Luiss
School of European Political Economy

Knowledge networks in joint research projects, innovation and economic growth across European regions

Daniela Di Cagno, Andrea Fabrizi,
Marco Marini and Valentina Meliciani

Working Paper 3/2021

LUISS

January 31, 2021

KNOWLEDGE NETWORKS IN JOINT RESEARCH PROJECTS, INNOVATION AND ECONOMIC GROWTH ACROSS EUROPEAN REGIONS

by

Daniela Di Cagno

(LUISS Guido Carli University, Rome)

Andrea Fabrizi*

(Presidency of the Council of Ministers, Rome)

Marco Marini**

(Agency for Territorial Cohesion, Rome)

Valentina Meliciani

(Luiss Guido Carli University, Rome)

ABSTRACT

This paper investigates the role played by the position of European regions in research networks on their rate of innovation and economic growth. The analysis is based on a panel of EU-28 NUTS2 regions participating in EU Framework Programmes observed over the 2004-2014 period. We find that regions that are more central in the network (higher strength centrality) and those that are surrounded by highly inter-connected regions (higher clustering index) show higher rates of innovation and higher economic growth. We also find that while the strength centrality affects growth only indirectly (i.e. through its impact on innovation), the clustering index shows a positive effect on growth both directly and indirectly. The position in the network has a different impact on innovation in regions belonging to different socio-economic groups and with different levels of development. We discuss the implications of these findings to better address research and innovation policies in Europe.

Keywords: R&D networks, EU Framework Programmes, patents, economic growth

JEL Classification: O33, O47, L14, C2

* The views and opinions expressed in this article are those of the author and do not necessarily reflect those of the Presidency of the Council of Ministers

** The views and opinions expressed in this article are those of the author and do not necessarily reflect those of the Agency for Territorial Cohesion

1. INTRODUCTION

The literature on regional convergence traditionally stresses the importance of geographic contiguity in forming clusters of regions that share similar rates of technological progress and development patterns (see among the others Jaffe et al., 1993; Jaffe et al., 1999; Maurseth and Verspagen, 2002; Le Gallo and Ertur 2003; Lopez-Bazo et al. 1999; Overman and Puga 2002). Transmission channels of convergence are traditionally identified in spillovers facilitated by the exchange of tacit knowledge requiring physical interaction. In a seminal paper, Boschma (2005) argues that, apart from geographic closeness, contiguity or proximity in a general sense (cognitive, organisational, social, and institutional) may be important for innovation and growth inasmuch as it favours the diffusion of knowledge flows.

The formation of networks facilitates these different types of proximity and favours the exchange and free circulation of information between multiplicities of actors also when geographical proximity is lacking (Autant-Bernard et al., 2007; Maggioni and Uberti, 2011).[1] This assumption informs the EU's Framework Programmes (FP) for Research and Technology Development (RTD), which highly encourage the formation of research networks in Europe. Differently from other cooperative initiatives spontaneously originating from the decision of private or public agents,[2] the FP consist in public investments of relevant and increasing amounts of resources with the specific purpose of generating knowledge and contributing to knowledge diffusion, thus fostering economic growth and convergence.

While there is growing literature examining the impact of participation in EU Framework Programmes on knowledge transfers (Maggioni et al., 2007; Hoekman et al., 2013; Di Cagno et al., 2014), we know very little about how networks contribute to fostering innovation and economic growth depending on the characteristics of the regions involved and of their position within the networks. This is an extremely relevant issue since different types of regions, with different location in their network, may contribute differently to the process of knowledge diffusion and economic convergence. Regions at the technological frontier may have an incentive to collaborate with partners from other research intensive regions in order to create networks of excellence, while for scientifically laggard regions participation in FP networks is a means to reduce the scientific and technological gaps with their more advanced partners.

[1] In particular, several empirical studies have examined the nature and the determinants of scientific cooperations among firms (Hagerdoon, 2000; 2002; Miotti and Sachwald, 2003; Caloghirou et al., 2006) or between firms and universities (Geuna, 1998; Hayashi, 2003; Laursen and Salter, 2004; Arundel and Geuna, 2004; Fontana et al., 2006; D'Este et al., 2011).

[2] For a discussion of the game theoretic literature on the private incentives to cooperate in R&D see Cassiman and Veugelers (2002).

Depending on the structure of the networks, therefore, we may observe processes of clustering of innovation leaders causing a widening of knowledge and development gaps among regions or a more inclusive network structure favouring technological and economic convergence.

This paper contributes to the literature on the role of knowledge networks in innovation and growth in several ways. First, we use two different indicators (the strength centrality and the clustering coefficient) to analyse the position of each region within the network in order to assess whether and how it affects the capability to create new knowledge, thus fostering innovation. Then, we introduce those indicators in a model linking innovative and economic performance to disentangle the direct and indirect impact - through the effects on regional innovation - of the region's position in the network on economic growth. Finally, we assess whether different types of regions (intermediate, industrial decline, peripheral and urban) occupy different positions within knowledge networks and whether this contributes to explaining their different innovation and economic performance.

2. LITERATURE REVIEW AND RESEARCH QUESTIONS

Networks are one of the major vehicles for knowledge exchange and may facilitate spillovers also among partners that are geographically dispersed. In Europe, the main initiative encouraging the formation of research networks is the Framework Programme (FP) for Research and Technology Development (RTD). Several papers have studied the contribution of networks in general (Cassi and Plunket, 2014; Marrocu et al. 2013; Miguelez and Moreno, 2013; Breschi and Lissoni, 2009; Cowan and Jonard, 2004; Morone and Taylor, 2004); and networks in FP in particular (Maggioni et al., 2007, 2014, 2017; Di Cagno et al. 2014, 2016; Hoekman et al. 2013, 2009; Protogerou et al. 2013, 2010; Scherngell and Barber. 2011, 2009; Maggioni and Uberti 2011, 2009; Breschi and Cusmano 2004) to knowledge exchange and innovation. One of the main messages emerging from this literature is that intentional aspatial networks can contribute to knowledge diffusion adding to unintentional flows of knowledge based on geographical proximity (Maggioni et al. 2017).

This evidence has important implications since networks per se, while facilitating knowledge exchange, do not necessarily favour technological convergence. In fact, the geographical concentration of knowledge spillovers can lead to an uneven distribution of innovation activities, thus exacerbating the disparities between the core and the periphery (Bottazzi and Peri, 2003; Crescenzi and Rodriguez-Pose, 2011), and, at the same time, the choice of partners with similar innovation capabilities can create strongly asymmetric networks with few connections between central partners (those with high innovation capabilities) and peripheral ones.

The few studies focusing on the impact of FP networks on convergence support the view that they positively contribute to knowledge diffusion. In particular, Hoekman et al. (2013) show that the returns on FP funding are highest when involving scientifically laggard regions, concluding that the current FP policy is in line with the EU Cohesion policy, while Di Cagno et al. (2016) find that the positive impact of relational spillovers is significantly higher in FP networks involving regions with heterogeneous levels of R&D, although this effect strictly relies on regions having a sufficient level of absorptive capacities. Maggioni et al. (2017) find more heterogenous effects, concluding that FP6 is a platform for knowledge barter exchange for EU-15, while it works as a mere one-way channel for knowledge diffusion from EU-15 toward Central and Eastern European countries.

Most of the studies using network analysis for investigating the impact of interregional knowledge flows on knowledge diffusion focus on the number of partners and the levels of knowledge of partners as captured by weight matrices similar to those used in spatial econometrics where physical proximity is substituted by the intensity of knowledge exchanges (joint projects, joint patents, etc.). In this paper, similarly to Sebestyén and Varga (2013) for Europe, Sun and Cao (2015) for China, Guan et al. (2015) for the G7 countries, we focus instead on the region's position in the network. Moreover, we ask how different groups of regions followed different trajectories in their participation in FP networks and if the participation benefits differ among them. In particular, we divide European regions in relation to two classifications: the first, by the year of accession to the European Union and the second, by the socio-economic characteristics of the regions.[3] The first type of classification divides the NUTS2 into two groups: EU-15 and EU-13, based on their country's year of adhesion to the European Union (EU-15 before 1995 and EU-13 since 2004). The second classification divides the regions into four classes: 1) capital and urban areas, 2) regions affected by industrial decline, 3) intermediate regions and 4) peripheral regions. Since those regions have performed differently in terms of technological and economic

[3] Socio-economic clusters are based on Rodríguez-Pose (1998), who classifies EU-12 regions into four groups: 1) capital and urban areas, 2) regions affected by industrial decline, 3) intermediate regions and 4) peripheral regions, and on Chapman and Meliciani (2012), who extend this classification to the countries that joined the EU later (EU-27).

convergence, we ask whether their different position in European knowledge networks helps explain the heterogeneity of their innovation path and growth performance. The process of globalisation is in fact fostering the concentration of capital and decision-making powers in a limited number of core urban spaces (Harvey, 1985; Cheshire and Hay, 1989; Frenken and Hoekman, 2006) where the concentration of skilled labour, of headquarter functions of multinational firms (Duranton and Puga, 2005) and of a dynamic service sector can lead to self-enforcing mechanisms of economic growth. Old industrialised regions have rigid social and economic conditions that may negatively affect their performance (Rodriguez-Pose, 1999) and may make it difficult to enter R&D networks. At the same time, participation in R&D networks may be particularly beneficial for regions requiring upgrading processes of knowledge and structural diversification. Many peripheral regions may suffer from their distance to the core, which makes it difficult to benefit from geographically bounded knowledge spillovers. Joining R&D networks is therefore particularly important for these regions for accessing knowledge and catching up.

This leads to our first set of research questions: how does the position in FP networks of regions belonging to different socio-economic groups affect knowledge production and diffusion?

While there are several studies investigating the impact of research networks on innovation and on technological convergence, their effect on economic growth and income convergence is hardly investigated.[4] This is somewhat surprising considering that international knowledge flows are a major factor in world growth, as is shown by the literature on the impact of technology spillovers on growth and productivity (for a review see Cincera and Van Pottelsberghe de la Potterie, 2001; Hall et al., 2010). This stream of literature finds that foreign R&D positively contributes to domestic economic performance. In general, it appears that small R&D spenders have relatively more to gain from foreign R&D than big R&D spenders, although the size of the spillovers depends also on the absorptive capacity of the receiver and its openness to transmission channels (Hall et al., 2010). Anyhow, this literature, while focussing on different measures of distance, rather disregards the role of formal networks.

At the micro level, the nexus between networks and firm performance has been investigated by several studies. Overall, theoretical research argued that being a member of a network is an important source of

[4] Di Cagno et al. (2014), using data from a panel of European countries participating in FP over the 1994–2005 period, find participation in EU funded projects helps laggard countries to reduce a part of their economic gap with more advanced countries (Macdissi and Negassi, 2002 for France; Medda et al., 2006 for Italy).

competitive advantage because it gives access to knowledge and resources at lower costs and helps to benefit from economies of scale (Gulati and Higgins, 2003; Zaheer and Bell, 2005; Watson, 2012). Empirical research mainly confirmed the positive effect of network participation on firms' performance (Cisi et al., 2020; Schoonjans et al., 2013; Park et al., 2010; Lechner et al., 2006; Havnes and Senneseth, 2001).

This leads to our second set of research questions: do the mechanisms which work at the firm level also apply at the regional level? Do regions that are more involved in R&D networks benefit from a reduction in costs and/or exploitation of synergies leading to a better economic performance? Moreover, since regions and countries' capacity to innovate is the main driver of their long-run economic growth,[5] does involvement in R&D networks indirectly foster GDP growth by enhancing regional innovation?

In order to answer these questions, we test a model where regional economic performance depends on some measures of a region's network position both directly and indirectly (through the impact of a network position on a region's innovation).

3. THE EU FRAMEWORK PROGRAMME NETWORKS

Our dataset includes data on joint research projects taken from EU OPEN DATA PORTAL,[6] where it is possible to download the datasets containing projects funded by the European Union under the Framework programmes for research and technological development (FPs) and the Horizon 2020 programme.

FPs are multi-annual and multi-thematic[7] financial instruments: over time they have grown in size, becoming one of the largest transnational efforts worldwide with the aim of stimulating research collaborations and the dissemination of knowledge in the European Union (Balland et al., 2019). They include both direct and indirect actions: direct actions are implemented by research institutes directly depending on the European Commission (such as the Joint Research Centre) and indirect actions are

[5] See both the literature on endogenous economic growth, e.g. Aghion and Howitt, 1992; Grossman and Helpman, 1994 and evolutionary models, e.g. Nelson and Winter, 1982; Fagerberg, 1994.
[6] EU ODP: https://data.europa.eu/euodp/en/home
[7] In terms of funding allocated, the most important issues are health, energy, transport, environment and, in the most recent FPs, climate change.

implemented by participants from different countries (mainly from Member States) and from different sectors: business, higher education, research and government (Di Cagno et al. 2014). Thanks to these indirect actions, heterogeneous networks are (intentionally) created (in terms of the geographical and sectoral belonging of the participants) with the aim of facilitating the creation, the exchange, and the dissemination of knowledge (Maggioni et al. 2013, Wanzenböck, 2018).

In our analysis, we focus on the FP6, FP7 and on a part of the Horizon 2020, from 2004 to 2019. We have selected projects from this time frame with at least two participants from the EU-28 countries for a total of 25,385 projects. Starting from these projects, we assigned a region to each participant (at NUTS2 level[8]) using the available information (address and postal code, where available, otherwise manual entry). Then, for each year, we analysed all the active projects. A project is active from the start-up year until its conclusion: it is therefore counted for its entire duration (life of the project). As mentioned, one or more European regions participate in each project with one or more participants (universities, research centres, companies, and government bodies). Considering our research objectives, in the empirical analysis we focus on the relationships established between NUTS2 within the joint research projects.

Data on FP projects can be analysed at the macro level with the methodology of the network analysis (Scherngell and Barber, 2009). The collaborations activated by the projects generate a network, i.e. a structure that can be represented through a graph in which the nodes are the European regions (NUTS2) and the edges (or ties) being the links established between them. A link between two regions is present if they have at least one project carried out together.

Each year presents a network structure (a region-by-region adjacency matrix), starting from active projects defined by the regions involved in the research projects and their relationships.

As it is shown in Table 1, the observed structure of the graphs is stable over time and, apart from 2004, the number of regions involved is always greater than 270, the number of edges is greater than 20,000, and a density (the fraction, between 0 and 1, of potentially observable edges that are present within the graph) is greater than 0.6 (Table 1). The set of these data (number of regions involved, the extent of the

[8] The NUTS classification subdivides the economic territory of the Member States. It ascribes to each territorial unit (NUTS) a specific code and name. The NUTS classification is hierarchical. It subdivides each Member State into NUTS level 1 territorial units, each of which is subdivided into NUTS level 2 territorial units, which in turn are subdivided into NUTS level 3 territorial units (source: REGULATION (EC) No 1059/2003).

links between them and how dense and rich these links are) highlights the relevance and potential economic effects of FPs.

Table 1. FPs network statistics

Year	Nodes	Density	Edges	NUTS2 Average Degree
2004	267	0.547	19,431	146
2005	272	0.617	22,732	167
2006	274	0.669	25,018	183
2007	275	0.669	25,216	183
2008	276	0.671	25,466	185
2009	276	0.661	25,072	182
2010	275	0.638	24,027	175
2011	274	0.634	23,697	173
2012	274	0.629	23,538	172
2013	275	0.641	24,163	176
2014	275	0.631	23,770	173
2015	275	0.636	23,948	174
2016	275	0.643	24,225	176
2017	275	0.655	24,664	179
2018	274	0.668	24,977	182
2019	275	0.654	24,645	179

Source: own elaborations on EU FPs Data

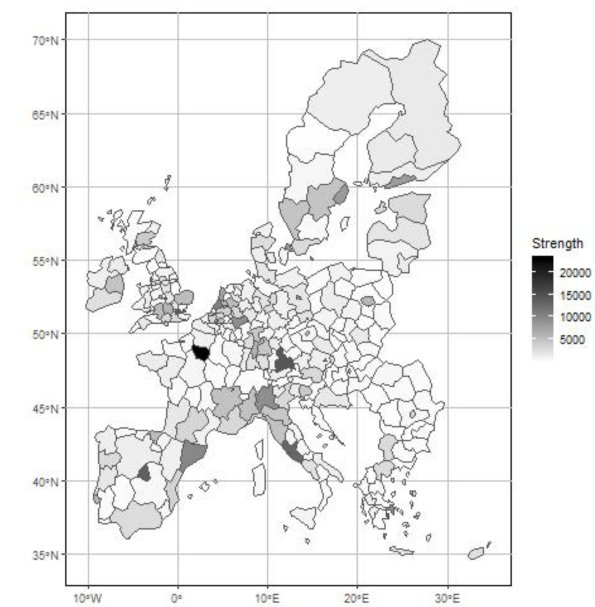
The role of the different regions in the network can be assessed more precisely with centrality measures. Centrality can be defined as the importance of a node in the network (Balland et al., 2019). The number of edges (degrees) of each region represents a simple centrality index of the network analysis (Borgatti, 2005, Butts, 2008) that allows us to identify, for each region, the number of connections with the others: a higher number indicates a reference role of the region within its network. However, the link between the two regions can be strengthened by their participation in several research projects. It is therefore possible to associate to each edge a weight equal to the total number of common projects of the two regions and then calculate a region’s strength index. In a weighted graph, this is represented by the sum of all the weights associated to the edges of the region of interest. In formula:

$$s_i = \sum_{j=1}^{N} a_{ij} w_{ij} \quad (1)$$

where s_i is the strength of vertex i, a_{ij} are elements of the adjacency matrix and w_{ij} are the associated weights. Thus, we obtain weighted degrees: a region in the network will play a central role, both in terms of how many connections it has with other regions and in terms of the intensity of these connections.

Figure 1 below represents the strength centrality measure constructed for each region as the average value for the 2004-2019 period. As expected, the top positions in the ranking are mainly occupied by the (core) regions: Île-de-France (Paris), Comunidad de Madrid, Lazio (Rome), Région de Bruxelles - Capitale, Inner London and Oberbayern (Munich). These regions host the main European capitals where universities and research centres are usually located. Paris stands out with values well above the average of other large cities.

Figure 1. EU-28 NUTS2 and strength centrality (mean 2004 – 2019)

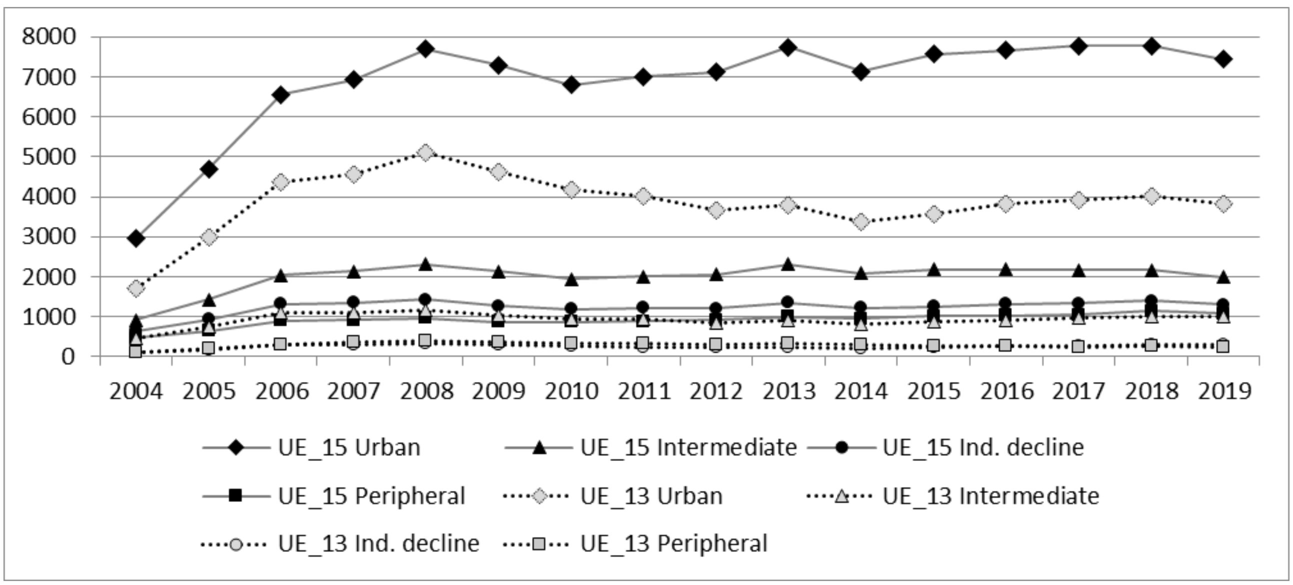


Source: own elaborations on EU FPs Data

Network data relating to EU regions can be analysed by distinguishing between 8 regional groups in relation to two classifications: the first, grounded on the year of accession to the European Union and the second, on socio-economic characteristics measured in terms of sectoral employment and capacity to create and absorb new knowledge. The first type of classification divides the NUTS2 into two groups: EU-15 and EU-13, on the basis of the year of adhesion to the European Union (respectively EU-15 for adhesion before 1995 and EU-13 since 2004). The second classification divides the regions into four classes: capital and urban areas; regions affected by industrial decline; intermediate regions and peripheral regions.

Regional data on strength centrality show heterogenous patterns across different groups of regions. It is interesting to observe that belonging to either urban or peripheral areas affects the position of the regions in the network more than their level of development (considering that EU-15 regions include regions with higher level of per capita GDP than EU-13 regions). Urban regions show the highest strength values and peripheral regions the lowest with respect to all the other regional groups, not only among old EU members but also in the newcomers. Generally, this trend is stable over time, although the difference in centrality between EU-13 urban areas and EU-15 intermediate regions decreases after 2008 (Figure 2).

Figure 2. Strength centrality over time by socio-economic EU-28 NUTS2 classes



Source: own elaborations on EU FPs Data

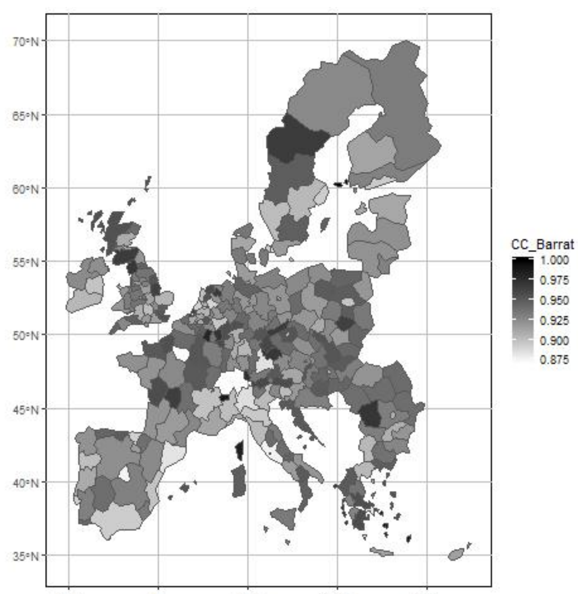
To study the neighbourhood interactions between regions in such a complex network, we construct a local transitivity measure (that is, a clustering coefficient). For node *i*, the local clustering coefficient (which varies between 0 and 1) is measured as the fraction of the number of ties connecting *i*'s neighbours over the total number of possible ties between *i*'s neighbours (Opsahl and Panzarasa, 2009). In our analysis, we adopt a weighted clustering coefficient, i.e., a measure of local cohesion that takes into account the relevance of the cluster structure given by the intensity of interaction actually found on the local triples of our region-by-region adjacency matrix (Barrat et al. 2004). This measure captures more precisely the effective level of cohesiveness and affinity due to the actual interaction strength. In formula:

$$CC_i^w = \frac{1}{s_i(k_i - 1)} \sum_{j,h} \frac{(w_{ij} + w_{ih})}{2} a_{ij} a_{ih} a_{jh} \quad (2)$$

where s_i is the strength of vertex i, a_{ij}, a_{ih}, a_{jh} are elements of the adjacency matrix (local triples), k_i is the node degree, and w_{ij} are the weights in terms of total number of common projects of the two regions.

Clustering enhances the information transmission capacity of the network (Guan and Zhao, 2013) but it can also signal redundancy and repeated information (a region's direct contacts are interlinked), which may harm innovation performance (Guan et al. 2015). As highlighted in Figure 3, the regional average values of this index give a different image of EU regions' networks than that obtained with the strength index, identifying the potential flows of knowledge activated within the FPs between the "core" regions and the others.

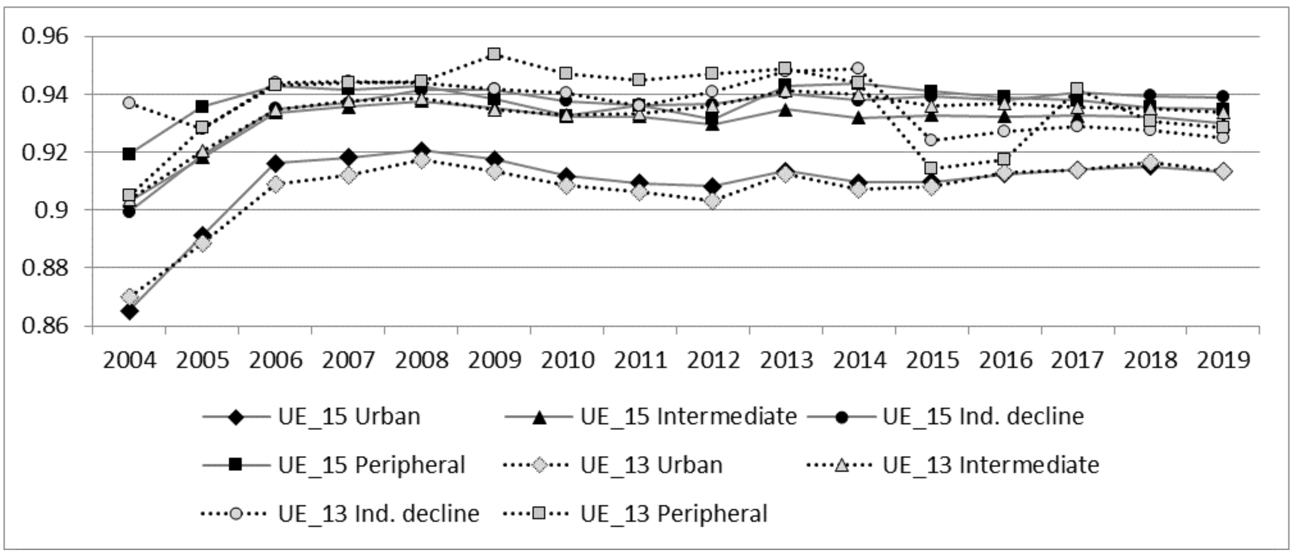
Figure 3. EU-28 NUTS2 and local clustering coefficient (mean 2004 – 2019)



Note: *CC_Barrat* = local clustering coefficient. Source: own elaborations on EU FPs Data

As is shown in Figure 4, urban regions (both EU-13 and EU-15) have the lowest values of this index due to the intensity of their ties and their gatekeeping role.[9] These regions do not require their neighbours to be highly connected since they are already central in the network and further links between their less connected neighbours could be redundant. Moreover, this could also result in a "knowledge trickle-down" effect from urban regions to other less connected regions. The opposite is true for the other regions, where the problem of redundancy is minimal and the need to be recipients of new knowledge flows is greatest.

Figure 4. Local clustering coefficient over time by socio-economic EU-28 NUTS2 classes



Source: own elaborations on EU FPs Data

4. NETWORKS, REGIONAL KNOWLEDGE PRODUCTION AND ECONOMIC GROWTH

4.1 ESTIMATED EQUATION AND METHODOLOGY

We gathered data available for the EU FP, as described in the previous paragraph, and economic variables from EUROSTAT, building an (unbalanced) panel data with 225 NUTS2 regions observed for the 2004 – 2014 period.[10] Thanks to this dataset, following Di Cagno et al. (2014) and Evangelista et al. (2013),

[9] We observe, as in other real-world networks, a negative correlation between the strength centrality and the local clustering coefficient (table A3 in the appendix). As pointed out by Opsahl and Panzarasa (2009), a node with more neighbors is likely to be embedded in relatively fewer closed triplets and therefore to have a smaller local clustering than a node connected to fewer neighbors.

[10] Time span of the analysis and the number of regions (nuts2) is influenced by the availability of EUROSTAT data.

we estimated first a regional knowledge production function (3) and then a regional GDP growth function (4). In formula:

$$lnPATINT_{i,t} = \beta_0 + \beta_1\, ln\, RDINT_{i,t-1} + \beta_2 \ln POPD_{i,t-1} + \beta_3\, ln\, EDU_{i,t-1} + \beta_4 \ln STRENGTH_{i,t-1} + \beta_5\, ln\, CC_{i,t-1} + \mu_t + v_{i,t} \qquad (3)$$

where, respectively, i = 1,…,225 stands for NUTS2 regions, and t = 2004, ..., 2014 refers to years. The dependent variable $PATINT_{i,t}$ is the (log) ratio between the total number of patent applications to the European Patent Office (EPO) and the population (patent intensity). The variables $RDINT_{i,t-1}$, $POPD_{i,t-1}$, $EDU_{i,t-1}$ are the (log) ratio of R&D total expenditure and GDP (R&D intensity), population and area (population density), and population with tertiary education and total population (a proxy of human capital), respectively. Variables $STRENGTH_{i,t-1}$ and $CC_{i,t}$ are the two (log) network variables referring to strength centrality (or node strength) and local clustering index. To account for heterogeneity between countries, we added country dummy variables in our estimation where β_0, μ_t and v_{it} are, respectively, a constant, a time dummy and a white noise residual.

The estimated equation for the rate of growth of GDP is:

$$Growth_{i,t} = \beta_1\, ln\, GDPPC_{i,t-1} + \beta_2\, ln\, POPGrowth_{i,t-1} + \beta_3\, ln\, INVINT_{i,t-1} + \beta_4\, ln\, EDU_{i,t-1} + \beta_5\, ln\, EPAT_{i,t-2} + \beta_6\, ln\, NET_{i,t-2} + \mu_t + v_{i,t} \quad (4)$$

where, respectively, i = 1, ….,216 stands for NUTS2 regions, and t = 2004, …, 2014 refers to years. The dependent variable $Growth_{i,t}$ is the variation of (log) GDP per capita; the (log) lagged dependent variable $GDPPC_{it-1}$ allows for the dynamic structure inherent in the data.[11] Variables $PopGrowth_{i.t-1}$, $INVINT_{it-1}$, and EDU_{it-1} are the variation of (log) population, the (log) ratio of gross fixed investment over *GDP*, and the (log) percentage of population with tertiary education (a proxy of human capital), respectively. Variables $EPAT_{it-2}$ and NET_{it-2} are the estimated patent intensity from equation (3) and the network variable (strength centrality or clustering coefficient), respectively. β_0, μ_t and v_{it} are, respectively, a constant, a time dummy and a white noise residual. The description of all variables is reported in the Appendix (table A1).

[11] The GDP of the NUTS2 region variables have been deflated using the corresponding national GDP deflator (2010=100).

Descriptive statistics and correlation for the variables described above are shown in Tables A2 and A3 in the Appendix. Figures A1 e A2 in the Appendix describe the geographical distribution of the two dependent variables (patent intensity and GDP per capita growth) in the European regions in the time frame of our analysis.

Equation (4) is estimated conditional on the results from the first step. This helps capture the impact of network variables on GDP growth both directly and through their impact on innovation. To consider the variability in predicted value, we correct the variance–covariance matrix of the estimators of equation (4) following the Murphy–Topel (1985) methodology.[12] Since for our sample the cross-section dimension (N = 225) is much larger than the time series one (T = 11), we do not include regional fixed effects, as these could not be adequately estimated. However, to account for the wide socio-economic differences between the regions, we add four dummy variables (*Industrial Decline*, *Intermediate*, *Peripheral* and *Urban*) and two dummies to account for the different years of adhesion to the EU (EU-13 and EU-15). Explanatory variables are lagged one period to deal with the endogeneity issue and/or the correlation of any of the regressors with the error term. We also include time-fixed effects to account for shocks affecting the regions in a common way.

4.2 RESULTS OF THE TWO STAGE MODEL

Tables 2 and 3 show the results obtained from the estimation of equations (3) and (4), respectively.

In Tables 2 and 3, specification (1) is the baseline model including only control variables. Specifications (2) and (3) include, respectively, the strength and the clustering indexes separately, while specification (4) includes both measures at the same time. Finally, specifications (5) and (6) introduce, respectively, dummies for socio-economic groups and dummies for regions that joined the EU before 1995 (EU-15) and since 2004 (EU-13).

Specifications from (2) to (6) form a two-stage model in order to analyse the possible channels through which the network structure of the European regions in the Framework Programmess influences the knowledge production and growth of the regions (our research questions), including the predicted value

[12] For details on how to implement this procedure see Hole (2006).

from stage 1 among the regressors of the second stage. The specifications are fitted conditional on the results from the first step. To consider the variability in predicted value, we correct the variance–covariance matrix of the estimators of the second equation following the Murphy–Topel (1985) methodology.[13]

Table 2. First-stage: regional knowledge production function. OLS estimates.

	(1) **Baseline**	(2) **Strength**	(3) **CC**	(4) **Strength & CC**	(5) **NUTS2 Classes**	(6) **EU Groups**
Patent intensity						
Population density	0.0199	-0.0489*	0.0100	-0.0420	-0.0796***	-0.0420
	(0.91)	(-1.83)	(0.42)	(-1.59)	(-2.79)	(-1.59)
R&D intensity	0.505***	0.307***	0.469***	0.297***	0.276***	0.297***
	(12.91)	(6.77)	(11.26)	(6.56)	(6.50)	(6.56)
Human Capital	1.103***	1.032***	1.119***	1.040***	0.910***	1.040***
	(9.60)	(8.68)	(9.54)	(8.85)	(6.95)	(8.85)
Node Strength		0.158***		0.210***	0.218***	0.210***
		(4.98)		(5.32)	(6.47)	(5.32)
Local CC			-1.123	3.083**	2.885**	3.083**
			(-1.13)	(2.34)	(2.52)	(2.34)
Ind. Decline					-0.076	
					(-0.87)	
Intermediate					0	
					(.)	
Peripheral					-0.859***	
					(-12.94)	
Urban					-0.289***	
					(-3.50)	
EU13						-3.993***
						(-22.64)
EU15						0
						(.)
Country Dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	-2.760***	-3.965***	-2.988***	-4.067***	-3.641***	-4.067***
	(-6.45)	(-8.80)	(-6.78)	(-9.11)	(-7.30)	(-9.11)
Number of Obs.	1261	1254	1254	1254	1254	1254
Number of Nuts2	225	225	225	225	225	225
F statistic	311.5	305.9	301.5	300.7	288.6	1667.8
Adjusted R^2	0.853	0.859	0.855	0.860	0.887	0.972
RMSE	0.652	0.640	0.650	0.639	0.573	0.639

Note: t statistics in parentheses. Significance: * p<0.1, ** p<0.05, *** p<0.01. In column (5), the coefficient of the *intermediate* group (base level) and those of the other groups, namely *Industrial Decline, Peripheral* and *Urban*, are respectively -3.717***, -3.641***, -4.500*** and -3.930***. In column (6), the coefficient of the *EU15* group (base level) and that of the *EU13* group are respectively -8.061*** and -4.067***

[13] For details on how to implement this procedure see Hole (2006).

Table 3. Second-stage: regional growth function. OLS estimates with Murphy–Topel Procedure.

	(1) Baseline	(2) Estimated Patent	(3) Strength	(4) CC	(5) Strength &CC	(6) EU Groups
GDP per capita growth						
GDP per capita	-0.0104***	-0.0114***	-0.0117***	-0.0120***	-0.0117***	-0.00260
	(-7.94)	(-3.68)	(-3.76)	(-3.89)	(-3.77)	(-0.78)
Investment over GPD	0.0164***	0.0163***	0.0159***	0.0155***	0.0158***	0.00974**
	(5.77)	(4.33)	(4.09)	(4.06)	(4.06)	(2.37)
Population growth	-0.939***	-1.042***	-1.037***	-1.027***	-1.031***	-1.039***
	(-11.51)	(-8.16)	(-7.98)	(-8.00)	(-8.10)	(-8.14)
Human Capital	0.00978***	0.00993***	0.0101***	0.0104***	0.0103***	0.0109***
	(6.14)	(4.20)	(4.30)	(4.43)	(4.41)	(4.72)
Patents (estimated)		0.00258**	0.00282**	0.00287**	0.00245*	0.00400***
		(2.21)	(2.18)	(2.42)	(1.85)	(3.65)
Node Strength			-0.000421		0.00105	-0.000261
			(-0.61)		(0.95)	(-0.22)
Local CC				0.0533*	0.0873*	0.0393
				(1.89)	(1.93)	(0.85)
Ind. Decline					-0.0045	
					(-1.27)	
Intermediate					0	
					(.)	
Peripheral					-0.007**	
					(-3.44)	
Urban					0.056*	
					(1.98)	
EU13						0.017***
						(5.55)
EU15						0
						(.)
Class Dummies	*Yes*	*Yes*	*Yes*	*Yes*		*No*
Time Dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	0.119***	0.067*	0.071**	0.074**	0.070*	-0.026
	(9.12)	(1.93)	(2.04)	(2.15)	(1.94)	(-0.07)
Number of Obs.	3091	1254	1254	1254	1254	1254
Number of Nuts2	225	225	225	225	225	225
F statistic	107.4	58.74	54.98	54.87	51.71	57.04
Adjusted R^2	0.426	0.452	0.451	0.452	0.452	0.468
RMSE	0.0267	0.0251	0.0251	0.0251	0.0251	0.0249

Note: t statistics in parentheses. Significance: * p<0.1, ** p<0.05, *** p<0.01. In column (5), the variable *patents (estimated)* is from Table 3 – column 5 and the coefficient of the *intermediate* group (base level) and those of the other groups, namely *Industrial Decline, Peripheral* and *Urban*, are respectively 0.154***, 0.156***, 0.149*** and 0.162 ***. In column (6), the variable *patents (estimated)* is from Table 3 – column 6 and the coefficient of the *EU15* group (base level) and that of the *EU13* group are respectively 0.069** and 0.0512.

Looking at Table 2, we observe that, as expected, investment in R&D and tertiary education are positively associated with patent intensity. We also find a strong positive association between strength centrality and clustering indexes with patent intensity. This confirms that regions that are more central in European research networks have a higher innovation intensity. This is consistent with the results found by Guan et al. (2015) in the case of the G7 countries. However, differently from Guan et al. (2015), we find evidence that clustering enhances the information transmission capacity of the network, leading to a higher level of patent intensity.

But do networks also help regions to grow faster? Table 3 shows that regional per capita GDP growth increases with investment in physical capital and education while it decreases with the increase in population growth. The results also show some evidence of convergence, although at a low rate. Moreover, the predicted level of patent intensity has a positive and significant impact on regional growth. Therefore, measures of network centrality and clustering indirectly affect regional growth by contributing to their innovation intensity. Finally, in the case of the clustering coefficient, we also observe a direct positive and significant impact on per capita GDP growth. It is worth observing that regions with high levels of the clustering index are more heterogeneous in terms of per capita GDP and innovation intensity than those with a high level of strength centrality, including laggard regions. Therefore, the positive effect of the clustering coefficient suggests that potential flows of knowledge are activated within the FPs between the "core" and the other regions which can help laggard regions to catch up by connecting to knowledge networks. Moreover, the degree of interconnectivity in the neighbourhood of a node contributes to regional growth not only through technological innovation (proxied by patents) but also via other channels, including possibly knowledge spillovers (not captured by patents). Overall, these results at the regional level confirm the positive role played by networks on performance at the firm level (Cisi et al., 2020; Schoonjans et al., 2013; Park et al., 2010; Lechner et al., 2006; Havnes and Senneseth, 2001).

The role of networks is further explored in Tables 4 and 5, which distinguish between groups of regions on the basis of their socio-economic conditions (urban, peripheral, industrial decline and intermediate) and on the basis of their country's year of adhesion to the European Union (EU-15 before 1995 and EU-13 since 2004).[14]

Table 4. First-stage: regional knowledge production function. OLS estimates and interaction terms.

	(1) **Classes & Strength**	(2) **Classes & CC**	(3) **EU Groups & Strength**	(4) **EU Groups & CC**
Patent intensity				
Population density	-0.0662**	-0.0811***	-0.0425	-0.0415
	(-2.55)	(-3.05)	(-1.59)	(-1.57)
R&D intensity	0.269***	0.270***	0.297***	0.294***
	(6.59)	(6.41)	(6.57)	(6.50)
Human Capital	0.928***	0.933***	1.054***	1.029***
	(7.40)	(7.26)	(8.35)	(8.53)
Node Strength		0.218***		0.215***
		(6.49)		(5.40)
Local CC	2.514**		3.133**	
	(2.30)		(2.40)	
Ind.Decline#Strength	0.108*			
	(1.72)			
Intermediate#Strength	0.206***			
	(6.60)			
Peripheral#Strength	0.313***			
	(5.82)			
Urban#Strength	-0.0383			
	(-0.70)			
Ind.Decline#CC		4.019		
		(1.43)		
Intermediate#CC		2.733**		
		(2.13)		
Peripheral#CC		0.252		
		(0.14)		
Urban#CC		9.302***		
		(4.56)		
EU13#Strength			0.198***	
			(3.60)	
EU15#Strength			0.212***	
			(5.29)	
EU13#CC				2.546
				(1.46)
EU15#CC				3.369**
				(2.38)
Class Dummies	Yes	Yes	No	No
Group Dummies	No	No	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Number of Obs.	1254	1254	1254	1254
Number of Nuts2	225	225	225	225
F statistic	1547.3	1545.8	1630.9	1615.9
Adjusted R^2	0.978	0.978	0.972	0.972
RMSE	0.566	0.570	0.639	0.639

Note: t statistics in parentheses. Significance: * p<0.1, ** p<0.05, *** p<0.01.

[14] In Appendix A, Tables A4 and A5 report the estimates of Tables 5 and 6 without considering the intermediate group dummy and EU15 countries' dummy, respectively, as a base level, so as to statically test the respective coefficient differences of the groups.

Table 5. Second-stage: regional growth function. OLS estimates with Murphy–Topel Procedure and interaction terms.

	(1) **Classes & Strength**	(2) **Classes & CC**	(3) **EU Groups & Strength**	(4) **EU Groups & CC**
GDP per capita growth				
GDP per capita	-0.0120***	-0.0124***	-0.00161	-0.00323
	(-3.80)	(-3.96)	(-0.49)	(-0.98)
Investment over GPD	0.0159***	0.0157***	0.0104**	0.00919**
	(4.11)	(4.06)	(2.57)	(2.27)
Population growth	-1.014***	-1.025***	-1.042***	-1.036***
	(-7.83)	(-8.10)	(-8.27)	(-7.90)
Human Capital	0.00982***	0.00999***	0.0112***	0.00992***
	(4.21)	(4.26)	(4.96)	(4.39)
Patents (estimated)	0.00262**	0.00270**	0.00376***	0.00404***
	(1.97)	(2.05)	(3.52)	(3.70)
Node Strength		0.00105		0.000100
		(0.95)		(0.08)
Local CC	0.0799*		0.0455	
	(1.72)		(0.95)	
Ind.Decline#Strength	-0.00042			
	(-0.17)			
Intermediate#Strength	0.00192			
	(1.60)			
Peripheral#Strength	0.000433			
	(0.26)			
Urban#Strength	-0.00583**			
	(-2.48)			
Ind.Decline#CC		0.0286		
		(0.29)		
Intermediate#CC		0.0566		
		(1.15)		
Peripheral#CC		0.106		
		(1.37)		
Urban#CC		0.291***		
		(3.37)		
EU13#Strength			-0.00155	
			(-0.78)	
EU15#Strength			0.000136	
			(0.11)	
EU13#CC				-0.0684
				(-0.70)
EU15#CC				0.0765*
				(1.70)
Class Dummies	Yes	Yes	No	No
Group Dummies	No	No	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Number of Obs.	1254	1254	1254	1254
Number of Nuts2	225	225	225	225
F statistic	43.47	44.33	53.86	53.57
Adjusted R^2	0.471	0.470	0.475	0.477
RMSE	0.0250	0.0250	0.0249	0.0249

Note: t statistics in parentheses. Significance: * p<0.1, ** p<0.05, *** p<0.01. The variable *patents (estimated)* in columns (1 – 2) is from Table 3 – column 5 and in column (3 - 4) is from Table 3 – column 6.

Interestingly, we can observe significant differences in the impact of network variables across socio-economic groups. In particular, surprisingly, strength centrality seems not to matter for urban areas. On the contrary, it exerts the strongest positive effect on patent intensity in peripheral and intermediate regions. Our interpretation is that urban areas have all reached high levels of connectivity to European research networks and therefore benefit less from increased connections (see Figure 1), while among peripheral and intermediate areas, those that succeed in increasing their centrality in the network benefit strongly from positive technology spillovers. Looking at the effects on economic growth, we find support for the existence of indirect effects (through patents), while there do not appear any significant direct effects, with the exception of a negative effect, for urban areas. This can be interpreted as possible congestion effects.

Looking at the results for the clustering index, we find a strong positive effect on patent intensity for urban and intermediate regions, while it does not seem to matter for peripheral areas and areas in industrial decline. We interpret this result for urban areas as evidence of the fact that the advantages in building networks characterised by trust and risk sharing outweigh the disadvantages of the overloading of perspectives and information (Guan et al 2015). The positive effect of high levels of clustering in urban areas applies also to economic growth (in addition to the indirect effect).

Overall, a general reading of the results of network variables seems to indicate that in areas that are already central in research linkages, centrality per se is achieved not leading to additional benefits in terms of technological performance; what matters for such areas is the reinforcement of the existing network linkages. In such areas the advantages of better cohesion, and possibly more trust and risk sharing among all participants, outweigh the costs of superfluous links. For peripheral regions, instead, what seems to matter is the achievement of a higher level of centrality, while the benefits of more interconnections among other participants involved in the same networks are capable of compensating for the costs. These results are encouraging since they show that a further interconnection of peripheral regions in research networks would create benefits in both the periphery and the core of Europe.

Finally, no relevant differences in the impact of strength centrality emerge between old and new EU members, while the clustering index is positively correlated with technological intensity only for the old members. This confirms our opinion that for new entrants it is important to gain centrality in the network, while for old members it is important to consolidate the links also among other participants. The more the network is interconnected, the larger is the network leaders' propensity to innovate. It is also worth noting that clustering also has a mild direct positive effect on growth for old EU members.

5. CONCLUSIONS

This paper assesses the impact of European regions' position in EU FP networks on their levels of innovation and economic growth. We assume that for peripheral regions joining a research network can be a strategy for benefitting from knowledge exchange and for overcoming the limits of geographical distance from the core, while for core regions it can contribute to enhancing their positional advantage. The overall effects of network participation on technological and economic convergence depend on the extent to which peripheral regions are included in the networks and on their capability to benefit from the knowledge spillovers (absorptive capacity) stemming from a higher involvement in research networks.

Differently from previous contributions, we estimate the overall effect of network participation on economic growth, distinguishing between the indirect effect coming from the contribution of network participation to technological innovation and the direct effect of knowledge spillovers on regional growth. Using our network indicators, we find strong support for the indirect effect on growth, while only the degree of interconnectivity in the neighbourhood of a node contributes directly to regional growth.

Moreover, we show that different groups of regions benefit differently from participation in FPs networks: in areas that are already central in research networks (urban areas), centrality per se is achieved and has no more additional benefits for technological performance, while what matters is to reinforce every linkage of the network (the advantages of more interconnected and cohesive networks overweigh the costs of superfluous links). On the contrary, for peripheral regions what matters is achieving a higher level of centrality, while the benefits of more interconnections among other participants involved in the same networks seems incapable of outweighing their costs. In the case of intermediate regions, both centrality and clustering are relevant.

From a policy perspective, our results give support to the effectiveness of FPs programmes. Strengthening the European actions financing the formation of research networks leads to a positive contribution to the technological performance of both central and peripheral regions. They also suggest that forming more interconnected networks (where the probability that two randomly selected regions cooperating with A also cooperate with each other) is beneficial, especially for urban regions. When forming research networks, these regions should not aim at further increasing their centrality, but rather at strengthening the cohesiveness of the networks in which they participate. This result is encouraging since it signals that more inclusive networks benefit innovation and growth both at the core and at the periphery of Europe. The heterogeneity in the impact of networks also suggests the importance of calibrating European innovation policy by considering the socio-economic characteristics of the regions.

This study has contributed to the literature on networks and innovation by measuring EU regions' position in FP. Further analyses could take into account also the composition of networks between universities, research centres and private companies. Moreover, it would be interesting to look for the possible differences in the structure and effectiveness of research networks in different thematic areas.

REFERENCES

Aghion, P. – Howitt, P. (1992). A Model of Growth Through Creative Destruction. *Econometrica*, 60(2), 323-351.

Arundel, A. - Geuna, A. (2004). Proximity and the use of public science by innovative European firms. *Economics of Innovation and new Technology*, *13*(6), 559-580.

Autant-Bernard, C. – Mairesse, J. - Massard, N. (2007), Spatial knowledge diffusion through collaborative networks. *Papers in Regional Science*, 86 (3), 341-350.

Balland, P. A.- Boschma, R.- Crespo, J.- Rigby, D. L. (2019). Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Regional Studies*, *53*(9), 1252-1268.

Barrat, A.- Barthélemy, M.- Vespignani, A. (2004). Modeling the evolution of weighted networks. *Physical review E*, *70*(6), 066149.

Bottazzi, L.- Peri G. (2003), Innovation and spillovers in regions: Evidence from European patent data, *European Economic Review*, 47, 687-710.

Breschi, S. - Cusmano, L. (2004), Unveiling the texture of a European Research Area: Emergence of oligarchic networks under EU Framework Programmes. *International Journal of Technology Management*, 27(8), 747-772.

Breschi, S. - Lissoni, F. (2009), Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. *Journal of Economic Geography*, 9 (4), 439-468.

Borgatti, S. P. (2005). Centrality and network flow. *Social networks*, *27*(1), 55-71.

Butts, C. T. (2008). Social network analysis: A methodological introduction. *Asian Journal of Social Psychology*, *11*(1), 13-41.

Cassi, L. - Plunket, A. (2014). Proximity, network formation and inventive performance: in search of the proximity paradox. *The Annals of Regional Science*, *53*(2), 395-422.

Cassiman, B. - Veugelers, R. (2002). R&D cooperation and spillovers: some empirical evidence from Belgium. *American Economic Review*, *92*(4), 1169-1184.

Caloghirou, Y. - Constantelou, A. - Vonortas, N. (Eds.). (2006). *Knowledge flows in European industry*. Routledge.

Chapman, S. A. - Meliciani, V. (2012). Income Disparities in the Enlarged EU: Socio-economic, Specialisation and Geographical Clusters. *Tijdschrift voor economische en sociale geografie*, *103*(3), 293-311.

Cheshire, P.C.- Hay, D.G. (1989). *Urban Problems in Western Europe: An Economic Analysis*. London: Unwin Hyman.

Cincera M. - Van Pottelsberghe de la Potterie B. (2001), International R&D spillovers: a survey, *Cahiers Economiques de Bruxelles*, 169 (1er trimestre), 3-32.

Cisi, M.- Devicienti, F.- Manello, A. - Vannoni, D. (2020). The advantages of formalizing networks: New evidence from Italian SMEs. *Small Business Economics*, *54*(4), 1183-1200.

Cowan, R.,- Jonard, N. (2004). Network structure and the diffusion of knowledge. *Journal of economic Dynamics and Control*, *28*(8), 1557-1575.

Crescenzi, R. - Rodriguez-Pose A. (2011) Innovation and regional growth in the European Union, Advances in spatial science. Springer, Berlin, Germany. ISBN 9783642177606.

D’Este, P. - Perkmann, M. (2011). Why do academics engage with industry? The entrepreneurial university and individual motivations. *The Journal of Technology Transfer*, *36*(3), 316-339.

Di Cagno, D. - Fabrizi, A. - Meliciani, V. (2014). The impact of participation in European joint research projects on knowledge creation and economic growth. *The Journal of Technology Transfer* 39, 836-858.

Di Cagno, D., Fabrizi, A., Meliciani, V., & Wanzenböck, I. (2016). The impact of relational spillovers from joint research projects on knowledge creation across European regions. *Technological Forecasting and Social Change*, *108*, 83-94.

Duranton, G. - Puga, D. (2005). From sectoral to functional urban specialisation. *Journal of urban Economics*, *57*(2), 343-370.

Evangelista, R. - Lucchese, M.- Meliciani, V. (2013). Business services, innovation and sectoral growth. *Structural change and economic dynamics*, *25*, 119-132.

Fagerberg, J. (1994). Technology and international differences in growth rates. *Journal of economic Literature*, *32*(3), 1147-1175.

Fontana, R.- Geuna, A. - Matt, M. (2006). Factors affecting university–industry R&D projects: The importance of searching, screening and signalling. *Research policy*, *35*(2), 309-323.

Frenken, K. - Hoekman, J. (2006). Convergence in an enlarged Europe: the role of network cities. *Tijdschrift voor economische en sociale geografie*, *97*(3), 321-326.

Geuna, A. (1998). Determinants of university participation in EU-funded R&D cooperative projects. *Research Policy*, *26*(6), 677-687.

Grossman, G. M., - Helpman, E. (1994). Endogenous innovation in the theory of growth. *Journal of Economic Perspectives*, *8*(1), 23-44.

Guan, J., Zhao, Q. (2013). The impact of university–industry collaboration networks on innovation in nanobiopharmaceuticals. *Technol. Forecast. Soc. Change,* 80 (7), 1271–1286.

Guan, J. - Zhang, J. - Yan, Y. (2015). The impact of multilevel networks on innovation. *Research Policy*, 44(3), 545-559.

Gulati, R. - Higgins, M. C. (2003). Which ties matter when? The contingent effects of interorganizational partnerships on IPO success. *Strategic Management Journal*, *24*(2), 127-144.

Hagerdoon, J.- Link, A. N. - Vonortas, N.S., 2000. Research partnerships,. *Research Policy* 29 (4-5), 567-586.

Hagerdoon J. (2002), Inter-Firm R&D Partnerships: An Overview of Major Trends and Patterns since 1960, *Research Policy*, 31, 477-492.

Hayashi, T. (2003). Effect of R&D programmes on the formation of university–industry–government networks: comparative analysis of Japanese R&D programmes. *Research Policy*, 32(8), 1421-1442.

Hall B. H. - Mairesse,J. - Mohnen, P. (2010), Measuring the Returns to R&D, *NBER Working Papers 15622*, National Bureau of Economic Research, Inc.

Harvey, D. (1985). *Consciousness and the urban experience: Studies in the history and theory of capitalist urbanization* (Vol. 1). Johns Hopkins University Press.

Havnes, P. A.- Senneseth, K., (2001). A Panel Study of Firm Growth among SMEs in Networks. *Small Business Economics,* 16(4), 293-302.

Hoekman, J.- Frenken, K. - Van Oort, F. (2009). The geography of collaborative knowledge production in Europe. *The Annals of Regional Science*, 43(3), 721-738.

Hoekman J. - Scherngell T. - Frenken, K.- Tijssen, R. (2013), Acquisition of European research funds and its effect on international scientific collaboration. *Journal of Economic Geography*, 13, 23-52.

Hole, A. R. 2006. Calculating Murphy–Topel variance estimates in Stata: A simplified procedure. *Stata Journal,* 6: 521–529.

Jaffee, A.B.- Trajtenberg, M. - Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108, 577-598.

Jaffee, A.B.- Trajtenberg, M., (1999). International Knowledge flows: Evidence from patent citations, *Economics of Innovation and new Technology*, 8 (1-2), 105-136.

Le Gallo, J. - Ertur, C. (2003). Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980–1995. *Papers in regional science*, *82*(2), 175-201.

Laursen, K. - Salter, A. (2004). Searching high and low: what types of firms use universities as a source of innovation? *Research policy*, 33(8), 1201-1215.

Lechner, C.- Dowling, M.- Welpe, I. (2006). Firm networks and firm development: The role of the relational mix. *Journal of business venturing*, 21(4), 514-540.

López-Bazo, E., Vayá, E., Mora, A. J., - Suriñach, J. (1999). Regional economic dynamics and convergence in the European Union. *The Annals of Regional Science*, 33(3), 343-370.

Macdissi, C., & Negassi, S. (2002). International R&D spillovers: an empirical study. *Economics of Innovation and New Technology*, 11(2), 77-91.

Maggioni, M. A. - Nosvelli, M. – Uberti, T.E. (2007). Space versus networks in the geography of innovation: A European analysis. *Papers in Regional Science*, 86 (3), 271-293.

Maggioni, M. - Uberti, T.E. (2009). Knowledge networks across Europe: which distance matters? *The Annals of Regional Science*, 43, 691-720.

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

Maggioni, M. A., Breschi, S., & Panzarasa, P. (2013). Multiplexity, growth mechanisms and structural variety in scientific collaboration networks. *Industry and Innovation*, 20(3), 185-194.

Maggioni, M. A. - Uberti, T. E. - Nosvelli, M. (2014). Does intentional mean hierarchical? Knowledge flows and innovative performance of European regions. *The Annals of Regional Science*, 53(2), 453-485.

Maggioni, M. A.- Uberti, T. E. - Nosvelli, M. (2017). The" Political" Geography of Research Networks: FP6 whithin a" Two Speed" ERA. *International Regional Science Review*, 40(4), 337-376.

Marrocu, E. - Paci, R. - Usai, S. (2013). Proximity, networking and knowledge production in Europe: What lessons for innovation policy? *Technological Forecasting and Social Change,* 80*,* 1484-1498.

Maurseth, P.B. - Verspagen, B. (2002). Knowledge spillovers in Europe: A patent citation analysis, *Scandinavian Journal of Economics*, 104 (4), 531-545.

Medda, G., Piga, C., & Siegel, D. S. (2006). Assessing the returns to collaborative research: Firm-level evidence from Italy. *Economics of Innovation and New technology*, *15*(1), 37-50.

Miguélez, E. - Moreno, R. (2013). Research networks and inventors' mobility as drivers of innovation: evidence from Europe. *Regional Studies*, *47*(10), 1668-1685.

Miotti, L., - Sachwald, F. (2003). Co-operative R&D: why and with whom? An integrated framework of analysis. *Research policy*, *32*(8), 1481-1499.

Morone, P. - Taylor, R. (2004). Knowledge diffusion dynamics and network properties of face-to-face interactions. *Journal of evolutionary economics*, *14*(3), 327-351.

Murphy, K. M., - Topel, R. H. (1985). Least Squares with Estimated Regressors. *Journal of Business and Economic Statistics,* 3(4), 370-379.

Nelson, R. R. - Winter, S. G. (1982). The Schumpeterian tradeoff revisited. *The American Economic Review*, 72(1), 114-132.

Opsahl, T. - Panzarasa, P., (2009). Clustering in weighted networks. *Social Networks* 31 (2), 155-163.

Overman, H. G., - Puga, D. (2002). Unemployment clusters across Europe's regions and countries. *Economic policy*, 17(34), 115-148.

Park, H. W. - Leydesdorff, L. (2010). Longitudinal trends in networks of university–industry–government relations in South Korea: The role of programmatic incentives. *Research policy*, 39(5), 640-649.

Protogerou, A.- Caloghirou, Y.- Siokas, E. (2010). Policy-driven collaborative research networks in Europe. *Economics of Innovation and New Technology*, 19(4), 349-372.

Protogerou, A.- Caloghirou, Y.- Siokas, E. (2013). Twenty-five years of science-industry collaboration: the emergence and evolution of policy-driven research networks across Europe. *The Journal of Technology Transfer*, 38(6), 873-895.

Rodríguez-Pose, A. (1998). *Dynamics of regional growth in Europe: Social and political factors*. Clarendon Press.

Rodríguez-Pose, A. (1999). Convergence or divergence? Types of regional responses to socio-economic change in Western Europe. *Tijdschrift voor economische en sociale geografie*, 90(4), 365-378.

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

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

Schoonjans, B.- Van Cauwenberge, P.- Vander Bauwhede, H. (2013). Formal business networking and SME growth. *Small Business Economics*, 41(1), 169-181.

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

Sun, Y. - Cao, C. (2015). Intra-and inter-regional research collaboration across organizational boundaries: Evolving patterns in China. *Technological Forecasting and Social Change*, 96, 215-231.

Wanzenböck, I. (2018). A concept for measuring network proximity of regions in R&D networks. *Social Networks*, *54*, 314-325.

Watson, J. (2012). Networking: Gender differences and the association with firm performance. *International Small Business Journal*, *30*(5), 536-558.

Zaheer, A.- Bell, G. G. (2005). Benefiting from network position: firm capabilities, structural holes, and performance. *Strategic management journal*, *26*(9), 809-825.

Appendix A

Table A1. List of regional variables (NUTS2 level)

Variable	Variable Code	Description	Source
Patent intensity	*PATINT*	Patent applications to the European Patent Office (EPO) per thousand inhabitants	Own elaborations on Eurostat data
Population density	POPD	Persons per square kilometre	Own elaborations on Eurostat data
R&D intensity	*RDINT*	R&D expenditure on GPD	Own elaborations on Eurostat data
Human Capital	*EDU*	Population with tertiary education (%)	Eurostat
Node Strength	*STRENGTH*	Strength centrality	Own elaborations on FPs data
Local CC	*CC*	Clustering coefficient	Own elaborations on FPs data
GDP per capita growth	*Growth*	Real GDP annual growth rate per capita	Own elaborations on Eurostat data
GDP per capita	*GDPPC*	Real GDP per capita	Own elaborations on Eurostat data
Investment over GDP	*INVINT*	Grosso fixed capital formation on GDP	Own elaborations on Eurostat data
Population growth	*POPGrowth*	Population annual growth rate	Own elaborations on Eurostat data

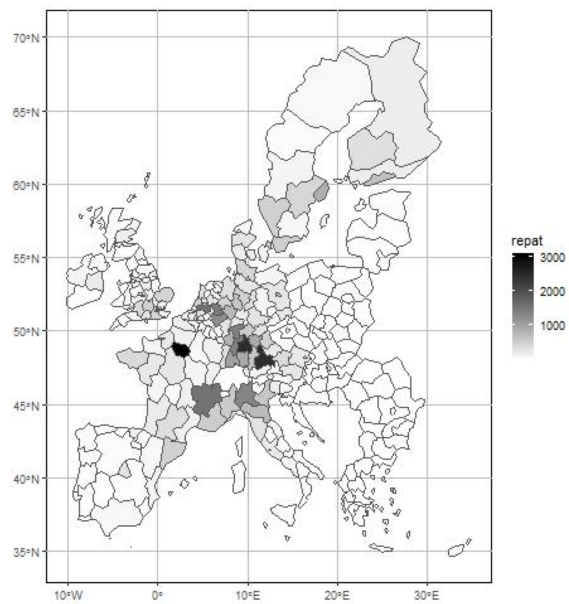
Table A2. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
PATINT	2,219	.1057519	.1259716	.0001769	.770542
POPD	3,113	453.2613	1166.413	3.070191	10624.81
RDINT	2,545	.0137511	.0115056	0	.1022998
EDU	3,985	26.53877	9.730922	6.5	74.7
STRENGTH	4,112	1996.153	2915.447	1	27160
CC	4,109	.9300032	.0282214	.66667	1
Growth	3,402	.0110302	.0351645	-.161191	.5438471
GDPPC	3,683	25896.37	14924.13	3016.976	194560.1
INVINT	3,553	.2147684	.0544294	.0738865	.6643131
POPGrowth	3,740	.0027469	.0082976	-.1170549	.0548229

Table A3. Correlation

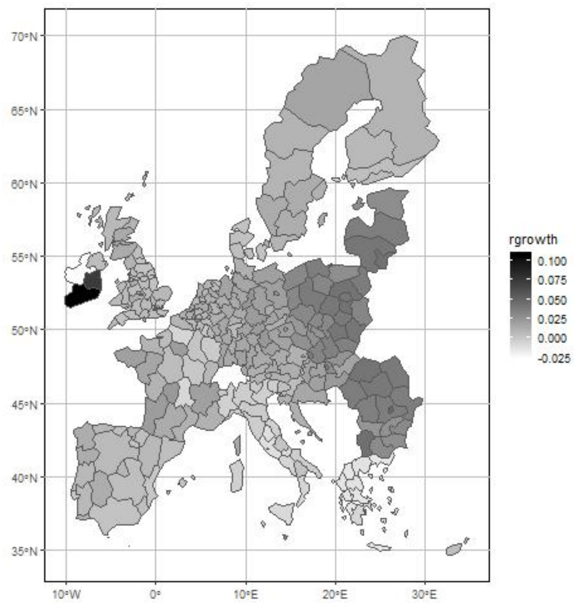
	Variables	1	2	3	4	5	6	7	8	9	10
1	*PATINT*	1.0000									
2	*POPD*	0.0745	1.0000								
3	*RDINT*	0.6751	0.0187	1.0000							
4	*EDU*	0.3294	0.3381	0.4360	1.0000						
5	*STRENGTH*	0.3463	0.3171	0.4463	0.4185	1.0000					
6	*CC*	-0.1665	-0.1079	-0.3113	-0.2230	-0.5549	1.0000				
7	*Growth*	0.0804	-0.0045	-0.0461	0.0244	-0.0326	-0.0384	1.0000			
8	*GDPPC*	0.5945	0.4864	0.4530	0.5416	0.5223	-0.2158	-0.0324	1.0000		
9	*INVINT*	-0.1602	-0.2520	-0.0172	-0.1725	-0.1368	0.0620	0.0941	-0.1366	1.0000	
10	*POPGrowth*	0.0164	0.2642	0.1459	0.3083	0.2044	-0.0656	-0.2312	0.3605	0.0963	1.0000

Figure A1. Patent applications to the EPO per 1000 inhabitants (mean 2004 – 2012)



Note*: repat* = regional patents applications to the EPO. Source: own elaborations on EU FPs data.

Figure A2. Regional GDP per capita growth rate (mean 2004 – 2018)



Note: *rgrowth* = Real GDP growth rate per capita. Source: own elaborations on EU FPs data

Table A4. First-stage: regional knowledge production function. OLS estimates and interaction terms (base level: intermediate NUTS2 and EU15 countries).

	(1) **Classes & Strength**	(2) **Classes & CC**	(3) **EU Groups & Strength**	(4) **EU Groups & CC**
Patent intensity				
Population density	-0.0662**	-0.0811***	-0.0425	-0.0415
	(-2.55)	(-3.05)	(-1.59)	(-1.57)
R&D intensity	0.269***	0.270***	0.297***	0.294***
	(6.59)	(6.41)	(6.57)	(6.50)
Human Capital	0.928***	0.933***	1.054***	1.029***
	(7.40)	(7.26)	(8.35)	(8.53)
Node Strength	0.206***	0.218***	0.212***	0.215***
	(6.60)	(6.49)	(5.29)	(5.40)
Local CC	2.514**	2.733**	3.133**	3.369**
	(2.30)	(2.13)	(2.40)	(2.38)
Ind.Decline#Strength	-0.0983*			
	(-1.66)			
Intermediate#Strength	0			
	(.)			
Peripheral#Strength	0.106**			
	(2.05)			
Urban#Strength	-0.245***			
	(-4.77)			
Ind.Decline#CC		1.286		
		(0.45)		
Intermediate#CC		0		
		(.)		
Peripheral#CC		-2.481		
		(-1.30)		
Urban#CC		6.568***		
		(3.31)		
EU13#Strength			-0.0146	
			(-0.32)	
EU15#Strength			0	
			(.)	
EU13#CC				-0.824
				(-0.49)
EU15#CC				0
				(.)
Class Dummies	Yes	Yes	No	No
Group Dummies	No	No	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Constant	-3.750***	-3.724***	-4.111***	-4.055***
	(-7.97)	(-7.62)	(-8.62)	(-9.03)
Number of Obs.	1254	1254	1254	1254
Number of Nuts2	225	225	225	225
F statistic	277.2	278.6	295.8	292.3
Adjusted R^2	0.890	0.889	0.860	0.860
RMSE	0.566	0.570	0.639	0.639

Note: t statistics in parentheses. Significance: * p<0.1, ** p<0.05, *** p<0.01.

Table A5. Second-stage: regional growth function. OLS estimates and interaction terms (base level: intermediate NUTS2 and EU15 countries)

	(1) **Classes & Strength**	(2) **Classes & CC**	(3) **EUGroups & Strength**	(4) **EUGroups & CC**
GDP per capita growth				
GDP per capita (lag1)	-0.0120***	-0.0124***	-0.00161	-0.00323
	(-3.83)	(-3.93)	(-0.48)	(-0.97)
Investment over GPD	0.0159***	0.0157***	0.0104**	0.00919**
	(4.11)	(4.02)	(2.56)	(2.26)
Population growth	-1.014***	-1.025***	-1.042***	-1.036***
	(-7.83)	(-8.03)	(-8.21)	(-7.85)
Human Capital	0.00982***	0.00999***	0.0112***	0.00992***
	(4.21)	(4.22)	(4.93)	(4.36)
Patents (estimated)	0.00262**	0.00270**	0.00376***	0.00404***
	(1.97)	(2.03)	(3.50)	(3.70)
Node Strength	0.00192	0.00105	0.000136	0.000100
	(1.60)	(1.14)	(0.11)	(0.08)
Local CC	0.0799*	0.0566	0.0455	0.0765*
	(1.72)	(1.14)	(0.95)	(1.69)
Ind.Decline#Strength	-0.00233			
	(-1.00)			
Intermediate#Strength	0			
	(.)			
Peripheral#Strength	-0.00149			
	(-0.91)			
Urban#Strength	-0.00775***			
	(-3.57)			
Ind.Decline#CC		-0.0280		
		(-0.27)		
Intermediate#CC		0		
		(.)		
Peripheral#CC		0.0496		
		(0.64)		
Urban#CC		0.235***		
		(2.82)		
EU13#Strength			-0.00169	
			(-0.88)	
EU15#Strength			0	
			(.)	
EU13#CC				-0.145
				(-1.48)
EU15#CC				0
				(.)
Class Dummies	Yes	Yes	No	No
Group Dummies	No	No	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Constant	0.154*	0.163***	0.0467	0.0684*
	(4.21)	(4.46)	(1.26)	(1.83)
Number of Obs.	1254	1254	1254	1254
Number of Nuts2	225	225	225	225
F statistic	43.96	44.94	56.43	56.10
Adjusted R^2	0.456	0.454	0.461	0.462
RMSE	0.0250	0.0251	0.0249	0.0249

Note: t statistics in parentheses. Significance: * p<0.1, ** p<0.05, *** p<0.01. The variable *patents (estimated)* in columns (1 – 2) is from Table 3 – column 5 and in column (3 - 4) is from Table 3 – column 6.