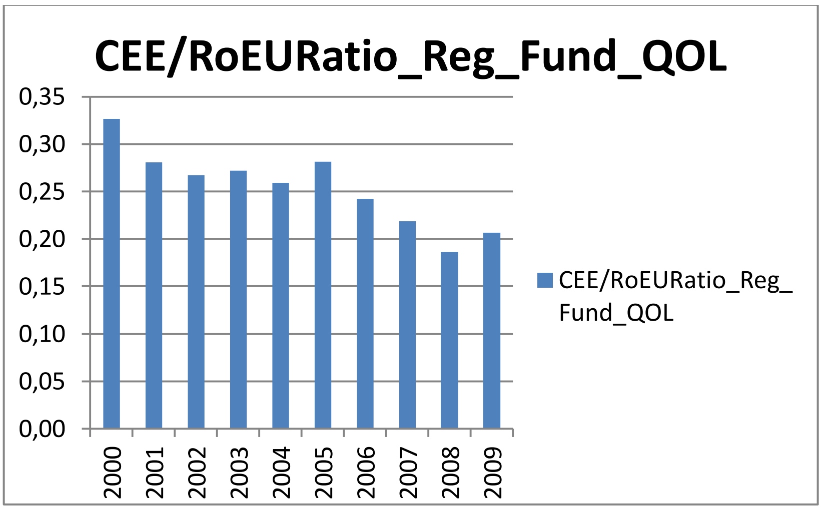
Figure 2 shows the average regional funding for CEE and non CEE regions in the sample. It is also apparent that CEE regions acquire far less funding through FP projects than non CEE ones. Moreover, while there is a slightly increasing trend in average funding for non CEE regions, CEE regions tend to lag behind in the second half of the sample period.

Figure 2. Average FP funding in CEE and non CEE regions



If we look at the relative funding (Figure 3), the relative fallback of CEE regions is apparent, throughout the whole period. The average FP funding of CEE regions (in the quality of life area) falls from 30% of the funding intensity of non CEE regions in 2000 to slightly above 20% at the end of the decade.

Figure 3. Relative FP funding of CEE and non CEE regions



Turning to the ENQ index, Figure 4 shows how the average ENQ indices[7] 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

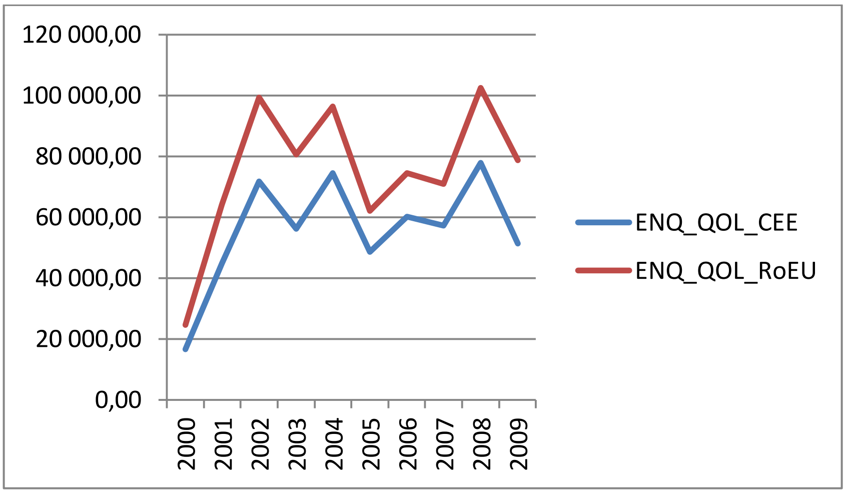
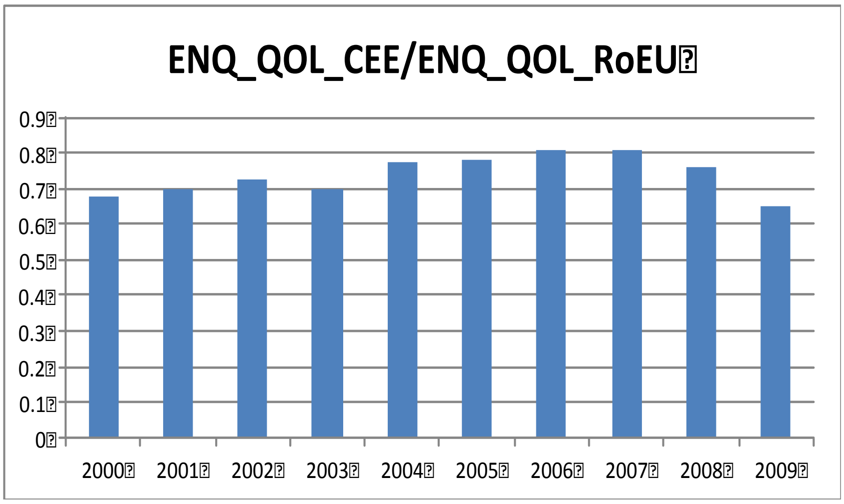


Figure 4 shows that non CEE regions step ahead of their CEE partners with respect to their ENQ index over the whole period, while the difference in absolute terms seem to remain the same. In contrast, the relative differences (Figure 5) increase from slightly below 70% to 80%, and there is a sharp decrease in the last two years. This shows that the position of CEE regions in interregional knowledge networks improved a bit over the first half of the decade but this improvement was lost during the last two years of the sample.

Figure 5. Relative ENQ indices of CEE and non CEE regions



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

If we look at the two subindices, it is apparent that CEE regions slightly increase their position with respect to Local Connectivity, from 80% to over 90% but the sharp decrease at the end is also present in this respect. In other words, CEE regions tended to reach better positions in interregional knowledge networks with respect to the connectedness of their neighborhood: they became better connected in the sense that more intensive collaboration structures surrounded them, getting almost similar in this respect to non CEE regions. However, this catch-up process was reversed during the last two years of our sample.

Figure 6. Average Local Connectivity values of CEE and non CEE regions

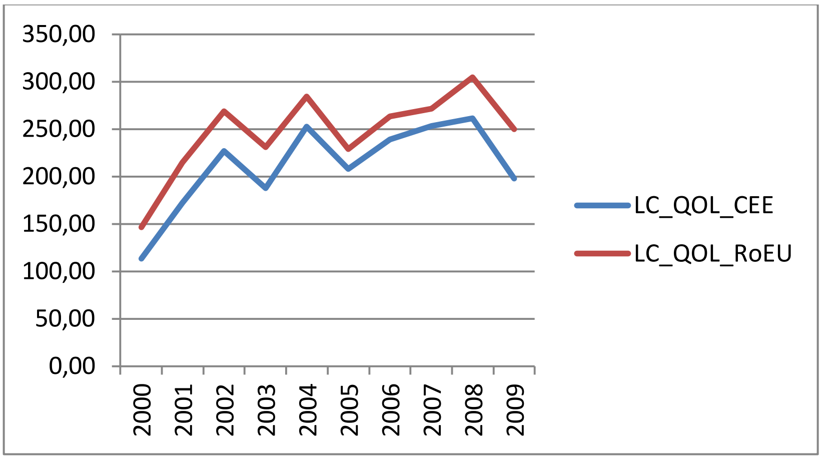
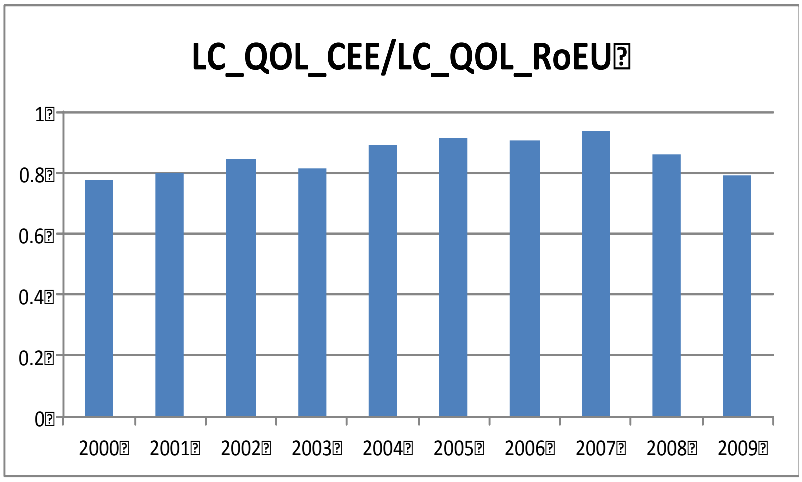


Figure 7. Relative Local Connectivity values of CEE and non CEE regions



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 almost 80% in 2006. However, the decline is apparent also in this respect in the last two years, the relative Knowledge Potential value of CEE regions falling below the starting value in 2000.

Figure 8. Average Knowledge Potential values of CEE and non CEE regions

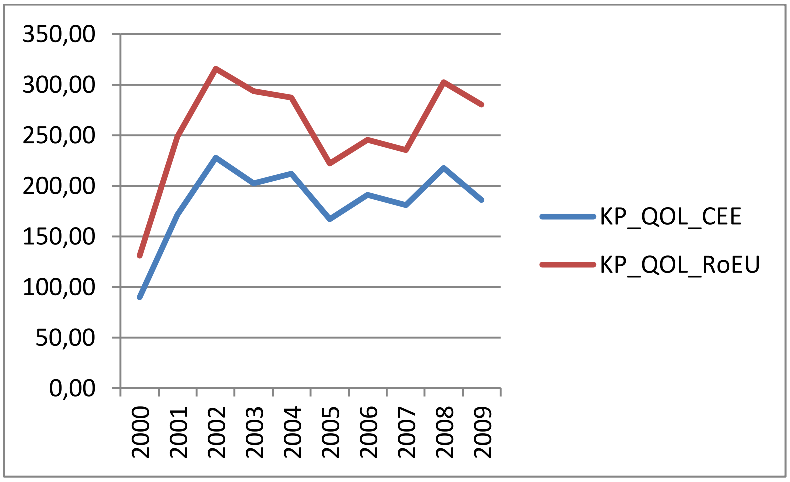
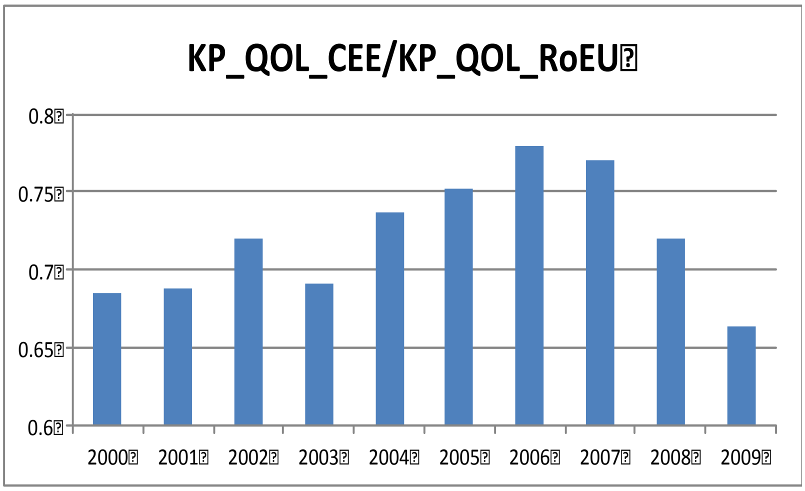


Figure 9. Relative Knowledge Potential values of CEE and non CEE regions



Overall, we can conclude that the relative catch up process of CEE regions in the first half of the sample 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 middle of the sample relative to their initial positions stems from both more knowledge in 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 intense collaboration structure among the partners. However, this relative gain was lost during the last two years where again, both Knowledge Potential and Local Connectivity fell back to a considerable extent.

Figure 10. Spatial distribution of ENQ values in CEE regions

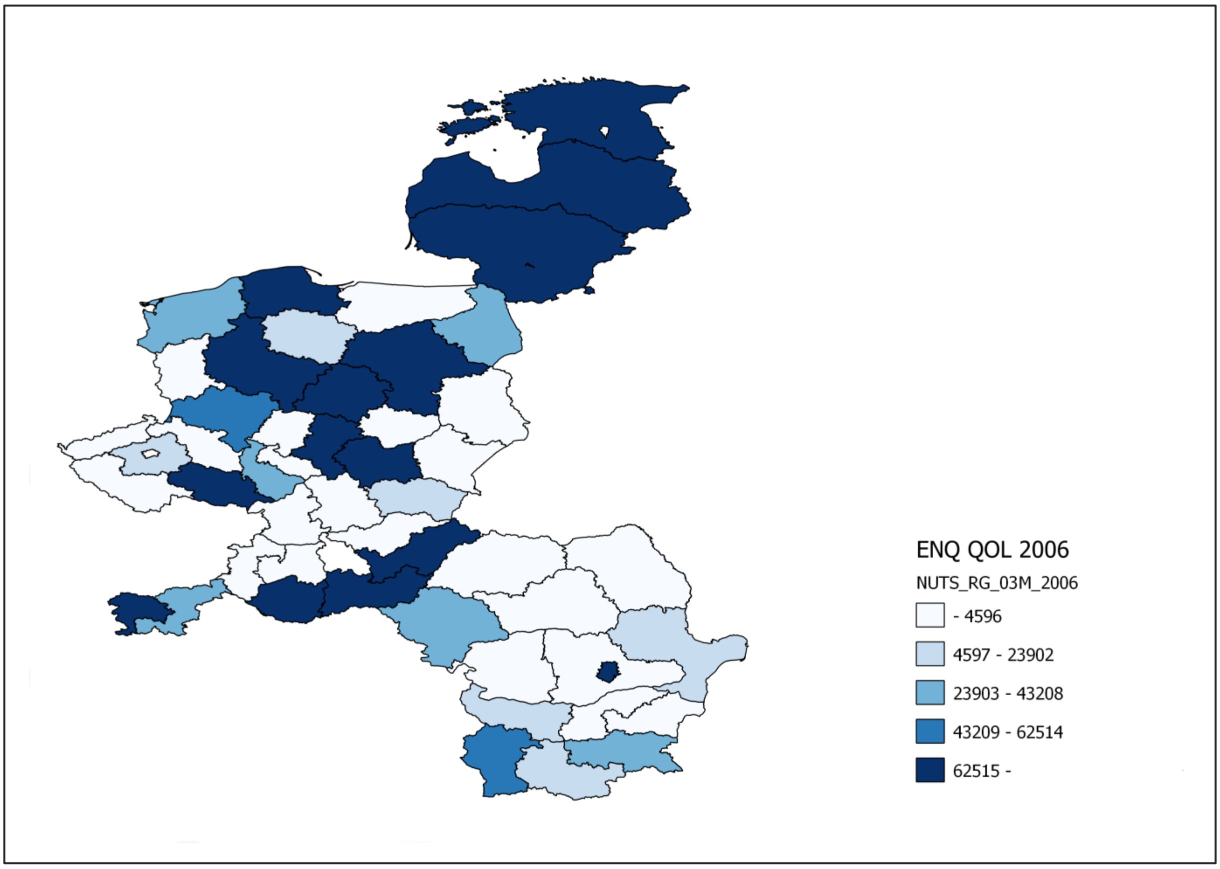


Figure 10 shows the spatial distribution of regional ENQ values calculated for 2008. There are marked differences between the countries and also the regions. Poland, the southern part of Hungary and the Baltic countries show above average regional ENQ values.

4. Empirical analysis

Tables 5 and 6 present the results of the regression analysis for regions in the two sub-samples of the EU for the Quality of Life 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 5 the two main variables of Equation (2) (R&D expenditures and stock of patents) appear with the expected positive signs and also with high significances. The fit of the regression (adjusted R-square equals 0.93) 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. In Model (2) the parameter of the ENQ variable is insignificant and negative indicating that knowledge flows from FP networks is not related to patenting in a direct manner. An alternative specification is Model (3) where log(RD) interacts with log(ENQ_DENS). The coefficient is negative and significant. The specification in Model (4) is a variant of the one in Model (3): the interaction of log(RD) with log(REG_FUND), which is the funding received through FP projects in the region under the QOL area. The parameter is again negative and significant. Since the fit of the regression (LIK) is somewhat better in Model (4) this will be the structure to be followed during the analysis. So far the results thus suggest that knowledge flows from FP networks negatively 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.

Table 5. Regression Results for Log (PAT) for 211 Non-CEE EU NUTS2 Regions and for the QOL sector, 2000-2009 (N=2110)

Model	(1) Pooled	(2) Pooled	(3) Pooled	(4) Pooled	(5) Pooled	(6) Pooled	(7) Pooled	(8) Pooled	(9) Spatial and time-period fixed effects
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	ML Spatial Durbin (Neigh)
Constant	-1.827*** (-42.21)	-1.826*** (-42.78)	-1.862*** (-40.90)	-1.892*** (-41.03)	-1.842*** (-38.75)	-1.842*** (-38.74)	-1.730*** (-37.24)	-1.804*** (-40.07)	
W_Log(PAT)									0.080** (2.24)
Log(RD(-2))	0.238*** (17.71)	0.239*** (16.40)	0.259*** (15.43)						
Log(RD(-2)-REG_FUND(-2))				0.246*** (18.10)	0.200*** (11.35)	0.200*** (11.35)	0.183*** (10.07)	0.193*** (10.91)	-0.068 (-1.43)
Log(ENQ_DENS(-2))		-0.001 (-0.22)							
Log(RD(-2))* Log(ENQ_DENS?(-2))			-0.001** (-2.04)						
Log(REG_FUND(-2))* Log(ENQ_DENS(-2))				-0.002*** (-3.48)					-0.001 (-1.59)
Log(REG_FUND(-2))* Log(ENQ_MIXD(-2))					-0.002*** (-4.04)				
Log(REG_FUND(-2))* Log(KP(-2))						-0.002*** (-4.04)			
Log(REG_FUND(-2))* Log(LS_DENS(-2))							-0.002*** (-3.46)		
Log(REG_FUND(- 2))*Log(LS_STRH(-2))								-0.004*** (-4.26)	
Log(PATSTOCK(-2)	0.776*** (68.83)	0.776*** (68.12)	0.775*** (68.69)	0.778*** (69.04)	0.761*** (63.63)	0.761*** (63.63)	0.766*** (63.64)	0.763*** (63.82)	0.088* (1.72)
Log(HTEMP(-2))					0.098*** (4.05)	0.098*** (4.05)	0.091*** (3.78)	0.098*** (4.05)	0.024 (0.40)
W_Log(RD(-2)-REG_FUND(- 2))									0.385*** (3.50)
W_Log(REG_FUND(2)* Log(ENQ_DENS(-2))									-0.001 (-1.07)
W_Log(PATSTOCK(-2)									0.523*** (4.74)
W_Log(HTEMP(-2))									0.348*** (2.79)
R^2-adj	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.97
LIK	-1457.32	-1457.30	-1455.23	-1451.11	-1442.94	-1442.92	-1445.10	-1442.03	-621.10
LM-Err									
Neigh					11.58***				
INV2					11.29***				
4-nearest neighors					12.43***				
LM-Lag									
Neigh					23.97***				
INV2					26.02***				
4-nearest neighors					23.53***				
Wald-Lag (Neigh)									86.47***
Wald-Err (Neigh)									92.13***
LR-test joint significance spatial fixed effects					1339***				
LR-test joint significance time-period fixed effects					135***				
Hausman random effects test									172.59***

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 Neigh. *** indicates significance at p < 0.01; ** indicates significance at p < 0.05; * indicates p < 0.1.

In Model (5) employment in high technology (HTEMP) enters the equation as an additional variable with a highly 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 other two matrices changes their position from the top (providing the highest level of significance) to the bottom (resulting in the lowest level of significance) while the results with the contiguity matrix (Neigh) keep the same position the weights matrix Neigh 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 exert the strongest negative impact. 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 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.

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 that while the regional R&D variable lost its significance and the size and significance of the regional patent stock variable decreased markedly the spatially lagged knowledge variables (W_Log(RD-REG_FUND), W_Log(PATSTOCK) and W_Log(HTEMP)) enter the equation with highly significant and positive coefficients. 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. Furthermore the geographical scale of localized interactions is larger than the average area of an individual NUTS 2 region covering larger agglomerations, which include neighboring regions as well.

Table 6 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 is an important difference in the results of Model (1) in the periphery compared to the rest of the EU. This is the apparently lower regression fit (adjusted R-square is 0.57 in Table 6 compared to 0.93 in Table 5). The other important difference is the significant and positive parameter of the interaction variable Log(REG_FUND)*Log(ENQ_DENS) for CEE-Objective 1 regions in Model (4). Though the parameter becomes less significant, the size of the indirect FP network impact remains unchanged after the introduction of the high technology employment variable in Model (5). It is also a meaningful difference between Model (5) in Table 5 and Model (5) in Table 6 that for CEE Objective 1 regions the estimated parameter of the high technology employment variable becomes negative. The spatial statistics in Model (5) 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 (7) to (10) in Table 6 provide additional details as to the individual impact of the ENQ components on regional patenting. Similar to what is found for Non-CEE regions incorporating the gatekeeper position to ENQ (ENQ_MIXD) does not change the size and significance of the respective estimated parameter in Table 6 either. Interestingly though, parameters of the variables including ENQ components as interaction variables are no longer significant in Models (8) to (10). The positive and highly significant parameter of the west border dummy in Model (6) clearly suggests that there are important unmeasured differences among regions 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 Wald-Lag and Wald-Error tests point towards the spatial and time-period fixed effects Spatial Durbin model.

Table 6. Regression Results for Log (PAT) for 51 CEE OBJ1 EU NUTS2 Regions and for the QOL sector, 2000-2009 (N=510)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Pooled	Spatial and time-period fixed effects
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	ML-Spatial Durbin (INV2)
Constant	-2.534***	-2.522***	-2.447***	-2.553***	-1.960***	-1.960***	-1.960***	-1.936***	-2.004***	-1.862***	
	(-17.98)	(-17.19)	(-15.12)	(-18.13)	(-10.20)	(-10.27)	(-10.20)	(-8.83)	(-10.02)	(-8.13)	
W_Log(PAT)											-0.046
											(-0.48)
Log(RD(-2))	0.559***	0.554***	0.528***								
	(14.76)	(13.27)	(11.13)								
Log(RD(-2)-REG_FUND(-2))				0.571***	0.768***	0.770***	0.769***	0.764***	0.772***	0.757***	0.370**
				(14.93)	(13.22)	(13.34)	(13.22)	(12.94)	(13.20)	(12.76)	(2.54)
Log(ENQ_DENS(-2))		0.002									
		(0.31)									
Log(RD(2))*Log(ENQ_DENS?(-2))			0.002								
			(1.09)								
Log(REG_FUND(-2))*LOG(ENQ_DENS(-2))				0.004**	0.003*	0.003*					0.004**
				(1.99)	(1.71)	(1.85)					(2.03)
Log(REG_FUND(-2))*Log(ENQ_MIXD(-2))							0.003*				
							(1.72)				
								9.51E-05			
Log(REG_FUND(-2))*Log(KP(-2))								(0.089)			
									0.004		
Log(REG_FUND(-2))*Log(LS_DENS(-2))									(1.33)		
										-0.003	
Log(REG_FUND(-2))*Log(LS_STRH(-2))										(-0.52)	
	0.492***	0.490***	0.484***	0.488***	0.477***	0.444***	0.477***	0.481***	0.480***	0.480***	0.195*
	(11.42)	(11.28)	(11.12)	(11.35)	(11.29)	(10.19)	(11.28)	(11.35)	(11.34)	(11.30)	(1.90)
Log(PATSTOCK(-2))					-0.467***	-0.465***	-0.467***	-0.478***	-0.466***	-0.486***	-0.549**
					(-4.45)	(-4.46)	(-4.45)	(-4.52)	(-4.42)	(-4.59)	(-2.47)
Log(HTEMP(-2))											
											0.124
W_Log(RD(-2)-REG_FUND(-2))											(0.27)
											0.005
W_Log(REG_FUND(2))*Log(ENQ_DENS(-2))											(0.78)
											0.621**
											(2.22)
W_Log(PATSTOCK(-2)											0.748
											(0.99)
W_Log(HTEMP(-2))						0.256***					
						(2.86)					
WEST_BORDER											
R^2-adj	0.57	0.57	0.57	0.58	0.59	0.60	0.59	0.59	0.59	0.59	0.78
LIK	-648.62	-648.58	-648.03	-646.68	-636.89	-632.79	-636.87	-638.35	-637.47	-638.22	-478.73
LM-Err (robust)											
Neigh					0.552						
INV2					5.699***						
4-nearest neighors					5.000***						
LM-Lag (robust)											
Neigh					0.488						
INV2					5.641***						
4-nearest neighors					5.116***						
Wald-Lag (INV2)											13.72***
Wald-Err (INV2)											13.58***
LR-test joint significance					276.7***						
spatial fixed effects					47.5***						
LR-test joint significance time-period fixed effects											
Hausman random effects test											19.65***

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 INV2. *** indicates significance at p < 0.01; ** indicates significance at p < 0.05; * indicates p < 0.1.

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 large 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 the Log(REG_FUND)*Log(ENQ_DENS) variable in the final model of Table 6 indicates that knowledge transferred from FP networks increase the impact of FP funds on the level of regional patenting. On the other hand the size and the significance of the local R&D and patent stock variables decreased in the final model.

An additional apparent difference between the results of the final models in Tables 6 and 5 is related to the role of extra-regional localized knowledge transfers in regional patenting. With the exception of the significant spatially lagged patent stock variable the estimated coefficients of the other lagged variables are insignificant for CEE Objective 1 regions.

5. Summary and conclusions

We investigated the role of EU Framework Programs-mediated extra-regional knowledge transfers in regional patenting in Central and Eastern European countries. 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 research field of study was the broad area of quality of life (QOL) covering research in biomedical, biological and life sciences. While analyzing the FP network impact we measured extra-regional knowledge in FP networks by the Ego Network Quality (ENQ) index. We also controlled for localized knowledge flows via a systematic panel spatial econometric methodology.

We found that important differences exist between CEE-Objective 1 and non-CEE regions with respect to the role of localized knowledge flows and FP network learning in patenting. While knowledge transferred from FP networks positively influences the impact of FP research subsidies on regional innovation in CEE-Objective 1 regions, network knowledge does not turn out to be significant input in patenting in regions of the old member states. With respect to the relevance of extra-regional localized knowledge flows in innovation also different patterns are evidenced. While localized learning is strongly important for the Non-CEE regions we found only a weak evidence for such impact for the Objective 1 regions located in Central and Eastern Europe. As a consequence, we can state that interregional knowledge networks can substitute for the critical mass of localized resources for innovation in lagging regions.

Our findings have an important message for regional policy. They suggest that strengthening research excellence and international scientific networking in lagging regions in CEE countries could be a viable option to increase their regional innovativeness. Thus furthering interregional knowledge network linkages in combination with other policies could form a base for a systematic support of regional development as it is suggested by the principles of the European Union's reformed Cohesion Policy (McCann, Ortega-Argiléz 2014).

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