The role of collaborative networks in supporting the innovation performances of lagging-behind European regions

Ivan De Noni[a], Luigi Orsi[a*], Fiorenza Belussi[b]

[a] University of Milan, Department of Environmental Science and Policy, Via Celoria 2, 20133 Milano, Italy.

[b] University of Padua, Department of Economics and Management, Via del Santo 33, 35123 Padova, Italy

* Corresponding author

E-mail addresses: ivan.denoni@unimi.it (I. De Noni), luigi.orsi@unimi.it (L. Orsi), fiorenza.belussi@unipd.it (F. Belussi)

Abstract

In rapidly changing regional economies, less innovative European regions (henceforth referred to as lagging-behind regions) must actively work to reduce the gap between them and knowledge-intensive regions. Recent literature has stressed that the lack of efficient institutional settings reduces the opportunities of local knowledge spillover and increases the need for local organisations to exploit collaborative networks to better support their innovation performance. In this light, since increasing attention has recently been directed at the role of inter-regional collaborations, we have measured the capacity of local innovative organisations embedded in lagging-behind European regions to develop internal and external regional inventors' networks by exploring their collaborative patenting processes. Then, a seven-year panel dataset (2002–2008) was organised using patents data at a regional level to validate the research hypothesis that collaborations, and specifically with highly innovative (knowledge-intensive) regions, positively affect the innovation performances of lagging-behind regions. Finally, the implications of EU policies for supporting lagging-behind regions are discussed.

Keywords

Regional innovation performance; collaboration; inventors network; lagging-behind regions; patent analysis.

1. Introduction

Over the last decade, many European Union (EU) cohesion programmes have pursued ambitious research and development (R&D) policies with the aim of fostering innovation and economic growth in the peripheral regions of Europe. Local conditions that have been critically discussed to make these policies effective include the minimum threshold of R&D expenditures, the possibility of benefitting from technological spillovers, and the availability of others socio-economic conditions (Bilbao-Osorio & Rodríguez-Pose, 2004). The European Commission traditionally identifies the regions needing support by adopting a classification based on Schürmann and Talaat's report (2000) which distinguishes core and peripheral regions focusing on productivity performance. In this light, peripheral regions are typically characterised by a lower GNP per capita (well below 75% of the EU average, which was the threshold for eligibility to receive financial support in many EU development projects), higher unemployment rates, and a less developed regional economy (Morgan, 2007; Puga, 2002). However, in the academic literature, this classification is not as rigorously adopted and many researchers are inclined to assume classification criteria based on different regional features. According Aiginger et al. (2012), the peripheral regions belong to underdeveloped European countries, such as Greece, Portugal and Spain. Tödtling and Trippl (2005) distinguish peripheral regions from metropolitan and old industrial regions by their lower R&D intensity and lower share of product innovations. Some studies attempt to capture the diversity of regional innovation systems across EU regions by looking at innovation disparities (Crescenzi et al., 2007; Navarro et al., 2009). Other studies mainly focus on the organisational and institutional thinness of less developed regional innovation systems (Trippl et al., 2016). Finally, the peripheral regions have sometimes been referred to as lagging-behind regions (Hajek et al., 2014).

Thus, because of the lack of a widely accepted classification and in the attempt to produce more robust findings, a map of lagging-behind and knowledge-intensive regions has been shaped by adopting two alternative classification methods. The first method is more specifically focused on the patenting activities of European regions, since evidence exists showing that patents are a good proxy for measuring innovation in specific spatial contexts (Acs et al., 2002; Cantwell & Iammarino, 2000; Co, 2002; Ronde & Hussler, 2005). The second refers to the Regional Innovation Scoreboard (European Commission, 2016) which provides a comparative assessment of innovation performance across European regions.

Based on this alternative classification, the study explores the role that collaborative inventors' networks, promoted by local innovative organisations, play in improving the innovation performance of these less innovative regions. According to Asheim et al. (2011), in fact, the participation in collaborative networks not only enables organisations to enhance firm-internal knowledge creation processes, but influences the innovation capacity of the entire region by providing fast access to specific knowledge components, supplying localised actors, and increasing the opportunities of knowledge spillovers. However, the literature extensively claims that knowledge spillover tends to be spatially bounded (Bottazzi & Peri, 2003) and depends on the region-specific institutional framework in which the organisations are embedded (Asheim & Gertler, 2005; Cooke, 2001; Tödtling, et al., 2013). This suggests that the knowledge-intensive regions are inclined to better support local knowledge spillovers than lagging-behind regions, thanks to the larger availability of resources and services supporting innovation processes and information exchanges (Tödtling & Trippl, 2005). Moreover, when regional capacity to sustain local knowledge spillovers is limited, organisations need to promote knowledge exchange and access external knowledge by collaborations, international partnerships and alliances, or other forms of global networking (Grillitsch & Nilsson, 2015). Thus, in order to compensate for the lack of local knowledge spillovers (Grillitsch & Nilsson, 2015), collaboration networks in lagging-behind regions are expected to enable the exchange and transfer of knowledge, foster the interactive learning process, create organisational proximity, and increase the opportunities to complement and combine knowledge available regionally with knowledge acquired from extra-regional sources (Asheim & Coenen, 2006; Cantner et al., 2010; Fitjar & Rodríguez-Pose, 2011; Tödtling et al., 2012; Trippl, 2011).

Based on such a framework, this study aims to explore to what extent the innovation performance of lagging-behind regions positively depends on the capacity of innovative *organisations embedded in lagging-behind regions* (OELRs) and engaged in knowledge-production processes to activate collaborative inventors' networks with external and knowledge-intensive regions. Therefore, the paper contributes to an enriched understanding of the interplay between collaboration networks, inter-regional knowledge flows, and regional innovation performance.

In order to investigate this issue, we apply a fixed effects regression model on a 7-year longitudinal dataset of 205 European regions. The OECD RegPat database is used for measuring both the networking capacity of OELRs as co-patenting activities from 2002 to 2008, and the innovation performance of lagging-behind regions as the 3-year lagged cumulative number of patents. Data from Eurostat are further collected to define the control variables more widely assumed by the literature on innovation.

Our findings are threefold. First, the innovation performance of the less innovative regions does not depend on the average size of inventors' networks (internal and external to the region) developed by local organisations. Second, the more the OELRs' collaborative networks are extended outside the region, the higher the level of regional innovation. Third, the more the OELRs' collaborative networks involve inventors from knowledge-intensive regions, the more innovative the lagging-behind region. This suggests that the quality and openness of collaborative networking are likely to be more important than network size.

The structure of the paper is as follows. The next section is devoted to the background literature and hypotheses building. We define and justify the main hypotheses linking regional innovation performance and collaboration networks in lagging-behind regions. In section 3, we address the methodology and, in the successive section, the main results are presented. Section 5 is devoted to discussing the results and implications for European regional innovation and cooperation policies. The last section is devoted to summarising the main conclusions, including some limitations.

2. Theory and hypotheses

The literature shows considerable evidence that the production of scientific and technological knowledge is increasingly considered a collective knowledge-driven process (Crescenzi et al., 2016), wherein knowledge is shared among a community of inventors who are often employed by organisations with competing intellectual property interests (Powell & Giannella, 2010), and wherein actors collaborate to combine organisation-internal and organisation-external knowledge.

The literature on inter-organisational knowledge transfer and knowledge spillovers has identified various formal and informal mechanisms for stimulating knowledge exchange and flows across organisations and regions. The former mainly involves joint research, licensing, acquisition of patents and consulting, the latter differently refers to social networks and non-contractual interactions (Cantner et al., 2010; Grimpe & Hussinger, 2013). The mixed mechanisms of knowledge spillover are labour mobility (Breschi & Lissoni, 2009) and spin-offs (Ponds et al., 2010), which could be both spontaneously developed or strategically encouraged. Each of these mechanisms enables organisations to access various external knowledge sources, increasing the opportunities for knowledge exchange, transfer and sharing, fostering knowledge spillovers and enhancing innovation performance at the organisational and regional levels (Asheim et al., 2011; Huggins & Thompson, 2014).

In addition, even though some studies have recently shown the complementary effect of the technological, social and organisational proximity to the geographical one (Paci et al., 2014), these mechanisms tend to stress the importance of the spatial proximity and the unequal level of innovativeness across regions (Chaminade & Plechero, 2015). Following these considerations, knowledge spillovers are often related to the structuring of regional innovation systems (Fritsch, 2000; Isaksen, 2001; Tödtling & Grillitsch, 2014; Tödtling & Trippl, 2005) and on the extent of the regional knowledge base (Asheim et al., 2011). The knowledge-intensive regions, in fact, are typically characterised by higher local public or private research and innovation-supporting services, investments and institutes/universities (Breschi & Lissoni, 2009) that facilitate and stimulate the local flows or exchanges of knowledge, resources and human capital, in order to promote the knowledge transfer, sharing, creation or recombination processes. Therefore, such an environment encourages organisations embedded in these elite regional innovation systems to network among themselves (Hoekman et al., 2009; Ter Wal & Boschma, 2009) and to benefit from local knowledge spillovers as undirected and spontaneous 'buzz' (Storper & Venables, 2004).

Conversely, lagging-behind regions are typically characterised by a lack of dynamic firms, organisational thinness, lowly specialised organisations, weak educational institutions, brain drain, loss of highly qualified personnel and weakly developed local networks (Tödtling et al., 2013). Here, spontaneous knowledge spillovers are limited. As a result, in lagging-behind regions where institutional systems are unable to foster local knowledge spillovers, OELRs must increase their collaboration processes in order to provide extra-organisational knowledge sources and better support the innovation processes of local firms. According to Wanzenböck et al. (2014), in fact, the knowledge creation success of regions depends not only on internal conditions but on the ability of local organisations to identify and access a diverse set of external knowledge sources, and on their ability to participate and position themselves in inter-organisational knowledge networks. Based on this issue, we can formulate the following wide hypothesis:

Hyp.1: The larger the collaborative inventors' network (number of nodes/inventors of the network) of organisations located in a lagging-behind region, the higher the number of innovations of that specific region.

In the last decade, several studies argued that both intra- and inter-regional extra-muros collaborations, as well as their balance (De Noni et al., 2017), enable organisations to exchange and combine knowledge across organisational and technological boundaries, and support organisations to improve innovation performance (Tsai, 2009). The effect of local networks has specifically been considered, for a long time, as being strongly related to spatial proximity because of the opportunity to better support interactive learning and innovation processes by providing actors with a shared base of collaborative links (Boschma, 2005). However, other types of proximity, such as cultural, cognitive, social or organisational proximity (Crescenzi et al., 2016), have recently been shown to be even more effective than geographical ones. Despite this consideration, local collaborations have still been expected to enable and boost network embeddedness and to strengthen social capital, stimulating the creation and development of a solid canvas of organisations and institutions (Fitjar & Rodríguez-Pose, 2013). Moreover, local ties are inclined to produce stronger and trusting relationships (Capaldo, 2007), which may decrease the cost of opportunism associated with the transmission and sharing of knowledge and interconnections for local organisations. Organisational and control criteria make it likely to be convenient for OELRs to support, in the short time, the development of intra-regional collaborations. Thus, we formulate the following hypothesis:

> *Hyp. 2: The higher the capacity of organisations located in a lagging-behind region to extend their collaborative networks to inventors of the same region, the higher the number of innovations of that specific region.*

Moreover, collaborative relationships with inventors embedded in other regional systems may foster access to a number of more diversified region-external knowledge sources, preventing firms and organisations from being locked into inferior technological paths of development (Broekel, 2012; Timmermans & Boschma, 2014). The lack of local spontaneous knowledge spillovers in knowledge periphery (Grillitsch & Nilsson, 2015) may lead organisations to build non-local pipelines to tap into knowledge from outside their region (Bathelt et al., 2004). Throughout the access to extra-region inventors' networks, firms and organisations may access and explore the potential embedded in different and diversified knowledge sources that, once transferred and integrated in the regional stock of knowledge, may give rise to new technological trajectories exploitable within the regional system (Sun, 2016; Zhao et al., 2015). In this way, extra-regional collaborations may enlarge the space of possibilities and identify new systems of use alongside the discovery of new functionalities and the recombination of new and old knowledge within a process of innovation cascades (Bonaccorsi, 2011; Lane, 2011). These considerations suggest that the innovation performance of a knowledge periphery may depend on the capacity of OELRs to promote and exploit formal and informal inter-regional collaborative links. Thus, we formulate the following hypothesis:

> *Hyp. 3: The higher the capacity of organisations located in a lagging-behind region to extend their collaborative networks to inventors outside the region, the higher the number of innovations of that specific region.*

In addition, because prolific inventors increase each other's productivity through collaboration innovation networks (Zhang et al., 2014), the linkages with inventors from knowledge-intensive regions (with a higher average productivity than inventors from knowledge periphery) is expected to enhance the innovation aggregated performance of OELRs. Similarly, Sebestyén and Varga (2013) observe that the quality of inter-regional knowledge networks in Europe is related to the level of knowledge accumulated by the partners in the networks, and consequently, the involvement of inventors from knowledge-intensive regions is likely to enhance access to a more broadly differentiated knowledge base. Finally, through collaboration with inventors from these knowledge-intensive regions, OELRs are, indirectly, also entitled to have access to the innovation support services they need for upgrading their technological assets and that are missing in the local regional environment (Graf & Henning, 2009; Pekkarinen & Harmaakorpi, 2006). In summary, the ability to create relationships with inventors embedded in innovation-intensive regions can grant access to a high quality and diversified knowledge base and compensate for the lack of local institutional support (Sun & Cao, 2015). Thus, hypothesis 3 should hold:

Hyp. 4: The higher the capacity of organisations located in lagging-behind regions to extend their collaborative networks to inventors of knowledge-intensive regions, the higher the number of innovations in that specific region.

3. Methodology

3.1 Setting and Data

As emphasised in the Introduction section, the measurement of collaboration and the mapping of lagging-behind regions are the critical elements of this study.

Firstly, collaboration is defined as a collaborative network of inventors and measured through co-patenting activities by using data about patents granted by the European Patent Office (EPO) and relative inventors per year and region, as provided by the OECD-RegPat database (release version February 2015). The RegPat database is organised so as to merge information about patents (i.e., identification number of patent, international patent classes, priority year), inventors (name and address of inventor) and applicants (name and address of organisation or of inventor if the patent is a personal patent). The dataset also provides the inventor (Inv_{share}), region (Reg_{share}) and applicant (App_{share}) shares per patent, allowing the user to specify if a patent is a co-invented patent involving multiple inventors, if an inventor is registered in different regions or if a patent is a co-applicant patent assigned to more inventors or organisations[1]. A general cleaning process was applied to make the dataset more effective. Because we are looking at knowledge flows across European regions, only EPO patents with at least one European inventor (based on the inventor's address

[1] *Reg_share* and *Inv_share* are directly provided by the RegPat database. *Inv_share* is 1 if the patent has a unique inventor, while it is less than 1 when the patent is co-invented. Thus, if a patent has more than one inventor, each is weighted equally based on the number of inventors. Similarly, *App_share* is less than 1 when the patent has co-applicants. *Reg_share* is less than 1 if the inventor has multiple address registrations due to the regionalization procedure applied in RegPat, which could be based on postal code, town name or mixed methods. When unique assignment is not possible, the same inventor is allocated to different regions, each having a regional share (where the sum is 1).

registered by European Patent Office) were considered. Moreover, data concerning 'not classified' regions were deleted.

Secondly, an original setting of 284 NUTS-2 (NUTS version 2010) regions of the EU-28 member states (plus Norway and Switzerland) is used to identify a map of lagging-behind and knowledge-intensive regions. Two alternative classification methods have been adopted in order to achieve more robust findings.

The first method focuses on the patenting activities of European regions because of the specific relevance of patents as a result of the organisations' innovation process. In this case, based on the quartile distribution of their cumulated patenting activities in a 30-year range of time (from 1980 to 2010), European regions were clustered in knowledge-intensive (the last quartile) and more, moderate and less innovative lagging-behind regions (respectively the third, second and first quartiles).

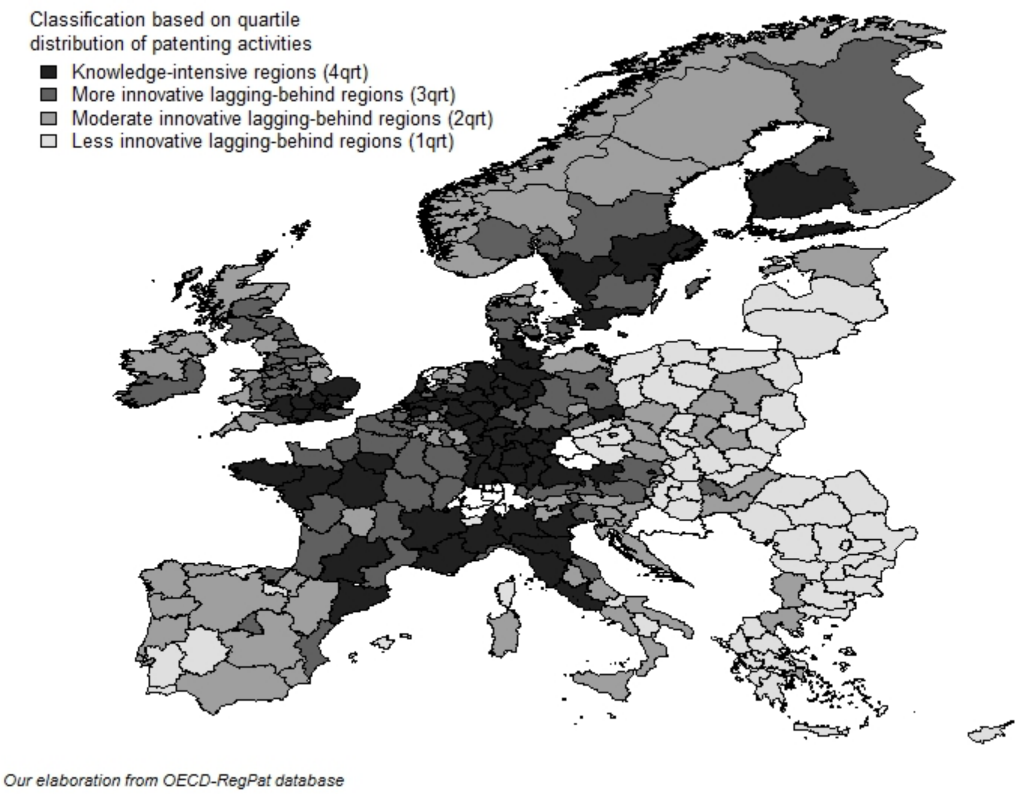

Figure 1 – Map of the sampled lagging-behind and knowledge-intensive regions based on the quartile patent distribution

Figure 1 shows the four clusters. In this step, individual and collaborative patents were assigned at the regional level by using inventors' addresses. Moreover, fractional counting is applied in case a patent has several inventors coming from more than one region (*Inv_share*) and in case an inventor's address could not be allocated to a unique NUTS2 region (*Reg_share*). Hence, the total weighted patent contribution per region *r* and per year *t* is counted as follows:

$$Number\ of\ patents_{r,t} = \sum_{r,t} \sum_{i} Inv_{share} * Reg_{share}$$

where Inv_{share} is the share that inventor i is involved in the creation of the patent, and Reg_{share} is the share that inventor *i* is registered in different regions.

The second method is based on the classification of innovative European regions provided by the European Commission through the Regional Innovation Scoreboard (RIS). The RIS is a composite index which integrates data from Eurostat (share of population aged 25-64 having completed tertiary education, R&D expenditures in the public and business sector, EPO patent applications, and Employment in medium-high/high tech manufacturing and knowledge-intensive services), European Commission reports (exports of medium and high tech products) and the Community Innovation Survey (CIS) (Non-R&D innovation expenditure by Small and Medium Enterprises (SMEs), SMEs innovating in-house, innovative SMEs collaborating with others, SMEs with product or process innovation, SMEs with marketing or organisational innovations and sales of new-to-market and new-to-firm product innovations by SMEs). According this classification, European regions are defined as Innovation Leaders, Strong Innovators, Moderate Innovators and Modest Innovators (European Commission, 2016).

If compared to the previous method, this classification considers not only the patenting activities but multiple forms of innovation. However, the RIS shows some weaknesses. It is collected only every two years (starting from 2008), data are not provided at the NUTS2 level for each region, and finally, data coming from the CIS are limited to a sample of small and medium local enterprises.

Operationally, we use the classification provided by the RIS in 2008 because it is more consistent with the period of analysis (from 2002 to 2008, as defined below). Moreover, in case only NUTS1 data are provided, we extend the classification at the NUTS2 regional-level. *Figure 2* shows the four RIS-based clusters.

The patent intensity by region indicator shows the existence of a highly concentrated core of innovative regions in the EU, along the densely urbanised region known as the 'Blue Banana', which starts in South England, descends through Germany, Switzerland, South East France, and Northern Italy. In addition, three newly urbanised spots are emerging in Europe: a) regions in the South of Sweden and Finland; b) some central regions of France (around Paris and, more recently, the area that connects Paris to the Brittany, and, finally, c) the areas belonging to the South of France (Provence, Rhone-Alps and Mid-Pyrenees, including Toulouse), recently Catalonia (centred in Barcelona) and Lazio (in Italy). The classification based on the RIS confirms the relevance of

South Germany and of some Scandinavian regions. Conversely, the main difference concerns Northern Italy, Southern England and some French regions.

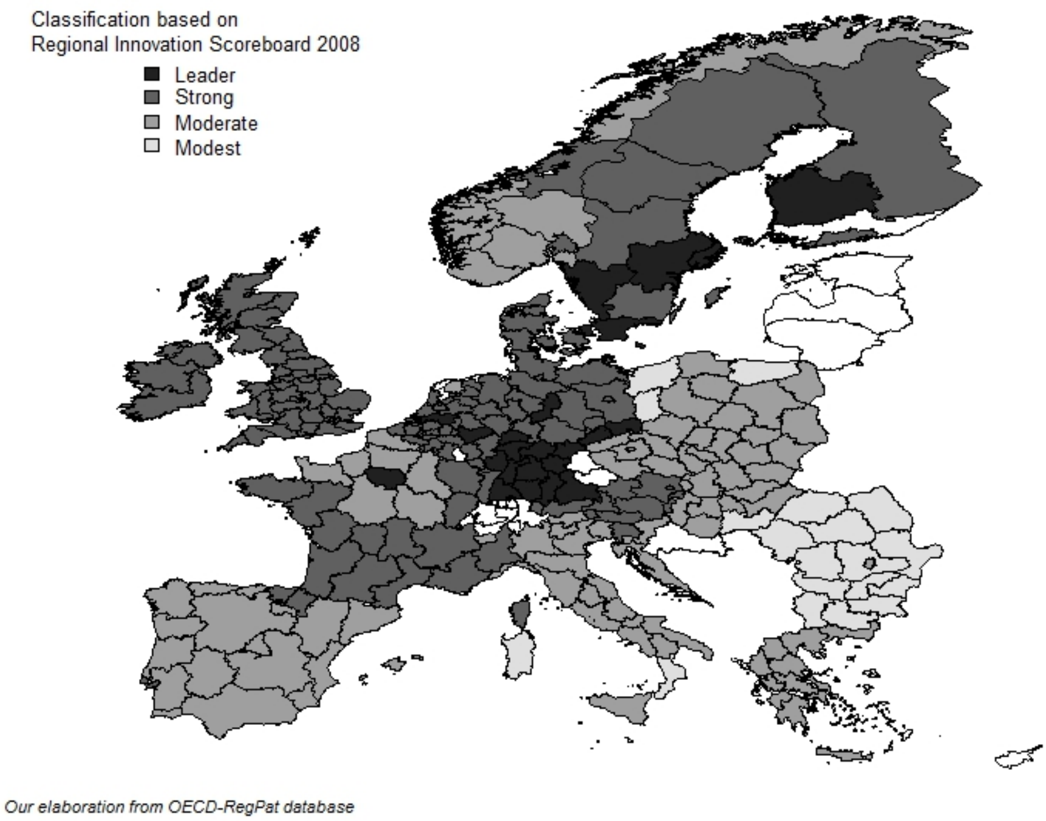

Figure 2 – Map of the sampled lagging-behind and knowledge-intensive regions based on the RIS 2008 distribution

Using both of the two classification methods, OELRs are defined as peripheral organisations (considering firms, universities or other R&D centres) addressed in lagging-behind regions (according to the address of the organisation's office) and applicants for at least one patent from 2002 to 2008. In this step, the OELRs' networking capacity was specifically measured based on the number and the address of inventors involved in the organisations' co-patenting activities. In other words, we only considered patents associated with an organisation embedded in a lagging-behind region and involving multiple inventors.

Data from Eurostat were further collected in order to define some typical control variables, such as GDP per capita, R&D expenditures or human capital. Because of missing data[2], 15 regions (the seven Swiss regions, the four French regions of Départements d'outre-mer, the German regions of Niederbayern and Oberpfalz, Kontinentalna Hrvatska in Croatia and South Finland) are deleted. Thus, the final sample of European regions is limited to 269.

Finally, a seven-year panel database involving only European lagging-behind regions (the number

[2] The lack of data may be primarily due to mergers between pre-existing regions, changes of borders, changes of NUTS code and non-availability of data.

of regions depending on the classification method is shown in Tables 3, 4, A1 and A2) was organised and a time-fixed effect panel regression model was implemented to exclude bias arising from the global crisis.

3.2 Variables

Dependent variable

Innovation performance of lagging-behind regions (INN.PERF). The innovation performance depends on the capacity of a region to create new knowledge by exploiting existing internal and external knowledge stock (Tavassoli & Carbonara, 2014). It is typically measured as the regional patenting capacity. Patents have been found to be a good proxy for innovative activity at a regional level (Acs et al., 2002) and a three-year lag is a good proxy to measure the lagged effect of the invention process (Castaldi et al., 2015). Hence, the innovation performance is operationalised as the regional cumulative number of patents per million inhabitants over a shifted window over the subsequent three years (e.g. with reference to 2008, the measure covers the period 2009-2011). As argued above, the regional cumulative number of patents is the result of a fractional counting process which considers both inventor and region share. A logarithmic transformation is finally adopted to linearise the variable and reduce its skewness.

Exploratory variables

Density of collaborative networks (DNS.NET). The density of the collaborative network is measured as the average number of inventors involved in collaborative patents by peripheral organisations. In other words, it defines at the regional level the capacity of OELR in developing small or large-sized collaborative inventors' networks and thus the regional potential to exploit socialization mechanisms for fostering knowledge transfer and creation processes.

Rate of local inventors (LOC.INV.RATE) represents the average capacity of peripheral organisations to extend their innovation networks by involving inventors of the same region. It is operationalised as the ratio between the number of local inventors involved in the OELR's collaborative patents and the total number of inventors involved in the same patents; the higher the ratio, the higher the invention potential based on local opportunities.

Rate of external inventors (EXT.INV.RATE) represents the average capacity of organisations at the regional level to promote and support inter-regional knowledge flows by developing collaborations with inventors from both knowledge-intensive and other lagging-behind regions. It is operationalised as the ratio between the number of external inventors from European regions (outside the focal region) involved in the OELR's collaborative network and the total number of inventors belonging to its network. The higher the rate of external inventors, the more open and globally larger the average networking capacity of peripheral organisations. The rate of external inventors is expected to positively affect the innovation performance of lagging-behind regions. Lower values may suggest a lack of networking activities or a propensity to develop primarily intra-regional collaborations.

Rate of inventors of European core regions (CORE.INV.RATE) represents the average capacity of organisations at a regional level to extend their innovation networks by involving inventors from knowledge-intensive regions. It is measured as the rate of inventors from knowledge-intensive regions with respect to the total number of external inventors involved in OELRs' collaborative patents per region. The higher the rate, the higher the invention potential and opportunities of regions in absorbing and utilizing knowledge from core regions.

Control variables

Business density (BUS.DEN) is measured as the number of organisations embedded in lagging-behind regions divided by the population of the region. The number of OELRs per capita is expected to be related to the potential innovative capacity of regions because of the role played by organisations in financing, promoting and supporting patent creation and opportunities to activate and exploit network collaborations and externalities (Trigilia, 1992; Wanzenböck et al., 2014).

GDP per capita (GDP.PC). Gross domestic product is an indicator of the output of a country or a region. It reflects the total value of all goods and services produced minus the value of goods and services used for intermediate consumption in their production. Thus, as a proxy of the wealth of a region, it reflects the availability of financial resources to support regional development, including R&D investments (Le Gallo & Ertur, 2003). GDP per capita allows the comparison of regional economies significantly different in absolute size. We operationalised this variable as a dichotomic variable (0 is equal to or below the average value and 1 is above the average value) to avoid unnecessary multicollinearity with R&D expenditure or number of OELRs.

R&D expenditures (R&D.EXP). Gross domestic expenditure on Research & Development (R&D) as a percentage of gross domestic product (GDP) is an indicator of high political importance at the EU, national and regional levels. R&D intensity is expected to have a positive impact on innovation because of the positive correlation existing between technological input and output (Castaldi et al., 2015; Gilsing et al., 2008; Marrocu et al., 2013).

Technological diversification (*TCN.DIV*). Technological diversification is adopted as a proxy for regional knowledge variety (Boschma et al., 2012; Castaldi et al., 2015; Frenken et al., 2007). It measures the distribution of regional patents across patent technological classes using the International Patent Classification (IPC). It is operationalised using the Shannon entropy index at the four-digit IPC classes' level. The higher the index, the more diversified the regional patent distribution across the IPC classes. Conversely, specialised innovation regional systems should show lower index values. In this case, we expect that a broader knowledge base has a positive impact on innovation performance. An average value is calculated at the regional level per year.

Human capital (*HUM.CAP*). Because the attitude of a region to innovate depends on the average level of human capital within the local economy (Lee et al., 2010), tertiary educational attainment is used as a proxy for human capital; the higher the educational level, the higher the potential number of inventors. The indicator is defined as the percentage of the population aged 25–64 who have successfully completed tertiary studies (e.g., university, higher technical institution, etc.) (Marrocu et al., 2013). The indicator is provided by Eurostat and is based on the EU Labour Force Survey. Specifically, educational attainment refers to ISCED (International Standard Classification of Education) 1997 level 5–6 for data until 2013.

Manufacturing specialisation (MAN.SPC). We introduced manufacturing specialisation to control for the sectoral effect on innovation performances. Because sectors have different technology and innovation opportunities, and manufacturing is typically more inclined to innovate than services (Hipp & Grupp, 2005; Marrocu et al., 2013), manufacturing specialisation is introduced as the control. Specifically, the manufacturing concentration index is operationalised as the share of regional employees operating within the manufacturing industry with respect to the total number of regional employees.

Population density (POP.DEN) is measured as the logarithm of the population density (population is divided by land area in square kilometres). It is usually applied as a proxy for externalities related to the urbanisation process. Urbanisation is expected to be positively associated with the presence of universities, industry research laboratories, trade associations and other knowledge-generating organisations (Audretsch & Feldman, 1996; Frenken et al., 2007). Thus, urbanisation of economies may better support regional innovation performance.

European funds per capita (EU.FUND). The European Regional Development Fund and the Cohesion Fund had a combined budget of € 160 billion for the years 2000–2006. The aim of these funds was to support economic development across all EU countries and regions. We operationalised this variable using only the portion of funds allocated to the R&D category divided by the population as a dichotomic variable (0 is equal to or below the average value and 1 is above the average value) to avoid unnecessary multicollinearity with other variables. We expect that this variable positively affects the regional ability to generate higher innovation performance (Mohl & Hagen, 2010; Rodriguez-Pose & Fratesi, 2004).

Number of neighbouring core regions (CORE.REG). The number of neighbouring knowledge-intensive regions is used to control for the spatial effect of being located in the proximity of highly innovative regions. It serves as a proxy to capture the impact of the spatial spillovers on the regional innovation performance (Capello, 2009; Corrado & Fingleton, 2012).

3.3 Model

Our dependent variable measures innovation performance by computing the fractionalised number of patents each European lagging-behind region filed in a given year. Because the dependent variable (INN.PERF) is a continuous variable, it excludes the possibility of using models for count data, such as Poisson or negative binomial, traditionally used in innovation performance contexts; consequently, a linear panel model specification is recommended.

After running poolability tests (F-test) and checking for the presence of random effects (Hausmann test), we adopted a fixed effect model with time effects because we expect a significant effect over time on regional innovation performance related to the financial crisis in 2007/2008. In addition, innovation diffusion in European regions is not likely to be randomised; rather, it is expected to be influenced by observed and latent time-invariant territorial features. Moreover, fixed effect models are the safest choice to eliminate possible omitted variables bias. We also used a logarithmic transformation of the dependent variable to linearise the variable.

These considerations are reflected in the following regression equation:

$$y_{i,t} = a_t + \boldsymbol{X}_{i,t}\beta + \epsilon_{i,t} \quad for\ t = 1, \ldots, 7\ and\ i = 1, \ldots, 205$$

where $y_{i,t}$ is the dependent variable observed for individual i at time *t*, $\boldsymbol{X}$ is time-variant *1 * K* regressor matrix, β represents the vector of the coefficients, a_t is the unobserved individual-invariant time effect and $\epsilon_{i,t}$ is the error term.

In order to make the results more robust, the model is further verified on a different sampling of peripheral regions as mentioned above. Specifically, the analysis of all lagging-behind regions, as defined in the three quartiles by the classification method based on cumulative patenting, and the analysis of the moderate and modest innovator regions, as identified by the Regional Innovation Scoreboard 2008, are both discussed in the paper. However, the analysis results based on different cut-off points, such as the first two quartiles and the first quartile only of the first classification method are also shown in the appendix.

In addition, clustered robust standard errors are also introduced to control for heteroscedasticity. As suggested by Bester et al. (2011), in the case of nested data, clustered robust standard errors should be computed at the highest level of aggregation (in our case at country level) to be conservative and

avoid bias. We similarly ran clustered robust standard errors at a regional level and Arellano-Bond robust standard errors, but we found no significant difference in the results.
Finally, tests based on adjusted R-squared, F-statistics and the residual sum of squares are used to assess the goodness of fit of the models and to compare the performance of nested models.
All estimates are obtained by using the package *plm* in R (version 3.3.1).

4. Results

Descriptive statistics and the correlation matrix are shown in Tables 1 and 2[3], respectively. Data show that the independent variables are tightly correlated to the dependent variable innovation performance (*INN.PERF)*. The correlation values among explanatory and control variables are relatively low; thus, no serious collinearity problems are expected. Collinearity is further supported by measuring the variation inflation factors (VIFs) for each model (see Tables 3 and 4) and was found not to be a problem, with the VIF values below the cut-off point of 5 (O'Brien, 2007).

Table 1 – Descriptive statistics (based on the first three quartile distribution)

	Variable	Mean	Std.dev	Coef.var	Min	Max
1	*INN.PERF (log)*	1.80	0.74	0.41	-0.75	3.26
2	*DNS.NET*	2.42	2.03	0.84	0	20
3	*LOC.INV.RATE*	0.51	0.37	0.71	0	3.5
4	*EXT.INV.RATE*	0.35	0.25	0.74	0	1
5	*CORE.INV.RATE*	0.17	0.20	1.18	0	1
6	*BUS.DEN *1000*	0.02	0.02	1.21	0	0.21
7	*GDP.PC (dummy)*	0.48	0.50	1.03	0	1
8	*R&D.EXP*	1.07	0.98	0.92	0.06	13.73
9	*TCN.DIV*	3.02	1.29	0.43	0	4.88
10	*HUM.CAP*	21.85	8.28	0.38	6.1	48.6
11	*MAN.SPC*	17.57	6.52	0.37	3.7	36.8
12	*POP.DEN (log)*	4.74	1.13	0.24	1.19	8.79
13	*EU.FUND (dummy)*	0.27	0.44	1.66	0	1
14	*CORE.REG*	0.70	1.17	1.67	0	6

From Tables 1 and 2, we can derive some interesting insights. First, the local inventor rate is higher when technological diversification in the region is high. Second, networks with external inventors and networks with core region inventors are positively correlated; in contrast, local networks and external networks are negatively correlated, to highlight a polarization of regional networks towards

[3] We report only the results of the quartile distribution for Tables 1 and 2 (the first three quartiles), because the RIS-based distribution results are very similar.

a specific model of collaboration. Third, the core inventor rate is higher where there is a neighbouring core region; this implies that proximity distance still matters.

Tables 3 (using the first three quartiles' cut-off on patent distribution) and 4 (using the RIS-based distribution cut-off) provide the results of the panel regression analysis based on the model specifications mentioned before. They specifically report the mean-centred standardized coefficients to better appreciate the actual significance of the variables and the robust country-level clustered standard errors in parentheses.

As a base model against which to compare our results, we first present the outcome with only the control variables. Models 1a and 1b present the estimates of the coefficients of the control variables. The density of organisations embedded in lagging-behind regions *(BUS.DEN)* has a significant ($p<0.001$ in mod1a and $p<0.001$ in mod1b) effect on *INN.PERF*. Thus, we can affirm that the larger the density of organisations located in the region, the higher the opportunity to activate networks for supporting and stimulating innovation processes at a regional level.

As expected, the GDP per capita ($p<0.01$ in mod1a and $p<0.05$ in mod1b) and the intensity of *R&D* expenditure ($p<0.01$ in mod1a and $p<0.001$ in mod1b*)* are positively and significantly correlated on *INN.PERF*. A GDP per capita higher than the average of the peripheral regions and a greater capacity to invest in R&D can lead to extremely favourable conditions for creating collaborative networks and achieving higher innovation performance, which surpasses that of regions without the same starting assets.

Furthermore, another important condition for innovation performance seems to be the technological diversification (*TCN.DIV*) of the region's knowledge base ($p<0.001$). Thus, we confirm that the technological variety of a region is a fundamental determinant of regional knowledge productivity (Basile et al., 2012; Boschma, 2005; Bottazzi & Peri, 2003).

The effect of the regional stock of human capital (*HUM.CAP*) shows differences across models. If it is positive for lagging-behind regions sampled in the first three quartiles (Table 3), it is inclined to be insignificant, but always positive, by referring to regions identified through the RIS-based cut-off (Table 4). Anyway, the presence of a well-educated labour force is commonly expected to be a critical factor in stimulating the innovative activities of regions.

To check for sectoral effects, we introduce the variable *manufacturing specialisation*. The manufacturing specialisation (*MAN.SPC*) of regions does not have a significant ($p>0.05$ in both models) effect on the innovation performance of peripheral regions.

Table 2 – Correlation matrix (based on the first three quartiles distribution)

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	*INN.PERF (log)*	1													
2	*DNS.NET*	0.33**	1												
3	*LOC.INV.RATE*	0.39**	0.11**	1											
4	*EXT.INV.RATE*	0.34**	0.34**	-0.66**	1										
5	*CORE.INV.RATE*	0.41**	0.35**	-0.05	0.45**	1									
6	*BUS.DEN*	0.69**	0.20**	0.16**	0.29**	0.27**	1								
7	*GDP.PC (dummy)*	0.53**	0.15**	0.14**	0.17**	0.16**	0.57**	1							
8	*R&D.EXP*	0.56**	0.30**	0.16**	0.17**	0.22**	0.47**	0.37**	1						
9	*TCN.DIV*	0.84**	0.36**	0.47**	0.29**	0.39**	0.53**	0.40**	0.49**	1					
10	*HUM.CAP*	0.57**	0.27**	0.16**	0.21**	0.14**	0.43**	0.45**	0.52**	0.49**	1				
11	*MAN.SPC*	-0.08**	-0.02	0.11**	-0.10**	-0.10**	-0.12**	-0.19**	-0.14**	0.01	-0.33**	1			
12	*POP.DEN (log)*	0.16**	0.23**	-0.02	0.25**	0.17**	0.11**	0.12**	0.15**	0.31**	0.15**	-0.02	1		
13	*EU.FUND (dummy)*	0.00	-0.01	0.15**	-0.08**	0.01	-0.12**	-0.17**	-0.01	0.06*	0.07**	-0.22**	-0.05	1	
14	*CORE.REG*	0.46**	0.12**	0.16**	0.11**	0.40**	0.29**	0.24**	0.19**	0.43**	0.00	0.09**	0.07**	-0.15**	1

Significant levels are ** $p < 0.01$, * $p < 0.05$

Surprisingly, but in line with other recent studies (Dijkstra et al., 2013; Marrocu et al., 2013; McCann, 2013), population density *(POP.DEN)* is negative and significant ($p<0.01$ in mod1a and $p<0.05$ in mod1b) in all models. Even though urbanisation economies are expected to better support the regional innovation performances, in largely populated areas negative externalities may be due to congestion costs, unskilled workers and immigrant inflows rather than talents, oversupply of labour, higher cost of living and insufficient infrastructure investments (Dijkstra et al., 2013).

The dummy variable *European funds per capita (EU.FUND)* allocated for R&D does not seem to have a significant effect, in both models, on improving peripheral regions' innovation performance. This may depend on how these development funds are effectively used in the real economy context of these regions. Future research should investigate more effective policies for using these development funds to driven innovation processes.

Finally, the importance of spatial proximity on the knowledge performance of regions is confirmed by the positive and significant ($p<0.001$ in mod1a and $p<0.001$ in mod1b) coefficient of the *number of neighbouring core regions* variable *(CORE.REG).* Several regional studies relying on notions of spatial interaction, diffusion effects, hierarchies of place and spatial spillovers strongly argue that being part of a highly innovative geographical context supports collaboration networks and knowledge productivity of regions (Basile et al., 2012; Capello, 2009; Marrocu et al., 2013; Ponds et al., 2010).

Models 2a and 2b introduce *density of collaborative networks (DNS.NET)* in order to test the first hypothesis (Hyp. 1). A positive but not statistically significant effect ($p>0.05$) of the density of collaborative networks *(DNS.NET)* on regional innovation performance is detected in both models. Contrary to expectations, we cannot affirm with statistical significance that OELRs with larger collaborative inventors' networks are able to better manage creative production processes and generate new knowledge in a more efficient way (Fleming et al., 2007). Thus, our Hyp. 1 is not confirmed.

Models 3a and 3b show the effect of *local inventors rate (LOC.INV.RATE)* on innovative regional performance to check our second hypothesis (Hyp. 2). Both models pinpoint a positive but not statistically significant effect ($p>0.05$) of the engagement rate of local inventors *(LOC.INV.RATE)* on regional innovation performance. This means that the development of local networks does not necessary support the knowledge creation process in lagging-behind regions and thus, the Hyp. 2 is not confirmed. However, in spite of such a result, we trust that local network plays a relevant role in fostering knowledge sharing and innovation and its insignificance may depend on other regional features, such as the organisational and institutional thinness of the region (Rodríguez-Pose & Di Cataldo, 2015) or the low internal technological variety (De Noni et al., 2017).

Models 4a and 4b provide support for our third hypothesis (Hyp. 3). Higher values of the rate of external inventors *(EXT.INV.RATE)* have a positive and significant (*p<0.001* in mod4a and *p<0.05* in mod4b) effect on the invention productivity of the lagging-behind regions. Therefore, the higher the organisations' ability to encourage and support inter-regional knowledge flows and collaborative networks with other regions, the higher the potential to generate new inventions at a regional level. Hyp. 3 is confirmed.

Models 5a and 5b highlight that the involvement rate of inventors from European knowledge-intensive regions (*CORE.INV.RATE*) is a significant (*p<0.001* in mod5a and *p<0.001* in mod5b) and positive driver of regional *innovation performance* (*INN.PERF*). The higher the OELRs' capacity to involve inventors from knowledge-intensive regions, the higher the regional ability to generate innovations. Hyp. 4 is confirmed, too.

Consequently, although proximity and local networks may help inventors to connect and interchange knowledge, regions locked in local enclaves, based only on local and close networks, might harm their innovative performance (Broekel & Boschma, 2012; Marrocu et al., 2013).

The robustness of our results is additionally tested by using alternative model cut-offs, such as the first two quartiles and only the first quartile (as identified by the quartile-based classification method we have described above). Results are reported in the appendix (see Tables A1 and A2). The findings appear to be consistent with respect to Tables 3 and 4. Only in Table A2, focusing on regions belonging to the first quartile, were found some appreciable differences related to our hypotheses. *DNS.NET* is positive but also significant (*p<0.001*), while EXT.INV.RATE becomes insignificant. We discuss the reasons for these differences in the next section.

Table 3 – Results of Fixed effect regression models (based on the first three quartiles distribution)

Dependent variable - Innovative performance (first three quartiles)	*Panel fixed effect models*				
	Mod. 1a	*Mod. 2a*	*Mod. 3a*	*Mod. 4a*	*Mod. 5a*
Explanatory variables					
DNS.NET		0.03 (0.016)			
LOC.INV.RATE			0.033 (0.018)		
EXT.INV.RATE				0.079 (0.021)***	
CORE.INV.RATE					0.059 (0.016)***
Control variables					
BUS.DEN	0.227 (0.057)***	0.228 (0.058)***	0.229 (0.056)***	0.212 (0.058)***	0.222 (0.055)***

GDP.PC (dummy)	0.201 (0.063)**	0.202 (0.062)**	0.197 (0.063)**	0.204 (0.062)***	0.208 (0.062)***
R&D.EXP	0.064 (0.023)**	0.06 (0.023)**	0.066 (0.023)**	0.068 (0.023)**	0.062 (0.023)**
TCN.DIV	0.555 (0.041)***	0.548 (0.041)***	0.535 (0.04)***	0.542 (0.04)***	0.54 (0.041)***
HUM.CAP	0.138 (0.038)***	0.135 (0.038)***	0.139 (0.038)***	0.135 (0.037)***	0.141 (0.038)***
MAN.SPC	-0.001 (0.025)	-0.002 (0.025)	-0.005 (0.026)	0.006 (0.025)	0.007 (0.025)
POP.DEN	-0.079 (0.024)**	-0.083 (0.025)***	-0.073 (0.025)**	-0.094 (0.022)***	-0.083 (0.024)***
EU.FUND (dummy)	0.043 (0.053)	0.047 (0.053)	0.032 (0.053)	0.061 (0.053)	0.042 (0.053)
CORE.REG	0.131 (0.027)***	0.131 (0.027)***	0.133 (0.027)***	0.132 (0.026)***	0.114 (0.026)***
No. of observationss	1435	1435	1435	1435	1435
EU NUTS-2 regions	205	205	205	205	205
No. of years	7	7	7	7	7
Residual Sum of Squares	238.38	237.36	237.31	230.86	234.65
Adj. R squared	0.831	0.832	0.832	0.836	0.834
F-stat	789.52***	713.76***	713.94***	737.84***	723.64***
Mean VIF	1.624	1.596	1.667	1.595	1.620
Max VIF	2.368	2.434	2.896	2.399	2.444

Notes: Robust clustered standard errors are in parentheses. Mean centred standardized coefficients are provided. Significant levels are *** p<0.001, ** p<0.01, * p<0.05

Table 4 – Results of Fixed effect regression models (based on the RIS2008 distribution)

Dependent variable - Innovative performance (RIS distribution)	*Panel fixed effect models*				
	Mod. 1b	*Mod. 2b*	*Mod. 3b*	*Mod. 4b*	*Mod. 5b*
Explanatory variables					
DNS.NET		0.037 (0.019)			
LOC.INV.RATE			0.032 (0.022)		
EXT.INV.RATE				0.052 (0.026)*	
CORE.INV.RATE					0.061 (0.017)***
Control variables					
BUS.DEN	0.207 (0.042)***	0.217 (0.042)***	0.206 (0.042)***	0.212 (0.041)***	0.208 (0.042)***
GDP.PC (dummy)	0.255 (0.103)*	0.255 (0.102)*	0.254 (0.103)*	0.252 (0.102)*	0.256 (0.102)*
R&D.EXP	0.13 (0.038)***	0.126 (0.037)***	0.132 (0.038)***	0.121 (0.038)***	0.129 (0.037)***

TCN.DIV	0.541 (0.053)***	0.525 (0.052)***	0.523 (0.05)***	0.538 (0.053)***	0.539 (0.053)***
HUM.CAP	0.02 (0.038)	0.02 (0.038)	0.019 (0.038)	0.026 (0.037)	0.02 (0.038)
MAN.SPC	0.007 (0.033)	0.006 (0.033)	0.005 (0.033)	0.007 (0.033)	0.007 (0.034)
POP.DEN	-0.056 (0.029)*	-0.06 (0.029)*	-0.054 (0.029)*	-0.061 (0.03)*	-0.056 (0.03)*
EU.FUND (dummy)	0.087 (0.072)	0.093 (0.073)	0.078 (0.074)	0.091 (0.073)	0.088 (0.073)
CORE.REG	0.137 (0.026)***	0.14 (0.026)***	0.138 (0.026)***	0.13 (0.025)***	0.136 (0.026)***
No. of observationss	826	826	826	826	826
EU NUTS-2 regions	118	118	118	118	118
No. of years	7	7	7	7	7
Residual Sum of Squares	150.11	149.20	149.56	148.01	147.9
Adj. R squared	0.814	0.815	0.814	0.816	0.819
F-stat	402.93***	364.87***	363.79***	368.47***	369.27***
Mean VIF	1.963	1.927	1.97	1.881	1.916
Max VIF	3.210	3.442	3.687	3.212	3.302

Notes: Robust clustered standard errors are in parentheses. Mean centred standardized coefficient are provided. Significant levels are *** p<0.001, ** p<0.01, * p<0.05

5. Discussion and conclusion

The extent to which the innovation performance of lagging-behind regions positively depends on the capacity of the local innovative organisations to activate collaborative inventors' networks seems to be related not so much to size as to the interregionality of the networks. Specifically, despite network density and openness, the involvement of inventors from knowledge-intensive regions plays a critical role.

The insignificant effect of network density suggests that regional innovation performance does not depend on the number of inventors involved in OELRs' co-patenting, but is more likely to be on the OELRs' propensity for extending their collaboration networks outside the region. The involvement of external (non-local) inventors, and, even more so, of inventors from knowledge-intensive regions, seems to better sustain higher regional innovation performance. This leads to the following considerations. First, the openness more than the size of collaboration networks fosters access to diversified knowledge sources and increases the opportunities for knowledge exchange, recombination, and spillovers. However, density remains important for the less developed regions included in the first quartile because a potential critical mass needs to be achieved in order to be attractive and stimulate the collaboration opportunities. Second, the involvement of inventors from knowledge-intensive regions, who are potentially more prolific than inventors from lagging-behind regions, is inclined to increase the productivity of connected inventors (Zhang et al., 2014). Third, because inventors in knowledge-intensive regions tend to have access to more pipelines and personal relationships (Lorenzen & Mudambi, 2013), this interconnectivity facilitates indirect access to more dispersed international networks, and produces additional knowledge spillover opportunities. In other words, inventors from knowledge-intensive regions may play an intermediating role in sustaining the global knowledge flows of OELRs. Fourth, interconnectivity with knowledge-intensive regions also enables OELRs to access external research and innovation, in order to compensate for regional organisational thinness (Grillitsch & Nilsson, 2015).

This study stresses that collaboration *per se* does not necessarily contribute to increasing EU cohesion at the regional level. The integration of cohesive and development strategies in less innovative regions needs to be promoted by stimulating linkages across regions (specifically with knowledge-intensive regions) and by sustaining and fostering the improvement of institutional frameworks. In this regard, two biases must be overcome: a) the propensity towards domestic collaboration, and b) the propensity of knowledge-intensive regions to network among themselves. Looking at the former, several studies argue the risk of lock-in, when proximal relationships are overly developed in the long run (Boschma, 2005; Nooteboom, 2000). There is evidence of the significant role that non-localised extended networks play in knowledge-intensive environments (Broekel & Boschma, 2012). Regarding the latter, even though the importance of spatial proximity is decreasing, some degree of organisational, technological, cultural and social proximity is required to make the collaboration process effective and productive (Crescenzi et al., 2016). The lagging-behind regions may be considered excessively distant for developing sustainable collaborations and consequently, incentives for collaboration should be provided to encourage their involvement in extended networks.

The increasing availability of financial resources, as a result of increasing EU funds for less innovative regions, is not enough to reduce the gap between the core and the periphery. The European innovation paradox highlights the fact that an increase in R&D expenditure in the peripheral regions has not yielded the expected socio-economic benefits. Similarly, even though the European Commission has implemented inclusive policies to promote inter-regional collaboration and linkages between peripheral and core regions, the success of such funding and policies has so far been limited. This suggests that the European innovation policies in the periphery areas need to be rethought in order to better acknowledge the importance of territorial specificity and to be adapted according to the specific conditions of each territory. In this regard, the European policies for stimulating innovation in lagging-behind regions must promote and address the integration of the territory and its actors into extended networks and global value chains in order to foster the creation of 'pipelines' that encourage the inflow of new knowledge. Collaboration with knowledge-intensive regions is a particularly important condition for OELRs and is even more critical if related to local inefficient institutional structures and organisational thinness.

Our analyses suggest that European Commission should implement policies focusing on organisational and institutional improvements and incentives for stimulating inter-organisational collaborations between lagging-behind and knowledge-intensive regions. On the one hand, lagging-behind regions are required to enhance the quality of government in order to create a more favourable environment for supporting networking and innovation activities of local organisations (Rodriguez-Pose & Di Cataldo, 2015). A more competitive local environment enables OELRs to be potentially more attractive partners for collaborative projects involving organisations from knowledge-intensive regions; especially, for those OELRs with a wider inter-regional collaboration network. The extent of networking needs to be stressed at both an organisation and a region level to increase the opportunities for developing links outside the region. Informal more than formal socialization mechanisms, such as participation in conferences, workshops or fairs may be crucial to increase the international visibility of OELRs. On the other hand, some form of incentive should be devised in order to encourage the governmental institutions in knowledge-intensive regions to define inter-regional agreements, with corresponding actors in lagging-behind regions, which may then increase the partnership opportunities by balancing trust-based and control-based benefits in order to moderate the risk of opportunistic behaviours (Zwikael & Smyrk, 2015). Similarly, organisations in knowledge–intensive regions should be stimulated to activate formal socialization mechanisms, such as labour mobility programmes, collaborative projects or consulting agreements able to favour the interaction and networking with OELRs.

Increasing the opportunities for knowledge transfer, sharing and spillover also requires EU policies promoting institutional efficiency, the improvement of regional knowledge infrastructures, research institutions/centres and educational institutions and the reduction of institutional barriers that may inhibit innovation. Some additional effort needs to be made to improve the absorption capacity of individuals and organisations to exploit the potential of external knowledge and variety (Niosi, 2002; Niosi & Bellon, 1994), to increase the participation of local organisations in the regional innovation system, to support starting up new global firms, to attract innovative companies from outside and to anchor them to the regional innovation system, and to build relationships with regional knowledge suppliers and transfer agencies. Mobility schemes should also be organised in order to foster network linkages with both knowledge-intensive and lagging-behind regions. Finally, a strong vertical and horizontal coordination of policies at different levels is necessary to ensure the consideration of local contextual conditions and maximise efficiencies and synergies across regions.

This study suffers from some limitations. First, a better and more comprehensive evaluation of intra- and inter-regional collaborations on the level of regional innovativeness should not rely only on patent measurements, but also on other indicators, such as the share of innovative or improved products or processes or more comprehensive growth indicators. Second, we have not distinguished between inter-regional collaborations within a country and across countries.

Furthermore, future research could attempt to draw the dynamics of innovation among European regions using not only intra- and inter-EU regional collaborations among organisations, but also distinguishing among collaborations from different types of organisations (e.g., SMEs, large firms, multinationals and public research organisations). It would also be interesting to understand if the more collaborative core regions with lagging-behind regions have advantages in terms of better innovative performances or growth.

The availability of more comprehensive datasets, providing further information on the patents, could allow future research to extend and improve our work.

References

Acs, Z.J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, *31*(7), 1069–1085.

Aiginger, K., Huber P., & Firgo, M. (2012). Policy options for the development of peripheral regions and countries of Europe. WWW for Europe Policy Brief 2, available online http://s3.amazonaws.com/academia.edu.documents.

Asheim, B.T., & Coenen, L. (2006). Contextualising regional innovation systems in a globalising learning economy: On knowledge bases and institutional frameworks. *The Journal of Technology Transfer*, *31*(1), 163–173.

Asheim, B.T., Boschma, R., & Cooke, P. (2011). Constructing regional advantage: Platform policies based on related variety and differentiated knowledge bases. *Regional Studies*, *45*(7), 893–904.

Asheim, B., & Gertler, M. S. (2005). The geography of innovation: regional innovation systems. *The Oxford handbook of innovation*, 291–317.

Audretsch, D.B. & Feldman, M.P. (1996). R&D spillovers and the geography of innovation and production, *American Economic Review*, *86*, 630–640.

Basile, R., Capello, R., & Caragliu, A. (2012). Technological interdependence and regional growth in Europe: Proximity and synergy in knowledge spillovers. *Papers in Regional Science*, *91*(4), 697–722.

Bathelt, H., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, *28*(1), 31–56.

Bester, C.A., Conley, T.G., & Hansen, C.B. (2011). Inference with dependent data using cluster covariance estimators. *Journal of Econometrics*, *165*(2), 137–151.

Bilbao-Osorio, B., & Rodríguez-Pose, A. (2004). From R&D to innovation and economic growth in the EU. *Growth and Change*, *35*(4), 434–455.

Bonaccorsi, A. (2011). European competitiveness in information technology and long-term scientific performance. *Science and Public Policy*, *38*(7), 521–540.

Boschma, R. (2005). Proximity and innovation: a critical assessment. *Regional Studies, 39*(1), 61–74.

Boschma, R.A., Minondo, A., & Navarro, M. (2012). Related variety and regional growth in Spain, *Papers in Regional Science*, 91, 241–256.

Bottazzi, L., & Peri, G. (2003), Innovation and Spillovers in Regions: Evidence from European Patent Data, *European Economic Review, 47*(4), 687–71.

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. doi: 10.1093/jeg/lbp008

Broekel, T. (2012). Collaboration intensity and regional innovation efficiency in Germany—a conditional efficiency approach. *Industry and Innovation*, *19*(2), 155–179.

Broekel, T., & Boschma, R. (2012). Knowledge networks in the Dutch aviation industry: the proximity paradox. *Journal of Economic Geography*, *12*(2), 409–433.

Cantner, U., Meder, A., & Ter Wal, A.L. (2010). Innovator networks and regional knowledge base. *Technovation*, *30*(9), 496–507.

Cantwell, J., & Iammarino, S. (2000), Multinational corporations and the location of technological innovation in the UK regions. *Regional Studies*, 34(4): 317–332.

Capaldo, A. (2007). Network structure and innovation: The leveraging of a dual network as a distinctive relational capability. *Strategic Management Journal*, *28*(6), 585–608.

Capello, R. (2009). Spatial spillovers and regional growth: a cognitive approach. *European Planning Studies*, *17*(5), 639–658.

Castaldi, C., Frenken, K., & Los, B. (2015). Related variety, unrelated variety and technological breakthroughs: an analysis of US state-level patenting. *Regional Studies*, *49*(5), 767–781.

Chaminade, C., & Plechero, M. (2015). Do regions make a difference? Regional innovation systems and global innovation networks in the ICT industry. *European Planning Studies*, *23*(2), 215–237.

Co, C. (2002). Evolution of the geography of innovation: evidence from patent data. *Growth and Change, 33*(4): 393–423.

Cooke, P. (2001). Regional innovation systems, clusters, and the knowledge economy. *Industrial and Corporate Change*, *10*(4), 945–974.

Corrado, L., & Fingleton, B. (2012). Where is the economics in spatial econometrics? *Journal of Regional Science*, *52*, 210–239.

Crescenzi, R., Nathan, M., & Rodríguez-Pose, A. (2016). Do inventors talk to strangers? On proximity and collaborative knowledge creation. *Research Policy*, *45*(1), 177–194.

Crescenzi, R., Rodríguez-Pose, A., & Storper, M. (2007). The territorial dynamics of innovation: a Europe–United States comparative analysis. *Journal of Economic Geography*, *7*(6), 673–709.

De Noni, I., Ganzaroli, A., & Orsi, L. (2017). The impact of intra-and inter-regional knowledge collaboration and technological variety on the knowledge productivity of European regions. *Technological Forecasting and Social Change*, *117*, 108–118.

Dijkstra, L., Garcilazo, E., & McCann, P. (2013). The economic performance of European cities and city regions: Myths and realities. *European Planning Studies*, *21*(3), 334–354.

European Commission. (2016). Regional Innovation Scoreboard. 1–64, Bruxelles, European Commission, doi: 10.2873/84730.

Fitjar, R.D., & Rodríguez-Pose, A. (2011). When local interaction does not suffice: sources of firm innovation in urban Norway. *Environment and Planning A*, *43*(6), 1248–1267.

Fitjar, R.D., & Rodríguez-Pose, A. (2013). Firm collaboration and modes of innovation in Norway. *Research Policy*, *42*(1), 128-138.

Fleming, L., King III, C., & Juda, A.I. (2007). Small worlds and regional innovation. *Organization Science*, *18*(6), 938–954.

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies*, *41*(5), 685–697.

Fritsch, M. (2000). Interregional differences in R&D activities - an empirical investigation. *European Planning Studies*, *8*, 409–427.

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., & van den Oord, A. (2008). Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. *Research Policy*, *37*(10), 1717–1731.

Graf, H., & Henning, T. (2009). Public research in regional networks of innovators: a comparative study of four East German regions. *Regional Studies*, *43*(10), 1349–1368.

Grillitsch, M., & Nilsson, M. (2015). Innovation in peripheral regions: Do collaborations compensate for a lack of local knowledge spillovers?. *The Annals of Regional Science*, *54*(1), 299–321.

Grimpe, C., & Hussinger, K. (2013). Formal and informal knowledge and technology transfer from academia to industry: Complementarity effects and innovation performance. *Industry and Innovation*, *20*(8), 683–700.

Hajek, P., Henriques, R., & Hajkova, V. (2014). Visualising components of regional innovation systems using self-organizing maps—Evidence from European regions. *Technological Forecasting and Social Change*, *84*, 197–214.

Hipp, C., & Grupp, H. (2005). Innovation in the service sector: The demand for service-specific innovation measurement concepts and typologies. *Research Policy*, *34*(4), 517–535.

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.

Huggins, R., & Thompson, P. (2014). A network-based view of regional growth. *Journal of Economic Geography*, *14*(3), 511–545.

Isaksen, A. (2001). Building regional innovation systems: is endogenous industrial development possible in the global economy? *Canadian Journal of Regional Science*, *1*, 101–120.

Lane, D.A. (2011). Complexity and innovation dynamics In C. Antonelli (Ed.), *Handbook on the Economic Complexity of Technological Change* (pp. 63–83). Northampton, MA: Edward Elgar Publishing.

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.

Lee, S.Y., Florida, R., & Gates, G. (2010). Innovation, human capital, and diversity. *International Review of Public Administration, 14*(3), 13–24.

Lorenzen, M., & Mudambi, R. (2012). Clusters, connectivity and catch-up: Bollywood and Bangalore in the global economy. *Journal of Economic Geography*, *13*, 501–534.

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*(8), 1484–1498.

McCann, P. (2013). *Modern urban and regional economics*. Oxford University Press.

Mohl, P., & Hagen, T. (2010). Do EU structural funds promote regional growth? New evidence from various panel data approaches. *Regional Science and Urban Economics*, *40*(5), 353–365.

Morgan, K. (2007). The learning region: institutions, innovation and regional renewal. *Regional studies*, *41*(1), 147–159.

Navarro, M., Gibaja, J.J., Bilbao-Osorio, B., & Aguado, R. (2009). Patterns of innovation in EU–25 regions: a typology and policy recommendations. *Environment and Planning C: Government and Policy*, *27*(5), 815–840.

Niosi, J. (2002). National systems of innovations are "x-efficient" (and x-effective): Why some are slow learners. *Research Policy*, *31*(2), 291–302.

Niosi, J., & Bellon, B. (1994). The global interdependence of national innovation systems: Evidence, limits, and implications. *Technology in Society 16*(2), 173–197.

Nooteboom, B. (2000). *Learning and Innovation in Organizations and Economies*. Oxford: OUP.

O'Brien, R.M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity*, *41*(5), 673–690.

Paci, R., Marrocu, E., & Usai, S. (2014). The complementary effects of proximity dimensions on knowledge spillovers. *Spatial Economic Analysis*, *9*(1), 9–30.

Pekkarinen, S., & Harmaakorpi, V. (2006). Building regional innovation networks: The definition of an age business core process in a regional innovation system. *Regional Studies*, *40*(4), 401–413.

Ponds, R., Van Oort, F., & Frenken, K. (2010). Innovation, spillovers and university–industry collaboration: an extended knowledge production function approach. *Journal of Economic Geography*, *10*(2), 231–255.

Powell, W.W., & Giannella, E. (2010). Collective invention and inventor networks. *Handbook of the Economics of Innovation*, *1*, 575–605.

Puga, D. (2002). European regional policies in light of recent location theories. *Journal of Economic Geography*, *2*(4), 373–406.

Rodriguez-Pose, A., & Fratesi, U. (2004). Between development and social policies: the impact of European Structural Funds in Objective 1 regions. *Regional Studies*, *38*(1), 97–113.

Rodríguez-Pose, A., & Di Cataldo, M. (2015). Quality of government and innovative performance in the regions of Europe. *Journal of Economic Geography*, *15*(4): 673–706. doi: 10.1093/jeg/lbu023

Ronde, P., & Hussler, C. (2005). Innovation in regions: What does really matter? *Research Policy*, *34*(8), 1150–1172.

Schürmann, C. and A. Talaat (2000), Towards a European Peripherality Index, Report for the General Directorate XVI Regional Policy of the European Commission. Dortmund: Institüt für Raumplanung.

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

Storper, M., & Venables, A.J. (2004). Buzz: face-to-face contact and the urban economy. *Journal of Economic Geography*, *4*(4), 351–370.

Sun, Y. (2016). The structure and dynamics of intra- and inter-regional research collaborative networks: The case of China (1985–2008). *Technological Forecasting and Social Change*, *108*, 70–82.

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.

Tavassoli, S., & Carbonara, N. (2014). The role of knowledge variety and intensity for regional innovation. *Small Business Economics*, *43*(2), 493–509.

Ter Wal, A.L., & Boschma, R.A. (2009). Applying social network analysis in economic geography: framing some key analytic issues. *The Annals of Regional Science*, *43*(3), 739–756.

Timmermans, B., & Boschma, R. (2014). The effect of intra- and inter-regional labour mobility on plant performance in Denmark: the significance of related labour inflows. *Journal of Economic Geography*, *14*(2), 289–311.

Tödtling, F., & Grillitsch, M. (2014). Types of innovation, competencies of firms, and external knowledge sourcing—findings from selected sectors and regions of Europe. *Journal of the Knowledge Economy*, *5*(2), 330–356.

Tödtling, F., & Trippl, M. (2005). One size fits all? Towards a differentiated regional innovation policy approach. *Research Policy*, *34*(8), 1203–1219.

Tödtling, F., Asheim, B., & Boschma, R. (2013). Knowledge sourcing, innovation and constructing advantage in regions of Europe. *European Urban and Regional Studies*, *20*(2), 161–169.

Tödtling, F., Grillitsch, M., & Höglinger, C. (2012). Knowledge sourcing and innovation in Austrian ICT companies—how does geography matter? *Industry and Innovation*, *19*(4), 327–348.

Trigilia, C. (1992) *Sviluppo senza autonomia. Effetti perversi delle politiche nel Mezzogiorno*, Bologna: Il Mulino.

Trippl, M. (2011). Regional Innovation Systems and Knowledge-Sourcing Activities in Traditional Industries: Evidence from the Vienna Food Sector, *Environment and Planning A*, *43*(7), 1599–1616.

Trippl, M., Asheim, B., & Miörner, J. (2016). Identification of regions with less developed research and innovation systems. In Parrilli, M.D., Fitjar, R.D., & Rodríguez-Pose, A. (Eds.). *Innovation Drivers and Regional Innovation Strategies*, Routledge, New York, pp. 23–44.

Tsai, K.H. (2009). Collaborative networks and product innovation performance: Toward a contingency perspective. *Research Policy*, *38*(5), 765-778.

Wanzenböck, I., Scherngell, T., & Brenner, T. (2014). Embeddedness of regions in European knowledge networks: a comparative analysis of inter-regional R&D collaborations, co-patents and co-publications. *The Annals of Regional Science*, *53*(2), 337–368.

Zhang, G., Lv, X., & Duan, H. (2014) How do prolific inventors impact firm innovation in ICT: implications from patent co-inventing network, *Technology Analysis & Strategic Management*, *26*(9), 1091–1110.

Zhao, S.L., Cacciolatti, L., Lee, S.H., & Song, W. (2015). Regional collaborations and indigenous innovation capabilities in China: A multivariate method for the analysis of regional innovation systems. *Technological Forecasting and Social Change*, *94*, 202–220.

Zwikael, O., & Smyrk, J. (2015). Project governance: Balancing control and trust in dealing with risk. *International Journal of Project Management*, 33(4), 852-862.

Appendix A

Table A1 – Results of Fixed effect regression models (based on the first two quartiles distribution)

Dependent variable - Innovative performance (first two quartiles)	*Panel fixed effect models*				
	Mod. 1c	*Mod. 2c*	*Mod. 3c*	*Mod. 4c*	*Mod. 5c*
Explanatory variables					
DNS.NET		0.016 (0.021)			
LOC.INV.RATE			0.005 (0.023)		
EXT.INV.RATE				0.091 (0.034)**	
CORE.INV.RATE					0.037 (0.013)**
Control variables					
BUS.DEN	0.239 (0.068)***	0.238 (0.068)***	0.239 (0.067)***	0.225 (0.069)**	0.236 (0.067)***
GDP.PC (dummy)	0.062 (0.059)	0.064 (0.059)	0.062 (0.058)	0.077 (0.057)	0.072 (0.059)
R&D.EXP	0.064 (0.023)**	0.062 (0.023)**	0.064 (0.023)**	0.068 (0.023)**	0.063 (0.023)**
TCN.DIV	0.376 (0.076)***	0.381 (0.078)***	0.376 (0.075)***	0.371 (0.075)***	0.364 (0.077)***
HUM.CAP	0.112 (0.033)***	0.11 (0.034)**	0.113 (0.034)***	0.107 (0.033)**	0.114 (0.033)***
MAN.SPC	0.025 (0.03)	0.025 (0.03)	0.024 (0.03)	0.043 (0.029)	0.032 (0.031)
POP.DEN	-0.071 (0.023)**	-0.074 (0.024)**	-0.071 (0.023)**	-0.085 (0.021)***	-0.074 (0.023)**
EU.FUND (dummy)	-0.098 (0.059)	-0.098 (0.059)	-0.099 (0.06)	-0.072 (0.058)	-0.099 (0.059)
CORE.REG	0.11 (0.021)***	0.108 (0.021)***	0.109 (0.021)***	0.11 (0.02)***	0.099 (0.022)***
No. of observations	966	966	966	966	966
EU NUTS-2 regions	138	138	138	138	138
No. of years	7	7	7	7	7
Residual Sum of Squares	88.11	87.94	88.10	84.94	87.43
Adj. R squared	0.725	0.726	0.725	0.735	0.727
F-stat	285.64***	257.51***	256.84***	296.96***	295.53***
Mean VIF	1.451	1.403	1.400	1.430	1.448
Max VIF	1.660	1.691	1.661	1.661	1.706

*Notes: Robust clustered standard errors are in parentheses. Mean centred standardized coefficients are provided. Significant levels are *** p<0.001, ** p<0.01, * p<0.05*

Table A2 – Results of Fixed effect regression models (based on the first quartile distribution only)

Dependent variable - Innovative performance (first quartile only)	*Panel fixed effect models*				
	Mod. 1d	*Mod. 2d*	*Mod. 3d*	*Mod. 4d*	*Mod. 5d*
Explanatory variables					
DNS.NET		0.083 (0.018)***			
LOC.INV.RATE			-0.07 (0.052)		
EXT.INV.RATE				0.073 (0.04)	
CORE.INV.RATE					0.093 (0.032)**
Control variables					
BUS.DEN	0.17 (0.048)***	0.164 (0.046)***	0.165 (0.049)***	0.159 (0.05)**	0.164 (0.045)***
GDP.PC (dummy)	0.046 (0.05)	0.039 (0.048)	0.048 (0.05)	0.052 (0.05)	0.066 (0.048)
R&D.EXP	0.116 (0.021)***	0.101 (0.016)***	0.116 (0.021)***	0.122 (0.022)***	0.116 (0.021)***
TCN.DIV	0.059 (0.07)	0.075 (0.076)	0.059 (0.068)	0.072 (0.064)	0.013 (0.064)
HUM.CAP	0.001 (0.027)	-0.008 (0.024)	-0.003 (0.026)	-0.007 (0.025)	-0.001 (0.024)
MAN.SPC	0.077 (0.036)*	0.082 (0.034)*	0.094 (0.034)**	0.093 (0.034)**	0.091 (0.034)**
POP.DEN	-0.026 (0.019)	-0.049 (0.017)**	-0.036 (0.019)	-0.038 (0.019)*	-0.024 (0.018)
EU.FUND (dummy)	-0.057 (0.057)	-0.075 (0.055)	-0.062 (0.055)	-0.049 (0.052)	-0.067 (0.054)
CORE.REG	0.064 (0.016)***	0.05 (0.016)**	0.062 (0.016)***	0.064 (0.016)***	0.038 (0.015)*
No. of observations	476	476	476	476	476
EU NUTS-2 regions	68	68	68	68	68
No. of years	7	7	7	7	7
Residual Sum of Squares	17.40	15.32	17.06	16.79	16.16
Adj. R squared	0.677	0.715	0.683	0.690	0.701
F-stat	112.77***	121.19***	104.26***	107.05***	112.55***
Mean VIF	1.422	1.439	1.495	1.479	1.488
Max VIF	2.160	2.176	2.183	2.202	2.162

*Notes: Robust clustered standard errors are in parentheses. Mean centred standardized coefficients are provided. Significant levels are *** $p<0.001$, ** $p<0.01$, * $p<0.05$*

Table A2 – Results of Fixed effect regression models (based on the first quartile distribution only)