

Regional knowledge asymmetries and innovation performance from collaborations across European regions

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Abstract

This study investigates the impact of collaborative networks on regional innovation performance across European regions. We analyze the dynamics of regional knowledge networks, emphasizing how their structural characteristics—such as privileged positions, leadership roles, and active participation—enhance a region's innovation capacity. We investigated through complex network analysis 8,424 collaborative projects of the Horizon 2020 strategy, comprising 14,608 participating companies from 232 regions between 2014 and 2020. Our results indicate that European regional innovation capacity is partly driven by collaboration between agents in the knowledge network. Indeed, having a privileged position, a leadership role, and being actively participative explains part of the innovation capacity of regions in Europe. Additionally, the study highlights the critical role of knowledge transfer capabilities, acting as a mediating factor that strengthens the benefits of well-structured networks. This research contributes to understanding how interconnectedness in regional ecosystems fosters innovation, offering insights for policymakers to enhance regional innovation strategies through better network facilitation and support.

Keywords

Knowledge transfer; network; collaboration; Regional Innovation Systems; innovation capacity

1. Introduction

Governments have traditionally relied on increasing R&D investment to drive innovation, often through policies aimed at funding individual firms' R&D efforts (Hervás-Oliver et al., 2021). Nevertheless, this approach has drawn criticism (Cooke, 1992). There is a growing recognition that innovation is increasingly collaborative, with the structure of ecosystems significantly influencing innovation levels. In this context, empirical evidence considers concepts such as actor embeddedness (Giulliani & Bell, 2005; Vicente et al., 2011) and actor proximity (Boschma & Ter Wal, 2007; Morrison, 2008) as key characteristics of knowledge networks that facilitate knowledge exchange. These studies emphasize the significance of an agent's position in the network for innovation performance, as it determines access to external knowledge (Chen & Hung, 2010; Villasalero, 2013). Additionally, research explores how leadership within networks influences innovation by fostering relationship creation (Szatmari et al., 2021). Moreover, more participative agents in networks are found to have increased access to external resources, thereby enhancing innovation performance (Tsouri & Pagoretti, 2021).

However, studying this new setting is complex (Ferrer-Serrano et al., 2021) due to the dynamic nature of the competitive and technological ecosystem. Boundaries are now less defined, making generalizing results from specific regions or industries less valuable. Additionally, the involvement of more actors has increased over time, as evidenced by the evolution of the Helix models (Couñago-Blanco et al., 2023). Despite this complexity, some efforts have been made to understand the relationships between different agents and how resources and capabilities are transferred to enhance innovation performance, considering regional specificities (Cooke, 1992). Collaboration for innovation underscores the importance of networks in fostering relationships and flows that drive innovation performance (Boschma & Ter Wal, 2007; Gertler & Levitte, 2005).

Anyway, scholars predominantly focus on examining network structures in specific contexts (Buchmann & Kaiser, 2019; Graf and Broekel, 2012; Szatmari et al., 2021; Tsouri & Pagoretti, 2021), often overlooking the complexity of innovation systems. Few studies incorporate geographical or temporal dimensions, despite their significance in understanding knowledge diffusion and its policy implications. There is a call for research to adopt a dynamic and structural perspective (Ferrer-Serrano et al., 2022; Volberda et al., 2014), particularly concerning Regional Innovation Systems (RIS), which are crucial frameworks for understanding innovation processes within regional economies. RISs emphasize that regional actors innovate collaboratively, integrating their innovativeness with others' capabilities through networking, facilitating knowledge generation and diffusion across regions. Therefore, RISs use networking to generate, diffuse, apply, or exploit knowledge at regional, national, and international levels (Doloreux & Parto, 2005; Höglund & Linton, 2018).

In this study, we elaborate on this idea to deepen into the understanding of the structure of regional knowledge networks. We analyze how the position, leadership role, and active participation of a given territory influence innovation within that territory. This study posits that regional innovation capacity hinges on a complex array of collaborative network variables, heavily contingent on the geographical locations of agents, which ultimately shape their capacity to innovate. Additionally, we examine the role of knowledge transfer (KT) across networks, contending that KT serves as a mediating factor in explaining innovation outcomes (Maurer et al., 2011).

At this point, two main questions emerge. First, to what extent does a particular structure of a knowledge network primarily reliant on collaboration foster greater innovation capacity. Here, we seek to understand the drivers of innovation capacity across

European regions, assessing how network characteristics enhance it. Second, we aim to understand the importance of having KT capacity for generating innovation.

An empirical study based on complex network analysis is conducted to answer these questions, using European collaborative projects from 2014 to 2020. The database includes a total of 8,424 projects, in which 14,608 companies from 232 European regions (NUTS2) have participated. This original database is handy for the purposes of our work for several reasons. First, it provides information from a complex ecosystem that involves different actors, countries, and industries. Second, it offers longitudinal information, complemented with additional and robustness estimations that allow us to make our results consistent.

The contribution of this work is twofold. Theoretically, it integrates the innovation systems literature into the Knowledge Based-View (KBV) through network theory, trying to advance a step further in their understanding: the KBV of the firm, as we focus on knowledge as one of the most valuable assets for innovation; the literature based on innovation systems, as we adopt the RIS level of analysis; and the networks theory, as we analyze network structure variables as drivers to innovation. Empirically, a two-stage empirical study based on network analysis and econometrics uses an original and large sample of data on collaborative projects in a dynamic international knowledge network.

2. Theoretical background

2.1. Innovation Systems and Regional Innovation Systems

Innovation systems are increasingly evolving and becoming more collaborative (Chen et al., 2019) and KT is crucial in this new setting. Previous studies on innovation systems have mainly focused on the organizational level, showing how companies

capable of transferring knowledge have improved their innovative performance (Gilbert & Cordey-Hayes, 1996). The reason behind is that, through collaboration, companies gain access to external knowledge that would otherwise not be accessible. These knowledge sources provide resources and capabilities that may eventually lead to new (or improved) products or services and thus, sustainable competitive advantages (Zhang & Zhang, 2018).

Given the importance of collaboration, policymakers have launched different initiatives that foster innovation through collaboration. For example, the European Commission (EC) has encouraged and subsidized research collaboration across its member states for over three decades to strengthen knowledge bridges and foster KT (Veugelers et al., 2015). This endeavor has aimed to deepen on European integration and cooperation while promoting innovation and ensuring Europe's competitiveness (Szücs, 2020). As a result, the so-called Framework Programmes (FPs) in the 1980s were budgeted with more than ten billion euros, the Seventh Framework Programme (FP7), from 2007 to 2013, received about fifty billion, the Horizon 2020 (H2020) program (2014-2020), around eighty billion and its successor, Horizon Europe (2021-2027) is expected to allocate more than a hundred billion euros.

This idea of fostering collaboration to strengthen innovation is based on the literature on innovation systems (Lundvall, 1992) and RISs, which explain that innovation is embedded in the regional territory in which companies are located (Cooke, 1992). In this paper, we followed the RISs definition provided by Cooke (2004) as it was identified as an “interacting knowledge generation and exploitation subsystem linked to the global, national and other regional systems”. In recent decades, supranational institutions have focused on improving, developing and strengthening RISs. This concept has attracted widespread attention from policymakers and researchers as a valuable

framework for understanding innovation processes within regional economies (Doloreux & Parto, 2005; Höglund & Linton, 2018). The central argument underpinning this conceptualization is that regional actors do not innovate in isolation but in cooperation and interaction with other actors within or outside the region (Höglund & Linton, 2018). This implies that the innovation capacity of a regional actor is embedded in the innovation capacities of other regional actors and the type of relationships developed between them (Doloreux & Parto, 2005). In other words, innovation will be determined by the technological and institutional capabilities of the economic agents that set up the regions (Hervás-Oliver et al., 2021; Parrilli et al., 2020).

2.2. Knowledge networks and Regional Innovation Systems

According to the KBV, knowledge networks are essential for technological and industrial ecosystems (Giuliani & Bell, 2005; Morrison & Rabellotti, 2009). Furthermore, they are necessary for developing RISs, as they determine the intensity, type and direction of knowledge flows (He & Hosein Fallah, 2009). A key idea in the RIS literature is that the functioning of a RIS depends on the successful development of the system's key resources and the interaction between them (Höglund & Linton, 2018). In many cases, the interaction between internal and external knowledge networks influences the long-term success of RISs (Bathelt et al., 2004). Therefore, the inflow of external knowledge is as crucial as its internal diffusion, as both avoid general blocking of the innovation processes (Broekel & Graf, 2012).

RISs use knowledge networks to generate, disseminate, apply or exploit knowledge at regional, national and international levels (Stuck et al., 2016). Networking, therefore, appears to be important for creating new knowledge and its transfer, as knowledge networks act as facilitators, channeling knowledge flows (Boschma & Ter Wal, 2007; Gertler & Levitte, 2005; Owen-Smith & Powell, 2004). In the context of RISs,

one of the key features is the creation of local knowledge that is not explicitly articulated between organizations located outside a particular RIS. If the knowledge produced within the RIS is combined with other regions or markets, the value created fosters local and global innovation (Bathelt et al., 2004).

Berman et al. (2020) pointed out that although local knowledge munificence is necessary for a region to achieve and sustain a leading position in the global knowledge development process, it is no longer sufficient. They found that the connectivity of actors and the consequent flow of knowledge has become increasingly central to regional economic success. Therefore, widespread collaboration networks to facilitate the flow of knowledge from different geographic regions are crucial for innovation (Isaksen & Karlsen, 2016). This implies that the innovativeness of a regional actor is integrated into the innovation capabilities of other regional actors and the relationships developed between them. So the generation and diffusion of knowledge rely on the networking of different actors located in different places (Doloreux & Parto, 2005; Höglund & Linton, 2018).

In this sense, for analytical purposes, RISs have been conceptualized as being composed of nested subsystems¹ (Binz et al., 2014). The functioning of a RIS depends on the successful interaction between the subsystems and the ability of actors to access resources outside their territory (Bergek et al., 2015). The interaction between these subsystems is referred to as structural couplings (Binz & Truffer, 2017). Structural couplings are important not only for the system's functioning but also for the actors in the knowledge network, allowing them to connect knowledge from a RIS to market segments

¹ Binz and Truffer (2017) propose the Global Innovation System perspective (GIS), which presented a multiscalar version of the innovation system, with nested national and regional systems, and multiple resources. In this paper, there is a minimum of multiscalarity in terms of geography, going from regions to Europe, but not in terms of resources as we just focus on knowledge.

in distant places. Resources tend to develop asymmetrically within a RIS given the different territorial preconditions, such as knowledge development and transfer (Binz et al., 2014). Due to this irregular distribution, firms may not have local access to all the resources in the system. Therefore, firms will have to establish extraterritorial couplings to access other system resources in the RIS (Binz & Truffer, 2017). Networks are, therefore, an essential type of structural coupling in RIS.

3. Hypotheses

3.1. Network structure and innovation

3.1.1. Position in the network

The literature has traditionally suggested that all actors in a RIS benefit from the regional knowledge network because it is assumed that all regional actors are equally embedded within it (Asheim, 1994). However, empirical studies have presented substantial evidence of significant heterogeneity in this embeddedness (Boschma & Ter Wal, 2007; Stuck et al., 2016). That is, some actors within the regional knowledge network adopt a key role and influence or are influenced to a greater extent by the developed relationships. These actors can be considered as having a privileged position (Tsouri & Pegoretti, 2021) within the network regarding connectivity (Berman et al., 2020). The privileged position of an actor constitutes an attractive attribute resulting from centrality (Barabási & Albert, 1999; Papadopoulos et al., 2012). These central actors are important for KT as they act as intermediaries and accumulate knowledge over time. Their role becomes vital to the KT and subsequent innovation (Autant-Bernard et al., 2014; Wanzenboeck et al., 2014). As a consequence, actors better positioned (with a privileged position) or, in other words, with better quality connections, provide several opportunities to foster the process of knowledge creation and diffusion, gaining easier

access to knowledge resources, benefiting from their direct or indirect collaboration with a variety of valuable actors and thus having an impact on the structure and functionality of the regional knowledge network (Balland et al., 2016; Ter Wal, 2013).

The relationship between the position of network agents and innovation has attracted the attention of academics over the last few years. Buchmann and Kaiser (2019) focused on the German biotech industry and found that the agent's better position in the network significantly increases innovation success. Tsouri et al. (2021) analyzed the case of offshore wind. They concluded that different types of knowledge networks and the location of the agents facilitate market access and structural coupling to varying extents. Finally, Berman et al. (2020) and Tsouri and Pegoretti (2021) focused their studies on understanding the Italian knowledge network, finding the importance of being well connected, so having a privileged position with the rest of the agents, to achieve innovation.

Although this relationship has usually been analyzed from a micro perspective, in recent years, some scholars have tried to approach it from a global and macro approach (Ferrer-Serrano et al., 2021; Neuländtner & Scherngell, 2022). These few papers seem to point to a direct and positive relationship between the better position of agents in a knowledge network and innovative outcomes. In particular, Neuländtner and Scherngell (2022) revealed interesting differences between regions that use networks to exploit and explore knowledge creation. They concluded that regions with better positions or surrounded by better-position neighbors benefit more from networks due to the accessibility of resources and capabilities. However, limitations have been highlighted as studies focused on particular industries or regions, making generalization difficult. We, therefore, argue that:

H1. The greater the privileged position (higher centrality) in the knowledge network, the better the innovation capacity of a regional system.

3.1.2. Leadership in the network

Leadership is about motivating and leading project participants to squeeze their potential and achieve more demanding and challenging organizational missions. It is also concerned with making decisions about processes and functions to improve efficiency, taking on such functions as planning, controlling and coordinating (Nishimura & Okamuro, 2018). Therefore, the leader's ability is critical to guide organization participants to reach a goal successfully (Bakar & Mahmood, 2014). Particularly, Zhu and Cheng (2015) concluded that leadership could balance autonomy and control, encourage members' participation and benefit innovation.

Davis and Eisenhardt (2011) pioneered the study of leadership when studying interfirm collaboration for innovation. They concluded that leadership is crucial for achieving innovation because a leader will foster collaboration through motivation. Alberti et al. (2021) also pointed out a strong positive correlation between rotational leadership² in organizational knowledge networks and innovation. Furthermore, Szatmari et al. (2021) explored how the status of the project leader affects the performance of innovation projects in the video game industry. In particular, they found that an intermediate status level was positively associated with average project performance and that high-status leaders present more extreme performance effects.

The previous arguments suggest evidence of a positive relationship between leadership and innovation achievement. It seems that the leader of the knowledge network plays an important role in the innovation performance of the group to which it belongs

² Decision control shifts among partners at different phases of the collaboration.

(Martiskainen, 2017; Marjanovic et al., 2020). However, the evidence points to the importance of exploring the role of leadership in innovation networks, the role of leadership in RIS contexts has hardly been discussed, and results do not add up to a common conclusion (Rosing et al., 2011).

Although leadership has been studied at the organizational level to a greater extent, in short, as argued above, regions represent a set of firms that build through their specificities the regional structure (Cooke, 1992). These specificities explain the characteristics of the RIS that derive from the set of firms that constitute it. Thus, regions made up of a group of innovation-driving companies will show high levels of regional leadership. On the other hand, regions with more traditional industries made up of less innovation-driven companies will have lower levels of leadership.

In this line of thought, when we translate these arguments to the context of a RIS, having a leading position will increase the legitimacy of that region and, therefore, will be perceived as an interesting agent with which to collaborate, reinforcing its leadership and allowing it to obtain greater resources and capabilities. Consequently, this will positively impact the innovative results of a region. Thus, we propose the second hypothesis:

***H2.** Being a regional leader in the knowledge network increases the innovation capacity of a regional system.*

3.1.3. Degree of participation in the network

From a structural network perspective, actors that participate intensively in various collaborative arrangements are directly interconnected with others, benefit from short pathways to multiple sets of network nodes and are thus highly integrated into the

network structure. In this sense, one of the most frequent learning indicators is knowledge development through the intensity of collaborative participation (Colombo et al., 2016).

These strategic collaborations help to maximize collective resources and increase the performance of individual actors. In this way, networks allow them to pool their resources on projects too large for firms to undertake on their own, achieving economies of scale (Hagedoorn et al., 2000; Wanzenböck et al., 2015). Therefore, firms that participate in collaborative networks gain access to external markets (Tsouri et al., 2021), opening up new opportunities to access resources and thus improving competitiveness.

At the regional level, organizations' network relationships are also crucial assets for their regional environments (Wanzenboeck et al., 2014). Participating actively in interregional networks provides the opportunity to quickly access specific knowledge resources outside the regional boundaries and supply localized actors with knowledge located at a greater geographical distance (Bathelt et al., 2004). Empirical studies dealing with interregional knowledge relationships typically address a particular type of network, and although they are usually focused on a country or industry (Broekel & Graf, 2012; Tsouri & Pagoretti, 2021) or on specific agents (Hoekman et al., 2010), they typically find a positive relation between the participation in those networks and innovation performance. By way of example, Tsouri and Pagoretti (2021) found that active participation in the Norwegian offshore wind network benefits R&D collaborations and access to external markets.

Regional participation in collaborative networks has previously been studied in a generic and holistic way, but it has not been analyzed as a variable in knowledge network structure. Therefore, we suggest that those RISs that are more participative in the KT network will have a greater capacity to take advantage of the synergies and

economies of scale they offer. Consequently, their innovative results will be greater. For this reason, we posit the following:

***H3.** Participating in the knowledge network positively affects the innovation capacity of a regional system.*

3.2. The mediation effect of KT capacity

Previous literature has struggled to explain the role of knowledge externalities in policy outcomes of regional innovation networks (Fernandes et al., 2021). However, to our knowledge, the RIS literature has not explicitly measured the ability to transfer knowledge, i.e., to be actively part of knowledge exchange processes.

The ideas presented in the previous sections highlight that KT is an important mechanism underlying innovation in RISs. In this sense, we would like to demonstrate that the ability of a region to take part in KT processes explains the effect of having adequate network structure properties on innovation capacity. The arguments provided lead us to believe that regions that are structurally well positioned in the network, with a leading role and great participation, should benefit from knowledge flows. Furthermore, regions with a weak network structure would suffer the disadvantage of not being able to access or generate KT, and consequently, their innovative capacity would be low. Therefore, KT capacity should contribute to the explanation of the above relationships.

We consider that part of the positive effect we theorized in the previous hypotheses on network structure and innovation may be partly explained by being more or less able to transfer knowledge. In other words, we believe that the fact that a RIS has a central, leading and participative position has a positive impact on the innovation capacity of that system. But still, this impact will be affected if the RIS is capable of transferring knowledge to other RISs while, at the same time, receiving external

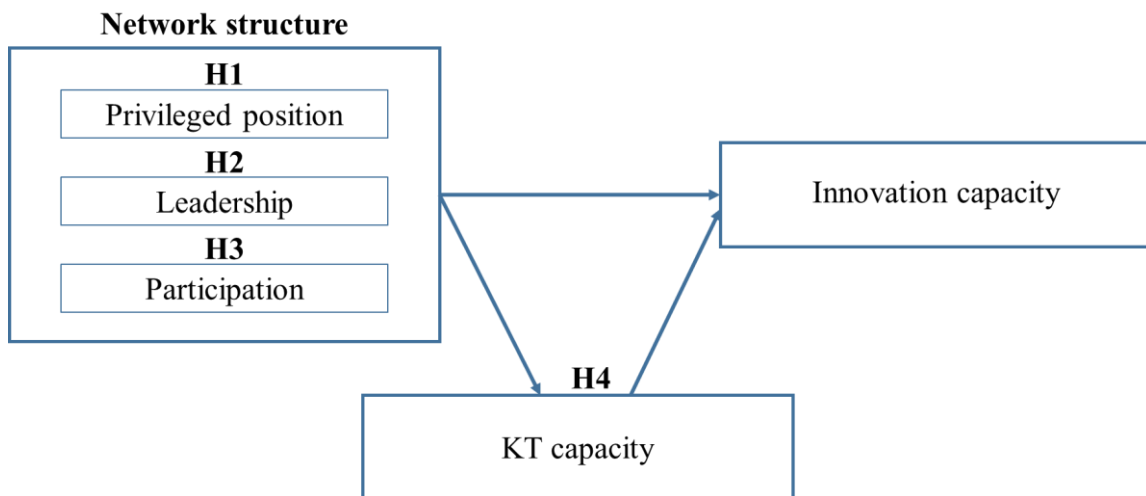
knowledge. Thus, having good structural characteristics in the network can stimulate KT and turn to innovation performance.

In sum, the network-based literature seems to point out that, among other explanations, the contribution of KT capability to the explanation of regional innovation should take place through mediation (Maurer et al., 2011). In other words, their influence seems to take place in a sequence. In the first stage, the KT capability of a region is determined by the position, role and level of participation in the complex knowledge network. After that, KT capacity explains the region's innovation capacity. Therefore, occupying an appropriate position would only indirectly affect the innovation of the regional system.

Airports can serve to exemplify these arguments. Airports with high KT capacity serve as major platforms for connecting individuals, representing clear examples of traffic hubs, acting as brokers or intermediaries in the system. These hubs act as central points that have the potential to gather resources from one part and disseminate it to another part efficiently. Because they lie on many shortest paths, airports with KT capacity have the potential to control or influence traffic. They can regulate traffic that passes through them and to which parts of the network it is directed (i.e. Airports like London Heathrow, Istanbul, Dubai International, and Singapore Changi serve as major hubs for intercontinental routes). All the above reasoning leads to our fourth hypothesis:

H4. The relationship between having a privileged position, leadership role and being participative in the knowledge network and innovation capacity is mediated by having KT capacity; that is, they are explained by KT capacity across regional systems.

Figure 1. Conceptual model



4. Data and methodology

4.1. Data sources

4.1.1. *KT and network structure data*

The previous hypotheses will be tested within the context of the H2020 strategy. According to the EC, H2020 was the biggest European Union research and innovation funding program from 2014-2020, with a nearly €80 billion budget.³ This initiative was launched to boost Europe's competitiveness through the collaboration of organizations, that is, to promote inter-organizational and international KT through the development of innovative projects based on the achievement of excellent science, industrial leadership and tackling societal challenges. Given the collaborative nature of this initiative, several studies have used H2020 data to analyze KT (Enger, 2018; Ferrer-Serrano et al., 2021; Grimpe et al., 2021).

H2020 is structured according to three pillars. The "Excellent Science" pillar is based on generating scientific and academic knowledge, with the industrial perspective

³ https://research-and-innovation.ec.europa.eu/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-2020_en#:~:text=Horizon%202020%20was%20the%20EU's,the%20archived%20Horizon%202020%20website.

relegated to second place. The "Industrial Leadership" pillar aims to accelerate the development of technologies and innovation in European industries. The EC defined this category as follows: "This pillar aims to speed up development of the technologies and innovations that will underpin tomorrow's businesses and help innovative European SMEs to grow into world-leading companies".⁴ And finally, the "Social Challenges" pillar addresses European problems from a social rather than an industrial perspective. Given the nature of our research objective, which is centred on understanding regional innovation through business performance, focusing on projects funded under the "Industrial Leadership" category (2014-2020) provides an adequate framework for our analysis. By concentrating on initiatives aimed at accelerating technological development and innovation within European industries, we can gain insights into the mechanisms driving regional innovation dynamics and business performance within these contexts. This focus allows us to directly address how investments on industrial leadership impact the ability of regional firms to innovate and compete in a globalized environment. Table 1 describes the main thematic priorities of projects under this pillar. The development of innovation related to "Information and Communication Technologies" (ICTs) is the main focus of Europe, as it attracts most of the contribution and number of projects, followed by projects that foster innovation for SMEs and innovation related to advanced processes and materials, among others.

⁴ <https://wayback.archive-it.org/12090/20220124105514/https://ec.europa.eu/programmes/horizon2020/en/h2020-section/industrial-leadership#Article>

Table 1. Description of the projects based on the thematic priorities in “Industrial Leadership”

	Word topic cloud	Net EU contribution	Average EU contribution per project	Signed grants	Participation	Average participation per project
Access to risk finance		9.71 M	747 k	13	49	3.77
Advanced manufacturing and processing		1.6 B	5.53 M	290	4,211	14.52
Advanced materials		1.14 B	6.19 M	184	2,997	16.29
Biotechnology		405.4 M	3.27 M	124	910	7.34
Information and communication tech.		6.64 B	3.57 M	1,860	17,977	9.67
Innovation in SMEs		1.35 B	519.2 k	2,591	5,003	1.93
Leadership in enabling and industrial tech.		34.73 M	17.37 M	2	34	17
Nanotechnology		554.7 M	1.55 M	357	1,415	3.96
Space		924.7 M	2.06 M	449	2,976	6.63

Note: All information has been extracted from the EC Dashboard. It just considers member states participation.
 Word cloud: Representation of the most recurrent words on the project abstracts. It reflects the EC main concerns.
 Net EU contribution: Total EU funding granted to the participants of the selected projects.
 Signed grants: Number of grant agreements signed, including suspended, terminated and closed grants.
 Participation: Number of organizations involved in the selected projects. One organization participating in N projects is counted N times.

To operationalize our data⁵, we first screened the projects, considering just the ones coordinated by an organization from a European country.⁶ Second, we exclusively considered projects with at least two organizations involved to ensure that a knowledge flow was taking place (8,424 projects). Finally, as we used regions as the unit of analysis, we matched each organization with the region where they were located,⁷ allowing us to identify knowledge flows between regions.

To understand the direction of the knowledge flows, we considered our graph as directed. Notice that, as in a knowledge network based on research projects, the participating actors may occupy the role of coordinators or merely executors. For our purpose, the origin is considered the coordinating region and the destiny is the executor region.

⁵ Data source: <https://data.europa.eu/data/datasets/cordish2020projects>.

⁶ More information in Appendix II.

⁷ H2020 provides the address of the offices involved in the project, so that if it is a subsidiary that is part of project, its address and therefore the region in which it is located is taken into consideration.

4.1.2. RIS and innovation capacity data

We have employed indicators extracted from the European Innovation Scoreboard produced by the EC. As in previous literature, we have used the indicators regionalized by the Regional Innovation Scoreboard initiative (Hervás-Oliver et al., 2021). This initiative, which aims to capture the innovation capacity of different European regions, uses primarily CIS (Community of Innovation Survey) data to build regional indicators and distinguish between advanced (leader and strong innovators) and less-advanced regions (moderate and emerging innovators). This is crucial for this paper since the aim is to identify how innovation capacity depends to a large extent on the characteristics of the collaboration dynamics of its regional technological and institutional ecosystem.

Regions in Europe differ in their innovative capacity because of their distinct resource endowments that depend, among other factors, on their levels of development. In particular, the Regional Innovation Scoreboard dataset includes information about framework conditions, investments, innovation activities and their impacts.⁸ Variation in development affects the innovation capacity of organizations located in each territory. The Regional Innovation Scoreboard 2021—including 2014–2020 data— covers 232 regions across 25 European countries.⁹ The Regional Innovation Scoreboard data are categorized on a scale between 1 and 12, to produce a composite indicator integrating variables from different scales.

⁸ For further details, see Appendix I.

⁹ More information in Appendix II.

4.2. Sample and methods

4.2.1. Sample and methods

A two-stage analysis is performed using European collaborative projects from 2014 to 2020. A total of 8,424 collaboration projects, in which 14,608 companies from 232 European regions participated, are analyzed. First, a complex network analysis is conducted to extract the structural network variables. For this preliminary analysis, we construct different matrixes (one for each year of the panel) with all the relationships between regions of the projects under study. We consider the starting date of the project as the date in which regions received the funding and begin to share knowledge to operationalize the project into a real innovation. Then, we built a panel by integrating the network data (independent variables) with the regional innovation data (dependent variables). The total observations amounted to 1,624.

Second, we chose the econometric models based on the characteristics of the dataset. Since the innovation capacity variable is double-censored, representing the level of innovation ranging between 1 and 12, the applicable methodology is a random effects Tobit regression (Bernal et al., 2019). Tobit models are particularly useful when dealing with data that are censored. In these cases, Tobit models provide more efficient estimates compared to traditional Ordinary Least Squares regression when dealing with censored data. In addition to the Tobit estimates, to guarantee the robustness of the analysis, we run alternative econometric models (see section 5.2) with no significant variations from the baseline model).

4.2.2. Variables

Dependent variable

Innovation capacity. We measure innovation capacity through the unweighted average of the scores of 21 indicators,⁸ that is, synthesized the regions' innovative capacity concerning four different categories: framework conditions, investments, innovation activities and impacts. The result was a continuous variable that ranged from 1 (emerging innovator) to 12 (leader innovator). This index has been used and validated by previous works analyzing regions' innovative capacity (Hervás-Oliver et al., 2021).

Independent variables

Privileged position. It is measured with the PageRank, also known as eigenvector centrality. It is the node's importance while considering the importance of its neighbors (Golbeck, 2013). PageRank considers (1) the number of in-bound links, (2) the quality of the linkers, and (3) the link propensity of the linkers (Hansen et al., 2020). Actors with a high value on this measure are connected to other nodes that are highly relevant or to many other nodes, perhaps less relevant. If a node is pointed to by many nodes (which also have high eigenvector centrality), then that node will have high eigenvector centrality. Therefore, the position occupied by agents with a high value in this measure will have a privileged position in the knowledge network.

Let $EC(G)$ be the centrality of a vector associated with a network G ; the crux is that the centrality of a node is proportional to the sum of the centrality of its neighbors. Its representation is:

$$\lambda \cdot EC^{v_i}(G) = \sum_{v_j} g_{ij} EC^{v_j}(G)$$

In which g_{ij} takes the value 1 if $(v_i, v_j) \in E$ and 0 otherwise and k is a proportional factor. This variable is normalized to adopt values between 0 and 1.

Leadership. This variable is measured through the out-degree centrality (Lee et al., 2010; Rehman et al., 2020). It represents the number of occasions in which a region occupies a coordination role in the knowledge network, that is, the number of outward-directed graph edges from a given graph vertex in a directed graph, or in other words, the number of connections that originate from a vertex and point outward to other vertices (Hansen et al., 2020). As we consider the graph has a direction flow (from the coordinator or leader of the project to the executors), this metric allowed us to measure the knowledge flow from the leader to the rest of the agents. This variable is normalized for values between 0 and 1.

Participation. Participation is measured as the degree centrality of a region in the whole knowledge network (Freeman, 1977), which identifies the number of links a node has (inflows and outflows). This variable measures the level of active participation in the knowledge network, whatever the role may be (coordinator or executor). Degree centrality allows examining the level of participation in the knowledge network defined as:

$$DC^{v_i} = \frac{d(v_i)}{|V| - 1}$$

Where $d(v_i)$ denotes the degree of centrality of the node v_i in the network. This variable was normalized for values between 0 and 1.

Knowledge transfer capacity. This variable is measured through betweenness centrality. This variable quantifies the frequency or number of times a node is between the two agents or shortest paths of other actors. An agent with greater intermediation power would have more control over the network because more information will pass

through that agent; or in short, it will have a greater capacity to transfer knowledge. It is a measure used in the previous literature to understand intermediary flows in a network (Tutzauer, 2007). It can be formally defined as follows:

$$g(v) = \sum_{s \neq v \neq t} \frac{\delta_{st}(v)}{\delta_{st}}$$

Where δ_{st} is the total number of shortest paths from node s to node t and $\delta_{st}(v)$ is the number of such paths passing through v . This variable was normalized for values between 0 and 1.

Control variables

Our model also controls for a set of variables that previous literature had identified as influencing our dependent variable. Several studies have suggested a positive relationship between a region's GDP per capita (provided by the World Development Indicators database) and its innovativeness (Turkina et al., 2019). Regions with higher GDP per capita typically have better access to resources such as skilled labor, technology, and capital, which are essential for fostering innovation (Turkina et al., 2019). Similarly, the literature has also argued that R&D investment increases the innovation capacity of regions (Turkina et al., 2019). Research suggests that regions or countries that allocate more resources to R&D activities tend to exhibit higher levels of innovation and technological advancement (Turkina et al., 2019). In addition, Zang et al. (2018) found that countries with a higher level of education have a higher innovation capacity. Higher levels of education, particularly tertiary education, are associated with greater cognitive skills, creativity, and problem-solving abilities, which are essential for innovation. Additionally, educated individuals are more likely to engage in knowledge-intensive activities and contribute to the generation and dissemination of innovative ideas. In this sense, we controlled for the percentage of graduates with tertiary education. We have also

controlled for the region's population size and population density (Hamidi et al., 2019; Zang et al., 2018). Larger populations provide a larger pool of potential innovators, consumers, and collaborators, fostering knowledge spillovers and idea exchange. Similarly, regions with higher population densities often have greater economic agglomeration, facilitating collaboration, specialization, and innovation diffusion. Finally, we included a measure for formal institutions at country level. We computed it with the information provided by the Index of Economic Freedom¹⁰ (Miller et al., 2018). Countries with well-established legal frameworks, secure property rights, and efficient regulatory systems tend to attract investment, encourage entrepreneurship, and promote innovation. Strong institutional frameworks provide stability, predictability, and incentives for innovation-driven activities. By controlling for these variables we are accounting for their potential confounding effects and isolating the relationship between the independent and dependent variables.

5. Results

5.1. Descriptive results

Table 2 shows the descriptive statistics of the sample as well as the correlation matrix. The mean of our dependent variable is 5.979, slightly below the center of the scale, with a standard deviation of 2.965. As explained before, our independent variables are normalized between 0 and 1. All of them had low means and standard deviations, in particular, leadership and participation. Suppose we delve more deeply into our data set. In that case, we notice that just a few regions concentrated the leadership and participation

¹⁰ Economic freedom is measured based on 12 quantitative and qualitative factors, grouped into four broad categories: Rule of Law (property rights, government integrity, judicial effectiveness); Government Size (government spending, tax burden, fiscal health); Regulatory Efficiency (business freedom, labor freedom, monetary freedom) and Open Markets (trade freedom, investment freedom, financial freedom).

power of the projects. At the same time, the rest occupied more discrete positions, acting simply as projects executors.

Finally, to check for multicollinearity, the variance inflation factors (VIFs) were computed to assess the severity of multicollinearity. The average VIF value was 5.10, below the cut-off point of 10 (Chatterjee et al., 2000), which means that multicollinearity was not a serious issue and all the variables can be included in the same regression. In addition, and given the inherent interconnectivity within regional innovation systems, none of the individual VIFs exceeds the commonly used threshold of 10 (see Appendix III), suggesting a manageable level of multicollinearity within our model. This methodological choice is reinforced by robustness checks, including monovariate regressions (Appendix VI) and alternative econometric models (Appendix VII), which consistently confirm the stability and reliability of our findings across different specifications.

Table 2. Descriptive statistics and correlations

Variables	Mean	Std. Dev	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Innovation capacity	5.979	2.965	1	12	1.000											
(2) Privileged position	0.374	0.236	0	1	0.410*	1.000										
(3) Leadership	0.074	0.145	0	1	0.305*	0.675*	1.000									
(4) Participation	0.095	0.147	0	1	0.365*	0.579*	0.655*	1.000								
(5) KT capacity	0.122	0.262	0	1	0.294*	0.561*	0.446*	0.485*	1.000							
(6) GDP pc (000)	35.929	18.610	7.075	97.019	0.768*	0.177*	0.111*	0.136*	0.063	1.000						
(7) R&D expenditure	1.889	0.839	0.382	3.527	0.741*	0.157*	0.088*	0.120*	0.069	0.705*	1.000					
(8) Population (000)	2,218	2,001	83.870	23,058.077	0.212*	0.419*	0.325*	0.379*	0.344*	-0.006	0.001	1.000				
(9) Tertiary education	30.136	9.704	11.4	59.6	0.624*	0.370*	0.327*	0.385*	0.326*	0.488*	0.273*	0.182*	1.000			
(10) Population density	350.278	871.781	3.4	7526.7	0.164*	0.213*	0.173*	0.208*	0.237*	0.030	0.063	0.093*	0.256*	1.000		
(11) Formal institutions	69.287	6.223	53.2	82.0	0.595*	0.090*	-0.003	0.035	-0.003	0.633*	0.573*	-0.027	0.443*	0.074	1.000	
(12) Network structure **	0.181	0.176	0	1	0.358*	0.689*	0.465*	0.596*	0.473*	0.125*	0.136*	0.253*	0.318*	0.183*	0.023	1.000

* p<0.1 / N=1,624

** Network structure represents the aggregation of the three main independent variables (Privileged position, Leadership and Participation). It is used in some of the regressions presented in the next section.

5.2. Econometric model

Table 3 shows the Tobit estimates for the relationship between network structure variables and innovation capacity. We run four nested models. Model 1 is the base model, which only includes the control variables. Model 2 introduces the direct effects of leadership, position and participation. Model 3 incorporates the mediation effect of KT capacity. As shown by the value of the Wald test, this Model 3 does not improve the explanatory power compared to the previous ones, probably due to the moderate correlation between our key independent variables (between 0.30 and 0.67). Consequently, Model 4 aggregates the three independent variables into only one named network structure to test the mediation effect. Since Models 2 and 4 are the ones with the highest Wald test values, our discussion will be focused on these two models.

Regarding the control variables, all of them (the only exception is Population) significantly influence our dependent variable. GDP per capita increases innovation capacity in line with previous studies (Turkina et al., 2019). R&D expenditure also has a positive and significant effect, consistent with previous literature (Turkina et al., 2019). Similarly, regions with a higher proportion of people with tertiary education increase their innovation capacity, which is also in line with previous research. Population density negatively influences regional innovation capacity, as in Hamidi et al. (2019) and Zang et al. (2018). Finally, economic freedom positively influences our dependent variable. Furthermore, the sign and significance of the control variables remain notably stable along the four models.

If we center on the three independent variables that approach the network structure, Model 2 confirms that, according to our expectations, they all positively and significantly affect innovation capacity. First, having a higher centrality position positively influences the innovation capacity of a regional system ($\beta = 0.00742$; $p < 0.05$),

thus offering support for H1. This finding is consistent with previous literature highlighting the power of centrality in a network in particular contexts and industries. Second, we hypothesize that those regions with higher levels of leadership in the network will increase their innovation capacity. The results show a positive and significant effect of this variable ($\beta = 0.0059$; $p < 0.1$), thus supporting H2. Finally, participating actively in a knowledge network, no matter the role adopted in that network, increases the regional systems' innovation capacity ($\beta = 0.00225$; $p < 0.001$), a result that is in line with our H3.

To test the mediation effect of KT, we run two different models. As pointed out before, the results in Model 3 (that do not provide support to H4, the variable is statistically significant and positive but does not show a strengthening effect over the direct effects) may be biased due to the existing correlation between the independent variables. As a consequence, we focus our analysis in Model 4, which is the one with the highest explanatory power. Interestingly, KT strengthens in this model the relation between network structure components and innovation capacity ($\beta = 0.0056$; $p < 0.001$).

Table 3. Random effects Tobit regression

	Model (1)	Model (2)	Model (3)	Model (4)
<i>Position</i>		0.00742** (0.00214)	0.00042** (0.00044)	
<i>Leadership</i>		0.00059* (0.00091)	0.00067* (0.00082)	
<i>Participation</i>		0.00225*** (0.00107)	0.00205** (0.00104)	
<i>Network structure</i>				0.0056*** (0.00097)
<i>KT capacity</i>			0.00168*** (0.00053)	0.00245*** (0.00047)
GDP per capita	0.315*** (0.0112)	0.304*** (0.0640)	0.344*** (0.0665)	0.337*** (0.0730)
R&D expenditure	0.131*** (0.00246)	0.0131*** (0.00152)	0.0157*** (0.00176)	0.0156*** (0.00132)
Population	-0.0134 (0.00101)	-0.0179 (0.0055)	-0.00718 (0.00043)	-0.0100 (0.0008)
Tertiary education	0.0127*** (0.00121)	0.00376*** (0.00128)	0.00389*** (0.00117)	0.00385*** (0.00121)
Population density	-0.00314*** (0.00165)	-0.00196*** (0.00087)	-0.0023*** (0.00059)	-0.00093*** (0.00107)
Formal institutions	0.00873*** (0.00257)	0.00342*** (0.00278)	0.00344*** (0.0039)	0.00342*** (0.00388)
Constant	5.303*** (0.00126)	4.678*** (0.00467)	4.872*** (0.00569)	4.887*** (0.00572)
Log likelihood	3041.849	3907.074	3959.280	3965.602
Wald chi-square	19922.18***	21739.82***	15873.83***	21766.14***
Observations	1,624	1,624	1,624	1,624
N	232	232	232	232

*** p<0.01, ** p<0.05, * p<0.1

We perform an addition analysis based on Baron and Kenny (1986) to better understand the mediation effect. Three conditions must apply: first, independent variables must affect the mediator; second, the mediator must affect the dependent variable; third, when including the mediating effect, previously significant relationships between independent and dependent variables should be eliminated or substantially reduced. The results of these three conditions are presented in Table 4, where we can observe that the

model fulfills the three considerations proposed by Baron and Kenny (1986). Network structure (the independent variable) influences innovation capacity (first condition). The mediator variable influences the dependent variable positively and significantly (second condition). Finally, when the mediator variable is added to the model, the influence of network structure on innovation capacity diminishes; that is, the direct effect of our dependent variable is lower than the total effect (third condition). Since the conditions are satisfied, but the influence of the dependent variable remains significant in the presence of the mediator, we are facing a partially mediated model.

The model is not fully mediated because network structure has its own direct effect on innovation capacity, in addition to the indirect effect through the mediator (see Table 4). This result suggests that the network structure is the initial part of the process of regional innovation capacity. Network structure influences innovation capacity by itself, but it could also result in greater integration through KT flows and, consequently, an additional positive effect on innovation capacity. Indeed, the mediation explains 52.1% of the independent variables over the dependent variable (Table 5).

Table 4. Test of Mediation. Comparison of standardized path coefficients for direct and mediation models

Path	Direct model	Direct model (2)	Mediation model
Network structure → Innovation capacity	0.00187***		0.00105***
KT capacity → Innovation capacity		0.00254***	0.00251***
Network structure → KT capacity → Innovation capacity			0.00294***

*** p<0.01, ** p<0.05, * p<0.1

Table 5. Equation-level goodness of fit

	Variance			R-squared	MC	MC2
	Fitted	Predicted	Residual			
Network structure → KT capacity	0.999	0.475	0.524	0.476	0.690	0.476
Network structure → Innovation capacity	0.999	0.166	0.835	0.166	0.407	0.166
Overall				0.521		

5.2.1. Additional analysis

An additional analysis based on variance differences (ANOVA) is performed to better understand the model's effects. For this purpose, the independent and dependent variables are categorized into four categories (from low to high in the case of the independent variables and, following the original classification of the Regional Innovation Scoreboard, from emerging innovator to leader innovator for the dependent variable).

Table 6 shows significant differences in all groups of the independent variables concerning the dependent variable, with notable intergroup variances in the case of the position variable. The variation is more discrete but equally significant for intermediate levels of leadership and participation. A posthoc HSD Tukey test is carried out (see Appendix IV), allowing us to verify the significance of the differences between conditions.

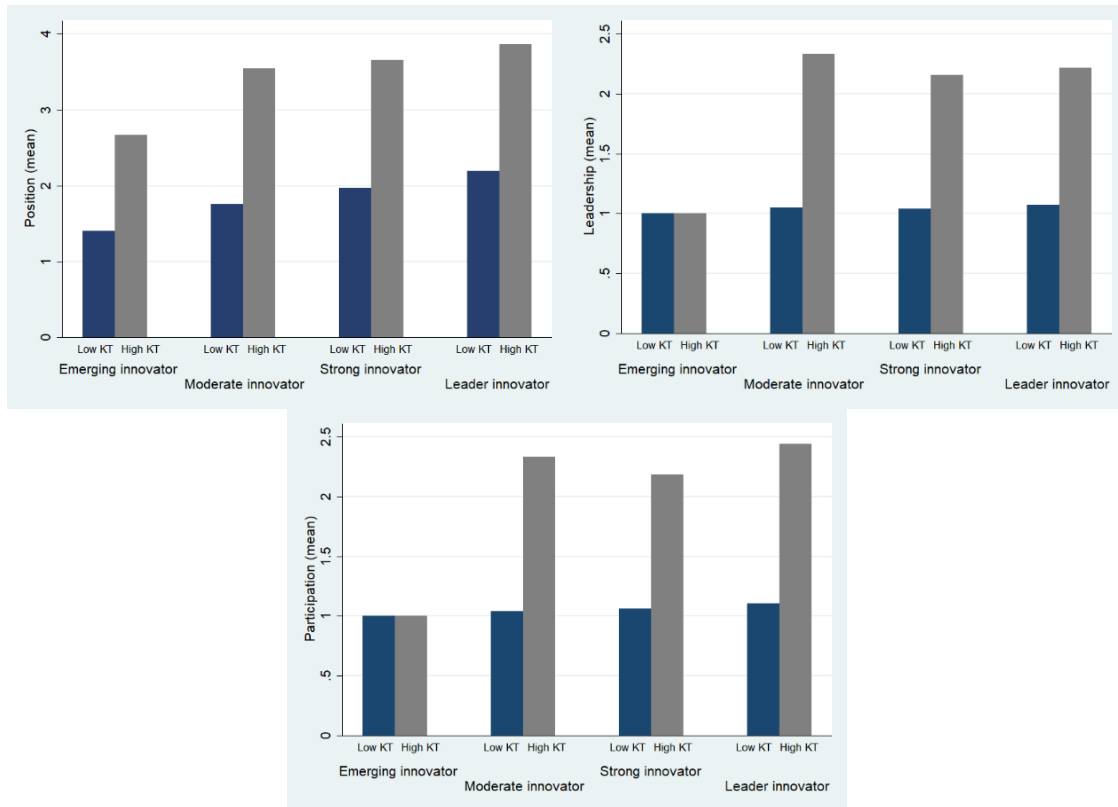
Table 6. One-factor ANOVA

Position	(1) IC	Participation	(2) IC	Leadership	(3) IC
Low	1.856*** (0.038)	Low	2.207*** (0.026)	Low	2.235*** (0.026)
Moderate -	2.399*** (0.037)	Moderate -	3.129*** (0.084)	Moderate -	3.008*** (0.093)
Moderate +	2.812*** (0.071)	Moderate +	3.137*** (0.140)	Moderate +	3.089*** (0.151)
High	3.152*** (0.073)	High	3.800*** (0.446)	High	3.429*** (0.383)

*** p<0.01, ** p<0.05, * p<0.1

Figure 2 displays these differences and incorporates the KT capacity mediation effect (categorized by low and high levels of KT capacity). First, the mediation effect is reflected in almost all situations, lending support to H4, except when we look at the impact of leadership and participation on regional emerging innovators (the KT mediation effect in these cases remains stable). Second, according to our hypotheses, we see the positive impact of our independent variables on innovation capacity. Finally, we can see through these representations how regions with a higher innovation capacity tend to have a better position and leadership level and actively participate more, thus supporting H1, H2 and H3.

Figure 2. ANOVA model representation



5.2.2. Robustness checks

We estimate an alternative model to control for possible problems of endogeneity (reverse causality), which would indicate that a higher innovation capacity could derive in better positioning in the network (see Appendix V). We conducted the Tobit model approach with continuous endogenous regressors (Newey, 1987; Wooldridge, 2010). We instrumented the possible endogenous variable, *position*. The instrument variable was the *EC contribution* to funded research projects. This variable is appropriate as an instrument as it correlates with the possible endogenous variable (position) but not with the dependent variable (*innovation capacity*). In other words, although the EC contribution has some relation with the region's position in the network, it has not with that region's innovation capacity, as argued in previous sections (Cooke, 1992; Hervás-Oliver et al., 2021). This variable is supported as an instrument by recent

studies that confirm the objectivity and transparency of this process, highlighting how the project selection criteria ensure that the allocation of funds reflects pre-existing merits and not external contemporaneous factors.¹¹ The significance of the statistic of the Wald test offers support to the instrument. Once the possible endogeneity is controlled for, the Tobit estimation results remain significant and positive. In addition, although the independent variables and the dependent variable are not highly correlated, and therefore there is not an issue of collinearity, we have performed robustness checks by adding the variables separately (Tsouri et al., 2021) without changes to the significance levels and signs (see Appendix VI). Then, we performed an additional robustness check using the Poisson model (see Appendix VII). The results obtained are consistent with those presented in Table 3.

We also have tested the absence of spatial autocorrelation (see Appendix VIII). We have geo-localized the regions of the sample and test the model at different distances between the points (200 km and 800 km to control for different regions sizes). The models were regressed including all the independent variables to check if they were facing spatial correlation. The results show no spatial autocorrelation and they remain significant and positive as in the baseline model. This lack of special correlation is not surprising insofar as the distribution of funds is not based on geographic issues, but on talent for the development of this research. The formation of collaborative consortia does not depend on geographic proximity. In fact, internationalization and heterogeneous consortia that

¹¹ Funding in H2020 is distributed through competitive calls for proposals, which are assessed using stringent criteria to ensure that the selected projects meet the program's innovation and scientific excellence goals. This process is designed to be objective and transparent, minimizing the influence of external political and economic factors. For more details:

https://research-and-innovation.ec.europa.eu/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-2020_en

https://commission.europa.eu/system/files/2020-06/db_2021_programme_statement_horizon_2020.pdf.

This decision is supported by recent studies that confirm the objectivity and transparency of this process, highlighting how the project selection criteria ensure that the allocation of funds reflects pre-existing merits and not external contemporaneous factors (Dotti, 2016; Ottone & Barbieri, 2023; Varga & Sebestyén, 2017).

include organizations of different types and areas of Europe are rewarded. For example, a consortium composed of a Slavic country, a Mediterranean country and a Nordic country will be better valued than a consortium of three Mediterranean countries (as long as the talent and value for the realization of the project is the same).

6. Discussion and conclusions

This study has sought to gain a better understanding of the effect of the structure of collaborative networks on regional innovation capacity in Europe. Following previous contributions (Parrilli et al., 2020), we have tried to determine whether three of the most widely used variables in the study of complex networks act as drivers in RISs and how they vary according to their intensity. In addition, we have studied the role played by KT in these collaborative networks and to what extent networks channel knowledge and impact the innovative capacity of the regions.

In doing so, we answered three questions. First, we have assessed to what extent the innovation capacity of regional systems is explained by the structure that these regions occupy in the European knowledge network. Secondly, we have verified the importance of having KT capacity for innovation generation. Thirdly, we have deepened the understanding of these relationships in a broad international context by using the H2020 strategy. When considering these three dimensions together, this study sheds light on the importance of collaboration as a driver of regional innovation and the importance of networks and their structure in KT.

Our results indicate that European regional innovation capacity is partly driven by collaboration between agents in the knowledge network. In this sense, we contribute to the innovation systems literature by providing evidence of innovation policies' strategies (Hervás-Oliver et al., 2021). It is no longer sufficient to invest in internal R&D,

but it is also crucial to strengthen the relationships between the agents that make up the ecosystem. In this regard, our study provides solid evidence about how these interactions work. Previous studies have also reached similar conclusions in more focused, specific contexts, such as offshore wind (Tsouri et al., 2021), and have found that emphasizing R&D as the primary input in the innovation process is far from the best way to advance innovation, particularly in less innovative regions (Hervás-Oliver et al., 2021) that may have more limited organizational structures and resources. Therefore, regional particularities influence firms' innovation (Cooke, 1992; Parrilli & Alcalde, 2016), particularly in a knowledge-based economy.

These peculiarities between regions suggest that understanding an ecosystem network structure is relevant to developing policies that contribute to improving innovation capacity. Firstly, and in line with previous industry- or firm-specific research, this work provides evidence that having a central position regarding your neighbors influences the regional innovative capacity, reinforcing the importance of adequately positioning within the innovation system.

Secondly, greater active participation in the knowledge network helps to develop the innovation capacity of a regional system. In other words, it is important to participate, actively or passively, in the collaborative network. Innovation is nourished by knowledge, and although participation in a research project sometimes does not derive in a direct economic return, our results indicate that the return in terms of access to knowledge is relevant for the generation of innovation. Otherwise, regional boundaries would prevent access to knowledge.

Thirdly, there is evidence that occupying a leading position (i.e., as coordinator) in a knowledge network has a spillover impact on regional innovation capacity. Regions that play a leading role in the network will benefit the most in their innovation capacity,

probably due to the knowledge centralization role of research project leaders. Among other functions, a project coordinator centralizes and organizes information and resources, which may be helpful to generate more trusting relationships, and in turn, to acquire external knowledge more efficiently, helping to develop the innovation capacity of the territory.

Our results also suggest that it is not only important to have adequate network properties and that the network acts as a channel through which knowledge is transferred. This conclusion allows us to understand innovation as a process (Maurer et al., 2011), which implies that achieving an adequate location in the ecosystem and transferring knowledge and absorbing it to develop innovation capacity is essential.

The main contribution of this research has been integrating the innovation systems literature into the KBV through network theory. This study answers some calls in the literature for developing a more unifying framework of KT that integrates innovation with other critical dimensions (Tsouri & Pegoretti, 2021). From an empirical perspective, our two-step analysis has allowed us to understand knowledge flows, the position of each agent in the complex network and the impact on their innovation capacity. Furthermore, incorporating a longitudinal perspective into the analysis confirms that regional innovation capacity and network structural properties vary over time. Finally, our approach widens previous literature, which has traditionally been focused on studying a particular industry or geographical area, by adopting an international perspective.

6.1. Policy and managerial implications

From a policy point of view, the centralized and internally oriented R&D model has become obsolete. In this sense, networked knowledge represents an opportunity for knowledge generation and economic growth of European regions. Our results stress the

need to develop policies that emphasize collaboration between regions. On the one hand, governments can facilitate this exchange, increasing dissemination to reuse and recombine knowledge created by companies, universities and research centres and made it available to society. On the other hand, policy makers can play a crucial intermediary role in facilitating the creation of new collaborations and in consolidating existing ones valuing KT activities. For example, developing a collaborative culture based on trust would strengthen linkages between companies and enhance the stimulation of KT.

Furthermore, innovation policies should incentivize less innovative regions to reach coordinating positions because it facilitates access to valuable knowledge pools. To strengthen the leadership position of a region with low innovation, it is essential to provide access to the technical, economic and support infrastructures necessary to develop innovative initiatives. In addition, the leadership position's awareness of the ecosystem will give key clues as to the unmet needs they cannot solve internally, which should be considered when planning public funding.

The relevance of KT processes from a network structure logic in public policy management should be greater. It would be interesting to generate strategically attractive relationships with other network agents to develop a collaborative mapping system to facilitate contact with a target network. This information can be helpful in the formulation of an innovation roadmap that would favor the achievement of particular objectives. Once we know which regions or companies lead the European R&D scene in a given field, it will be easier to develop the appropriate actions to facilitate a firm's competitiveness or identify industries that can reach central positions in the networks in case of receiving initial support.

When designing innovation policies, local policymakers must consider the strategic behaviour of actors inside the KT network. Since more central actors benefit

most from innovation, collaboration policies will likely reinforce their dominance in the network, slowing down the emergence of local peripheral actors and new entrants. Therefore, innovation policy might be even more effective if it targets balanced sub-networks to strengthen the position of the local peripheral actors in the system by including them in the innovation process. Consequently, these local peripheral actors would be more attractive for future collaboration with new entrants, strengthening the entire knowledge network and facilitating KT.

To sum up, regional innovation capacity is strengthened not only through internal research and development but also by strategic collaboration within knowledge networks, central to the open innovation paradigm (D'Ambrosio et al., 2017). Organizations should prioritize greater involvement and leadership in these networks, aligning with initiatives like H2020 in Europe, to promote inter-organizational collaboration effectively. Leadership roles in open innovation networks not only boost a region's innovativeness but also facilitate crucial KT, enhancing sustainability and competitiveness in the global market (Leydesdorff and Etzkowitz, 1996; Chesbrough, 2006). This leadership orientation should foster collaboration both internally and externally, maximizing synergies across various knowledge domains. Additionally, policies should support technological infrastructure and provide training in open innovation skills to optimize innovation outcomes (Bogers et al., 2017). Acknowledging the dynamic nature of regional networks, policies should strike a balance between internal R&D investment and collaboration efforts to enhance the effectiveness of innovation initiatives.

On their side, managers should invest in relationship management capabilities and negotiate strategic alliances beyond regional boundaries to capitalize on the benefits of innovation networks. By expanding networks beyond traditional geographic confines,

managers open up avenues for accessing diverse expertise, resources, and market insights. This broader scope enables cross-pollination of ideas, fostering creativity and innovation. Additionally, alliances with partners from different regions can facilitate entry into new markets, mitigate risks, and optimize resource allocation, laying the foundation for long-term collaborations and mutual value creation. Both, policymakers and managers should be responsible for establishing mechanisms to ensure the effectiveness of KT between the players in research programs. They should also be conscious of the leverage they have when adopting an active role in the innovation ecosystem.

6.2. Limitations and future research avenues

Our study is not without limitations. Firstly, the definition we use for knowledge is a proxy that, although previously used in the literature, presents some limitations. This is a weakness that knowledge management literature has identified before but also a strength that allows us to examine knowledge flows. Future studies should try to develop a more complex measure of knowledge to overcome this inconvenience and go deeper into analyzing the effect of network structures on innovation capacity. Secondly, we do not consider the nature of the organizations involved. In other words, according to previous studies that conclude that the role of agents differs according to their organizational nature (Ferrer-Serrano et al., 2021), we believe it will be of interest to examine the level of contribution to the regional innovation depending on the organization model. For example, regions with more scientific centers or prestigious universities will probably have better network properties and innovation capacity. In this line of research, future research could try to understand how networks behave depending on the thematic area of the projects. This would let us know the key drivers of European innovation systems, check for differences between thematic areas, and, more importantly, foster the development of particular policy strategies in the Horizon Europe frame.

Finally, one of the main limitations of this data is precisely the postal address indicated by the companies. This may pose a problem in that (1) the address indicated refers to a particular subsidiary or department and the headquarter belongs to another region or country; and (2) the address refers to the parent company but the innovation is developed by a team located in another region (for example, in the case of a university located in a particular region whose address corresponds to the headquarters). Although the availability of this information is limited by data constraints, we have verified that all the organizations in our sample are from the country indicated. In this regard, if it is a subsidiary, we have verified that the parent company is located in the same country as the subsidiary.

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Appendix I

Regional Innovation Index	
Indicators	Definition
Framework Conditions	
1	Human Resources Percentage of population aged 25-34 having completed tertiary education. Lifelong learning, the share of population aged 25-64 enrolled in education or training aimed at improving knowledge, skills and competences.
2	Attractive Research Systems International scientific co-publications per million population. Scientific publications among the top-10% most cited publications worldwide as percentage of total scientific publications of the country.
3	Digitalization Individuals who have above basic overall digital skills. Own estimates using Households with broadband access.
Investments	
1	Finance and Support R&D expenditure in the public sector as percentage of GDP. R&D expenditure in the business sector as percentage of GDP.
2	Firm Investments Non-R&D innovation expenditures as percentage of total turnover. Data for SMEs. Innovation expenditures per person employed in innovation-active enterprises. Data for SMEs.
3	Use of ITs Employed ICT specialists. Estimates using Employment in information and communication.
Innovation Activities	
1	Innovators SMEs introducing product innovations as percentage of SMEs. SMEs introducing business process innovations as percentage of SMEs.
2	Linkages Innovative SMEs collaborating with others as percentage of SMEs. Public-private co-publications per million population.
3	Intellectual Assets PCT patent applications per billion GDP (in Purchasing Power standards). Trademark applications per billion GDP (in Purchasing Power standards). Individual design applications per billion GDP (in Purchasing Power standards).
Impacts	
1	Employment Impacts Employment in knowledge-intensive activities as percentage of total employment. Employment in medium-high and high-tech manufacturing and knowledge-intensive services. Employment in innovative enterprises. Data for SMEs.
2	Sales Impacts Sales of new-to-market and new-to-enterprise product innovations as percentage of total turnover. Data for SMEs.
3	Environmental Sustainability Air emissions in fine particulates (PM2.5) in Industry.

Appendix II

	RIS		RIS		RIS		RIS			
1	<i>Austria</i>		AT1		DE3		ITH5		SI04	
			AT2		DE4		ITI1		ES11	
			AT3		DE5		ITI2		ES12	
2	<i>Belgium</i>		BE1		DE6		ITI3		ES13	
			BE2		DE71		ITI4		ES21	
			BE3		DE72		ITF1		ES22	
3	<i>Bulgaria</i>		BG31		DE73		ITF2		ES23	
			BG32		DE8		ITF3		ES24	
			BG33		DE91		ITF4		ES3	
			BG34		DE92		ITF5		ES41	
			BG41		DE93		ITF6	21	<i>Spain</i>	ES42
			BG42		DE94		ITG1		ES43	
4	<i>Croatia</i>		HR02		DEA1		ITG2		ES51	
			HR03		DEA2	14	<i>Lithuania</i>	LT01	ES52	
			HR05		DEA3		LT02		ES53	
			HR06		DEA4		NO01		ES61	
5	<i>Czech Republic</i>		CZ01		DEA5		NO02		ES62	
			CZ02		DEB1		NO03		ES63	
			CZ03		DEB2	15	<i>Norway</i>	NO04	ES64	
			CZ04		DEB3		NO05		ES7	
			CZ05		DEC		NO06		SE11	
			CZ06		DED4		NO07		SE12	
			CZ07		DED2		PL21		SE21	
			CZ08		DED5		PL22		SE22	
6	<i>Denmark</i>		DK01		DEE		PL41	22	<i>Sweden</i>	SE23
			DK02		DEF		PL42		SE31	
			DK03		DEG		PL43		SE32	
			DK04		EL3		PL51		SE33	
			DK05		EL41		PL52		CH01	
7	<i>Finland</i>		FI19		EL42		PL61		CH02	
			FI1B		EL43	16	<i>Poland</i>	PL62	CH03	
			FI1C		EL51		PL63	23	<i>Switzerland</i>	CH04
			FI1D		EL52		PL71		CH05	
	FI2	10	<i>Greece</i>	EL53		PL72		CH06		
8	<i>France</i>		FR1		EL54		PL81		CH07	
			FRB		EL61		PL82		NL11	
			FRC		EL62		PL84		NL12	
			FRD		EL63		PL91		NL13	
			FRE		EL64		PL92		NL21	
			FRF		EL65		PT11		NL22	
			FRG		HU11		PT15	24	<i>The Netherlands</i>	NL23
			FRH		HU12		PT16		NL31	
			FRI		HU21	17	<i>Portugal</i>	PT17	NL32	
			FRJ	11	<i>Hungary</i>	HU22		PT18	NL33	
	FRK		HU23		PT2		NL34			
	FRL		HU31		PT3		NL41			
	FRM		HU32		RO11		NL42			
	FRY		HU33		RO12		UKC			
9	<i>Germany</i>		DE11		IE04		RO21		UKD	
			DE12	12	<i>Ireland</i>	IE05	18	<i>Romania</i>	RO22	UKE
			DE13		IE06		RO31		UKF	
			DE14		ITC1		RO32		UKG	
			DE21		ITC2		RO41	25	<i>United Kingdom</i>	UKH
			DE22		ITC3		RO42		UKI	
			DE23		ITC4		SK01		UKJ	
			DE24	13	<i>Italy</i>	ITH1		SK02	UKK	
			DE25		ITH2	19	<i>Slovakia</i>	SK03	UKL	
			DE26		ITH3		SK04		UKM	
			DE27		ITH4	20	<i>Slovenia</i>	SI03	UKN	

Appendix III

Variable	VIF	Variable	VIF
Participation	9.88	GPD pc	3.54
Leadership	8.75	R&D expend.	3.19
Net. Structure	7.85	Instit. Distance	2.82
KT Capacity	6.26	Tertiary education	1.65
Prositon	5.4	Population density	1.25
Mean VIF 	5.066		

Appendix IV

Posthoc test pairwise comparisons of means with equal variances - Tukey

IC	Contrast	Std. Err.	t	P>t	[95% Conf. Interval]	
Position						
2 vs 1	0.543	0.053	10.25***	0.000	0.407	0.68
3 vs 1	0.957	0.080	11.89***	0.000	0.75	1.164
4 vs 1	1.297	0.082	15.76***	0.000	1.085	1.508
3 vs 2	0.413	0.08	5.19***	0.000	0.209	0.618
4 vs 2	0.753	0.081	9.25***	0.000	0.544	0.963
4 vs 3	0.34	0.101	3.35**	0.005	0.079	0.601
Participation						
2 vs 1	0.922	0.088	10.45***	0.000	0.695	1.148
3 vs 1	0.930	0.142	6.55***	0.000	0.565	1.295
4 vs 1	1.593	0.447	3.57**	0.002	0.445	2.741
Leadership						
2 vs 1	0.774	0.097	8.02***	0.000	0.525	1.022
3 vs 1	0.854	0.153	5.57***	0.000	0.46	1.248
4 vs 1	1.194	0.384	3.11*	0.010	0.207	2.181

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix V

	Coefficient	Std. Err.	z	P>z	[95% Conf. Interval]	
position	9.699	0.619	15.68	0.000	8.487	1.091
_cons	2.336	0.243	9.62	0.000	1.860	2.812
corr(e.position,e.inncap)	-0.388	0.041			-0.465	-0.305
sd(e.inncap)	3.032	0.074			2.891	3.180
sd(e.position)	0.201	0.004			0.194	0.208
Instrumented: <i>position</i>						
Instruments: <i>eucontr</i>						
Wald test of exogeneity	(corr = 0):	chi2(1)=73.1		Prob>chi2=0.000		

Appendix VI

Random effects Tobit regression – Robustness autocorrelation check

	Model 1	Model 2	Model 3	Model 4
<i>Position</i>	0.00762** (0.00426)			
<i>Leadership</i>		0.00366* (0.00569)		
<i>Participation</i>			0.00260*** (0.00493)	
<i>KT capacity</i>				0.0312*** (0.00265)
GDP per capita	0.331*** (0.0308)	0.328*** (0.0381)	0.451*** (0.0391)	0.338*** (0.03816)
R&D expenditure	0.158*** (0.00104)	0.156*** (0.00215)	0.153*** (0.00211)	0.173*** (0.00187)
Population	-0.0404 (0.00237)	-0.0276 (0.00714)	-0.0217 (0.00853)	-0.0340 (0.00511)
Tertiary education	0.00280*** (0.001603)	0.00733*** (0.00173)	0.00725*** (0.00180)	0.00596*** (0.00160)
Population density	-0.00017*** (0.00092)	-0.00026*** (0.00073)	-0.00037*** (0.00078)	-0.00098*** (0.00112)
Formal institutions	0.00489*** (0.000135)	0.00107*** (0.000419)	0.00338*** (0.000283)	0.00685*** (0.000230)
Constant	5.724*** (0.0660)	5.933*** (0.0278)	6.217*** (0.0141)	5.451*** (0.0113)
Observations	1,624	1,624	1,624	1,624
Number of idnum	232	232	232	232

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix VII

Poisson estimation – Robustness check

	Model 1	Model 2	Model 3	Model 4	Model 5
<i>Position</i>	0.00697** (0.00632)				0.00035** (0.00874)
<i>Leadership</i>		0.00207* (0.00859)			0.00059* (0.00027)
<i>Participation</i>			0.00161*** (0.00580)		0.00144** (0.00203)
<i>KT capacity</i>				0.0302*** (0.0344)	0.00127*** (0.0011)
GDP per capita	0.289*** (0.0332)	0.289*** (0.03134)	0.291*** (0.03134)	0.291*** (0.03135)	0.287*** (0.03138)
R&D expenditure	0.291*** (0.0267)	0.295*** (0.0269)	0.292*** (0.0269)	0.294*** (0.0271)	0.285*** (0.0276)
Population	-0.0351 (0.00792)	-0.03.87 (0.00779)	-0.0371 (0.00787)	-0.0389 (0.00781)	-0.0372 (0.00789)
Tertiary education	0.0152*** (0.00212)	0.0155*** (0.00214)	0.0150*** (0.00216)	0.0155*** (0.00215)	0.0156*** (0.00222)
Population density	-0.00152* (0.00183)	-0.0049* (0.00185)	-0.00316* (0.00185)	-0.00214* (0.00187)	-0.00272* (0.00192)
Formal institutions	0.00171*** (0.000199)	0.00180*** (0.000451)	0.00162*** (0.000393)	0.00195*** (0.000335)	0.00218*** (0.00373)
Constant	5.322*** (0.0215)	5.355*** (0.217)	5.354*** (0.216)	5.365*** (0.218)	4.413*** (0.220)
Observations	1,624	1,624	1,624	1,624	1,624
N	232	232	232	232	232

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix VIII

SPATIAL CORRECTION – 200 km

Inn.Capac.	Coefficient	Std. Err.	z	P> z	[95% conf.	Interval]
Position	5.151741	0.8589311	6.00	0.000	3.468267	6.835215
Leadership	3.638517	0.6539265	4.33	0.001	2.674321	4.652854
Particip.	4.285672	0.9734865	5.23	0.000	3.827842	5.864386

SPATIAL CORRECTION – 800 km

Inn.Capac.	Coefficient	Std. Err.	z	P> z	[95% conf.	Interval]
Position	4.165936	0.8854279	5.36	0.000	3.276548	6.175428
Leadership	3.175397	0.7543862	3.88	0.001	2.379825	4.428964
Particip.	3.754272	0.9965438	4.96	0.001	3.424839	5.286349