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The innovation networks of city-regions in Europe: exclusive clubs or inclusive hubs?

by

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Abstract

Which role do city-regions play in European innovation diffusion? We study the evolution of innovation collaborative networks in European city-regions outlining two opposite models: in the *exclusive network* model city-regions establish a closed network of innovators among themselves; in the *inclusive network* models city-regions build a network of innovators which includes the peripheral regions. Employing a Temporal Exponential random graph model on 248 regions in the period 2000-2016, we find that the two models coexist. We conclude that in the EU the city-regions act as both engines of generation and diffusion of innovation.

Key words: innovation network; city-regions; European regions; network analysis.

JEL classification: O3; O33; R12.

1. Introduction

City-regions have become the main engines of innovation and economic growth. The growing concentration of innovation into a few city-regions raises significant concerns in terms of uneven territorial development. In the European Union (EU) the issue of regional disparities plays a central role both in the academy and in policy circles (Iammarino et al., 2019). A central topic regards the role that city-regions play in the European model of economic development. This paper addresses the following question: are city-regions becoming an exclusive clubs of innovators or rather central nodes of diffusion of knowledge and innovation? In other words, is the rise of city-regions making innovation more concentrated or more diffused across the EU? The two scenarios bring about very different implications for local economic development, the path of economic convergence, and ultimately cohesion within the EU.

Both the generation and diffusion of innovation are necessary to sustain wealth creation in advanced countries. The generation of innovation has always shown an inherent tendency towards spatial concentration. Following a sort of fractal dynamic, innovation tends to get concentrated across countries, across regions, and across territories. The recent globalization wave coupled by the transition towards the knowledge economy which started in the 1980s, has exacerbated the concentration of innovation driven by stronger agglomeration economies and localised knowledge spillovers, as well as the restructuring of the international division of labour along global value chains. This has been further reinforced by supply-side policies aiming at concentrating resources into those territories that would boost aggregate national competitiveness (Baldwin, 2011; Iammarino and McCann, 2013; McCann, 2008; Moreno et al., 2005; Paunov et al., 2019; Simmie et al., 2002).

The worldwide rise of the so-called *city-regions* is a macroscopic outcome of these dynamics. Over the past decades city-regions have become the key engines of economic growth by being central generators of new ideas, knowledge and innovation (Scott, 2019; Storper, 2013). They have grown in size throughout a cumulative process which has attracted inventors, high-skilled labour force, entrepreneurs and start-ups, together with foreign direct investment of multinational corporations in hi-tech industries and knowledge intensive sectors, attracted by universities and research centres (Florida et al., 2017; Glaeser, 2011; Iammarino and McCann, 2013; Moretti, 2012; Rodriguez-Pose and Crescenzi, 2008). Two key features of city-regions are their concentration of innovative activities and their global reach. City-regions are characterised by unprecedented flows of ideas, knowledge, people and capital which cross the borders and connect city-regions among themselves. Today, less than 10% of all functional urban regions account for more than 90% of science output in most countries (Andersson and Andersson, 2015). A significant increase in the concentration of innovation activities and high-skilled jobs in urban centres has been documented (Bettencourt et al., 2007; Korpi and Clark, 2019; Moretti, 2012; Storper, 2013).

From a policy perspective, the diffusion of innovation and knowledge is a desirable feature of the economic system. It improves the sustainability of economic development by giving the opportunity to less innovative regions to catch up by adopting new processes, products and services generated elsewhere. As such, the diffusion of innovation makes the concentration of the generation of innovation more sustainable.

Since mid-1990s the EU has developed specific public policies to foster the generation of innovation and its diffusion as a means for improving economic convergence, e.g. Science and Technology policies, the European Research Area and Cohesion Policy - part of which is devoted to R&D and innovation activities. However, in some cases these policies have had the (unintended) effect of reinforcing divergence across more developed and less developed regions (Amoroso et al., 2018; Barrios et al., 2019; Bosker, 2009; Molle and Boeckhout, 1995).

The risk is that cases such as that of England's South East, whose development has been based from the role of London as a global centre "largely delinked from the declining cities and regions located elsewhere within the UK" (Brenner, 1999; p. 444) are becoming more frequent, not only around the U.S., but also in the EU (Dijkstra et al., 2013; Tosics, 2007). Cities are increasingly depicted as 'creative islands' and innovative city regions with global linkages, but disconnected from the surrounding territory (Andersson and Andersson, 2015; Brenner, 2004). If we want to understand the implications of city-regions in the EU development process, we need to take a broad perspective. Our concern is whether the innovative activities in city-regions are detached from the rest of the territory or if, vice versa, they develop interconnections and linkages with the other regions. A systematic concentration of innovation in city-regions, *if* coupled with their detachment from the rest of the regions, would hamper the diffusion of innovation, with the risk of further exacerbating regional uneven development, hence putting economic convergence and social cohesion in the EU at risk.

This paper aims to contribute to empirical research which has questioned the city-regions model of economic development (Bristow, 2005; Ward and Jonas, 2004) which shows three main limitations. Firstly, empirical research is mostly North American based and only marginally covers the EU (Dijkstra et al., 2013; Tosics, 2007). Second, it is mostly based on case studies which tend to focus on the 'places that are doing well' thus limiting our understanding on the other regions and territories. Thirdly, much of the emphasis is on the 'internal' effects of city-regions, e.g. congestion, inequality etc. (Castells-Quintana et al., 2020; Etherington and Jones, 2009).

Our concern is instead about the broader impact of city-regions, particularly regarding their linkages in innovation activities outside their borders. We take the regions with a large metropolitan areas, defined by the OECD as cities with more than population above 1.5 million, as a proxy for the city-region. A key form of innovation generation and diffusion across regions is 'collaborative innovation'. Throughout collaborative innovation knowledge flows across people, firms, universities and research centres across regions. We depict two possible outcomes depending on the patterns of innovation linkages of city-regions. In the former, city-

regions tend to establish collaborative innovations mostly among themselves without the involvement of the remaining regions. In the latter, city-regions carry out collaborative innovation reaching out other regions. We will call the former *exclusive clubs* and the latter *inclusive hubs.* The former depicts a model in which collaborative innovation taking place within city-regions does not involve other regions; the latter depicts a model in which collaborative innovation taking place within city-regions involves also other regions. From the perspective of European regional policy and the sustainability of economic development, the inclusive hub model is clearly more desirable than the first one.

We study the evolution of the innovation networks among European regions employing data on co-patenting as a proxy for innovation collaboration in 248 NUTS2 European regions over the period 2000-2016. We estimate a Temporal Exponential Random Graph Model which is designed to accommodate inter-temporal dependence in longitudinally observed networks (Hanneke et al., 2010; Leifeld et al., 2018). The results point to the co-presence of the two models. City-regions increase their centrality and reinforce their collaboration among themselves; at the same time city-regions also strengthen innovative collaborations with the other regions – we study in particular collaborations among pairs of regions.

2. Background and two models of city-regions innovation network

2.1 The rise of the city regions

After a decade of crisis following on the de-industrialization process in developed countries, cities have re-gained a new centrality in the cognitive capitalism or the knowledge-economy as engine of innovation and economic growth. This is also taking place in emerging countries where large cities have grown as the centres for their technological catch up, investment in human capital, and localization of foreign affiliates of multinational corporations (MNCs).

The evolution of the urban socio-economic landscape which led to the rise of city-regions has been studied from several perspectives (Florida, 2017; Friedrichs, 1993). The growth of *global* cities has been explained as a result of the globalization process and global capitalism restructuring coupled by the re-scaling of the nation states (Brenner, 1999). This approach is based on the understanding of globalization which goes beyond the mere increase in the interdependencies among countries due to the intensification of trade, foreign direct investments, financial capital and migration. In fact, these processes have re-shaped the nature and functions of the territories within nation states, and in particular the urban centres (Brenner, 2004, 1999).

The management of international activities of MNCs and their global value chain needs a variety of specialised functions and services which tend to aggregate in large cities (Iammarino and McCann, 2013). A key point for our argument is that cities have, on the one hand, increased the connections with their pairs.

On the other hand, they have been increasingly dethatching themselves from their national territory. As such they have developed into 'neo-Marshallian nodes within global networks' (Amin and Thrift, 1992): the city space has become increasingly 'de-nationalised', that is autonomous and independent from their own country as long as it has grown connected to the network of global cities (Sassen, 2002, 1991).

The result of this process has been the growth of the cities far beyond their administrative borders. This process led to the rise of the so-called city-regions. City-regions have been defined in several ways and we currently lack an official definition. However, there are some characteristics that are common to them: a) they extend their economic and political power beyond the administrative borders of the city to include an area which is somewhere between the city and the region; b) their area involves not only the commuting hinterland but also the area which is economically dependent on the city; c) they concentrate fundamental resources such as skilled human capital, financial capital, large universities and affiliates of MNCs; d) these resources are increasingly connected in extra-national relationships representing an extension of their reach (Iammarino and McCann, 2013; Scott, 2019; Tosics, 2007).

It is therefore not surprising that cities have led to a reshaping of the public policies agenda since the 1980s. Within the re-scaling of the state and the rise of neo-liberal agenda which replaced the Keynesian local development policies, city-regions became a key engine of the competitiveness of the whole countries, or the 'regional motors of the global economy' (Scott, 1996). This was fuelled by supply-side incentives directed towards the cities, including public investment in education, research, and infrastructures (e.g. high-velocity railways and broadband) (Kantor and Savitch, 2010). As Brenner (1999) contends, today national policies are no longer shaped to increase the 'national' level of productivity but rather to reinforce the local competitive advantages of the more advanced urban centres: "*A major goal of these `glocally' oriented state institutions is to enhance the locational advantages and productive capacities of their territorial jurisdictions as maximally competitive nodes in the world economy*" (p. 440). In Europe, the high-speed trains between cities such as London, Paris, Brussels etc., testify how major cross-borders infrastructures have been also built in order to improve the connection among major cities, thus reinforcing the thickness of their network.

The transformation of large cities into nodes of a global network which connects each city to the others has brought about an intensification of knowledge flows, circulation of ideas and collaborative innovation (Archibugi and Michie, 1995; Scott, 2019). Empirical studies have found evidence of a global network of collaboration in basic research among large cities by examining co-authorships in scientific articles (Matthiessen et al., 2010; Matthiessen and Schwarz, 2006). As far as innovation is concerned, applied research has flourished mostly grounded upon case studies in specific city-regions (Wolfe, 2016); by contrast, there is a lack of empirical evidence about the existence and functioning of innovative collaborative networks among city-regions, and between city-regions and the other regions.

2.2 Exclusive clubs versus inclusive hubs innovation networks

This paper investigates the evolution of innovation networks among regions in Europe and aims to improve our understanding about the role of city-regions. We focus on innovation collaboration - employing data on co-patenting - as a means of identifying collaborative innovation networks among European regions. We have identified the city-regions as the regions with a large metropolitan area (LMA) (Oecd, 2012), and we have built three types of (paired) innovation networks: 1) the first is defined as a network where collaboration takes place between two LMA-regions; 2) the second is defined as a network where collaboration takes place between one LMA-region and another region); 3) the third is defined as a network where collaboration takes place in two regions neither of which is an LMA-region.

We study the dynamic of these three types of collaborative innovation networks over time aiming at testing two contrasting scenarios, namely the *exclusive club* model versus the *inclusive hub* model. In the *exclusive* model LMA-regions tend to establish innovation collaboration among themselves, dethatching from the other regions, thus establishing a sort of *exclusive club* of the greater innovators within the EU. By contrast, the *inclusive* model is characterized by the fact that LMA-regions do engage in innovation collaboration with the other regions, thus playing the role of innovation hubs within the EU.

The two scenarios have significant implications in terms of knowledge circulation across European regions and ultimately on economic convergence. The *exclusive* scenario limits knowledge spillovers and the diffusion of innovation within the elite of the LMA-regions which are also those in which most of innovations themselves are generated. The *inclusive* scenario encourages knowledge circulation and innovation diffusion outside the LMA-regions, a desirable feature to improve technological catching up of the less developed regions.

It has been contended that the danger of growing disparities in innovative capabilities may lead to divergence also in income and well-being and that convergence in innovation is a crucial component of a successful European integration (Archibugi et al., 2021; Lorenz and Lundvall, 2006). The key of the reasoning is that the problem of the polarization of innovation in major centres, which is both an outcome of agglomeration economies and supply side policies, can be made sustainable *if* knowledge and innovation are diffused outside these major innovation poles. Indeed, LMA-regions as innovation machine can do a lot of good for the European economy by acting as gatekeepers between the central regions and the other regions, as already found out in other contexts (Sigler et al., 2021)

3. Data and the model

3.1 Model's variables

Dependent Variable. The dependent variable is the presence or absence of a co-patent linkage between two European NUT2 areas (248) in the period 2000-2016. A linkage among two regions exists when at least two inventors from different regions (regardless the country) are reported in the same patent document; hence, the dyad is our unit of analysis. We consider patents' inventors at the European Patent Office with priority year 2000-2016. We built a undirected network that depicts the inter-regional patent-filing relationships from the inventor regions by applying network principles, in which the vertices represent the regions and the links represent the relationship among the regions. Over a total of 248 regions from 22 European countries (the list of countries is reported in Table A1 in the Appendix), V_i indicates the *ith* region, and an adjacency matrix $A = [a_{ij}]$ indicates the patent collaboration between regions, where $a_{ij} = 1$ indicates the patent collaboration between two regions, and $a_{ij} = 0$ otherwise. Self-loops (i.e., links connecting *i* with themselves) are not considered. On the basis of the co-patenting network we have built the networks among all regions between 2000 and 2016.

Explanatory Variables. Our model includes what are known as endogenous (network-based variables) and exogenous attributes (characteristic-based variables) in social network analysis (see Table 1). Among the endogenous variables, i.e. configurations, we include the following: *Edge*, *Triadic Closure, Edge Memory* and *Edge time*. *Edge* controls for the number of edges in the network and it can be treated as a "base rate" similar to the intercept term in a OLS. *Triadic Closure* is the geometrically weighted edgewise shared partner (GWESP), which is referred to as the shared partner structure; it measures the closure effect of the network, that is transitivity by implying linkages between nodes who share neighbours. To make the computation easier, the decay parameter for GWESP was set to 0.5 (following Leifeld et al., 2018). *Edge Memory* reflects a dyadic stability memory term, that is whether the ties and non-ties at one point in time remain the same at the next; this captures the presence of consistency (or inconsistency) of the links over time. *Edge time* is a time covariate that tests for a time trend in the number of alliance edges over time. In the *Edge time* variable we consider the financial crisis to be a structural break in the data-generation process: time points before 2010 are set to 0 while time points after 2010 are set to 1. We chose 2010 as threshold for two reasons. Firstly, the crisis' initial effects are different across countries, but they all get impacted in 2010. Secondly, our descriptive analysis reveals a shift in course beginning in 2010 (this year seems to be the year of recovery for links).

Our proxy for the city-region is a region which includes a large metropolitan area (LMA region). OECD (2012) defines a LMA as a city with population above 1.5 million. A different possible options was to take

regions with a metropolitan areas - with population between 500,000 and 1.5 – as a proxy for city regions. We preferred the former option for three reasons. Firstly, LMA are more likely to overlap with the whole area of the region compared to the smaller metropolitan areas. Secondly, including metropolitan areas would give us a large number of regions for the large countries. Thirdly, LMA are more comparable with capital cities which have been also used for empirical analysis; in fact, capital cities tend to represent a high-income cluster when analysing regional club convergence in the EU (von Lyncker and Thoennessen, 2017). For the purpose of comparability and robustness checks we report in the Appendix (Table A2) the results of our main estimates using the regions with the capital-cities as a proxy for the city-region. Table A1 in the Appendix reports the sample of city-regions comparing the two definitions – i.e. LMA and capital cities. The latter sample includes one region per country regardless their size in population. When taking the LMA as a proxy of city-regions, the largest countries have more than one city-regions, e.g. Germany, France and Italy, while a few countries have none, i.e. Finland, Croatia, Slovenia and Slovakia.

The *LMA-Region* variable is a binary variable that indicates whether or not the region is a LMA-region (1= LMA-region; 0=region). The *Region* variable is a categorical variable that determines how likely it is that a tie is formed between regions that exhibit the same value of *LMA-Region* with those of a different value of the same variable. We are therefore considering the following possible combinations of LMA-regions and regions: 1) 0-0 (Base outcome)=link between two regions; 2) 0-1=link between a region and a LMA-region; 3) 1-1=link between two LMA-regions.

Among exogenous attributes we consider a dichotomous variable – *Country* - that captures the presence of a country effect, that is whether two regions belonging to the same country collaborate significantly more than two regions belonging to different countries. We include *GDP per capita* as a proxy for economic development of regions. The variable *GERD Difference* indicates the standardised difference in gross domestic expenditure in Research and Development (R&D) between two regions (for more details on calculation see Table 1); positive (negative) values suggest that regions with different (similar) R&D levels are more (less) likely to establish a link. *Geo proximity* measures geographical proximity; it is computed as the inverse of the distance in kilometres among the centroids of each region. Finally, *EU Accession* is a binary variable that indicates whether or not a certain country in which the region is located is a member of the European Union (EU) or not; this would control for the fact that some countries in the sample – i.e. Eastern European countries - have joined the EU during the considered period.

In Table 1 we provide a complete description of the model's variables.

Table 1. Model's variables

Variable	Description
Link (dependent variable)	Connection between two regions that are linked by the same patent. a_{ij} = 1 patent collaboration a_{ij} = 0 no patent collaboration
Edge	In classical models it is analogous to the intercept term. It is equal to the density, namely the number of observed ties over all possible number of ties.
Triadic Closure	It indicates the tendency to form triangles, or triads, between three nodes. This term is a edgewise shared partner statistics. That implies that if an edge connects region[a] and region[c], and region[b] and region[c], there is a higher probability an edge also connects region[a] and region[b].
Edge Memory	It identifies the link's memory. This variable denotes the consistency of connections across time.
Edge time	It is a term for similarity on the size attribute (categorical nodal attribute). It counts the number of edges (i,j) for which Size(i)=Size(j).
Country	It is a term that indicates whether two regions in the same country collaborate significantly more than two regions in different countries. It counts the number of edges (i,j) for which country(i)=country(j). 0= Different country 1= Same country
LMA-region	The LMA-region variable is a binary variable that indicates whether or not the region is a Large Metropolitan Area (LMA) 0= No LMA-region 1= LMA-region
Region	This variable determines the likelihood of a tie forming between regions with the same value and those with a different value of the same variable. 0-0 (Base outcome)=link between two Regions 0-1=link between one region and one LMA-region 1-1=link between two regions
GDP	It is the regional gross domestic product per capita. Continuous variable
GERD Difference	It is a term for similarity on the gross domestic R&D expenditure between region. It captures the effect of the absolute difference in the GERD on the probability of a link between two regions. [abs(GERD[i]- GERD[j])^pow], with pow= 1. Continuous variable
Geo proximity	Computed as the inverse of the kilometres distance between the i-th and the j-th region. Continuous variable
EU Accession	This refers to the European Union memberships of a specific country within which the region is located. 0= non-European Union country

	1= European Union Member country

3.2 The Temporal Exponential Random Graph Model

We employ the Temporal Exponential Random Graph Model (TERGM) - an extension of the Exponential Random Graph Model (ERGM) - which is designed to accommodate inter-temporal dependence in longitudinally observed networks (Hanneke et al., 2010; Leifeld et al., 2018). The TERGM is particularly suitable for the analysis of longitudinal knowledge and innovation networks because it employs a Markov structure that allows us to simulate the transition of a network from two subsequent time points using various endogenous and exogenous attributes (Zinilli, 2016). The TERGM allows to observe the networks at discrete and equidistant time points. The SAOM model (Stochastic actor-oriented model) has also been used in the context of dynamic networks (Balland, 2012). To gain a thorough understanding of the empirical comparison of the two models, we refer to Leifeld and Cranmer (2019). Since we are modelling an inter-regional network, we chose the TERGM over the SAOM, which is based on actor-based behavioural assumptions (Park and Newman, 2004). Further, we use the TERGM to explain the observed network structure instead of traditional statistical models because it is based on the assumption of node and link (connection) dependence (through the so-called Markov dependence).

Using a first-order Markov dependence structure and conditioning on the previous network, the model can be factorized in the following way:

$$P_\theta(Y_T, \ldots, Y_2 | Y_1, x_1, \ldots, x_T) = P_\theta(Y_T | Y_{T-1}, x_T) \ldots P_\theta(Y_3 | Y_2, x_3)\, P_\theta(Y_2 | Y_1, x_2)$$

The preceding formula divides the joint distribution into yearly transitions from Y_{t-1} to Y_t.

The TERGM undertakes that the transition from Y_{t-1} to Y_t is generated according to an exponential random graph distribution with the specific parameter θ, namely:

$$P_\theta(Y_t = y_t | Y_{t-1} = y_{t-1}, x_t) = \frac{\exp\left\{\theta^T s(y_t, y_{t-1}, x_t)\right\}}{\kappa(\theta, y_{t-1}, x_t)}$$

Where y_t and y_{t-1} are the realizations, Y_t and Y_{t-1} the random networks, $s(y_t, y_{t-1}, x_t)$ a vector of statistics of both networks y_t and y_{t-1}. $\kappa(\theta, y_{t-1}, x_t)$ is a normalizing quantity to ensure the model with a proper probability distribution (Robins et al., 2007; Zinilli and De Marchi, 2020).

When estimating the ERGMs, or its extension such as the TERGM, the normalization constant $\kappa(\theta, y_{t-1}, x_t)$ in the model's denominator is frequently an impediment (except for very small networks) since an analytical calculation is not possible. This is because it requires summation over all possible networks $y \in Y$. The Monte Carlo–Markov maximum likelihood estimation (MCMCMLE) is used to solve this problem and to compute the estimations' bootstrap confidence intervals.

Degeneracy is a problem that is frequently encountered when fitting ERGMs (or its generalizations) with endogenous network statistics (Schweinberger, 2011; Zinilli, 2016); this happens when the majority of the probability mass is allocated to network realizations that give either full or empty networks. Because we use endogenous variables and assume the presence of triads in our case, the model may not converge. It may be unable to find better model and thus degenerate. The quality of a non-degenerated model in simulating the observed network must be further tested. For this reason, we compare the average statistical values of the observed network and the simulated networks to determine goodness-of-fit (cf. Annex 2). The similarity of the two distributions, even though they are not identical, suggests that the TERGM adequately described the observable network.

4. Results

4.1 Descriptive Analysis

In this section we report the descriptive analysis from co-patenting network to illustrate the nature and the dynamic of the collaborative network across European regions, as well as the evolving nature of the links among different types of regions (i.e. LMA-region versus other regions).

In order to provide a graphical visualization of the evolution of the whole network, we generated a set of graphs between the years 2000 and 2016 (see Figure 1), where each node is a region and the lines represent the existence of (at least) one link. One can observe that the number of peripheral nodes has decreased over time, reflecting a dynamic of growing integration across the European regions in the considered span of time.

In Table 2 we report the yearly number of links (co-patents) grouped by region typology to highlight the relationships between the regions. The table provides initial insights about how the collaboration network has evolved with respect to the type of region. The metrics of nodes, edges and density indicate that in the 17-year period co-patenting has evolved with increasing number of connections, increasing the intensity of the relationships, and greater density. The steady increase of the *weighted density* suggests that the network as a whole has increased in terms of the number of collaborations. This trend is also reflected in the increase of the strength of connections between regions, i.e. the number of times two regions collaborate by year (*weighted edges*).

Figure 1. Collaborative innovation network evolution among European regions from 2000 to 2016

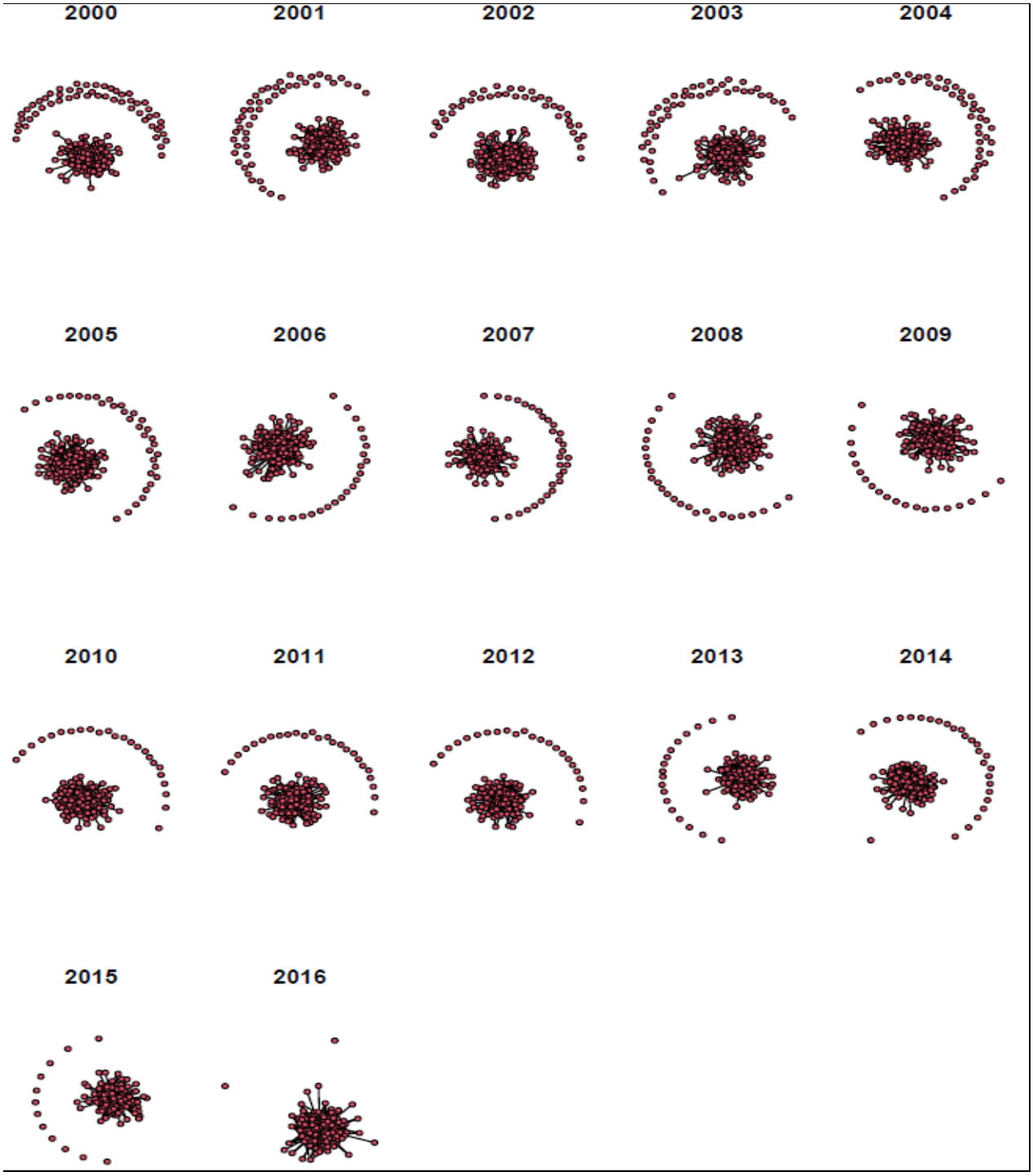


Table 2. Basic statistics of co-patent network in the period of 2000–2016.

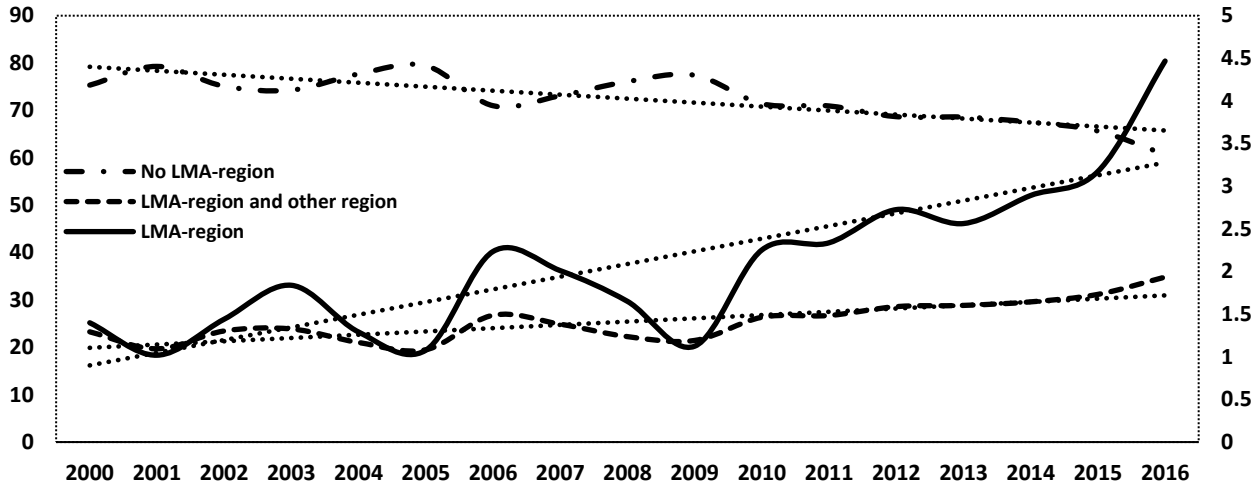
Year	Nodes	Weighted Edges	Weighted Density	Unique Edges *between regions*	Unique Edges *between LM-regions*	Unique Edges *between regions and LMA-regions*
2000	248	6,576	0.106	4,954	92	1,530
2001	248	7,070	0.114	5,606	72	1,392
2002	248	6,524	0.105	4,900	94	1,530
2003	248	7,506	0.121	5,576	138	1,792
2004	248	6,974	0.112	5,418	90	1,466
2005	248	7,800	0.126	6,196	84	1,520
2006	248	8,234	0.133	5,846	184	2,204
2007	248	8,654	0.140	6,326	174	2,154
2008	248	8,240	0.133	6,270	136	1,834
2009	248	8,896	0.144	6,888	100	1,908
2010	248	8,968	0.145	6,404	202	2,362
2011	248	9,244	0.149	6,558	216	2,470
2012	248	9,318	0.1508	6,400	254	2,664
2013	248	9,444	0.1529	6,478	242	2,724
2014	248	9,752	0.1579	6,584	282	2,886
2015	248	10,022	0.1622	6,580	318	3,124
2016	248	10,922	0.1768	6,630	488	3,804

Note: the table lists the total number of regions (nodes); weighted edges – defined as how many times two regions collaborate; density – defined as the proportion of actual relationships in the network over all possible relationships for each year; the unique edges - defined as the weighted edges between different types of regions.

Figure 2 shows the trend in the weighted[1] edges between the European regions from 2000 to 2016. The dash-dotted line represents links between non LMA-regions, the solid line represents the links between LMA-regions, and the dotted line illustrates the connections between all region typology combinations. For each year, the values are calculated as a percentage of the overall number of links.

[1] Since the regions collaborate through patents several times in the same year, the ties are weighted to reflect the relative intensity of the relationships between regions.

Figure 2. Percentage of weighted links in the period 2000-2016



Note: the primary axis refers to the No LMA-region, and LMA-region and other region. The secondary axis refers to the LMA-region.

To highlight the trend we have fitted a straight line (dot line). The number of links among regions declines over time, whereas both the number of links between LMA-regions and other regions and within two LMA-regions increases. The graph also shows how collaborative innovation involving LMA-regions has grown in the considered period. The share of links between LMA-regions has improved from 1.4% to 4.5%; the share of links between LMA-regions and other regions has also grown from 23.3% to 34.8%; as a consequence the links between the other regions have decreases from 75.3% to 60.7%.

4.2 Model results: the TERGM

This section reports the results from the estimated TERGM. Given the computational complexity of the estimated model and to ensure model consistency, we took a step-by-step strategy, first including only endogenous attributes and then adding exogenous attributes to the other three models. The fitting of the models 1–4 is convergent; the model is estimated with 1,000 bootstrap replications to infer valid confidence intervals (a 95% confidence interval is shown around the estimates).

As far as our variables of interest are concerned, the variable *LMA-Region* is positive, suggesting a greater propensity of LM-regions to connect within the overall network. The positive coefficient of the interaction variable *Edge Time*LMA-Region* suggests that LMA-regions become, *over time,* more likely to create linkages between them. The variable *Region*, which is composed of three levels (0-0, 0-1 and 1-1) is always positive for the levels 0-1 (links between regions and LMA-regions) and 1-1 (links between LMA-regions), compared to the base outcome 0-0 (links between non LMA-regions).

Table 3. TERGM in the period 2000-2016 on link probability formation

	Model 1	Model 2	Model 3	Model 4
Triadic Closure	1.32* [1.23; 1.40]	1.31* [1.23; 1.39]	1.31* [1.19; 1.38]	1.32* [1.25; 1.40]
Edge Memory	0.46* [0.37; 0.53]	0.46* [0.40; 0.52]	0.46* [0.40; 0.56]	0.45* [0.38; 0.51]
Edge Time (Economic Crisis control)	0.008* [0.002; 0.018]	0.008* [0.003; 0.017]	0.008* [0.002; 0.015]	
*Edge Time*LMA (Economic Crisis control)*				0.007* [0.003; 0.016]
Country		0.03[-0.05; 0.13]	0.03[-0.06; 0.10]	0.02 [-0.08; 0.13]
LargeMetropolitanArea (LMA) regions		**0.21* [0.05; 0.32]**		
Links bw. regions and LMA regions (0-1)			**0.21* [0.08; 0.36]**	**0.17* [0.06; 0.25]**
Links bw. LMA-regions (1-1)			**0.42* [0.01; 0.70]**	**0.30* [0.07; 0.48]**
GDP per capita				0.15* [0.09; 0.23]
GERD Difference				-0.04* [-0.05; -0.02]
Geo Proximity				0.0011* [0.0009; 0.0012]
EU Accession				-0.14 [-0.21; 0.02]
Edges	-3.49* [-3.65; -3.31]	-3.55* [-3.69; -3.39]	-3.54* [-3.70; -3.29]	-6.15* [-7.58; -5.12]

Note: including coefficients and confidence intervals (= 95%).*

As far as the endogenous variables are concerned, the *Edge* term is always statistically significantly negative across all models. *Triadic Closure* – which refers to the number of connections that two nodes share - is always positively statistically significant; this suggests the presence of a network self-organizing effect in the evolution of inter-region co-patent network. *Edge memory* is always positive and significant, suggesting that the co-patent linkages between regions are persisting over the years; that is, regions are more likely to work with a consolidated group of partnerships, and less likely to broaden their network of partners. *Edge Time* incorporates the effects of the economic crisis in all four models. This variable is always positive and significant indicating that the density of networks increased in the second period (2010–2016) (Models 1, 2, 3). Only in the model 4, we combined the *Edge Time* term with the LMA-region variable to produce an interaction effect in order to investigate if the joint patents among LMA-regions rise or decrease over the years. The coefficient is also positive and significant in this case, indicating an upward trend in LMA-region connections over time.

Regarding our additional set of control variables, the *Country* variable is not significant in our analysis, suggesting that the country does not play a preferred role for cooperation – in fact it is very likely that the largest part of this effect is captured by geographical proximity (see below). *GDP per capita* arises as

significantly positive suggesting that regions tend to collaborate more with pairs at the same level of economic development. *GERD Difference* is also negative and significant, suggesting that over time regions are more likely to establish collaborations if they have similar levels of R&D. This is consistent with the trend outlined above (Figure 1) which shows greater collaborations of LMA-regions. The coefficient of *Geo Proximity* is significantly positive, reflecting the well-established finding that physical proximity matters when it comes with innovative collaboration. Finally, EU accession is not statistically significant. This finding is somehow surprising, since we would eexpect this to be positively correlated with out dependent variable. One conceivable explanation is that the accession process of the EU has spurred innovation collaboration, and hence collaborations started before accession benefiting from a sort of announcement effect (see also comment in the next section regarding the ERGM model).

For the sake of robustness checks and comparability with other studies, in the Appendix (Table A2) we report the same estimates as for Table 3. In Table A2 city regions are considered as those which include the capital region of the country. Hence the sample of the city-regions consists of one region per country – that with the capital city – regardless the dimension of the country (see Table A1). The results are virtually unchanged.

4.3 Model results: the ERGM

In addition to the TERGM, we ran an ERGM for count data by year to better understand the role of different endogenous and exogenous variables in the link formation of co-patent networks. An ERGM by year is a static network modelling approach based on single-year data that does not assume pre-existing network relationships. Compared to the TERGM, in the case of ERGMs, we are able to model the network taking into account the *weight* of the links. As a result, the TERGM and ERGM results can be compared to improve our understanding of co-patent relationship among regions. The results of the ERG models are reported in detail in Annex 3. All variables in the TERGM are addressed in the ERGM, with the exception of Edge Memory and Edge Time (which are obviously not available for the static model).

Differences in ERGM model coefficients over time (2000–2016) indicate that the likelihood of connections between regions has changed from year to year. As far as our variables of interest are concerned, the coefficient of the variable *Region* lies above zero for the level 0-1 (links between regions and LMA-regions), except for the first two years (2000-2001) and 2009 (the year of the great recession). The coefficient of the *Region* variable at the 1-1 level (links between LMA-regions) is negative for the first two years, than is always non-significant until 2009; from 2010 onwards it becomes significant and positive.

The coefficient of *Edges* is always negative. When used in an ERGM, this term controls the network's overall density. In the period of the economic crisis, one can observe how the coefficient tends to zero,

reflecting an increase in the number of links. The dynamic of the coefficient of the variable *Triadic Closure* indicates that the transitivity effect is significant, but it becomes less relevant over time. Except for the years 2000 and 2001, the *GDP per capita* is always positive. *GERD Difference* shows a clear trend, the coefficients are always negative and significant. For the years 2002, 2004, 2014, and 2016, the coefficient is not significant. This suggests that regions with similar levels of R&D are more likely to be connected. The coefficient of *Geo Proximity* is always significantly positive. The *Country* variable does not show a clear evidence over time, confirming that regions in the same country do not tend to collaborate more. Finally, from 2003 onwards, the EU Accession coefficients show a negative sign particularly from 2007. Consistently to the presence of an anticipation effect, we can now observe that new collaborations start *before* the EU accession, while after the accession the collaborations tend to stabilise.

ERGM is stable for all years, rendering its validity to be used as model specification for TERGM. Furthermore, we can say that the dynamic TERGM model accurately captures changes in ERGM results.

4.4 Discussion

Our analysis shows that the European innovation collaboration network has become more integrated over time, and that LMA-regions play today a more central role compared to the year 2000. LMA-regions have become more central nodes within the European innovation system, consistently with research emphasizing how LMA-regions have been growing central in the generation of innovation (e.g. Florida et al., 2017).

We demonstrate that the links *between* the LMA-regions have grown more likely over the considered period; however, at the same time the links between the LMA-regions and the remaining regions have also grown more likely. Hence, LMA-regions are establishing innovation collaboration with their peers as well as with dissimilar regions.

These combined pieces of evidence do not allow us to accept our *exclusive club* hypothesis, that is the idea that LMA-regions have grown more integrated within them and at the same time detached from the others. The results point to the co-existence of a double role of the LMA-regions: they are strengthening the linkages among themselves, thus reinforcing the presence of a network of great innovators; at the same time, they are also increasing their collaborative innovation *outside* the network of the LMA-regions.

This double pattern of collaborative innovation of LMA-regions in Europe confirms that the concentration of innovation in Europe does not follow the same pattern as that in the United States where concentration in metropolitan cities has become a distinctive feature of local development (e.g. Moretti, 2012). In fact, we can also see a similar pattern in the emerging countries such as China where the growth of cities has reached a scale which is by far greater than that in Europe (Theurillat, 2021). Within the EU we are in presence of a model in which the LMA-regions do play a pivotal role in collaborative innovation, but their role is also one

of *inclusion* and *integration* of peripheral regions, where a more distributed network of innovation seems to emerge. This is consistent with studies pointing to different patterns of local economic development between Europe and North America, due to different policy approach – i.e. supply side incentives – and more general neoliberalism urbanism (Kantor and Savitch, 2010; Peck et al., 2009), as well as the polycentric urban structure which characterizes Europe (Camagni et al., 2015; Dijkstra et al., 2013) and the presence of 'regional' cities (Simmie et al., 2002).

This can conjecture some explanation for this European pattern of innovative collaboration.

Firstly, the integration process which has taken place within the EU, and in particular the enlargement process which has involved the Central Eastern European (CEEs) countries, has altered the geography of production. A mass volume of foreign direct investments (FDI) from Western countries towards the CEEs countries, especially in some industries such as the automotive and the mechanical sector, has helped establishing new linkages between the more advanced and the lagging behind regions, contributing to the overall integration of the network documented above. A Report from the Joint Research Centre of the European Commission on the top R&D performers shows that a substantial share of patents invented in CEEs countries is in fact owned by companies based in Western member countries (Hernández et al., 2018). For instance, German applicants own 27% of the Hungarian patents, 23% of the Lithuanian patents, and 51% of the Romanian patents. Most of these linkages are associated to the activity of a few multinational corporations and have grown following on the enlargement process and the associated expansion of the European common market.

Another source of integration between LMA-regions and the other regions lies in the EU Cohesion policy, which operates at the region level and aims at reaching cohesion also by supporting science and technology (S&T). In fact, "*existing EU S&T policies might have a twofold effect on cohesion. Competitive S&T schemes may end up favouring areas of excellence and leading players and regions […] However, the explicit collaborative setting of part of such policies, aiming at the creation of an integrated European Research Area, may complement cohesion policies in reducing regional gaps.*" (Archibugi et al., 2021, p. 2). Archibugi et al. (2021) demonstrate that while EU funding for research – i.e. Horizon Europe – is correlated to the level of technological capabilities of the regions, there is also a re-balancing effect in the regional allocation of H2020. They find that less developed regions tend to receive a larger fraction of the funding given their level of technological development, and they attribute this effect to a collaborative-inclusive logic of this program (see also Amoroso et al., 2018 for results on previous EU research schemes).

These results are also speaking to the long-standing debate about economic convergence across European regions. On the one hand we can speculate that the increases centrality of LMA-regions and their innovation network is possibly exacerbating economic divergence; on the other hand, the integration of the other regions encourages might lean towards a convergence process. Our results are consistent with two major

trends in S&T patterns of regions, where the uneven distribution of technological capabilities and the innovation persistence of the more advance regions is coupled by the presence of some degree of technological convergence of the most peripheral regions of Europe with respect to more advanced core EU regions (Evangelista et al., 2016; Filippetti et al., 2020). Regions in New Member countries, especially those in CCEs countries, have experienced a remarkable technological upgrading (Evangelista et al., 2016). It is reasonable to believe that their integration within the European network might have played a role.

5. Conclusions

Over the past decades empirical research has shown an increase in the process of concentration of innovation in large urban areas, favoured by agglomeration economies, global capital flows, and supply-side public policies. This has given rise to the concept of city-regions. Our evidence brings two main messages about the role of city-region in the EU. Firstly, they have become more relevant actors within the innovation networks of European regions, in that their centrality within collaborative innovation has grown. Secondly, there is evidence of some degree of openness (inclusiveness) of the city-regions in that they establish collaborative innovation activities also with the other regions.

The presence of an *inclusive* attitude of the city-regions might, in principle, contribute to regional convergence by improving the circulation of knowledge and innovation outside the city-regions. From a normative standpoint, this is a desirable feature of economic development in that it implies a sort of *redistributive mechanism* of innovation and knowledge. While concentration of the generation of innovation is (partly) an outcome of the current organization of the economy, the diffusion of innovation can be pursued by specific public policies, such as the European Research Area.

The results suggest (and somehow confirm) the presence of a *European way* of local development which differs from that of Northern America, recently mimicked by many emerging economies, where city-regions, or mega-cities, detached from the territory, have become the pillars of the model of economic development. The polycentric structure of the European economy, and the role of middle cities, can here represent a source of competitiveness and sustainability in the long term (Camagni et al., 2015; Dijkstra et al., 2013). We do not know to what extent LMA-regions collaborations outside their network favour economic convergence; this should be further studied. Further, we do not know whether their openness is enough to counter-balance the concentration of innovation activities, especially in the Central-Eastern European member states where disparities between capital regions and peripheral regions have grown remarkably since their integration within the EU. Yet, the fact that the LMA-regions have not established a closed club of innovators is something upon which to build upon to make the concentration of innovation compatible with a sustainable path of territorial development and cohesion in the EU.

There are limits of the analysis and prospects for further study into this area. Case studies have helped understanding the complex phenomenon of city-regions, as for instance their patterns of growth over time, as well as their internal dynamic of disparities and inequalities. Our approach is an attempt to broaden the perspective focusing on the role of city-regions within the broader European economy. By definition, our analysis based on co-patenting captures only one aspect of innovation collaboration. We know that patents capture only a part of innovation, and that innovation is increasingly taking place in sectors and ways which are only partially captured by patents. The knowledge that travels via co-patenting is only part of it, while other components of knowledge travel via personal interactions and people mobility. As such, our evidence is by definition partial and able to capture part of the complex range of flows of innovation and knowledge which travel across regions. Further research should look at whether there can be other forms of knowledge exchange which play a role. Further, delving into the mechanisms of innovative collaboration, such as for instance the role of the European Research Area and the Horizon programmes, will provide good insights for policies. Finally, identifying the pre-conditions (e.g. absorptive capacity) that help regions to get involved into innovative collaborations with the city-regions is also interesting – e.g. technological capabilities, including human capital, formal and informal institutions, specialization etc. Here the literature about the determinants of collaborations at the micro level (e.g. Crescenzi et al., 2016; D'Este et al., 2013) can be fruitfully extended at the meso level.

References

Amin, A., Thrift, N., 1992. Neo-Marshallian nodes in global networks. International journal of urban and regional research 16, 571–587.

Amoroso, S., Coad, A., Grassano, N., 2018. European R&D networks: a snapshot from the 7th EU Framework Programme. Economics of Innovation and New Technology 27, 404–419. https://doi.org/10.1080/10438599.2017.1374037

Andersson, E., Andersson, D.E., 2015. Creative cities and the new global hierarchy. Applied Spatial Analysis and Policy 8, 181–198.

Archibugi, D., Evangelista, R., Vezzani, A., 2021. Regional technological capabilities and the access to H2020 funds. JCMS: Journal of Common Market Studies.

Archibugi, D., Michie, J., 1995. The globalization of technology: a new taxonomy. Cambridge Journal of Economics 19, 121–140.

Baldwin, R., 2011. Trade and industrialisation after globalisation's 2nd unbundling: How building and joining a supply chain are different and why it matters. National Bureau of Economic Research.

Balland, P.-A., 2012. Proximity and the evolution of collaboration networks: evidence from research and development projects within the global navigation satellite system (GNSS) industry. Regional studies 46, 741–756.

Barrios, C., Flores, E., Martínez, M.Á., 2019. Club convergence in innovation activity across European regions. Papers in Regional Science 98, 1545–1565. https://doi.org/10.1111/pirs.12429

Bettencourt, L.M., Lobo, J., Helbing, D., Kühnert, C., West, G.B., 2007. Growth, innovation, scaling, and the pace of life in cities. Proceedings of the national academy of sciences 104, 7301–7306.

Bosker, M., 2009. The spatial evolution of regional GDP disparities in the 'old' and the 'new' Europe*. Papers in Regional Science 88, 3–27. https://doi.org/10.1111/j.1435-5957.2008.00183.x

Brenner, N., 2004. New state spaces: urban governance and the rescaling of statehood. Oxford University Press, USA.

Brenner, N., 1999. Globalisation as reterritorialisation: the re-scaling of urban governance in the European Union. Urban studies 36, 431–451.

Bristow, G., 2005. Everyone's a 'winner': problematising the discourse of regional competitiveness. Journal of Economic Geography 5, 285–304.

Camagni, R., Capello, R., Caragliu, A., 2015. The Rise of Second-Rank Cities: What Role for Agglomeration Economies? European Planning Studies 23, 1069–1089. https://doi.org/10.1080/09654313.2014.904999

Cantwell, J., Iammarino, S., 2003. Multinational Enterprises and European Regional Systems of Innovation. Routledge, London.

Castells-Quintana, D., Royuela, V., Veneri, P., 2020. Inequality and city size: An analysis for OECD functional urban areas. Papers in Regional Science 99, 1045–1064. https://doi.org/10.1111/pirs.12520

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

D'Este, P., Guy, F., Iammarino, S., 2013. Shaping the formation of university–industry research collaborations: what type of proximity does really matter? Journal of Economic Geography 13, 537–558.

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

Etherington, D., Jones, M., 2009. City-regions: New geographies of uneven development and inequality. Regional Studies 43, 247–265.

Evangelista, R., Meliciani, V., Vezzani, A., 2016. The Distribution of Technological Activities in Europe: A Regional Perspective. Joint Research Centre (Seville site).

Filippetti, A., Gkotsis, P., Vezzani, A., Zinilli, A., 2020. Are innovative regions more resilient? Evidence from Europe in 2008–2016. Econ Polit 37, 807–832. https://doi.org/10.1007/s40888-020-00195-4

Florida, R., 2017. The new urban crisis: How our cities are increasing inequality, deepening segregation, and failing the middle class-and what we can do about it. Basic Books.

Florida, R., Adler, P., Mellander, C., 2017. The city as innovation machine. Regional Studies 51, 86–96. https://doi.org/10.1080/00343404.2016.1255324
Friedrichs, J., 1993. A Theory of Urban Decline: Economy, Demography and Political Elites. Urban Stud 30, 907–917. https://doi.org/10.1080/00420989320080851
Glaeser, E., 2011. Triumph of the city: How urban spaces make us human. Pan Macmillan.
Hanneke, S., Fu, W., Xing, E.P., 2010. Discrete temporal models of social networks. Electronic journal of statistics 4, 585–605.
Hernández, H., Grassano, N., Tübke, N., Potters, L., Gkotsis, P., Vezzani, A., 2018. The 2018 EU Industrial R&D Investment Scoreboard. European Union, Luxembourg.
Iammarino, S., McCann, P., 2013. Multinationals and economic geography: location, technology and innovation. Edward Elgar Publishing.
Iammarino, S., Rodriguez-Pose, A., Storper, M., 2019. Regional inequality in Europe: evidence, theory and policy implications. J Econ Geogr 19, 273–298. https://doi.org/10.1093/jeg/lby021
Kantor, P., Savitch, H.V., 2010. The politics of city regions in comparative perspective. Métropoles.
Korpi, M., Clark, W.A.V., 2019. Migration and occupational careers: The static and dynamic urban wage premium by education and city size. Papers in Regional Science 98, 555–574. https://doi.org/10.1111/pirs.12328
Leifeld, P., Cranmer, S.J., 2019. A theoretical and empirical comparison of the temporal exponential random graph model and the stochastic actor-oriented model. Network science 7, 20–51.
Leifeld, P., Cranmer, S.J., Desmarais, B.A., 2018. Temporal exponential random graph models with btergm: Estimation and bootstrap confidence intervals. Journal of Statistical Software 83, 1–36.
Lorenz, E., Lundvall, B.A., 2006. How Europe's economies learn. Oxford University Press, Oxford.
Matthiessen, C.W., Schwarz, A.W., 2006. World cities of knowledge: research strength, networks and nodality. Journal of knowledge management.
Matthiessen, C.W., Schwarz, A.W., Find, S., 2010. World cities of scientific knowledge: Systems, networks and potential dynamics. An analysis based on bibliometric indicators. Urban Studies 47, 1879–1897.
McCann, P., 2008. Globalization and economic geography: the world is curved, not flat. Cambridge J Regions Econ Soc 1, 351–370. https://doi.org/10.1093/cjres/rsn002
Molle, W., Boeckhout, S., 1995. Economic Disparity Under Conditions of Integration — a Long Term View of the European Case. Papers in Regional Science 74, 105–123. https://doi.org/10.1111/j.1435-5597.1995.tb00631.x
Moreno, R., Paci, R., Usai, S., 2005. Spatial spillovers and innovation activity in European regions. Environment and Planning 37, 1793–1812.
Moretti, E., 2012. The new geography of jobs. Houghton Mifflin Harcourt.
Oecd, 2012. List of urban areas by country. OECD Publishing, Paris.
Park, J., Newman, M.E., 2004. Statistical mechanics of networks. Physical Review E 70, 066117.
Paunov, C., Guellec, D., El-Mallakh, N., Planes-Satorra, S., Nüse, L., 2019. On the concentration of innovation in top cities in the digital age. OECD, Paris. https://doi.org/10.1787/f184732a-en
Peck, J., Theodore, N., Brenner, N., 2009. Neoliberal Urbanism: Models, Moments, Mutations. The SAIS Review of International Affairs 29, 49–66.
Robins, G., Snijders, T., Wang, P., Handcock, M., Pattison, P., 2007. Recent developments in exponential random graph (p*) models for social networks. Social networks 29, 192–215.
Rodriguez-Pose, A., Crescenzi, R., 2008. Research and Development, Spillovers, Innovation Systems, and the Genesis of Regional Growth in Europe. Regional Studies 42, 51–67.
Sassen, S., 2002. Global networks, linked cities. Psychology Press.
Sassen, S., 1991. The global city. New York.
Schweinberger, M., 2011. Instability, sensitivity, and degeneracy of discrete exponential families. Journal of the American Statistical Association 106, 1361–1370.
Scott, A.J., 2019. City-regions reconsidered. Environ Plan A 51, 554–580. https://doi.org/10.1177/0308518X19831591
Scott, A.J., 1996. Regional motors of the global economy. Futures 28, 391–411.

Sigler, T., Neal, Z.P., Martinus, K., 2021. The brokerage roles of city-regions in global corporate networks. Regional Studies 0, 1–12. https://doi.org/10.1080/00343404.2021.1950914

Simmie, J., Sennett, J., Wood, P., Hart, D., 2002. Innovation in Europe: A Tale of Networks, Knowledge and Trade in Five Cities. Regional Studies 36, 47–64. https://doi.org/10.1080/00343400120099852

Stöllinger, R., 2016. Structural change and global value chains in the EU. Empirica 43, 801–829.

Storper, M., 2013. Keys to the city: How economics, institutions, social interaction, and politics shape development. Princeton University Press.

Theurillat, T., 2021. Urban growth, from manufacturing to consumption and financialization: the case of China's contemporary urban development. Regional Studies 0, 1–15. https://doi.org/10.1080/00343404.2021.1901871

Tosics, I., 2007. City-regions in Europe: The potentials and the realities. The Town Planning Review 775–795.

von Lyncker, K., Thoennessen, R., 2017. Regional club convergence in the EU: evidence from a panel data analysis. Empir Econ 52, 525–553. https://doi.org/10.1007/s00181-016-1096-2

Ward, K., Jonas, A.E., 2004. Competitive city-regionalism as a politics of space: a critical reinterpretation of the new regionalism. Environment and Planning A 36, 2119–2139.

Wolfe, D.A., 2016. Innovation and creativity in city-regions. Handbook on the Geographies of Innovation.

Zinilli, A., 2016. Competitive project funding and dynamic complex networks: evidence from Projects of National Interest (PRIN). Scientometrics 108, 633–652.

Zinilli, A., De Marchi, M., 2020. Value-added in high technology and industrial basic research: A weighted network observing the trade of high-tech goods. International Journal of Computational Economics and Econometrics 10, 398–418.

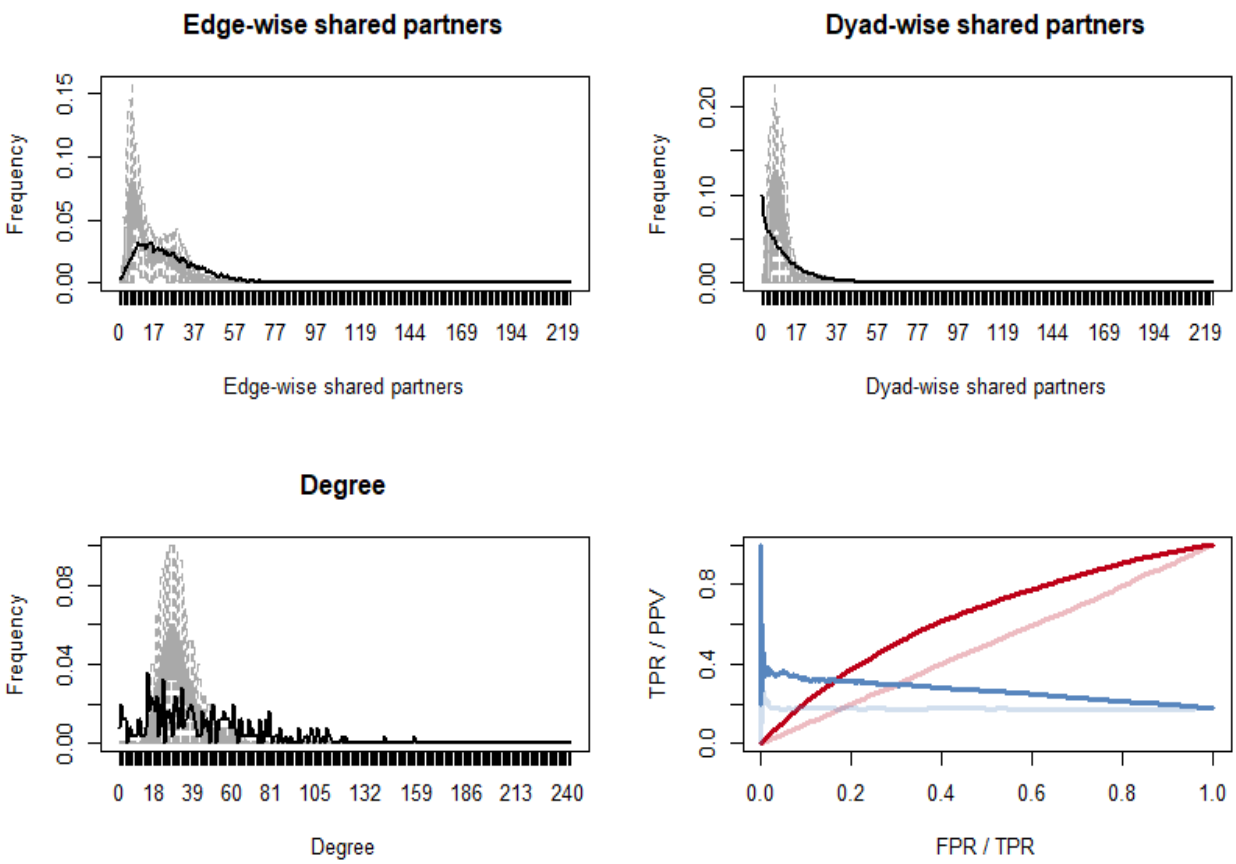
APPENDIX

Table A1. Countries included in the sample (column 1); city-regions included in the sample for each country defined as those including one Large Metropolitan Area (column 2); city-regions included in the sample for each country defined as those including the capital cities (column 3).

Country	Large Metropolitan Area	Capital cities
Austria	Wien	Wien
Belgium	Brussels	Brussels
Bulgaria	None	Sofia
Check Republic	Prague	Prague
Germany	Berlin; Hamburg; München; Frankfurt on the Main; Stuttgart; Cologne	Berlin
Denmark	Copenhagen	Copenhagen
Greece	Athens	Athens
Spain	Madrid; Barcelona	Madrid
Finland	*none*	Helsinki
France	Paris; Lyon; Marseille	Paris
Hungary	Budapest	Budapest
Croatia	*none*	Zagreb
Ireland	Dublin	Dublin
Italy	Rome; Milan; Turin; Naples	Rome
Netherland	Amsterdam	Amsterdam
Poland	Warsaw; Katowice	Warsaw
Portugal	Lisbon	Lisbon
Romania	Bucharest	Bucharest
Sweden	Stockholm	Stockholm
Slovenia	*none*	Ljubljana
Slovakia	*none*	Bratislava
United Kingdom	London; Birmingham; Manchester	London

Note: The list of functional urban areas takes into account the results of the consultation with the European National Statistical Institutes launched by Eurostat in June 2011 on the definition of cities and by the OECD with Delegates from the Working Party on Territorial Indicators (Oecd, 2012).

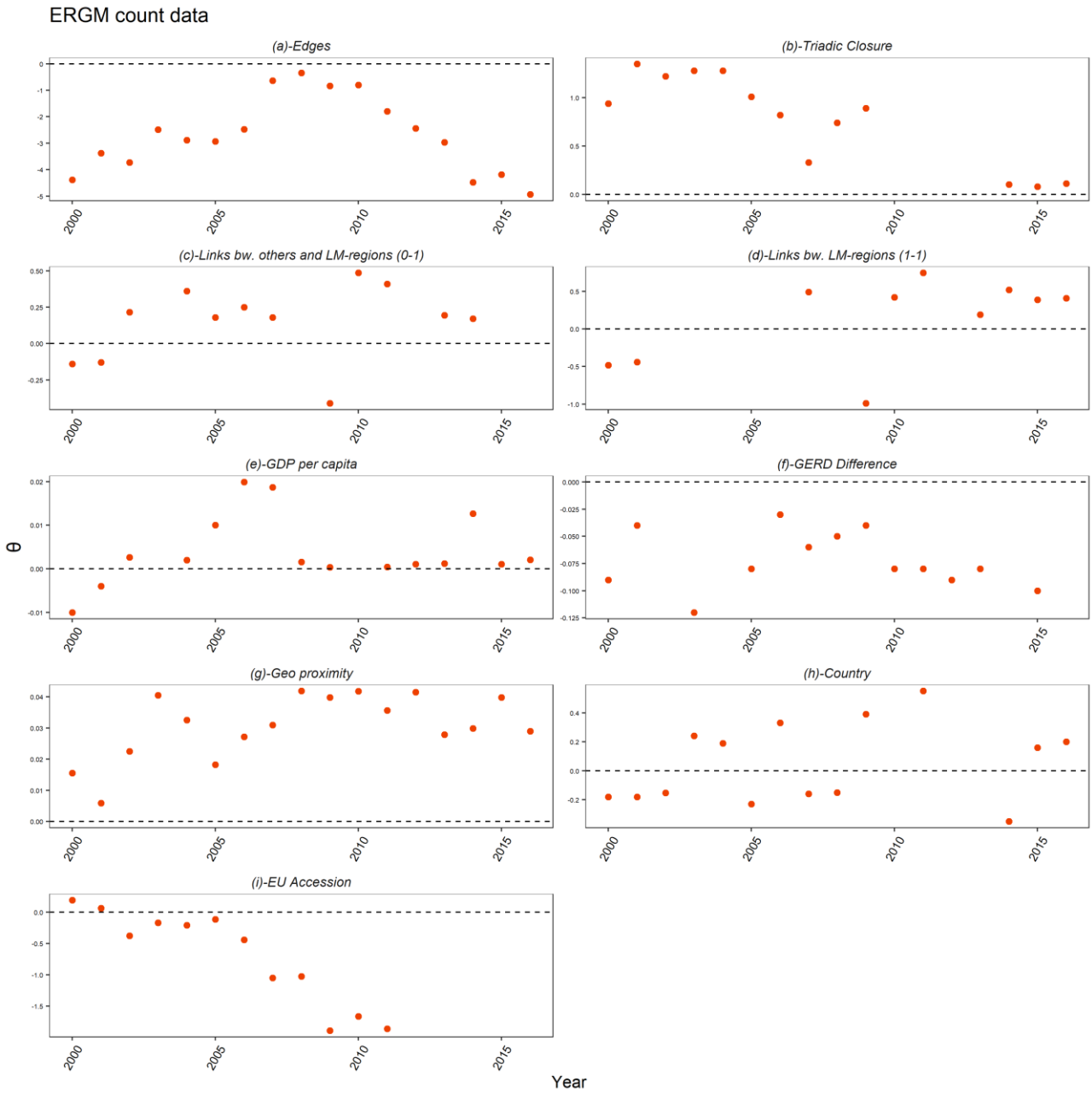
Figure A2. Model goodness of fit for the TERGM



The results' validity is determined using a goodness-of-fit analysis. In our case, the goal of goodness-of-fit is to compare simulated and observed network matrices along a vector of values, which are edge-wise shared partners, dyad-wise shared partners, degree distribution and ROC curve.

The black thick line represents the observed network's distribution of network statistics, while the gray area represents the matching confidence intervals from the simulated networks. Even if the two distributions are not identical, their similarity indicates that our TERGM accurately described the observable network.

Figure A3. ERGM by year



Note: When a red circle is not shown in the estimation picture, it means that the variable is not statistically different from zero. Because all regions are in Europe, EU Accession is not available after 2013. For each ERGM, the goodness of fit test was calculated. For each observed network, we simulated a sample of 1000 graphs, and the results show that all models fit well (below the value of 0.1).

Appendix II

In this appendix we report the same estimates of Table 3 using a different definition of city regions for robustness checks. Here city regions are those regions which include the capital city of each country, regardless the population of the cities (see Table A1 for a comparison of the city-regions).

Table A2. TERGM for City Regions defined as capital cities

	Model 1	**Model 2**	**Model 3**	**Model 4**
Triadic Closure	1.32* [1.25; 1.40]	1.32* [1.25; 1.41]	1.32* [1.23; 1.39]	1.32* [1.26; 1.40]
Edge Memory	0.46* [0.40; 0.54]	0.46* [0.39; 0.52]	0.46* [0.38; 0.50]	0.45* [0.38; 0.52]
Edge Time (Economic Crisis control)	0.01* [0.00; 0.01]	0.01* [0.00; 0.02]	0.01* [0.00; 0.02]	
*Edge Time*City Region (Economic Crisis control)*				0.01* [0.00; 0.02]
Country		0.12 [-0.06; 0.28]	0.12 [-0.08; 0.22]	0.08 [-0.04; 0.17]
City-region		**0.21* [0.12; 0.28]**		
Links bw. city-regions and regions (0-1)			**0.21* [0.10; 0.28]**	**0.13* [0.03; 0.21]**
Links bw. city-regions (1-1)			**0.43* [0.15; 0.57]**	**0.28* [0.06; 0.41]**
GDP per capita				0.01* [0.00; 0.00]
GERD Difference				0.01 [-0.001; 0.01]
Geo Proximity				0.01* [0.00; 0.00]
EU Accession				-0.09 [-0.22; 0.01]
Edges	-3.49* [-3.65; -3.32]	-3.55* [-3.69; -3.39]	-3.55* [-3.72; -3.42]	-4.20* [-4.64; -3.77]