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FULL ARTICLE

Collaboration networks, geography and innovation: Local and national embeddedness

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Abstract

The relationship between collaboration, geography and innovation has been analysed in economic geography. However, little is known from a social-network perspective about whether different geographical levels of embeddedness may determine the way networks affect innovation. To address this issue, we compare the effects of regional vs. country-level Spanish networks on future patenting. If we consider the country-wide network, our statistical analysis reproduces the findings of the previous literature. However, negative effects prevail at the regional level, while the influence seems to be rather positive at the country level. We thus conclude that the embeddedness at different geographical scales exerts differing influence on innovation.

KEYWORDS
innovation, network embeddedness, networks, patents, Spain

JEL CLASSIFICATION
O31; R11; D85

1 | INTRODUCTION

Innovation activities usually take place under a framework of co-operative links between agents. Firms, universities and research centres increasingly share information and resources in co-operative R&D projects, aiming to obtain collective synergies and individual advantages from strategic collaborations (Jones, Wuchty, & Uzzi, 2008; Wuchty, Jones, & Uzzi, 2007). Previous research in various disciplines has shown that collaboration patterns represent a crucial aspect of innovation processes and determine the success of individual agents and territories (see, e.g., Brusco, 1999; Allen, 1983; Saxenian, 1994). Applying social network analysis, more recent literature characterizes the particular structural properties of collaboration networks that enhance or inhibit both present and future innovation outcomes (see e.g., Fleming, King, & Juda (2007) for analysis of regional performance and Schilling and Phelps (2007) for firm-level analysis; see also Section 2).

Although collaboration networks can improve knowledge diffusion and co-ordination mechanisms among agents, which will positively influence innovation processes (Fleming et al., 2007; Katz & Martin, 1997; Nelson & Winter, 1982), collaboration patterns might also have negative impact by increasing the transaction costs and generating lock-in situations (Koput, 1997; Fritsch, 2004). Hence, firms and research organizations willing to improve their innovation outcomes should take into account the structure of their collaboration patterns while performing research activities with other agents. At the same time, policy-makers who seek to encourage innovation should consider how to enhance or inhibit certain features of collaboration networks within and across regions to maximize the knowledge spillovers.

However, innovators are embedded in collaboration networks at different geographical levels, developing projects with local actors while simultaneously collaborating with players located in distant regions or even in other countries. This poses the question of how managers or policy-makers should consider network embeddedness at different geographical levels when designing policies for enhancing innovation. Do local networks influence innovation outputs in a different way than larger-scale networks?

Potential differences between local and non-local innovation networks have been analysed in economic geography (e.g., Capello & Caragliu, 2018; Grillitsch & Trippl, 2014), but this issue is understudied from a social-network perspective. To fill this gap, this paper investigates how different geographical levels of embeddedness determine the way network structural properties affect innovation.

This study focuses on innovators who, in our data, are mostly firms, research centres and other organizations involved in innovation processes. The focus on innovators allows us to study actors who operate in the territory in various ways, including agents who act mostly locally (e.g., small firms or individuals) as well as entities with a national and even transnational character (e.g., large research institutions or multinational corporations). We study the Spanish case. To analyse collaboration networks among innovators, we use all the European patents submitted to the Spanish Patent Office between 1978 and 2008. The particular advantage of these data is that, in contrast to other patent data, it contains the address of both the innovators and inventors, enabling a fine classification according to where the innovation took place. These features are key for the question that our research poses. We focus on a period, during which Spain has experienced a steady economic growth, investment expansion and catching up to the advanced nations, which came to a halt with the arrival of the 2008 global financial crisis (Prados de la Escosura, 2017). This trend has reversed after 2008, a structural break particularly visible in patenting (Hidalgo & Gabaly, 2012; Belda et al., 2014).

The nodes in our networks are patent applicants (i.e., innovators). A link between two innovators exists if they presented a patent together or they collaborated with the same inventor in different patents (Cantner & Graf, 2006; Graf & Henning, 2009; see below for details). We then break the networks down into the three most important regions in terms of patenting outcomes and apply econometric techniques to contrast how the structure and the position in the full Spanish network compares to the local networks in affecting future patenting by organizations. To ensure comparability with previous studies, the selection of network features for our analysis follows as far as possible the previous literature modelling the influence of network properties on firms' innovation outputs (e.g., Ahuja, 2000; Fleming et al., 2007; Schilling & Phelps, 2007).

We observe that the associations between the properties of collaboration networks and subsequent patenting detected in the above literature are reproduced using our Spanish national network. Furthermore, the individual, node-level positioning within the local and national networks seems to affect future innovations similarly. However, the whole-network topological measures affect innovation differently at both geographical scales. The collaboration patterns seem to be more relevant for innovation at the national-level, exerting mostly positive influence. In contrast, regional networks have less impact and, when they do, the negative effects on innovation predominate. Thus, our study contributes to the previous literature by providing empirical evidence that shows how different geographical levels of embeddedness determine the way networks structural properties affect innovation.

Our findings may inform firm-level management policies about what positions to seek in what networks to improve innovation outcomes, and inform policy-makers about what aspects of collaboration patterns to promote and at what geographical levels. We also contribute to the understanding of the interaction between geography at different levels and collaboration patterns, a research agenda initiated recently (see Section 2). The classic innovation literature typically assumes local knowledge externalities (e.g., Glaeser, Kallal, Scheinkman, & Shleifer, 1992), but the network approach to knowledge creation—including the present study—document important non-localized externalities embedded in the overall architecture of collaboration patterns.

The rest of the paper is structured as follows: Section 2 introduces the theoretical framework, Section 3 describes the data and the methodology of our research, Section 4 presents the results and Section 5 concludes.

2 | THEORETICAL FRAMEWORK

Knowledge creation is commonly analysed from two perspectives. Economic geography emphasizes advantages of spatial proximity and clustering as a key determinant of knowledge creation (Jaffe, Trajtenberg, & Henderson, 1993), while economic sociology rather stresses the role of collaborative activities and the resulting structure or network of collaborations (Ahuja, 2000; Allen, 1983; Saxenian, 1994). Since inventors and organizations are naturally embedded in both social and geographical spaces, the interplay of these two perspectives has more recently received attention (e.g., Breschi & Lissoni, 2009; Coffano, Foray, & Pezzoni, 2017; Innocenti, Capone, & Lazzeretti, 2019; Lobo & Strumsky, 2008; Strumsky & Thill, 2013; Whittington, Owen-Smith, & Powell, 2009).

2.1 | Geography and innovation

The early literature on knowledge spillovers and consequently the growth theories are built on the assumption that knowledge spills over only locally (Glaeser et al., 1992). Extensive literature has indeed reported considerable advantages of geographic agglomeration in many types of economic activities, including knowledge creation (Almeida & Kogut, 1999; Bettencourt, Lobo, & Strumsky, 2007; Glaeser, 1999; Jaffe et al., 1993). Furthermore, complex and innovative activities are highly concentrated and they have progressively evolved towards greater geographic concentration (Balland, Jara-Figueroa, et al., 2020).

In certain activities such as transportation or trade, economies of scale apply naturally. As for innovation, physical proximity of firms and industries provides access to a pool of inventors who are embedded in dense networks of social relations that span the boundaries of individual firms. Fleming et al. (2007) document direct effects of labour mobility on innovation. Moreover, agglomerations of innovative entities are traditionally located close to non-private research institutions such as universities, leading to additional spillovers (Whittington et al., 2009). All these features facilitate localized knowledge flows. Indeed, innovation is closely linked to urban areas (Carlino, Chatterjee, & Hunt, 2007) and Bettencourt et al. (2007) provide evidence that the advantages of such spatial clustering scale up superlinearly with the population size of cities and agglomerations.

2.2 | Networks and innovation

The structure of research collaborations may be viewed as a network, in which nodes represent innovators (firms or researchers) and a link between two innovators exists if they have collaborated in a research activity. The literature initially used the term collaboration network as a metaphor for interdependencies and interactions between firms (see e.g., Almeida, Hohberger, & Parada, 2011; de Faria, Lima, & Santos, 2010). However, recent work presents collaboration networks as the sets of nodes and links, applying social network analysis to characterize collaboration patterns. In particular, a growing body of research analyses the impact of collaboration networks on the innovation outputs of organizations and territories (see Pippel (2013) or Phelps, Heidl, & Wadhwa (2012) for critical reviews).

In this study, we focus on several network features that have received particular attention in the literature from two basic approaches: node-level and network-wide perspective. Node-level approach considers that the relative positioning of each node in the network can influence its innovation results. In particular, being central or connected to a large component may increase the exposure to information flows and facilitate capturing knowledge spillovers, generating positive impacts on innovation activities (Ahuja, 2000; Burt, 2000; Owen-Smith and Powell, 2004; Whittington et al., 2009). However, being well positioned in the network can entail transaction costs as well, since networking is time-consuming and requires efforts to process information (Giuliani & Bell, 2005; Laursen & Salter, 2014).

The network-wide approach rather focuses on the patterns describing the whole architecture of interactions. According to this perspective, certain network-wide topologies can influence the innovation outputs of interconnected agents. Therefore, such topologies can be considered as a collective capital since they depend on (and belong to) all actors embedded in the network (see e.g., Galaso, 2018 for a review).

Previous literature has documented two broad types of mechanisms, through which network topologies can influence innovation: knowledge diffusion and co-ordination among actors. Regarding knowledge diffusion, networks where nodes are well connected and close to each other, enable information transfers, increasing its accessibility and reliability (Fleming et al., 2007; Fritsch & Kauffeld-Monz, 2010). The interconnection of actors in large components enhances knowledge spillovers and cross-disciplinary fertilization (Bettencourt et al., 2007; Coffano et al., 2017; Fleming et al., 2007). Furthermore, networks with densely connected clusters facilitate the dissemination of tacit, non-codified and complex knowledge, allowing the members of the cluster to pose any potential questions regarding the information shared (Fleming et al., 2007; Fritsch & Kauffeld-Monz, 2010). Moreover, decentralized networks, with different hubs and/or separated clusters, may facilitate the creation of diverse and rich ideas within different parts of the network (Schilling & Phelps, 2007), avoiding collective stalemate (TerWal, 2013), and therefore fostering innovation.

Nevertheless, the influence of networks on knowledge diffusion might not always be positive. Over-connected networks and those with excessive levels of clustering can cause the recirculation of redundant information, increasing the homogeneity of shared knowledge (Burt, 2000, 2004; Fleming et al., 2007; Granovetter, 1973; Schilling & Phelps, 2007; Uzzi, 2008; Uzzi & Spiro, 2005). Furthermore, highly centralized networks, where only a few powerful actors dominate connections, may lead to monopoly over crucial knowledge (Shi & Guan, 2016). Some studies suggested an inverted U-shaped relationship between these network topologies and innovation (Shi & Guan, 2016; Uzzi & Spiro, 2005): there appears to be optimal levels for such properties that will foster knowledge diffusion, while networks below or above those levels will fail to generate and disseminate valuable knowledge for innovation.

As for co-ordination, network architectures may serve as co-operation and co-ordination mechanisms among network members and, in this way, influence innovation processes. For example, centralization can be an efficient structure to setup interoperability among actors with heterogeneous capabilities, reducing system dysfunctions and improving co-ordination (Crespo, Suire, & Vicente, 2016). Moreover, clustering impulses collaborative solutions and facilitates trust between nodes, as links in closed triplets enable mutual control and reduce the possibility of free-riding (Schilling & Phelps, 2007; Uzzi & Spiro, 2005). However, excessive levels of centralization may facilitate free-riding and/or rule imposition by central players at the cost of smaller actors and the system as a whole, whereas excessive clustering can create entry barriers, preventing the arrival and integration of new actors that could contribute to innovation processes (Shi & Guan, 2016; Uzzi, 2008).

2.3 | Networks, geography and innovation

Previous literature has studied the interaction between innovation networks and geography, reporting evidence on the differences between local and global networks (e.g., Capello & Caragliu, 2018; Grillitsch & Trippl, 2014; Hazır, LeSage, & Autant-Bernard, 2018; Herstad & Ebersberger, 2015). Yet, from a social-network perspective, only few recent studies have investigated the interaction between geography and structural network properties. Each of them typically asks one particular question, but their results suggest the role of collaboration networks on innovation cannot be fully understood from a local perspective only. Most of them have taken a region or a city as the unit of observation and asked what determines their innovation outcomes. In particular, Bettencourt et al. (2007) report that collaboration networks cannot fully explain the superlinear association between innovation and population of US cities. Lobo and Strumsky (2008) directly contrast the relative importance of the non-network features of urban areas against the local structural properties of co-patenting networks, concluding that the former is more important than the latter. Breschi and Lenzi (2016) ask whether short distances are important at the local or global level, or whether they interact. They report that social proximity within regions and to inventors in other cities reinforce each other in the determination of the area-level innovation.

The study most closely related to ours is Whittington et al. (2009). The authors analyse the interplay between geographical and network closeness, reporting complementary but contingent impacts of both dimensions on firm-level innovation outcomes. They additionally show that the centrality of an organization within both global and local networks has similar effects on its innovation rates. We complement this part of their analysis by studying whether this holds not only for centrality but also other node-level characteristics and whether this is still true for network-level measures.

All this evidence notwithstanding, the existing social-network analysis does not answer the main research question of our work: How do different geographical levels of embeddedness may determine the way networks affect innovation?

To address this question, we propose the following analytical framework. Consider a firm which is embedded in collaboration networks at two different geographical levels: local and national (Figure 1). According to the discussed

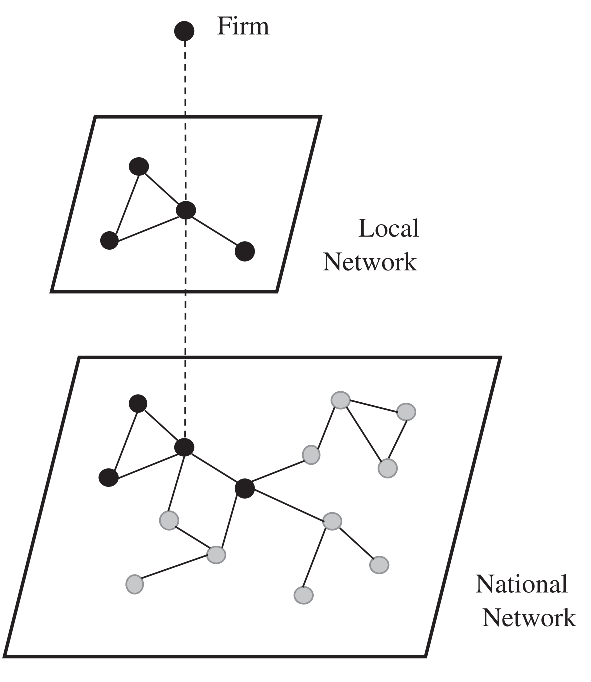

FIGURE 1 Network embeddedness at different geographical levels

literature, certain network properties may influence the firm's innovation performance. However, given that the firm is embedded at two geographical levels, it may be affected by the properties of both the local and the national networks. This raises the question of whether the two networks would influence the firm's patenting performance in the same way.

In this study, we hypothesize that the same network properties will matter differently at different geographical levels. For example, being a central node in the local network might play less or more important role than being central in the national collaboration structure. Likewise, being embedded in a dense regional network might have different effects than being embedded in a dense national network.

Previous literature on economic geography, social capital and social networks provides theoretical and empirical support for our argument by pointing out crucial differences between local and non-local networks. The first difference lies in the spatial proximity among nodes at the two scales. Obviously, actors in local networks are geographically closer to each other than those in nation-wide networks. Geographical proximity is associated with other forms of proximity that are crucial for innovation as well, such as cognitive, organizational, institutional and social (Boschma, 2005; Balland, Boschma, & Frenken, 2020; Capello & Caragliu, 2018). As a result, as we expand the geographic boundary of the network, we will have not only a greater geographical distance among nodes but also a greater variety and heterogeneity of actors.

These aspects have strong implications for the strength of the relationships. On the one hand, local networks tend to be composed of many strong ties where information is transferred through channels of *local buzz*, that is, "information and communication ecology created by face-to-face contacts, co-presence and co-location of people and firms within the same industry and place or region" (Bathelt, Malmberg, & Maskell, 2004, p. 38). This aspect of local networks can also be related with the notions of bonding social capital (Putnam, 2000) and strong ties (Granovetter, 1973), which reflect the strong and durable relationships among co-located actors that allow the circulation of tacit and complex knowledge, facilitate mutual vigilance and increase local trust (Uzzi & Spiro, 2005). In contrast, non-local networks tend to be made of weaker ties, or ties in less strongly embedded social systems. Such weak ties, however, can provide access to novel and non-redundant information (Granovetter, 1973). The literature on clusters refers to such distant interactions in extra-local networks as pipelines that bring external knowledge enhancing innovation processes (Bathelt et al., 2004; Owen-Smith & Powell, 2004). These pipelines connecting geographically distant actors often transmit analytical and codified knowledge, which is particularly relevant in formal and science-based innovation processes (Grillitsch & Trippl, 2014).

Based on these arguments, we expect differences in the *mechanisms* through which local and national networks influence innovation. Moreover, although both types of networks can influence innovation positively as well as negatively, the *strength* of the effects may vary according to the geographic scale. To state the general hypothesis of this study,[1] we particularly focus on the above discussed mechanisms: knowledge diffusion and co-ordination role of networks. We ask whether and to what extent each of them affects knowledge creation differently at different geographical scales. Concerning knowledge diffusion, greater heterogeneity of actors in national networks may strengthen the positive effects related to accessibility and diversity of knowledge flows, reducing the risks of redundant information recirculation. Meanwhile, in local networks, the negative effects associated with homogeneous knowledge will be relatively stronger, since the local actors are more homogeneous. Furthermore, the flow of knowledge and information can be monopolized more easily locally. The two arguments predict that network features enhancing information flows will be more relevant at larger geographical scales, while those inhibiting the flows will exert stronger negative effects at regional level.

Second, certain network features facilitate co-ordination and co-operation among network members. Since spatial proximity and greater homogeneity of actors promote collaborative solutions and trust through channels other than networks, the co-ordination role of collaboration structures should be more relevant at the country level. We

[1]The particular hypotheses for each network property under study are stated in the next section.

therefore hypothesize that network features facilitating efficient co-operation among heterogeneous actors will play a particularly key role in more distant geographical spaces.

In the next section, we present the individual network properties widely studied in the literature and, based on our general theoretical framework, we provide particular hypotheses regarding the expected direction and the strength of the effect that each property exerts on innovation at regional vs. national level.

3 | DATA AND METHODOLOGY

We use data from all the European patents registered at the Spanish Patent Office from 1978 to 2008. We have constructed a detailed database which enables us to identify the following information on each patent: (i) the date of application; (ii) the names of the companies which applied for the patent, which are referred to as innovators throughout the study; (iii) the names of the inventors; and (iv) the locations of *both* the innovators and the inventors.[2] We use the European patent applications because these data include the addresses of innovators (applicants) and inventors, while the Spanish patent applications—as well as other patent data—only register the address of the innovators. As explained below, we need both addresses to locate geographically the networks. Our data covers the period from the starting year of European patent records in Spain to 2008. We focus on years, during which Spain has experienced a steady economic growth, investment expansion and catching up to the advanced nations, which came to a halt with the arrival of the 2008 global financial crisis (Prados de la Escosura, 2017). This trend has reversed after 2008, a structural break particularly visible in patenting (Belda et al., 2014; Hidalgo & Gabaly, 2012). Hence, relating pre-2008 collaboration patterns to post-2008 patenting may not be comparable with the pre-2008 analysis. We thus focus on years 1978–2008.

Previous research using patent data have focused on two different types of collaboration networks, depending on the nodes they consider: networks of inventors (Fleming et al., 2007; van der Wouden, & Rigby, 2019) and networks of applicants or innovators (Breschi & Lissoni, 2009; Cantner & Graf, 2006; Graf & Hening, 2009; Innocenti et al., 2019; Singh, 2005). We follow the second perspective and trace our networks as follows:

- Nodes: the innovators or applicants who register the patent and hold the right to use it. These are mostly private companies, but research institutes, universities, and individuals can also be found among the nodes of our networks.
- Links: following Cantner and Graf (2006) and Graf and Hening (2009), we trace a link between two innovators when they jointly apply for a patent or when the same inventor work for them in different patents. These links are based on the idea that firms or research institutes are related either when they collaborate on joint patents or when they employ the same inventors (and thus share knowledge indirectly).

Regarding the geographical location of nodes, using only the innovator's address can cause a bias towards larger cities, since firms operating in different regions often attribute patents to the headquarter, regardless of where the innovation process took place. To address this potential problem, we follow Ter Wal and Boschma (2009) and Graf (2011), and use also the inventor's address in order to locate the innovators.[3] As a result, some nodes appear in more than one region if either they operate in different regions or if the inventors developing their patents report an

[2]Some studies use algorithms to disambiguate inventors (Li et al., 2014; van der Wouden & Rigby, 2019; Ventura, Nugent, & Fuchs, 2015). We have corrected and disambiguated the data of those inventors and innovators with higher number of patents manually. We stress that, since two surnames (in addition to the name) are registered for each individual in Spain, the likelihood of two different inventors having the same name and surnames is low. Indeed, we observed almost no such inventor confounding in the data.

[3]The address reported by the inventor can be the place of residence and not the place of work. However, by considering also the address of the applicant, we believe that we adequately cover the possible geographical location(s) where innovation activities can take place.

address in a different region. We believe that this approach reflects local-level interactions better than disregarding the activities of innovators in multiple regions. See subsection 3.4 and Figure 1 for more details.

We use the application date for each patent to determine the timing of links because such date reflects the timing of the collaboration better than the granting date. This information is used to classify the trends in collaboration patterns over time. In our analysis, we split our data into six five-year periods. For each period, we consider only the nodes and links active in the corresponding five years.[4] This is a crucial aspect of our strategy to relate networks to future patenting rates.

Since we focus on innovators and their embeddedness in networks with different geographical boundaries, we break the national Spanish network down into regional networks. The geographical boundaries considered to delimit the regions correspond to the NUTS 3 territorial division proposed by the European Union (Eurostat European Commission, 2011). We focus on the three largest regions in terms of innovation outcomes: Barcelona, Madrid and Valencia.[5] The objective is to contrast the association between network and patenting at different geographical levels. To that end, we model the link between a set of both node-level and network-level characteristics and the number of patents that companies register in the subsequent period. As mentioned above, the independent variables were carefully selected to reproduce as far as possible the econometric models in the literature (e.g., Ahuja, 2000; Fleming et al., 2007; Schilling & Phelps, 2007; Whittington et al., 2009). The contribution of this analysis is that the network variables are computed from the national as well as the three regional networks and their effects on future patenting are compared.

3.1 | Dependent variable

We follow the literature and use the number of registered patents as a measure of novel invention. Patent data present a good indicator of the innovation activities taking place in a given economy (Andersen, 2001; Archibugi, 1992; Griliches, 1990) but also entail several difficulties (see Fleming et al. (2007) or Schilling & Phelps (2007) for a discussion). As explained below, some of the difficulties can be addressed, such as patenting differences across time and space (by considering the location of the nodes and periods) and firm-specific differences (by controlling for past patenting).[6]

The idea is to observe how network properties influence future innovation results. Hence, to differentiate between current and subsequent outcomes, we label our dependent variable *Future Patents*$_{it}$ throughout the analysis. Note that *Future Patents*$_{it}$ is defined as the number of patent applications by organization i in period $t + 1$ and thus corresponds to *Patents*$_{it+1}$. It is a discrete ordinal variable (see Table 1).

3.2 | Independent variables

All our explanatory variables refer to network properties.[7] Two of them (*Betweenness and In-Giant*) measure individual characteristics of nodes based on their positions in the network. These node-level variables take different values

[4]We choose this time distribution in order to have enough periods with significant data to observe the changes in networks over time. The results are robust to considering different time windows.

[5]During the period under study, the selected three provinces accounted for 61.6 per cent of all European patents registered in Spain. Although Barcelona and Madrid were always the most dynamic regions, Valencia experienced great growth in recent years, progressively approaching the two leading territories. It should be pointed out that to compute the network characteristics at national level we use the whole network including the innovators from regions other than the three under scrutiny, but the subsequent econometric analysis only focuses on innovators from the three regions.

[6]We cannot control for industry-level differences in patenting, but we hope that past patenting will capture a large part of the variation due to differing patenting cultures in different industries. Since our results corroborate the previous literature that controls for industrial differences, we are confident that they are not driven by different patenting rates across industries.

[7]To save on space, we do not include the formal definitions of the variables. They can be found in, for example, Fleming et al. (2007) and Schilling and Phelps (2007).

TABLE 1 Descriptive statistics

	(1)	(2)	(3)	(4)	(5)
Variables	N	mean	sd	min	max
Future patents	385	6.075	24.25	1	415
Patents	385	3.351	9.720	1	169
Regional networks:					
Betweenness	385	4.201	50.38	0	961.5
Clustering	385	0.113	0.0522	0	0.457
Centralization	385	0.0292	0.0265	0.00695	0.108
Reach	385	0.00342	0.00437	0.00114	0.0372
Density	385	0.00260	0.00429	0.00111	0.0372
In Giant	385	0.0831	0.276	0	1
Giant share	385	0.0413	0.0308	0.0107	0.176
National networks:					
Betweenness	385	19.04	253.7	0	4,908
Clustering	385	0.140	0.0312	0.0549	0.168
Centralization	385	0.0194	0.0113	0.00522	0.0325
Reach	385	0.000990	0.000658	0.000564	0.00467
Density	385	0.000601	0.000688	0.000352	0.00467
In giant	385	0.0909	0.288	0	1
Giant share	385	0.0283	0.0159	0.00915	0.0466

for each actor, reflecting the extent to which each entrepreneur is embedded in the network and, therefore, we expect them to be associated with innovation.

The remaining variables (*Density*, *Centralization*, *Clustering*, *Reach* and *Giant Share*) are indicators of the network as a whole, that is, they take the same value for each member of one network. These indicators measure structural properties reflecting general patterns of collaboration between all actors that may enhance or restrict innovation processes.

3.2.1 | Betweenness centrality

The betweenness centrality of agent *i* measures the number of shortest paths between all pairs of nodes in a network (other than *i*) that pass through *i*.[8] Betweenness is one measure of a firm's access to the information available on the network, which can foster firm innovation (Ahuja, 2000; Powell, Koput, & Smith-Doerr, 1996; Tsai, 2001). Given the greater diversity of knowledge available at the national level, such positive effect of betweenness may be stronger at the national vs. regional level. However, maintaining links that enable the firm to remain central in a network is costly in terms of time and resources (Giuliani & Bell, 2005) and may also result in knowledge leaks to competitors (Khanna, Gulati, & Nohria, 1998). Since transaction costs increase naturally with geographical distance, these negative effects should be higher in the national network. Consequently, betweenness centrality may be correlated with *Future Patents* positively as well as negatively. Since the arguments hold for both geographical scales, we have

[8]We also repeated the whole analysis using the variable *Degree* (instead of *Betweenness*), which measures the number of collaboration partners of each node. The results were almost the same. We focus on betweenness in the final regressions because it reflects the position of an agent in the whole network better than the simple local degree.

no particular hypothesis regarding whether the net effects will be positive or negative and weaker or stronger at national vs. local level.

3.2.2 | In-Giant

The variable labelled as $In\text{-}Giant_{it}$ is a binary variable that takes a value of 1 if node *i* belongs to the giant component of the network and 0 otherwise. It reflects whether a firm is embedded in the largest group of innovators. Giant components allows for knowledge diffusion and cross-disciplinary fertilization of ideas among group members (Cantner & Graf, 2006; Fleming et al., 2007). Therefore, we posit that belonging to this group improves future innovation. We expect this effect to be stronger in the case of the national network because it allows for larger-scale network synergies.

3.2.3 | Density

Network density measures the number of actual links as a proportion of all the $n(n\text{-}2)/2$ possible connections in a network of *n* nodes. Nodes in denser networks are more interconnected than nodes in less dense networks. Density may increase information dissemination and make it more trustworthy (Fritsch & Kauffeld-Monz, 2010), but excessively high density can lead to the circulation of homogeneous and redundant information (Bettencourt et al., 2007; Lobo & Strumsky, 2008), especially at the local level. Consequently, while density may both stimulate and inhibit innovation, the net effect will be more positive in the national network.

3.2.4 | Centralization

Centralization compares the degree distribution of the network in relation to the most centralized star-shaped network.[9] This property can affect patenting activity in two different ways. First, a centralized network has shorter distances between its nodes, facilitating information flow and stimulating innovation (Schilling & Phelps, 2007) and additionally enhancing co-ordination mechanisms among the different components of the network (Crespo et al., 2016).[10] However, in highly centralized networks activity is unevenly distributed and too concentrated in the hands of a small proportion of nodes. This provides them with monopoly power over the flow of information and may reduce the aggregate patent production (Shi & Guan, 2016). Therefore, the positive effects of centralization might reach a threshold, beyond which higher centralization reduces innovation outputs. Due to the high levels of centralization shown by the Spanish networks, we expect this variable to be negatively correlated with the response variable. Since the monopolization of information flows is easier at smaller networks, we hypothesize that centralization will inhibit innovation more strongly at the local level.

3.2.5 | Clustering

The clustering coefficient of a network describes the extent to which a network contains highly interconnected groups of nodes. In particular, the average clustering coefficient is the fraction of neighbours of the nodes that are also mutually connected, averaged over the whole population. Again, this can affect innovation in several ways,

[9] A star-shaped network is an architecture in which one node is connected to all other nodes and all other nodes are connected only to the central node.
[10] Rather than a centralization index, Crespo et al. apply the slope of the degree distribution, which essentially measures centralization.

depending on the levels of network clustering. Under low clustering, an increase in this coefficient may improve innovation results by accelerating the circulation of information. However, when a network is already highly clustered a further increase in clustering might lead to the circulation of homogeneous and redundant information and thus limit positive cross-cluster collaborations (Cowan & Jonard, 2003; Uzzi & Spiro, 2005). Since clustering is generally low in our networks, we expect it to affect our dependent variable positively. In line with the above arguments, as the role of clustering while promoting co-operation and trust is more important at larger geographical space where actors are more heterogeneous, we hypothesize that the beneficial role of clustering will be stronger at the national level.

3.2.6 | Reach

The Reach of a network is the average inverse distance between two nodes in the network (Schilling & Phelps, 2007). This variable reflects how close to each other the network members are. If they are closer, the reach is high, and *vice versa*. A higher reach may improve innovation outputs by facilitating communication and the flow of information between agents; however, if too high a further increase may lead to homogeneity of information (Uzzi, 2008; Uzzi & Spiro, 2005). The reach is low in our networks, so we expect Reach to have a positive impact on our dependent variable, especially in the case of the national network.

3.2.7 | Giant Share

Giant Share, the fraction of nodes in the giant component, reflects the relative importance of the main group of innovators in a given network. If the majority of agents belong to the giant component, then large-scale dissemination of knowledge is possible (Fleming et al., 2007). Consequently, we expect this variable to have a positive influence on the dependent variable, with a stronger effect of the national network compared to that of the local structures.

3.3 | Control variables

The propensity to patent may of course vary due to non-network firm characteristics or other factors. To account for these possibilities, our modelling approach includes the following control variables:

3.3.1 | (Current) patents

To assess the role of collaboration patterns on future patenting we control for the current innovation outcome of each innovator. The variable Patents accounts for a large part of the unobserved heterogeneity in firms' propensity to innovate, such as size, management, industry, etc.

3.3.2 | Region dummies

Different regions naturally provide different innovation and collaboration opportunities. Hence, it is imperative to account for this in the regression analysis. To that end our models include two dummies, one for Madrid and one for Valencia. Their estimated parameters illustrate the different propensities to innovate in these regions, compared to the Barcelona area.

3.3.3 | Period fixed effects

Finally, we control for period fixed effects in our model to reflect potential different propensities to innovate over time. These differences may arise because of macroeconomic, political, or other factors that influence innovation.

3.4 | Regional vs. national boundaries

Given the objective of this study, all network-related variables have been computed using both the regional and national networks. This provides an opportunity to study the influence of regional vs. national collaboration patterns on future innovation outcomes.

Figure 1 illustrates the construction of the local and national networks in which a hypothetical firm is embedded. The black circles represent the innovators in the local network while grey nodes operate in other regions of the country. All innovators in our data are embedded in the national network, while some of them are also embedded in one of our three local networks (Madrid, Barcelona and Valencia). Therefore, innovators operating in one of such regions may be influenced by the architecture and their position in the national and/or local networks. Comparing the influence of these networks on innovator's outputs is the aim of our regression analysis.[11]

Table 1 provides the descriptive statistics of all the network variables presented above both at the regional and national level. Table 2 displays the correlations among all these variables.

3.5 | Model specification

Our dependent variable, Future Patents, is a count variable that takes strictly positive integer values. As a result, a linear regression model is inadequate because it assumes homoscedastic, normally distributed errors, an assumption that is violated in count data. Poisson regression is more appropriate (Hausman, Hail, & Griliches, 1984) but it assumes the equality of the mean and the variance of the variable. Nevertheless, patent data typically present overdispersion and this is also our case. Table 1 shows that the standard deviation of our dependent variable is fourfold higher than its mean (see also the histograms of future patenting in the Appendix). Hence, applying the Poisson model may underestimate the standard errors of coefficients, leading to spuriously high levels of significance (Cameron & Trivedi, 2005). We thus estimate a negative binomial model, which generalizes the Poisson model by incorporating individual, unobserved effects into the conditional mean, allowing for such overdispersion (Hausman et al., 1984). This approach is also taken in the related literature analysing patent data (Fleming et al., 2007; Schilling & Phelps, 2007; Whittington et al., 2009). We follow these studies closely.

We propose the following general model specification:

Future Patents = f (Betweenness, In-Giant, Density, Centralization, Clustering, Reach, Giant Share, Patents, Region, Period).

[11]Some innovators operate in regions that are not analysed in this study. They are accounted for in the derivation of country-wide network measures, but they are not included in the local analysis. Furthermore, certain innovators operate simultaneously in more than one (analysed) local network. This may be due to two reasons: either such innovators have branches in different regions or the innovator and the inventor report different addresses. We argue that including such innovators provides a more complete picture of the geographical radius of operation of innovators. In case of innovators in multiple regions, we estimate—separately—the impact of each regional network on their performance. We assume all of them may be relevant for its innovative activities.

TABLE 2 Correlation matrix

		1	2	3	4	5	6	7	8
1	Future Patents	1							
2	Patents	0.9374**	1						
Regional network:									
3	Betweenness	0.8810**	0.8908**	1					
4	Density	−0.0119	−0.0167	−0.0166	1				
5	Centralization	0.1387**	0.1494**	0.1361**	0.2086**	1			
6	Clustering	−0.0066	−0.0236	0.0051	0.4782**	0.1113	1		
7	Reach	0.0352	0.0360	0.0323	0.9471**	0.4979**	0.4649**	1	
8	Giant Share	0.1241*	0.1295*	0.1163*	0.4078**	0.9589**	0.2160**	0.6500**	1
9	In Giant	0.3220**	0.3167**	0.2754**	−0.0119	0.2069**	−0.0391	0.0563	0.1897**
National network:									
10	Betweenness	0.8912**	0.9058**	0.9841**	−0.0123	0.1408**	−0.0048	0.0380	0.1196*
11	Density	−0.0387	−0.0254	−0.0292	0.5566**	0.0552	−0.1794**	0.4841**	0.1941**
12	Centralization	0.0868	0.0887	0.0869	−0.1080*	0.5626**	0.3638**	0.0683	0.5772**
13	Clustering	0.0828	0.0803	0.0689	−0.1221*	0.4338**	0.3840**	0.0193	0.4118**
14	Reach	0.0101	0.0234	0.0197	0.4526**	0.3510**	0.0180	0.4803**	0.4891**
15	Giant Share	0.0875	0.0891	0.0866	−0.0977	0.5649**	0.3497**	0.0775	0.5848**
16	In Giant	0.3274**	0.3032**	0.2622**	0.0286	0.2168**	0.0647	0.1002*	0.2033**

Note:
*$p > 0.05$;
**$p > 0.05$. Correlation between the corresponding local and global measures in bold. In all these cases, $p < 0.0001$.

TABLE 2 Continued

	9	10	11	12	13	14	15	16
1								
2								
Regional network:								
3								
4								
5								
6								
7								
8								
9	1							
National network:								
10	0.2491**	1						
11	−0.0177	−0.0266	1					
12	0.1155*	0.0803	−0.1351**	1				
13	0.1073*	0.0633	−0.2140**	0.8316**	1			
14	0.0446	0.0186	0.8495**	0.4052**	0.2166**	1		
15	0.1175*	0.0800	−0.1127*	0.9973**	0.8283**	0.4258**	1	
16	0.7885**	0.2372**	−0.0827	0.1363**	0.1405**	−0.0062	0.1336**	1

Note:
*$p > 0.05$;
**$p > 0.05$. Correlation between the corresponding local and global measures in bold. In all these cases, $p < 0.0001$.

TABLE 3 Basic network properties in Spain (1977–2008)

		Spain	Barcelona	Madrid	Valencia
Network size	Nodes	8,215	2,459	1,614	604
	Links	5,475	1,558	1,114	458
Density (%)		0.02	0.05	0.09	0.25
Degree	Av.	1.33	1.27	1.38	1.51
	St. Dev.	4.44	2.33	5.25	3.24
Giant component	Size	852	208	278	67
	% of total	*10.37*	*8.46*	*17.22*	*11.09*
Second largest	Size	17	16	10	11
	% of total	*0.21*	*0.65*	*0.62*	*1.82*
Isolates	Number	4,139	1,203	811	300
	% of total	*50.38*	*48.92*	*50.25*	*49.67*
Diameter		11	12	9	5

This general specification omits the indices for innovators, time, and regions, as they differ depending on whether the model is estimated using the national or regional network characteristics.

4 | RESULTS

Table 3 presents the general network statistics for our networks. Figure 2 provides a view of the giant component of the Spanish network in the period under scrutiny and Figure 3 illustrates the three local networks. Roughly 60% of innovators (nodes) and collaborations (links) can be found in all three regions under study. Barcelona is the largest local network in terms of both nodes and links. There are substantial regional differences in the organization of innovation activities. Barcelona has fewer isolated innovators, a lower density, a smaller share of innovators in the giant component, and more inequality in the number of collaborators. In contrast, Valencia and Madrid show larger proportions of isolates, larger shares of nodes in the main component, and more concentration.[12]

We estimate several variations of the proposed model, reporting four of them here. The models are labelled as models (1)–(4) in Tables 4 and 5 (and Table A1 in the Appendix).[13] The model specifications differ in the network variables included in the analysis. The criteria that we followed while selecting the four models were: (i) to test the effect of all the network measures presented above in at least one model; and (ii) to avoid multicollinearity issues. As is common in network data, many network measures are correlated; this is also our case (see Table 2). The severity of the multicollinearity of each model was assessed using the variance inflation factor (VIF). We report the VIF quotient for each selected regression in Tables 4, 5 and A1. We follow the standard practice of accepting models, for which VIF < 10 in simple linear regression model (Kutner, Nachtsheim, Neter, & Li, 2005).

Most importantly for this study, each model was run three times. First, we relate future patenting to the local collaboration structures (labelled as *Regional* in Tables 3, 4, and A1). Second, we repeat each estimation with the collaboration patterns at the country level (labelled as *National*). Last, we combine both geographical scales in one

[12]The high levels of centralization in Madrid's network can be partially explained by the presence of the Spanish National Research Council (*Consejo Superior de Investigaciones Científicas*), which mainly operates in this region. It is possible to identify this node in Figure 3, as the most central hub, connected to many other nodes.

[13]Table A1 reports a variant of model (4), in which *Centralization* is replaced by *Giant Share*. We cannot include both measures in the same regression due to their collinearity. Such variation of model (4) reinforces the conclusions presented here. Other model specifications are available upon request from the authors.

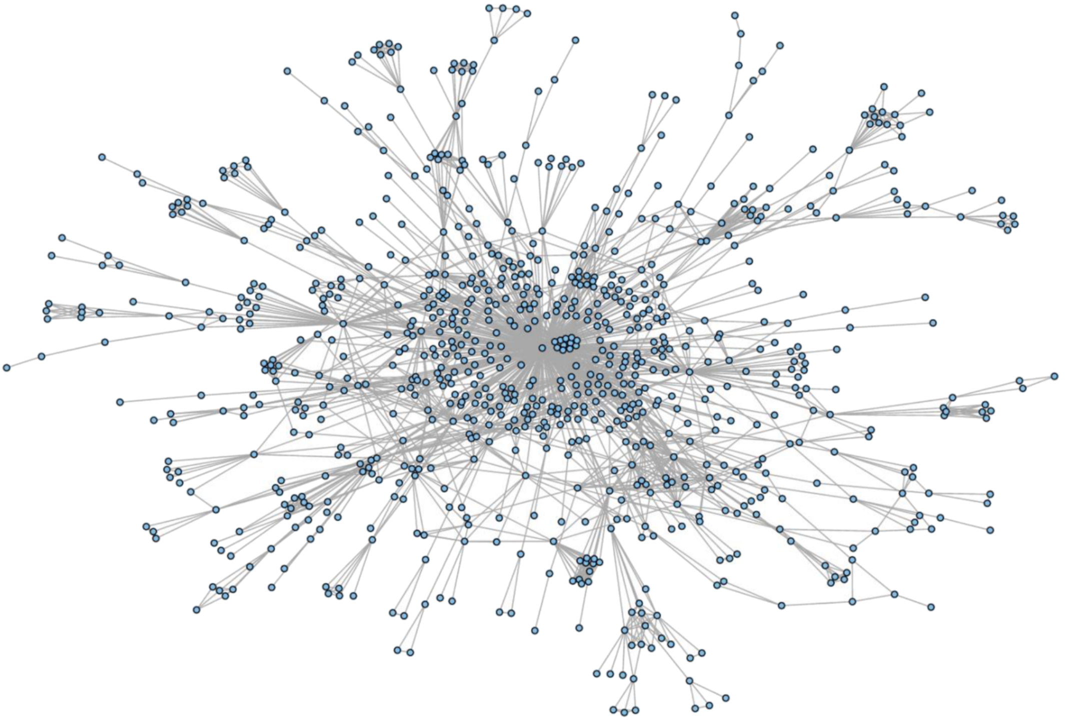

FIGURE 2 Giant component of the Spanish innovation network (1978–2008)

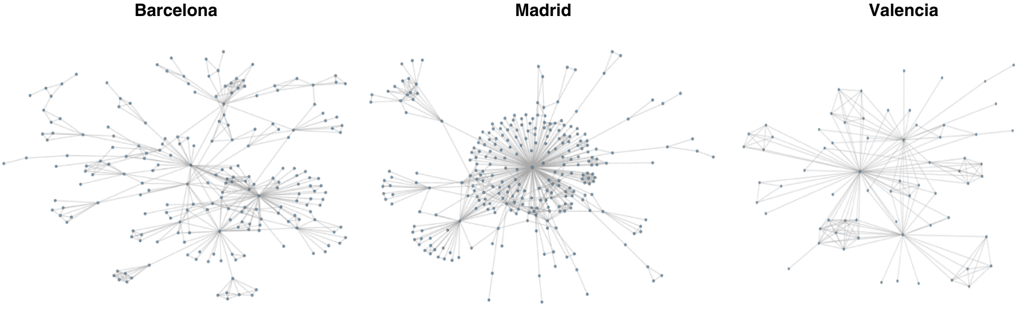

FIGURE 3 Giant components of the three regional innovation networks: Barcelona, Madrid and Valencia (1978–2008)

regression to the extent possible (labelled as *Both*).[14] This last specification enables to evaluate to what extent both variable types "compete" while explaining the dependent variable.

Tables 4 and 5 report the regression results. Table A1 in the Appendix provides an alternative model (4), in which centralization is replaced by giant share. Our models account for a total of 385 observations. That is, there were 385 innovators that appeared in any of the networks during at least two consecutive periods. The VIF quotient is generally below four in our regressions with regional and national networks and, since the regional and national network features are correlated, VIF is generally higher (around five) in the models that include networks at both spatial

[14]Most local and country-wide measures are correlated. See Table 2.

TABLE 4 Negative binomial regressions: models (1) and (2)

	Model (1)			Model (2)		
	Regional	National	Both	Regional	National	Both
No. patents	0.0441*** (0.00754)	0.0563*** (0.00741)	0.0546*** (0.00758)	0.0468*** (0.00777)	0.0563*** (0.00741)	0.0563*** (0.00761)
Regional network:						
Betweenness	−0.00458*** (0.00114)			−0.00493*** (0.00115)		
Density	−3.943 (16.47)		−4.496 (15.98)			
Centralization	−7.551** (3.819)		−7.685** (3.728)	−5.543 (4.371)		−5.839 (4.271)
Clustering				2.669 (2.124)		2.377 (2.038)
Reach				−38.36 (31.52)		−36.34 (31.08)
National network:						
Betweenness		−0.00129*** (0.00021)	−0.00119*** (0.000216)		−0.00129*** (0.00021)	−0.00122*** (0.000215)
Density		−51.22 (76.83)	11.64 (95.30)			
Centralization		0.705 (4.878)	12.07* (7.289)		−30.05 (20.34)	−33.46 (23.15)
Clustering					20.94* (11.42)	23.38** (11.53)
Reach					−9.908 (92.44)	202.6 (161.0)
Constant	1.284*** (0.476)	1.038*** (0.211)	0.933*** (0.219)	1.515*** (0.493)	−1.484 (1.301)	−2.074 (1.367)
Observations	385	385	385	385	385	385
Number of id	295	295	295	295	295	295
Region & Period FE	YES	YES	YES	YES	YES	YES
Wald chi2 (p-value)	120.55 (0)	133.45 (0)	142.73 (0)	125.02 (0)	133.45 (0)	146.91 (0)
Overd. chi2 (p-value)	105.47 (0)	87.75 (0)	86.38 (0)	102.35 (0)	87.75 (0)	86.24 (0)
Max likelihood	−917.92	−915.93	−913.47	−917.11	−915.94	−912.76
VIF (mean)	2.96	3.30	3.17	2.84	3.96	5.17
Pseudo R2	0.1296	0.1381	0.1405	0.1298	0.1381	0.1406
Moran *I* (observed)	−0.04444	−0.02272	−0.04354	−0.0007	−0.02792	−0.04463
Moran (p-value)	0.2426	0.6158	0.2569	0.8493	0.5186	0.2502

Notes: Robust standard errors in parentheses;
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Overd. = Overdispersion.

TABLE 5 Negative Binomial Regression Models 3 and 4

	Model (3)			Model (4)		
Variables	**Regional**	**National**	**Both**	**Regional**	**National**	**Both**
No. patents	0.0383*** (0.00752)	0.0521*** (0.00687)	0.0499*** (0.00740)	0.0409*** (0.00782)	0.0521*** (0.00687)	0.0522*** (0.00742)
Regional network:						
Betweenness	−0.00379*** (0.00112)			−0.00413*** (0.00115)		
In giant	0.511*** (0.172)		0.00618 (0.262)	0.498*** (0.171)		−0.0214 (0.252)
Density	1.870 (16.26)		−3.751 (14.75)			
Centralization	−7.385** (3.730)		−7.815** (3.604)	−5.810 (4.284)		−5.851 (4.056)
Clustering				2.444 (2.113)		2.804 (1.929)
Reach				−30.01 (31.23)		−41.18 (28.94)
National network:						
Betweennes		−0.00117*** (0.000192)	−0.00106*** (0.000208)		−0.00117*** (0.000192)	−0.00111*** (0.000206)
In_giant		0.588*** (0.161)	0.592** (0.252)		0.588*** (0.161)	0.630*** (0.245)
Density		−38.19 (75.93)	22.97 (92.98)			
Centralization		−0.855 (4.745)	10.86 (7.163)		−31.26 (19.65)	−33.85 (21.71)
Clustering					20.41* (11.06)	21.85** (11.05)
Reach					3.746 (91.32)	239.1 (153.9)
Constant	1.180** (0.473)	1.051*** (0.207)	0.940*** (0.217)	1.411*** (0.489)	−1.405 (1.265)	−1.925 (1.305)
Observations	385	385	385	385	385	385
Number of id	295	295	295	295	295	295
Region and Period FE	YES	YES	YES	YES	YES	YES
Wald chi2 (p-value)	143.22 (0)	177.09 (0)	189.57 (0)	147.03 (0)	177.09 (0)	193.88 (0)
Overd. chi2 (p-value)	96.26 (0)	76.81 (0)	75.67 (0)	93.12 (0)	76.81 (0)	75.83 (0)
Max likelihood	−913.89	−910.04	−907.27	−913.24	−910.04	−906.73
VIF (mean)	2.63	2.93	2.94	2.58	3.54	4.74
Pseudo R2	0.1382	0.1490	0.1518	0.1384	0.1490	0.1518

(Continues)

TABLE 5 (Continued)

Variables	Model (3) Regional	National	Both	Model (4) Regional	National	Both
Moran *I* (observed)	−0.02373	−0.02373	−0.02937	−0.04369	−0.02373	−0.02981
Moran *I* (p-value)	0.6285	0.6285	0.5158	0.2659	0.6285	0.5103

Notes: Robust standard errors in parentheses;
***p < 0.01,**p < 0.05,*p < 0.1; Overd. = Overdispersion.

scales but still well below the critical value of ten. We thus conclude that the presented models do not suffer from multicollinearity. We never reject overdispersion (chi-square tests; $p < 0.0001$), supporting the choice of the negative binomial model. None of the reported models exhibit spatial correlation in model residuals (Moran *I* tests; $p > 0.24$). Hence, the error terms seem to be well estimated.

In what follows, we highlight the main conclusions drawn from our analysis. Note first that most network variables influence future innovation in at least one model at one geographical scale. Hence, the patterns of collaboration are a major determinant of innovation in our data.

Using the Spanish-wide network, the estimated effects are in harmony with the literature (Fleming et al., 2007; Schilling & Phelps, 2007; Uzzi, 2008; Whittington et al., 2009): Centralization is bad for innovation, whereas higher clustering and higher reach enhance patenting activities.[15,16] Hence, we can conclude that our results are not an artefact of the Spanish market for patents.

By contrast, these effects are not corroborated in our analysis using the local, regional networks. The two node-specific characteristics, Betweenness and In-Giant, matter for innovation and they both matter similarly in the local and national networks if considered separately, suggesting that the individual positioning of actors in the network is highly relevant for innovation regardless of the geographical level of embeddedness. These findings corroborate Whittington et al. (2009) with respect to centrality. Since the effect of In-Giant is very similar at both scales, our analysis shows that their findings extend to other node-level characteristics. This notwithstanding, once we include In-Giant at both levels in the same model, the estimated role of belonging the national giant component actually increases slightly. In contrast, the role of the regional giant component becomes statistically insignificant. This is the first result indicating that the larger-scale, national network matters more for innovation outcomes than the regional architecture. Unfortunately, we cannot include inventors' local and global betweenness centralities simultaneously into one model as the two measures are strongly correlated ($\rho = 0.9841$, $p < 0.0001$); if we do, VIF increases dramatically, generating multicollinearity.

Crucially, the impact of the local vs. the national architectures differs considerably if we focus on network-wide properties. Overall, the Spanish network plays a larger and more positive role in patenting than the regional structures. Apart from centralization of regional collaboration that reduces patenting, none global feature of regional collaboration patterns exerts significant influence on patent productivity of innovators in any estimated model.

In contrast, the clustering coefficient of the national network systematically increases patenting. In addition, reach, centralization and giant share explain future patenting in at least one regression in Tables 3, 4 or A1. More precisely, local link density—measured by the average clustering coefficient—and reach within the country-wide network enhance the creation of co-operative patterns and the circulation of information among actors and higher reach facilitates fast, reliable dissemination. Such effects have previously been detected by for example, Schilling and

[15]Reach and Giant share (see below) are found to be significant in Table A1 in the Appendix.
[16]In an alternative model specification, we included the small-world property that combines clustering and reach. Since it is never significant in any model and increases VIF considerably, we eliminated it from the analysis. This finding contrasts with Uzzi and Spiro (2005) and Schilling and Phelps (2007), but others do not find a robust effect of the interaction of high clustering and smaller distance (Fleming et al., 2007).

Phelps (2007) and Uzzi (2008). These two structural properties are only relevant at the national level in our data. As for centralization, the effect of regional centralization is consistently negative but, although the productivity decreases in national networks that are too centralized in national regressions, this effect either becomes statistically insignificant or significant and actually positive (model (3)) in the regressions that introduce both regional and national centralization in the model. We thus conclude in line with our hypothesis that, at regional level, the negative effects of centralization prevail while the negative and positive role of this variable seem to cancel out at larger-scale networks. Hence, centralization is the only network-wide feature that matters more at the regional level. Giant share becomes significant in model (4) in Table A1 in the Appendix; its estimated effect is negative suggesting that, *ceteris paribus*, larger share of nodes in the giant component of the national network is harmful for innovation. This finding contrasts our hypothesis that Giant share will play a positive role in knowledge creation.

In sum, the role of the collaboration structure in innovation activities is highly sensitive to the geographical boundaries of the network. The node-level properties seem to influence innovation at both geographical levels similarly. However, the only whole-network topological feature that matters at the local, regional level is centralization, while the clustering coefficient, reach and giant share are relevant for innovation at the national-level.[17]

5 | CONCLUSIONS

Previous research reports that the patterns of collaboration influences future innovation. However, the social-network approach typically sets one particular geographic level to characterize the collaboration network in one region, state or country. This naturally raises the question of whether these findings are robust to considering different geographic levels of embeddedness. We argue that this question is of crucial importance for policy-makers and business management, especially in knowledge-intensive industries (Owen-Smith & Powell, 2004; Whittington et al., 2009). Policy-makers aim to promote innovation by financing public and private research directly as well as indirectly by stimulating collaboration, and this happens at different geographic levels. In a similar vein, organizations relying on innovation strategically choose their collaboration partners in their innovation activities and the question is whether they should consider bringing in potential partners in local, national, and even worldwide collaboration networks and which of them provide the most advantage for their future innovation.

We test these issues using the Spanish patent data from 1978 to 2008, contrasting the role of local and national collaboration patterns. Our results highlight that the conclusions in the literature may be specific to the geographical level that the researcher, policy-maker or manager selects for the analysis. Our results corroborate the previous studies mostly applied to US data in many respects (Fleming et al., 2007; Schilling & Phelps, 2007; Uzzi, 2008; Whittington et al., 2009) when the country-wide network is analysed. Even if we find no crucial differences between the local and nationwide networks in the influence of the node-level characteristics on innovation, the network-level properties of national networks play larger and more positive role in patenting than those of the local networks. Consequently, the association between collaboration networks and innovation depends on the network geographic level. Corroborating Hess's view (Hess, 2004), our results demonstrate the relevance of non-local forms of embeddedness, without neglecting the role of territorial embeddedness in certain aspects. Our social-network approach is in line with the analogous findings in economic geography (e.g., Grillitsch & Trippl, 2014).

These findings have important implications. First, they corroborate that collaboration networks impact future patenting and that this extends to less knowledge-intensive economies such as Spain, since when national collaboration patterns are used the effects detected of the network structural properties on innovation are relatively similar to those found in other studies (Schilling & Phelps, 2007; Whittington et al., 2009).

[17]All our conclusions are robust to controlling for regional socio-economic variables and their evolution, retrieved from FEDEA (2020); see Tables A2–3 in the Appendix.

Second, our findings illustrate that scholars should be well aware that focusing on particular regions, such as Silicon Valley or the Boston Area, might mean missing an important part of the general picture of collaboration systems, leading to an overestimation or underestimation of the significance of the collaboration structure. This is akin to the emerging network econometric literature that reports that observing network data of only a part of the population biases considerably the observed network properties and using them in regressions leads to incorrect inferences regarding both the *strength* and even the *direction* of estimated network effects (Chandrasekhar & Lewis, 2016; Hsieh, Ko, Kovářík, & Logan, 2019). Our study shows that the same issue arises while estimating the impact of collaboration networks on innovation.

Third, our results contribute to the literature analysing the interaction of proximity, geography and innovation networks (see e.g., Balland, Boschma, et al., 2020 for a recent review). From a social-network approach, we show that the geographical level matters and the externalities embedded in collaboration networks may be stronger and more positive in larger-scale systems than in localized areas. This has important implications for future empirical and theoretical modelling of innovations systems.

Fourth, we inform both policy-makers and managers about what type of collaboration and innovation patterns they should promote. In particular, firms while designing their research collaboration policies should consider network embeddedness in different contexts, looking not only at their local or regional innovation systems but also at higher geographic levels. Policy-makers should promote certain patterns of collaboration and discourage others in function of their territorial scope (national or local). In particular, while national policy-makers should encourage highly connected clusters of innovators and higher reach, local policy-makers should avoid overly centralized patterns of collaboration, encouraging the participation of multiple local agents, so that innovation networks do not rely excessively on a small group of actors. Our results additionally suggest that country-level and regional policy-makers should align their goals regarding research and innovation while promoting collaboration through collaboration patterns.

Needless to say, this study has several limitations. The most important one is the country under study: Spain's economy is less knowledge-intensive than that of other countries and more systematic patenting has been observed only recently. This explains why the number of observations is relatively low in the regression analysis and calls for a robustness analysis using, for example, US data so as to prevent other researchers from drawing too general conclusions from our analysis. However, the internationalization of research activities and globalization lead us to believe that our main conclusion would remain valid in comparisons of the Spanish vs. the European collaboration network and even in comparisons of the European or the US networks with worldwide collaboration patterns. These hypotheses represent a major question for future research.

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REFERENCES

Ahuja, G. (2000). Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly*, *45*(3), 425–455.

Allen, R. C. (1983). Collective invention. *Journal of Economic Behavior and Organization*, *4*(1), 1–24.

Almeida, P., Hohberger, J., & Parada, P. (2011). Individual scientific collaborations and firm-level innovation. *Industrial and Corporate Change*, *20*, 1571–1599.

Almeida, P., & Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, *45*(7), 905–917.

Andersen, B. (2001). *Technological change and the evolution of corporate innovation. The structure of patenting, 1880–1990*. Cheltenham: Edward Elgar Publishing.

Archibugi, D. (1992). Patenting as an indicator of technological innovation: A review. *Science and Public Policy*, *19*(6), 357–368.

Balland, P. A., Boschma, R., & Frenken, K. (2020). Proximity, innovation and networks: A concise review and some next steps. In A. Torre & D. Gallaud (Eds.), *The handbook of proximity relations*. Cheltenham: Edward Elgar. forthcoming

Balland, P. A., Jara-Figueroa, C., Petralia, S. G., Steijn, M. P., Rigby, D. L., & Hidalgo, C. A. (2020). Complex economic activities concentrate in large cities. *Nature Human Behaviour*, *4*, 248–254.

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.

Belda, I., Penas, G., Alonso, A., Marquina, D., Navascués, E., & Santos, A. (2014). Biotech patents and science policy: The Spanish experience. *Nature Biotechnology*, *32*(1), 59–61. https://doi.org/10.1038/nbt.2781

Bettencourt, L. M. A., Lobo, J., & Strumsky, D. (2007). Invention in the city: Increasing returns to patenting as a scaling function of metropolitan size. *Research Policy*, *36*, 107–120.

Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, *39*(1), 61–74. https://doi.org/10.1080/0034340052000320887

Breschi, S., & Lenzi, C. (2016). Co-invention networks and inventive productivity in US cities. *Journal of Urban Economics*, *92*, 66–75.

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.

Brusco, S. (1999). The rules of the game in industrial districts. In A. Grandori (Ed.), *Interfirm networks. Organization and industrial competitiveness* (pp. 17–40). London: Routledge.

Burt, R. S. (2000). The network structure of social capital. *Research in Organizational Behavior*, *22*, 345–423.

Burt, R. S. (2004). Structural holes and good ideas. *American Journal of Sociology*, *110*(2), 349–399. https://doi.org/10.1086/421787

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: methods and applications*. Cambridge: Cambridge University Press.

Cantner, U., & Graf, H. (2006). The network of innovators in Jena: An application of social network analysis. *Research Policy*, *35*(4), 463–480. https://doi.org/10.1016/j.respol.2006.01.002

Capello, R., & Caragliu, A. (2018). Proximities and the intensity of scientific relations: Synergies and nonlinearities. *International Regional Science Review*, *41*(1), 7–44.

Carlino, G. A., Chatterjee, S., & Hunt, R. M. (2007). Urban density and the rate of invention. *Journal of Urban Economics*, *61*(3), 389–419.

Chandrasekhar, A., & Lewis, R. (2016). Econometrics of sampled networks. Unpublished manuscript.

Coffano, M., Foray, D., & Pezzoni, M. (2017). Does inventor centrality foster regional innovation? The case of the Swiss medical devices sector. *Regional Studies*, *51*(8), 1206–1218.

Cowan, R., & Jonard, N. (2003). The dynamics of collective invention. *Journal of Economic Behavior & Organization*, *52*(4), 513–532. https://doi.org/10.1016/s0167-2681(03)00091-x

Crespo, J., Suire, R., & Vicente, J. (2016). Network structural properties for cluster long-run dynamics: Evidence from collaborative R&D networks in the European mobile phone industry. *Industrial and Corporate Change*, *25*(2), 261–282.

de Faria, P., Lima, F., & Santos, R. (2010). Co-operation in innovation activities: The importance of partners. *Research Policy*, *39*, 1082–1092.

Eurostat European Commission. (2011). Regions in the European Union. *Nomenclature of territorial units for statistics. NUTS 2010/EU-27*. https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/KS-GQ-14-006

FEDEA. (2020). Regional and urban economic data. URL: https://www.fedea.net/datos-economia-regional-y-urbana.

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

Fritsch, M. (2004). Cooperation and the efficiency of regional R&D activities. *Cambridge Journal of Economics*, *28*(6), 829–846. https://doi.org/10.1093/cje/beh039

Fritsch, M., & Kauffeld-Monz, M. (2010). The impact of network structure on knowledge transfer: an application of social network analysis in the context of regional innovation networks. *The Annals of Regional Science*, *44*(1), 21–38. https://doi.org/10.1007/s00168-008-0245-8

Galaso, P. (2018). Network topologies as collective social capital in cities and regions: A critical review of empirical studies. *European Planning Studies*, *26*(3), 571–590.

Giuliani, E., & Bell, M. (2005). The micro-determinants of meso-level learning and innovation: Evidence from a Chilean wine cluster. *Research Policy*, *34*(1), 47–68. https://doi.org/10.1016/j.respol.2004.10.008

Glaeser, E. L. (1999). Learning in cities. *Journal of Urban Economics*, *46*(2), 254–277.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy*, *100*(6), 1126–1152.

Graf, H. (2011). Gatekeepers in regional networks of innovators. *Cambridge Journal of Economics*, *35*(1), 173–198.

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. https://doi.org/10.1080/00343400802251460

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology*, *78*, 1360–1380. https://doi.org/10.1086/225469

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, *28*, 1661–1707.

Grillitsch, M., & Trippl, M. (2014). Combining knowledge from different sources, channels and geographical scales. *European Planning Studies*, *22*(11), 2305–2325.

Hausman, I. A., Hail, B. H., & Griliches, Z. (1984). Econometric Models for Count Data with an Application to the Patents R&D Relationship. *Econometrica*, *52*, 909–938.

Hazır, C. S., LeSage, J., & Autant-Bernard, C. (2018). The role of R&D collaboration networks on regional knowledge creation: Evidence from information and communication technologies. *Papers in Regional Science*, *97*(3), 549–567.

Herstad, S. J., & Ebersberger, B. (2015). On the link between urban location and the involvement of knowledge intensive business services firms in collaboration networks. *Regional Studies*, *49*(7), 1160–1175.

Hess, M. (2004). Spatial relationships? Towards a reconceptualization of embedded ness. *Progress in Human Geography*, *28* (2), 165–186.

Hidalgo, A., & Gabaly, S. (2012). Use of prediction methods for patent and trademark applications in Spain. *World Patent Information*, *34*(1), 19–29.

Hsieh, C. S., Ko, S. I., Kovářík, J., & Logan, T. (2019). Non-randomly sampled networks: Biases and corrections. National Bureau of Economic Research Working Paper 25270.

Innocenti, N., Capone, F., & Lazzeretti, L. (2019). Knowledge networks and industrial structure for regional innovation: An analysis of patents collaborations in Italy. *Papers in Regional Science*, *99*(1), 55–72.

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

Jones, B. F., Wuchty, S., & Uzzi, B. (2008). Multi-university research teams: Shifting impact, geography, and stratification in science. *Science*, *322*, 1259–1262.

Katz, J. S., & Martin, B. R. (1997). What is research collaboration? *Research Policy*, *26*, 1–18.

Khanna, T., Gulati, R., & Nohria, N. (1998). The dynamics of learning alliances: Competition, cooperation, and relative scope. *Strategic Management Journal*, *19*(3), 193–210. https://doi.org/10.1002/(sici)1097-0266(199803)19:3<193::aid-smj949>3.0.co;2-c

Koput, K. W. (1997). A chaotic model of innovative search: Some answers, many questions. *Organization Science*, *8*, 528–542.

Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. (2005). *Applied linear statistical models* (Vol. 5). New York: McGraw-Hill Irwin.

Laursen, K., & Salter, A. J. (2014). The paradox of openness: Appropriability, external search and collaboration. *Research Policy*, *43*(5), 867–878. https://doi.org/10.1016/j.respol.2013.10.004

Li, G. C., Lai, R., D'Amou, R. A., Doolin, D. M., Sun, Y., Torvik, V. I., & Fleming, L. (2014). Disambiguation and co-authorship networks of the US patent inventor database (1975–2010). *Research Policy*, *43*, 941–955.

Lobo, J., & Strumsky, D. (2008). Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects. *Journal of Urban Economics*, *63*, 871–884.

Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Cambridge, MA: Belknap Press of Harvard University Press.

Owen-Smith, J., & Powell, W. (2004). Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. *Organization Science*, *15*, 5–21.

Phelps, C., Heidl, R., & Wadhwa, A. (2012). Knowledge, networks, and knowledge networks: A review and research agenda. *Journal of Management*, *38*(4), 1115–1166.

Pippel, G. (2013). The impact of R&D collaboration networks on the performance of firms: A meta-analysis of the evidence. *International Journal of Networking and Virtual Organisations*, *12*(4), 352–373.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly*, *41*(1), 116. https://doi.org/10.2307/2393988

Prados de la Escosura, L. (2017). *Spanish economic growth, 1850–2015*. Cham: Palgrave Macmillan.

Putnam, R. D. (2000). *Bowling alone: The collapse and revival of American Community*. New York: Simon & Schuster.

Saxenian, A. L. (1994). *Regional advantage. Culture and competition in Silicon Valley and Route 128*. Cambridge, MA: Harvard University Press.

Schilling, M. A., & Phelps, C. C. (2007). Interfirm collaboration networks: The Impact of Large-Scale Network Structure on firm innovation. *Management Science*, *53*(7), 1113–1126.

Shi, Y., & Guan, J. (2016). Small-world network effects on innovation: Evidences from nanotechnology patenting. *Journal of Nanoparticle Research*, *18*(11), 329.

Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science*, *51*(5), 756–770.

Strumsky, D., & Thill, J. C. (2013). Profiling US metropolitan regions by their social research networks and regional economic performance. *Journal of Regional Science*, *53*(5), 813–833.

Ter Wal, A. L. (2013). Cluster emergence and network evolution: A longitudinal analysis of the inventor network in Sophia-Antipolis. *Regional Studies*, *47*(5), 651–668.

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.

Tsai, W. (2001). Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance. *Academy of Management Journal*, *44*(5), 996–1004. https://doi.org/10.2307/3069443

Uzzi, B. (2008). A social network's changing statistical properties and the quality of human innovation. *Journal of Physics A: Mathematical and Theoretical*, *41*(22), 224023. https://doi.org/10.1088/1751-8113/41/22/224023

Uzzi, B., & Spiro, J. (2005). Collaboration and creativity: The small world problem. *American Journal of Sociology*, *111*(2), 447–504.

van der Wouden, F., & Rigby, D. L. (2019). Co-inventor networks and knowledge production in specialized and diversified cities. *Papers in Regional Science*, *98*(4), 1833–1853.

Ventura, S. L., Nugent, R., & Fuchs, E. R. (2015). Seeing the non-stars: (Some) sources of bias in past disambiguation approaches and a new public tool leveraging labeled records. *Research Policy*, *44*(9), 1672–1701.

Whittington, K. B., Owen-Smith, J., & Powell, W. W. (2009). Networks, propinquity, and innovation in knowledge-intensive industries. *Administrative Science Quarterly*, *54*, 90–122.

Wuchty, S., Jones, D. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, *316*, 1036–1039. https://doi.org/10.1126/science.1136099

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APPENDIX

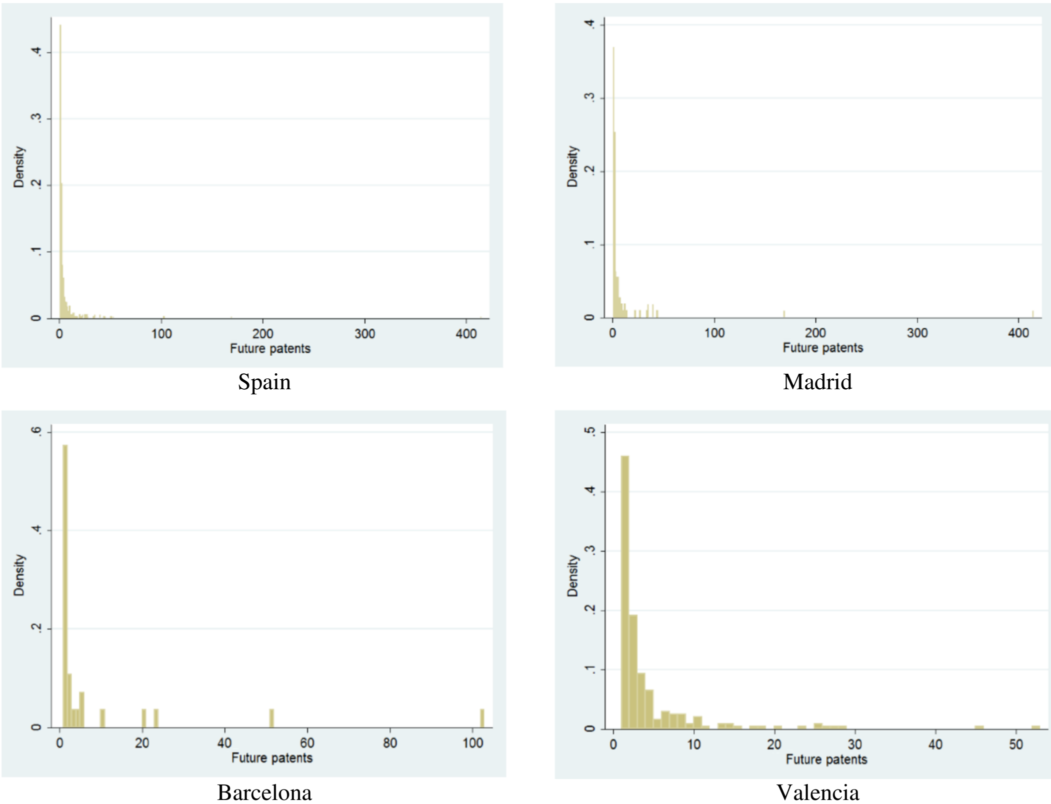

FIGURE A1 Histograms of the variable patents

TABLE A1 Negative binomial regression, alternative models

	Model 4		
Variables	Regional	National	Both
No. Patents	0.0412*** (0.00789)	0.0521*** (0.00687)	0.0523*** (0.00746)
Regional network:			
Betweenness	−0.00425*** (0.00115)		
In giant	0.496*** (0.171)		−0.0183 (0.249)
Clustering	2.987 (2.055)		3.240* (1.882)
Reach	−34.71 (34.74)		−42.08 (31.86)
Giant Share	−4.341 (5.518)		−5.179 (5.287)
National network:			
Betweenness		−0.00117*** (0.000192)	−0.00113*** (0.000207)
In giant		0.588*** (0.161)	0.632*** (0.242)
Clustering		29.96* (16.93)	35.09** (17.12)
Reach		47.21 (105.8)	342.3** (167.7)
Giant Share		−34.46 (21.66)	−41.82* (23.60)

(Continues)

TABLE A1 (Continued)

	Model 4		
Variables	**Regional**	**National**	**Both**
Constant	1.555*** (0.526)	−2.472 (1.911)	−3.435* (1.985)
Observations	385	385	385
Number of id	295	295	295
Region & Period FE	YES	YES	YES
Wald chi2 (p-value)	143.26 (0)	177.09 (0)	197.67 (0)
Overd. chi2 (p-value)	93.49 (0)	76.81 (0)	75.46 (0)
Max likelihood	−913.83	−910.04	−906.19
VIF (mean)	2.72	3.56	5.42
Pseudo R2	0.1381	0.1490	0.1514
Moran *I* (observed)	−0.04339	−0.02373	−0.03033
Moran *I* (p-value)	0.2693	0.6285	0.4988

Notes: Robust standard errors in parentheses;
***$p < 0.01$,**$p < 0.05$,*$p < 0.1$; Overd. = Overdispersion.

TABLE A2 Negative binomial regressions with regional controls, models (1) and (2)

	Model (1)			Model (2)		
Variables	**Regional**	**National**	**Both**	**Regional**	**National**	**Both**
No. Patents	0.0467*** (0.00683)	0.0566*** (0.00742)	0.0541*** (0.00754)	0.0466*** (0.00684)	0.0565*** (0.00739)	0.0557*** (0.00762)
Regional network:						
Betweenness	−0.00499*** (0.00104)			−0.00498*** (0.00104)		
Density	2.456 (13.49)		−2.557 (14.81)			
Centralization	−5.148* (2.855)		−7.795** (3.226)	−4.392 (3.571)		−5.853 (4.060)
Clustering				0.457 (1.404)		2.069 (1.976)
Reach				−5.639 (22.03)		−29.29 (29.22)
National network:						
Betweenness		−0.00130*** (0.000211)	−0.00117*** (0.000216)		−0.00129*** (0.000210)	−0.0012*** (0.000216)
Density		6.396 (99.09)	138.4 (111.4)			
Centralization		0.408 (7.449)	7.063 (7.672)		−1.625 (10.23)	−6.945 (13.00)
Clustering					1.516 (3.132)	−0.324 (3.332)

TABLE A2 (Continued)

	Model (1)			Model (2)		
Variables	**Regional**	**National**	**Both**	**Regional**	**National**	**Both**
Reach					2.920 (113.7)	291.0 (182.2)
Regional controls:						
GDP per capita	−0.0297 (0.0400)	−0.0194 (0.0463)	−0.0645 (0.0492)	−0.0386 (0.0464)	−0.0260 (0.0485)	−0.0780 (0.0529)
Years of education	0.388* (0.201)	0.207 (0.180)	0.556** (0.220)	0.399* (0.208)	0.210 (0.180)	0.656*** (0.243)
Constant	−1.235 (0.878)	−0.247 (0.790)	−1.876* (1.057)	−1.161 (0.872)	−0.288 (0.789)	−2.422** (1.204)
Observations	385	385	385	385	385	385
Number of id	295	295	295	295	295	295
Region & Period FE	NO	NO	NO	NO	NO	NO
Wald chi2 (p-value)	121.88 (0)	135.73 (0)	143.95 (0)	121.49 (0)	137.00 (0)	146.69 (0)
Overd. chi2 (p-value)	106.73 (0)	85.96 (0)	87.30 (0)	107.28 (0)	86.05 (0)	87.23 (0)
Max likelihood	−919.39073	−916.8997	−913.34756	−919.35402	−916.78066	−912.76816
VIF (mean)	5.59	5.63	6.54	6.01	6.01	8.43
Pseudo R2	0.1266	0.1378	0.1403	0.1265	0.1378	0.1404
Moran *I* (observed)	0.04363	0.09359	0.09148	0.05056	0.09634	0.09470
Moran *I* (p-value)	0.1586	0.0047	0.0056	0.1079	0.0037	0.0042

Notes: Robust standard errors in parentheses;
***p < 0.01,**p < 0.05,*p < 0.1; Overd. = Overdispersion.GDP per capita and Years of education downloaded from FEDEA (2020). Both variables for Madrid, Valencia and Barcelona correspond to the NUTS 2 regions where these provinces are located: Community of Madrid, Valencian Community and Catalonia, respectively. In case of Madrid, the province coincides with the NUTS 2 region; Valencia and Barcelona constitute the main territories of their respective NUTS regions: in 2008, Valencia had 51% of the inhabitants of the Valencian Community and Barcelona had 74% of the population of Catalonia.

TABLE A3 Negative binomial regressions with regional controls, models (3) and (4)

	Model (3)			Model (4)		
Variables	Regional	National	Both	Regional	National	Both
No. Patents	0.0398*** (0.00693)	0.0524*** (0.00692)	0.0497*** (0.00738)	0.0396*** (0.00695)	0.0524*** (0.00688)	0.0517*** (0.00743)
Regional network:						
Betweenness	−0.00403*** (0.00104)			−0.00401*** (0.00104)		
In giant	0.527*** (0.171)		−0.00327 (0.263)	0.523*** (0.171)		−0.0179 (0.255)
Density	5.800 (13.48)		−1.960 (13.61)			
Centralization	−5.547** (2.788)		−7.828** (3.098)	−5.095 (3.517)		−5.656 (3.871)
Clustering				0.333 (1.392)		2.435 (1.870)
Reach				−0.629 (21.90)		−33.02 (27.17)
National network:						
Betweenness		−0.00119*** (0.000195)	−0.00105*** (0.000209)		−0.00118*** (0.000194)	−0.00110*** (0.000208)
In giant		0.576*** (0.161)	0.592** (0.252)		0.576*** (0.161)	0.618** (0.246)
Density		−1.158 (97.78)	129.7 (108.7)			
Centralization		0.228 (7.240)	6.954 (7.541)		−1.653 (9.972)	−7.413 (12.31)
Clustering					1.624 (3.109)	−0.553 (3.295)
Reach					−5.811 (112.0)	301.3* (172.9)
Regional controls:						
GDP per capita	−0.0160 (0.0396)	−0.0218 (0.0456)	−0.0631 (0.0493)	−0.0230 (0.0460)	−0.0288 (0.0476)	−0.0805 (0.0529)
Years of education	0.321 (0.197)	0.178 (0.177)	0.509** (0.215)	0.328 (0.204)	0.181 (0.176)	0.627*** (0.235)
Constant	−1.015 (0.861)	0.0323 (0.771)	−1.551 (1.020)	−0.940 (0.855)	−0.0119 (0.769)	−2.159* (1.141)
Observations	385	385	385	385	385	385
Number of id	295	295	295	295	295	295
Region and Period FE	NO	NO	NO	NO	NO	NO
Wald chi2 (p-value)	145.41 (0)	180.53 (0)	190.73 (09	144.48 (0)	182.16 (0)	195.96 (0)

TABLE A3 (Continued)

	Model (3)			Model (4)		
Variables	**Regional**	**National**	**Both**	**Regional**	**National**	**Both**
Overdisp. chi2 (p-value)	98.12 (0)	75.49 (0)	76.20 (0)	98.60 (0)	75.61 (0)	75.83 (0)
Max likelihood	−915.09038	−911.20993	−907.28775	−915.12639	−911.07198	−906.41186
VIF (mean)	5.01	5.07	5.88	5.44	5.47	7.56
Pseudo R2	0.1351	0.1483	0.1514	0.1352	0.1483	0.1515
Moran *I* (observed)	−0.01083	−0.03701	−0.04256	−0.00457	−0.03545	−0.03773
Moran *I* (p-value)	0.9420	0.4184	0.3372	0.9071	0.447	0.4188

Notes: Robust standard errors in parentheses;
p < 0.01,p* < 0.05,**p* < 0.1; Overd. = Overdispersion.GDP per capita and Years of education downloaded from FEDEA (2020). Both variables for Madrid, Valencia and Barcelona correspond to the NUTS 2 regions where these provinces are located: Community of Madrid, Valencian Community and Catalonia, respectively. In case of Madrid, the province coincides with the NUTS 2 region; Valencia and Barcelona constitute the main territories of their respective NUTS 2 regions: Valencia had 51% of the inhabitants of the Valencian Community in 2008, and Barcelona had 74% of the population of Catalonia.

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Resumen. La relación entre la colaboración, la geografía y la innovación ya se ha analizado en la geografía económica. Sin embargo, desde la perspectiva de las redes sociales se sabe poco acerca de si los diferentes niveles geográficos de integración pueden determinar la forma en que las redes afectan a la innovación. Para abordar esta cuestión, este estudio compara los efectos de las redes españolas regionales y nacionales sobre las futuras patentes. Si se considera la red nacional, el análisis estadístico reproduce las conclusiones de la literatura previa. Sin embargo, los efectos negativos prevalecen a nivel regional, mientras que la influencia parece ser más bien positiva a nivel nacional. Por lo tanto, se concluye que la integración a diferentes escalas geográficas ejerce una influencia diferente en la innovación.

抄録: 経済地理学ではコラボレーションと地理、そしてイノベーションの関連性について分析が行われてきた。しかし、埋め込み（embeddedness)の地理的レベルの違いによって、ネットワークのイノベーションに対する影響の与え方が異なるかどうかについては、社会的ネットワークの観点からはほとんど解明されていない。そこで、将来の特許取得に対する効果を、スペインの地方レベルのネットワークと国レベルのネットワークとで比較した。全国的なネットワークを検討した場合では、統計分析により既存研究の結果が再現された。国レベルではかなりプラスの影響が認められたが、地方レベルではマイナスの効果が優勢であった。以上から、埋め込みは、地理的な規模の違いによって、イノベーションに対して異なる影響を与えていると結論する。