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Understanding the network structure of Agri-Food FP7 projects: An approach to the effectiveness of innovation systems

Abstract

Innovation Systems (IS) have emerged as focal points for innovation and technology, facilitating interaction between private companies, research centres and institutional actors. For over 30 years, the Framework Programmes (FPs) have been one of the primary mechanisms through which collaboration among research institutions and industry has been promoted within the European Common Market. Over time, these research consortia financed by FPs have created a network of relations among partners, which permits the exchange of information and knowledge among institutions and firms. While the literature on innovation systems has highlighted this network as a driver of innovation development, little is known about the properties of the network structure. This paper aims to fill this gap in the literature by using social network analysis to describe the topological properties of the Agri-Food network funded by the FPs between 2008 and 2014. We extend the literature on innovation systems in terms of its modelling and effectiveness. We conclude that the effectiveness of innovation systems depends on several factors such as heterogeneity and geographic diversity of the participants as well as their position in the network. Importantly, our paper highlights the importance of the structural properties of the network underlying an IS when assessing the effectiveness of R&D policies.

Keywords: *Innovation Systems, Framework Programmes; Agri-Food; Network Analysis.*

1. Introduction

Innovation Systems (IS) have emerged as focal points for innovation and technology, facilitating the interaction between private companies, research centres and institutional actors (Arranz et al., 2020b; Kashani and Roshani, 2019; Kapetaniou et al., 2018; Wang et al., 2017; Lundvall, 2007). In fact, Freeman (1987) considered IS as a network of institutions in the public and private sectors whose activities and interactions initiate, import, modify and diffuse new technologies. In this context, governments and supra-national authorities have sought ways to strengthen this network. An example of such a supranational authority is the European Union (EU), which has promoted a number of policies to promote the creation of an innovation system at the European level. For over thirty years, the funding and the promotion of research consortia[1] among firms, universities and other organisations have been the primary mechanisms employed by the European Union to support knowledge creation and transfer. They have facilitated the creation of links between the industry and research organisations, with the ultimate goal of improving the competitiveness of the European industry as well as creating an environment where knowledge exchange is facilitated (Sá and Pinho, 2019; de Juana-Espinosa and Luján-Mora, 2019). Although initially they were established to support research, their role changed over time as the emphasis of the last Framework Programmes (FPs)[2] shifted towards projects that favour knowledge exchange among the participants while achieving broader socio-economic objectives (de Juana-Espinosa and Luján-Mora, 2019; Kashani and Roshani, 2019; Kuhlmann and Edler, 2003). Additionally, the latest Framework Programs started funding projects that could promote the creation of a European Innovation System (Amoroso et al., 2018) - a vital element of the EU research and innovation policy (De Marco et al., 2020; Pinheiro et al., 2016; Delanghe and Muldur, 2007; Kuhlmann and Edler, 2003).

While the literature has exhaustively studied the performance of these research consortia from the point of view of the joint project and of the participating companies (Delanghe, 2007; Pinheiro et al., 2016; Muldur et al., 2007; Arranz and Fernandez de Arroyabe, 2006), the system of relationships created by the research consortia and their impact on the research objectives have not been analysed extensively (see, for example, Muniz et al., 2018) with the result that we have several inconclusive results in this area (see, for example, Kang and Hwang, 2016; Muñiz and Cuervo, 2018). There are many reasons for this: first, previous studies have focused mostly on several issues - such as the study of regional cohesion (see, for example, Amoroso et al., 2018; Di Cagno et al., 2016), the study of interactions among countries (Muñiz et al., 2018; Scherngell and Barber, 2009) or the problems of integrating SMEs in innovation systems (De Marco et al., 2020) that did not require an analysis of the underlying network. Second, most of the work has focused on the institutional and political impact of the various

[1] Research consortia are defined as organisational mechanisms, where the tasks are distributed among partners who are interconnected to achieve a common objective (Aarikka-Stenroos and Rittala, 2017; Bendoly et al., 2010).
[2] Since 1984, European Community research and technological development activities have been defined and implemented by a series of multi-annual Framework Programmes: the 4th RTD FP (1994-1998), the 5th FP (1998-2002), the 6th FP (2002-2006), the 7th FP (2007-2013) and currently Horizon 2020 (2014-2020). The Framework programmes have been the main financial tools through which the European Union supports research and development activities covering almost all scientific disciplines. FPs are proposed by the European Commission and adopted by the Council and the European Parliament following a co-decision procedure.

programmes (Gallego-Alvarez et al., 2017; DiMaggio and Powell, 1983) and in doing so, they have neglected the study of the network and its properties[3].

Our paper addresses this gap in the literature by *studying the properties of the networks generated by the EU-funded research consortia and how they affect the objectives of the EU's research and development policy*. First, we assume that the research consortia create a network of relationships that make up the innovation system at the European level. So, partners are related to one another because they work together on projects, allowing knowledge exchange. Projects are related to one another because they share partners, which increases the level of project information as a result of the partners' participation in other projects. This creates a network of relationships between projects and partners that facilitates the exchange of information among them. Secondly, unlike previous works (for example, Kang and Hwang, 2016) that analysed the network properties and topology structure passively[4], we assume that the node has an active role in the network. It is the node that participates in the various innovation activities, taking an active role in achieving the network's objectives. Following Arranz et al. (2020a), Arranz and Fernandez de Arroyabe (2013) and Grewal et al. (2006), we assume that the position in the network gives a positional value to the node. Therefore, we consider that how the node is positioned within the network will affect the information it receives and therefore, its research and innovation activity. Moreover, we take into account that in the network nodes are heterogeneous (firms, SMEs, universities, research centres, institutions) and geographically diverse: we hypothesise that both the connectivity of the nodes as well as their heterogeneity will have an impact on the achievement of the objectives of the EU's research and development policy.

For our empirical analysis, we use a dataset of 224 research consortia funded by the FP7 initiative entitled Knowledge-Based Bio-Economy (KBBE) Activity 2.1. FP7 initiative Activity 2.1 aims to increase the need for high-quality food production, developing sustainable agriculture/fishery in light of climate change. The dataset provides detailed information about the research consortia funded between 2008 and 2014, involving 1,529 organisations from all European countries. Using social network analysis, we measure the position of each

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[3] The only exceptions are Kang and Hwang (2016) that have analysed the sustainability energy network and Muñiz and Cuervo (2018), who focus on information and technology networks created by the FP7.

[4]Previous works have addressed the study of networks, analysing their properties (density, clustering, hubs, size, etc.), and how these affect the dissemination of information. In our case, we emphasize the role of the node, as a generator of information and innovation, and the position of the node which affects the dynamics of the network.

organisation in the network through different centrality measures (*degree, betweenness, eigenvector, closeness*).

Our findings indicate the need to conceptualise the IS in terms of a network of relationships; we conclude that the effectiveness of the IS depends on the heterogeneity and geographic diversity of the nodes as well as on their position. Moreover, our results show how the topology and the structural properties of the network affect its technological trajectory and the cohesion of the network, both in terms of knowledge transfer between universities and companies, as well as in terms of geographic cohesion between countries.

The structure of the paper is the following. Section 2 surveys the existing literature on research consortia in the EU while providing details about the Framework Programmes and introducing our research questions. Section 3 presents the data and the techniques employed in this paper. Section 4 introduces the results, while some concluding remarks are offered in Section 5.

2. Conceptual framework and Research Questions

2.1 Innovation and innovation System (IS).

From the perspective of open innovation (Chesbrough, 2012), innovation is an evolutionary process of collective learning in which different stakeholders (companies, research institutions, clients, governments, financial institutions) can join and cooperate in carrying out collaborative projects (Arranz et al., 2020a). In this context, the innovation process consists of managing inputs and outputs of knowledge that accelerate the development of innovation and expand the commercialisation of innovation (Chesbrough, 2003; Rahman and Ramos, 2010). Chesbrough (2012) points out that the effective innovation process requires a flexible and dynamic organisational structure based on collaboration, where diverse stakeholders are involved in this process, forming innovation systems.

Since the seminal works of Freeman (1987), Lundvall (1988, 1992), Nelson (1993) and Edquist (1997), the innovation system approach has gained much scholarly attention and has been primarily adopted by practitioners and policymakers in both developed and developing countries (Lundvall et al., 2006; Muchie et al., 2005; Mytelka and Smith, 2002; Edquist and Hommen, 2008). According to Freeman (1987), the IS is "a network of institutions in the public and private sectors whose activities and interactions initiate, import, modify, and diffuse new technologies." Lundvall (1992) defined it as the "elements and relationships which interact in the production, diffusion, and use of new, and economically useful, knowledge, and are either located within or rooted inside the borders of a nation-state". Thus, the innovation system appears as an interactive organisational process that goes from the generation of knowledge to the successful introduction of an innovation in the market (Mytelka and Smith, 2002; Chaminade and Edquist, 2006, 2010). In this context, the interactions have a positive impact on business performance by increasing innovation capabilities (Cheng & Chen, 2013), sharing risks and resources, reducing development times, improving employee participation and increasing access to new knowledge, technologies and markets (Enkel et al., 2009; Huang et al., 2013; Kumar et al., 2012; Ades et al., 2013; Parida et al., 2014).

The conceptualisation of innovation ecosystems takes into account in the first place that it is a system in a *geographical and institutional setting*. Ades et al. (2013) and Parida et al. (2014) highlight the institutional impulse as a critical element of the innovative capacity of the system so that companies find the incentives to collaborate and develop innovation projects. The geographical scope determines the institutional configuration and public policies, which means that in different geographical areas, there may be differences in the institutional impulse, which affects the innovative performance. Second, it is a *'system' where institutions, universities and companies interact*. Thus, the IS emphasises the interaction among components of the system, creating their mutual interactions as well as their relationships with the social and institutional framework in which the system is embedded (Lundvall, 2007).

2.2 Institutional theory: The role of the EU in creating the European Innovation System (EIS)

Institutional theory has been widely applied to explain the adoption of organisational practices among firms (Wang et al., 2019; Gao et al., 2019; Gallego-Alvarez et al.,2017; Berrone et al., 2013; Wahba, 2010; Scott, 2005). This theory argues that organisations are not isolated individual organisations and that their behaviour is determined by norms, structures, constraints, common cognitions and social expectations by relevant audiences (DiMaggio and Powell, 1983; Scott, 2005; Berrone et al., 2013). DiMaggio and Powell (1983) and Scott (2005) noted that institutional pressures push organisations to adopt shared notions and routines. In this context, the EU has not been oblivious to the importance of the institutional drive to develop competitive innovation systems within the scope of the European Union. Thus, under the umbrella of coercive pressure, the European Union developed the Framework Programs as funding programs to support and foster research in the European Research Area (ERA). Over the last thirty years, the European Union has invested a substantial amount of resources through its FPs to promote research consortia where a variety of organisations (including private companies and research institutes) would work on ambitious research projects and share the costs of the research.

This institutional drive through the EU's FP had several objectives. Firstly, it wants *to achieve dissemination and collaboration between institutions and companies within the EU*. Framework programs are emphasising knowledge sharing among participants and collaborative research (de Juana-Espinosa and Luján-Mora, 2019; Kashani and Roshani, 2019; Kuhlmann and Edler, 2003). Cooperative research offers several benefits as it allows for the dissemination of information and ideas, providing access to resources, capabilities and markets (Arranz et al., 2020b; Amoroso et al., 2018; Pinheiro et al., 2016; Arroyabe et al., 2015; Caloghirou et al. 2004). Secondly, the FP aimed at *increasing the competitiveness of companies within the EU*. Therefore, the framework programs prioritised the main areas of research and innovation to be financed, comprising a broad portfolio of activities to be financed.[5] Thirdly, the FP aimed at *promoting cohesion through international cooperation*. The EU comprises a heterogeneous and broad spectrum of countries, with various levels of development in research and innovation. Therefore, the projects financed are based on the development of consortia formed by partners from various European countries[6], with the final objective of reducing the differences in research and innovation between the different countries. Finally, one of the EU's objectives was *to achieve the effective transfer of knowledge between centres of excellence and knowledge and companies*. Since the green book on innovation (European Commission, 2009), which emphasised the deficit that the EU had in terms of innovation as compared to the US and Japan, the EU has fostered competitive innovation, involving companies in projects. Ferraris et al. (2018a) introduced the concept of multi-stakeholder networks and highlighted how collaboration in the implementation of innovation projects of universities, institutions and firms is a crucial element in innovative development. These authors further emphasise the role of collaboration between universities and companies which can foster knowledge transfer from the university to the firm. Moreover, as it is well known that the European economic fabric is dominated by SMEs, the EU has made it a priority objective to encourage the participation of SMEs in funded consortia.

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[5] The main areas of research and innovation included in the FP7 are Health; Food, Agriculture and Fisheries, and Biotechnology; Information and Communication Technologies; Nanoscience, Nanotechnologies, Materials and new Production Technologies; Energy; Environment (including Climate Change); Transport (including Aeronautics); Socio-economic Sciences and the Humanities; Security and Space.

[6] In fact, to be able to access a funded research consortium, at least two EU countries must be included.

2.3 Social capital: network perspective in the European Innovation System

The social capital perspective provides a compelling theoretical framework from which to explain the actual and potential resources embedded in the networks of relationships (Gatignon et al., 2002; Nahapiet and Ghoshal, 1998; Subramaniam and Youndt, 2005; Mitsuhashi and Min, 2016; Ferraris et al., 2018b; Lyu et al., 2019; Zhang et al., 2019; Arranz et al., 2020a). Moran (2005, page 1129) points out that "the social capital is a valuable asset and that its value stems from the access to resources that it engenders through an actor's social relationships". Zhang et al. (2019, p. 13) conclude that network structure could yield specific outcomes for the participant in the network. In this context, Granovetter (1992) and Nahapiet and Ghoshal (1998) introduce the concept of network embeddedness to characterise the structure of firms' relationships with other firms. Ruef et al. (2003) and Moran (2005) point out that network embeddedness provides access to information through the relations among firms, which generates social capital for the participating firms.

As we have seen before, the instruments on which the EU's institutional drive is based on are the research consortia. Arranz and Fernandez de Arroyabe (2013) consider a research consortium as a joint project in whose execution various partners intervene. Throughout their development, these consortia create a network of relationships, in which partners' and projects' interactions facilitate the exchange of information and knowledge. As we have pointed out, partners are related to one another because they work together on projects; and projects are related to one another because they share partners. Echols and Tsai (2005) and Lyu et al. (2019) point out that the specific structure and extent of a firm's inter-relationships with others creates an innovation network, which is considered one of the most crucial factors in innovation practice (Chesbrough and Crowther, 2006; Koka and Prescott, 2008).

This network of interactions between research consortia (project/partners) has a double effect. First, the link and position of organisations in the network of relationships determine the network embeddedness, and therefore their access to information. Gulati (1995, 1998) highlights the informational value of the structural position of nodes in the network. In this line, Ferraris et al. (2018b) emphasise network embeddedness as a way to access knowledge. Moreover, Arranz et al. (2020a) point out that not all positions in the network affect the firm in the same way, as they provide differential access to information in terms of *quantity, diversity, importance and accessibility of the information* received by the nodes, determining their research and innovation performance. Second, these interactions determine the topology of the network. Newman (2003) pointed out that the network topology is responsible for its diffusion and cohesion. Moreover, this author stressed that unlike simple networks[7], the technological networks can be considered complex by virtue of a non-trivial structure. Such non-trivial features include a hierarchical structure that is embodied in the centrality of the network and the heterogeneous distribution of connections in it (Moran, 2005). The affinity and privileged relations between the nodes are a result of the different roles that they adopt. In general, Newman (2003) highlights three structural attributes that characterise the topology of social networks: *centrality* (i.e. which individuals are best connected to others or have the most influence), *connectivity* (i.e. whether and how individuals are connected through the network) and *community structure* (i.e. how cohesive the network is).

2.4 Research questions: How does the EIS network affect the achievement of the objectives of the research and development policy?[8]

In our modelling of the EIS network, the nodes are the various organisations that intervene in the network, which display heterogeneity both in terms of typology (companies, SMEs, research centres and universities, institutions) and geographic diversity. The links are the relationships between them, which arise from participating in the research consortia.

Regarding the objectives of the research and innovation policy of the EU, the EIS must be able to fulfil them[9] (Echols and Tsai, 2005; Lyu et al., 2019). As we have seen previously, the topology of the network is characterised by three structural attributes (*centrality, connectivity, cohesion*), which influence both the dissemination of information and the cohesion of the network (Moran, 2005; Borgatti and Halgin, 2011; Ferraris et al., 2018b). Kapetaniou et al. (2018) have highlighted access to information as a critical element of research and innovation development. Moreover, Newman (2003) has pointed out that more cohesive networks facilitate collaboration, which has been highlighted in the innovation literature as a critical element for its development (Koka and Prescott, 2008; Ferraris et al., 2018b). Lyu et al. (2019) note that high centrality [10] has significant advantages in knowledge acquisition, recombination

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[7] Simple networks are typically represented by graphs such as a lattice or a random graph, which exhibit a high similarity in terms of homogeneity of connections among nodes.
[8] This is an exploratory study, and we are not following the standard deductive structure of other papers (hence the lack of formal hypotheses).
[9] Woolthuis et al. (2005) point out that the difference between natural systems and innovation systems is the ability to govern it and to be able to lead it to fulfil its objectives.
[10] Centrality in a network implies that there is a core, composed of a reduced number of nodes, which have greater interconnection with the rest of the nodes in the network. Sometimes, the concept of centrality is also related to that of the hierarchy of the network.

potential and control. Therefore, regarding the first objective of the EU's research and development policy, which is to promote the diffusion and collaboration between institutions and companies within the framework of the EU, it is expected that the structure and properties have an impact on achieving them. Our first research question is:

RQ1: How do the structural attributes (centrality, connectivity, cohesion) of the EIS network affect the diffusion of information and collaboration between institutions and companies?

Complex networks are characterised by a hierarchical structure - embodied in the core of the network - and by the heterogeneous distribution of its connections. According to Wasserman and Faust (1994), central actors (nodes) must be the most active because of the number of nodes they are connected to. Moreover, these authors point out that networks create these cores as a consequence of a higher affinity and similarity in activities, leading to more cohesive areas. Considering that the second objective of the EU's research and development policy is the competitiveness of companies within the EU, the activities of the network should be aimed at developing priority areas of research in line with the Framework Programs. We would, therefore, expect that the structure and properties of the network will influence the achievement of this objective. Therefore, we pose a second research question:

RQ2: How do the structural attributes (centrality, connectivity, cohesion) of the EIS network affect the achievement of the EU competitiveness objectives?

The EIS network is characterised by the heterogeneity of the nodes that form it. Thus, the heterogeneity comes from the diversity of typology that can distinguish universities, research centres, industries, firms, SMEs, and institutions. Suppose we combine the heterogeneity of the nodes with the connectivity of each node. In that case, we can see that the position in the network of the various nodes allows accessing a differential typology of information, which is expected to influence the activity of research and development of the node. Since the third objective of the EU's research and development policy is to achieve effective transfer between research centres and companies, it is expected that the structure and properties of the network together with the heterogeneity of the nodes have an impact on the transfer of knowledge. Therefore, we pose a third research question:

RQ3: How do the structural attributes (centrality, connectivity, cohesion) and the heterogeneity of the EIS network affect the dissemination of information between universities and companies?

Lastly, we argue that the research consortia emerging from the projects are transnational, implying geographical heterogeneity among partners. Thus, the heterogeneity of the nodes comes from the geographic diversity that the EIS encompasses. Another objective of the EU is cohesion between countries; therefore, it is expected that the geographical linkages of the various nodes to the network determine the access to information. Hence, considering that the fourth objective is to promote transnational cohesion in terms of research and development, we propose a fourth research question:

RQ4: How do the structural attributes (centrality, connectivity, cohesion) and the diversity of the EIS network affect the cohesion of EU policy?

3. Empirical analysis

3.1 The data

For our empirical analysis, we have used the EU datasets containing the 224 research projects funded by the FP7 initiative titled Knowledge-Based Bio-Economy (KBBE) Activity 2.1 (i.e. focused on food, agriculture, fisheries and biotechnology)[11] (European Union, 2019). The dataset provides detailed information about the projects funded between 2008 and 2014, involving 1529 organisations. As the most significant connected component comprises 1514 out of 1529 institutions and 222 out of 224 projects, we focus on the largest component in the following.

The main descriptive statistics related to all projects included in the dataset is provided in Table 1. As far as the timescale of projects is concerned, the median length of funded projects for all members is 48 months. In terms of funding, the mean project funding is 3.428,522 euros, which is not significantly different from the overall median funding.

3.2 Methodology

As mentioned in the introduction, we will first use social network analysis to examine the main topological features of the networks that have emerged from the research consortia under examination. For this analysis, we assume that the networks that emerge from the membership

[11] The socio-economic challenges addressed by FP7 initiative Activity 2.1 are: Sustainable agriculture/fishery under climate change; Increasing need for high quality and sustainable food production; Food-related disorders; Infectious animal diseases and zoonoses; Renewable energy sources.
Knowledge-Based Bio-Economy (KBBE) in the FP7 research agenda (Theme 2 Cooperation: Food, Agriculture & Fisheries and Biotechnology) uses the bio-economy concept. The definition of bio-economy means "the sustainable, eco-efficient transformation of renewable biological resources into food, energy and other industrial products" (DG Research, 2007). The term 'bio-economy 'covers all industries and economic sectors that produce, utilise or manage biological resources. The European bio-economy has an annual turnover of more than 1500 billion € and employs 22 million people.

of EU-funded research projects are "affiliation networks" which can be represented as bipartite graphs of members joined by undirected edges. To construct our sample, we will be using the nominalist approach, which is frequently adopted in similar research contexts (e.g., Wasserman and Faust, 1999). As a first step in this approach, we identify the firms that are linked together through the development of projects. For this, following Wasserman and Faust (1999), we built one affiliation matrix network A in which the rows represent firms, and the columns represent the projects. The entries take the value 1 when a firm is an assignee related to a project and 0 otherwise. Hence, we obtained the network matrix for institutions and firms (XF^t) as $XF^t = AA^T$, where A^T is the transpose matrix.

3.3 Positional indicators of the nodes in the network

Regarding the analysis of the EIS network structure, we will derive some overall positional indicators of the nodes in the structure of the network. We assume that the various organisations that make up the network of relations in the EIS will have an active role in the development of research and innovation so that their links and therefore their position in the network are a crucial element in achieving the objectives of the EIS. Gulati (1995, 1998) argues that network embeddedness highlights the informational value of the structural position of nodes in the network, while Arranz et al. (2020a) and Grewal et al. (2006) emphasise the position of the node in the network, pointing out that not all positions in the network affect the organisations in the same way (as they provide differential access to information).

From a structural point of view, Grewal et al. (2006) have introduced four dimensions about the structural position of nodes in the network, emphasising the level of centrality that nodes have in the network. The first indicator is d*egree centrality,* which focuses on the quantity of information that a node can access and acquire thanks to its interrelations. Thus, a high value of degree centrality of the node means that the institution or firm is connected to a large number of nodes, something which provides access to more information (Borgatti and Halgin, 2011; Grewal et al., 2006). The second indicator is the *closeness centrality*. This indicator focuses on the distance of each node from all others. Arranz et al. (2020a) point out that closeness centrality gives an idea of the viability of access to node information.

Additionally, a higher distance among nodes implies a weaker link between each node and the rest of the nodes, which makes access to information difficult. The third indicator is the *eigenvector centrality* (Borgatti et al., 2002; Bonacich, 1987). This index refers to the proximity of the node to the core of the network. Wasserman and Faust (1999) and Borgatti et al. (2002)

emphasise that the core of a network determines the most active nodes. So, this index captures the notion that connections to nodes at the core, which are well connected are more important than connections to poorly connected organisations, in terms of information. Finally, *betweenness centrality* highlights the extent to which a node acts as a connector of other nodes, i.e. nodes with a high betweenness connect different groups. Thus, when the betweenness centrality is high, the node has access to different and new flows of information through partners who have participated in mutually unconnected projects (Gilsing et al., 2008; Gilsing and Nooteboom, 2006).

3.4 Measures of Indicators

Freeman (1979) proposes a normalised measure of *degree centrality*, obtained by dividing the node degree of each firm by the maximum possible number of links. The domain of the score is [0, 1]; 0 representing no connections and 1 indicating links with all firms in the network.

The next measure is *betweenness centrality*. Freeman (1979) defines betweenness as the number of geodesic or shortest paths that go through a particular node. Freeman also proposes the following approach to calculate betweenness computed in its normalised form, i.e., with a score in the range of [0, 1]:

$$C'_B(p_k) = \frac{2C_B(p_k)}{n^2 - 3n + 2}$$

where *n* represents the number of links in the network and $C_B(p_k)$ is the sum of all partial betweenness of a particular node p_k. Note that when p_k is the only geodesic path connecting two nodes, the score $C_B(p_k)$ is increased by 1. In contrast, if there are alternative geodesic paths, the score grows proportionately to the number of times that p_k is part of the alternative shortest paths (Freeman, 1979). From an information flow perspective, betweenness can be interpreted as an index measuring the extent to which a node can control the information flows; for example, in the case of a star network, the central node, which connects every node in the network with others, has relative betweenness value of 1. In contrast, the rest of the nodes have a score of 0.

Eigenvector centrality considers the characteristics of a node's neighbour to determine the centrality, i.e., it measures whether a partner is connected to partners that are well embedded in the network. Introduced by Bonacich (1987), eigenvector centrality examines the values of the first eigenvector of the network's adjacency matrix. The scores contained in this vector are derived from the centrality of the nodes to which a particular agent is connected to, that is, the centrality of a node is proportional to the sum of the centralities of the nodes it is linked to. Under the definition of eigenvector centrality, central nodes are those who are connected to many nodes, which in turn are connected to many others (Newman, 2003).

Finally, *closeness centrality* is defined as the sum of distances from a node to all other nodes in the network, where the distance is measured as the number of links contained in the shortest path (Freeman, 1979); in other words, it measures the number of steps required to reach every other node. The concept of closeness is related to the efficiency by which information is transmitted from one node to any other, and it can be interpreted as the expected time until the arrival of a particular piece of information flowing in the network (Borgatti et al., 2002; Newman, 2003). In this context, a node is considered central if all its shortest paths to every other node in the network are minimum so that it will tend to receive the information sooner than other nodes with lower scores (Sabidussi, 1966). Therefore, closeness is measured as the inverse of the sum of all geodesic distances of a particular node from all the other nodes; a node is considered to be central if the score in closeness is high. Beauchamp (1965) refined this measure by normalising Sabidussi's index:

$$C'_C(p_k) = \frac{n-1}{\sum_{i=1}^{n} d(p_i, p_k)}$$

where *n* is the number of nodes in the network, and $\sum_{i=1}^{n} d(p_i, p_k)$ is the number of links in the geodesics connecting node p_i and p_k.

3.5. Network Measures

The first measure on the network level is *density*. Following Borgatti et al. (2002), density is measured as the ratio between the actual number of edges and the number of possible edges. Thus, values close to 1 correspond to very dense networks; on the contrary, values close to 0 correspond to very sparse networks. Additionally, we measure the *diameter of the network*, which is defined as the maximum length of all geodesic distances (i.e. indicate the farthest path). Further, we analyse the *size of the network*, which is defined as the number of nodes in the network. Finally, our last indicator of interest is *clustering*. Following Borgatti et al. (2002), we measure the clustering coefficient (or transitivity) as the number of transitive triples divided by the number of potential transitive triples. Thus, if the value is near 1, the partners of any node have a high probability of being partners with each other.

4. Results and discussion

In our paper, we have assumed that the IS appears as a network of institutions and organisations, whose activities and interactions initiate, import, modify and diffuse new technologies. In this context, the European Union has developed actions to promote the creation of an innovation system at the European level, financing and promoting the creation of research consortia. These research consortia create a network of relationships that make up the innovation system at the European level. In this context, our results confirm the existence of a network emerged from the Agri-Food consortia. The network indicators (2008-2014) are reported in Table 2. Except for the 15 nodes that are disconnected, the rest forms a connected network, consisting of 1514 nodes, bringing together 222 projects. These results are similar to those of Kang and Hwang (2016), who find two related networks formed by 1,366 nodes (FP6) or 1,770 nodes (FP7) in their longitudinal study of sustainable energy projects. Our results are also in line with the works of Muñiz and Cuervo (2018), who show a connected network of 43 countries with 730 links between countries, in their study of ICT projects in the FP7. Therefore, this network is responsible for promoting the diffusion and collaboration between institutions and firms within the framework of the Agri-Food program.

As we have postulated in our paper, the topology of the EIS network is responsible for achieving the EU innovation policy goals. More specifically, regarding the first and second research questions (RQ1 and RQ2) on how the structural attributes (*centrality, connectivity, cohesion*) of the EIS affect both the diffusion and collaboration between institutions and firms and the competitiveness of EU, we examine the main topological features of the networks that have emerged from the research consortia. To delve into the structural attributes of the network, we analyse the centrality variables of the network nodes. In Figure 1, we show the densities of the distributions of our centrality indicators on the node level. In Table 3, we further show the corresponding results for the top 10 companies in terms of the total number of connections. If we look at the table, we see that two institutions have a high level of connection. The institution *Stichting Dienst Landbouwkundig Onderzoek-Alterra (ALT)*[12] which has participated in 80 projects out of a total of 222, with an average of partners in each project of 16.9. The other organisation in our ranking is the *Institut National de la Recherche Agronomique (INRA*)[13],

[12] Stichting Dienst Landbouwkundig Onderzoek (DLO) is part of Wageningen UR (University and Research centre). Within FunDivEUROPE, researchers from Alterra (ALT) will be involved, being one of the specialised research institutes of DLO. Alterra is the leading Dutch centre of expertise on rural areas.

[13] National Institute of Agricultural Research is a French public research institute dedicated to agricultural science.

with a similar level of connection, participating in 75 projects, with a partner average of 17.6. Continuing with our analysis of company 3 to 10, we observe that the number of projects is decreasing from participation in 30 projects to 17 projects. A priori, from these results, we can infer that the network topology corresponds to a centralised network. To investigate the degree of centralisation, we used the measures of degree and eigenvector centrality in each node. *Degree centrality*, from an operational point of view, measures how the node is embedded in the network, emphasising the number of links it has in the network, which gives access to a large amount of information. As expected the two institutions *Stichting Dienst Landbouwkundig Onderzoek - Alterra* and *Institut National de la Recherche Agronomique* have a high level of degree centrality (0.947 and 0.918, respectively) with values being close to 1, which means that they are interconnected to more than 90% of the nodes through the project/partner combination, providing a significant informational asset in terms of the amount of information. Moreover, analysing companies from 3 to 10 in the ranking, we see that their degree centrality decreases to between 0.260 and 0.399 which confers a degree of connection in terms of the amount of information, approximately between 20% and 40% of nodes. In general, our results show a high degree centrality, contrasting previous studies in the FP7, such as the work by Kang and Hwang (2016) for the case of renewable energy, who obtain values for the degree centrality between 0.1190 and 0.0735. Furthermore, if we analyse the *eigenvector centrality* of these nodes, which shows the proximity to the core of the most active group of nodes, we see results that are very similar to those provided by the degree centrality. In this case, the *Stichting Dienst Landbouwkundig Onderzoek-Alterra* has an eigenvector centrality value of 0.913, while the value of the *Institut National de la Recherche Agronomique* is 1, which shows that these two institutions are the most active and form the core of the network. The eigenvector centralities of the actors located between positions 3 and 10 range between 0.590 and 0.295, which shows a second level centrality in the network. In conclusion, we see that the main characteristic of the network is its centrality, made up of a central core of two actors. Moreover, connected to this central core, we can find several nodes that form the second level of connection with the central core. Therefore, the network topology, in terms of centrality and connectivity, constitutes a *concentric network*, with a few nodes being the centre of the network while the rest of the nodes are connecting concentrically to them. These results differ from previous works on the FP6 and FP7, which show a lower degree of centrality as a consequence of having multiple cores in the networks (Kang and Hwang, 2016; Muñiz and Cuervo, 2018). The existence of centrality in the network can be explained by the higher concentration of projects in a determined research stream. Thus, from the IS point of view, the existence of a core can be related to the concept of the *technological trajectory* (Arranz et al., 2020a). The concept of technological trajectory was introduced by Carlota Perez and showed the existence of a degree of concentration of technological projects that are more viable or successful in a particular research field (Perez, 2010, 1983). If we analyse the core of our network, we see that the two institutions are two research centres in biodiversity and sustainability development. Moreover, we see that in Table 3, all the nodes that are in the ranking of the top 10 are universities and research centres whose activities are framed in sustainable projects and eco-efficient transformation of renewable biological resources. Therefore, we can see that it coincides with a technological trajectory. If we analyse the FP7 descriptor in the Agri-food field, we can conclude the coherence between the research line proposed by the EU and the technological trajectory. This is in contrast with previous works in FP7 (Kang and Hwang, 2016; Muñiz and Cuervo, 2018), which reported more than one core. However, this is most likely due to the diversity of technological trajectories in the fields of renewable energy and ICT. This allows us to conclude that the EIS topology, in terms of network centrality and node connectivity for the Agri-food program, meets the objectives of increasing competitiveness, since it shows a clear technological trajectory derived from its centrality, and it is a unique and concentric network, which allows each node to access all kinds of information.

However, if we analyse the *cohesion of the network*, an attribute that shows the ease and accessibility to information in the network, we see that the results are not as positive, as shown by the low value of closeness centrality (0.4113), indicating a great distance between nodes. A complementary analysis shows a low level of network *density* with a mean of 0.026 (notice that it is a normalised value from 0 to 1, see Table 2). Although we have a connected network, the density level is low since each node only connects with 2.6% of the nodes (39 nodes on average). These results show a very sparse network, which is a negative aspect under the prism of the R&D policy, as it hinders access to information and a priori hinders the establishment of future collaborations. Moreover, Muñiz and Cuervo (2018) point out that a sparse network is usually accompanied by a high level of clustering, as a consequence of the formation of a group of connections derived from the proximity or affinity between nodes. In our case, this is confirmed by the level of clustering measured, which is 0.251 (see Table 2). If we compare our density and clustering results with previous studies in FP7, we see that the results are similar, as we observe a low density and a high level of clustering (Kang and Hwang, 2016; Muñiz and

Cuervo, 2018). Arranz et al. (2020a) have pointed out that this may be because research consortia are repeatedly established with the same partners, which makes the transmission of information and cohesion in the EIS difficult.

Our third research question (RQ3) focused on technology transfer between universities, companies and SMEs. In Table 4, we see how the network is structured based on the typology of nodes. Firstly, from Table 4, we see that the research institutions (REIs) are composed of 808 universities and research centres. As compared to other studies, we find a surprisingly high level of SMEs (De Prato et al., 2015). This shows a very positive balance for EU policy, as we see an exciting blend of knowledge generators and users (655 companies, compared to 808 research centres). In fact, for years, the EU's technology policy has pursued the link between universities and companies in order to reduce the innovation deficit that the EU had as compared to the US and Japan. A significant challenge for the EU was to link SMEs to other actors, considering that they constitute more than 90% of the EU's business structure, and to increase their participation in international projects. Secondly, considering network connectivity, which assesses the possibility of accessing information by network nodes, Table 5 shows that the average values of degree and eigenvector centrality are low both in terms of the number of connections (quantity of information) and the proximity to the core of the network (REI (degree centrality: 0.0338; eigenvector: 0.0401); SMEs (degree centrality: 0.01462; eigenvector: 0.0123); large enterprise (degree centrality: 01805; eigenvector: 0.0186)). Moreover, the values of closeness centrality (REI: 0.0003; SME: 0.00038; Large enterprise: 0.0003), show that although connected, the average distance is very high, having low connectivity and cohesion. This raises concerns over the transfer of information between REI and firms. However, if we consider the high level of the centrality of the network, the transfer problem can be solved. Thus, it is to be expected, that there is not a deep connection of many firms with many REIs, but preferably that firms are interconnected through the core (few REIs) which consists of the most active nodes and those that set the technological path of the network. This changes the transfer model between the university and the company from a *distributed model*, in which the number of links between university and company prevails, to a *model in trajectories*, where companies are indirectly linked to the most successful research centres. This can have a positive effect on the competitiveness of the EU's innovation and technology policy.

Regarding the fourth research question (RQ4), which considers how the structural attributes of the network affect the geographic cohesion between countries, Table 6 shows the distribution of node organisations involved by country. From the results, it seems that the number of nodes is roughly proportional to the size of the countries. This is an aspect that the EU takes excellent care of; in fact, this is a legal requirement as the research consortia have to be balanced in terms of the type of partner and countries. Moreover, an unwritten norm is that on top of being transnational, projects must be balanced between northern and southern countries. A priori, the number of connections of each type of country is balanced as it shows that the average of connections is between 35 and 52, which shows that the access in terms of the amount of information is balanced. In Table 7, we see the leading average indicators of the position of each country in the network. We analyse the three attributes of the network such as centrality, connectivity and cohesion. Regarding the connectivity, we see that the degree centrality of the five largest EU countries is quite balanced, ranging from 0.237 in Germany to 0.345 in France, which tells us that on average the Spanish, UK, German, French and Italian institutions have an average number of connections between 23% and 34.5%. In the case of smaller countries (such as Denmark, Greece, Belgium), we see that there is more significant variability in the degree of connections, but in the same order of magnitude, ranging from 20% of connections to 40%. This variability can be explained by the fact that the number of institutions involved in these countries is small. If we consider eigenvector centrality, the results are similar to those of degree centrality. Thus, the eigenvector of the five major countries is balanced, meaning that their proximity to the core and therefore, their access to the main technological trajectory of the network is similar. Finally, in terms of cohesion, we see that the degree of cohesion is low, as shown by its closeness, which is very close to zero. We can conclude that in terms of regional cohesion, we see a balanced situation between the different countries in terms of connectivity of the institutions and centrality. However, we also see a low level of cohesion, which can make it difficult to strengthen ties between countries, which is striking because different countries are required to take part in each consortium. Following Arranz and Fernandez de Arroyabe (2013), this can produce an effect of assortativity or clustering, with a tendency to always collaborate with the same partners, which can cause it to turn its back on the core of the network.

Therefore, our results show how the relationships created by the EU research consortia are a crucial element in EU innovation policies. First, in line with previous works analysing the research consortia created by the EU and their effect on firms' performance (see, e.g., Arranz and Fernandez de Arroyabe, 2013), we have provided empirical evidence that the research consortia created over time by the EU allow the creation of a network of relationships between organisations and institutions, which is responsible for the dissemination of information and the establishment of collaboration between firms. Second, unlike previous works that have focused on analysing the institutional and political effect of the various actions on achieving the objectives of the EU innovation policy (Gallego-Alvarez et al., 2017; DiMaggio and Powell, 1983), our results show that the network created by the consortia determines the efficiency of innovation systems, and therefore of EU innovation policies. Our work shows that to achieve the objectives of the EIS, the consortia network must be analysed as a complex network, where the topology of the network determines the efficiency of the EIS. Third, our study complements previous works that have analysed the influence of cohesion as a topological property of the network; for example, Muñiz et al. (2018), and Scherngell and Barber (2009) study cohesion between countries in terms of innovation, or the work of De Marco et al. (2020) who study the problem of the integration of SMEs in innovation systems. Our work expands these works by showing that not only cohesion is an essential property in EIS efficiency, but that it is also necessary to consider both the centrality and the connectivity of the network.

Moreover, unlike previous works that passively study the properties of the network (Kang and Hwang, 2016; Muñiz and Cuervo, 2018), our results show that the position and characteristics of the nodes determine the dissemination, collaboration and transfer of information. Therefore, our results provide empirical evidence that the position and heterogeneity of the nodes in the network determine the topology of the network and therefore the effectiveness of the EIS. Moreover, from an operational point of view, the study of the centrality of the nodes (*degree, closeness, eigenvector, betweenness*) allows determining the effectiveness of the objectives of the EU innovation policy (*competitiveness, cohesion and information transfer*). That is, the results show how degree and eigenvector centrality allow us to analyse the main technological trajectories of the EIS. The closeness and degree centrality indicators allow us to analyse the cohesion of the network. This is especially important for the EU's innovation policy as cohesion between countries and knowledge transfer between universities and companies - especially to SMEs - are the main objectives to achieve. Finally, betweenness allows us to analyse the connection of heterogeneous technological trajectories. Although it has not been used extensively in our study - because the Agri-Food system has a single trajectory - this indicator can be crucial when the IS have different trajectories as it allows us to consider cross-cutting research areas.

5. Conclusions

Our paper has analysed the European Innovation Systems and its impact on the achievement of the objectives of the EU's research and development policy. We assume that the research consortium is the mechanism that the EU uses for the development of its research and development policy, which is creating a network of relationships between projects and partners forming the EIS.

From the theoretical point of view, our first group of contributions extends the literature on innovation systems in terms of its modelling and effectiveness (Kashani and Roshani, 2019; Kapetaniou et al., 2018; Lundvall, 2007). Firstly, we extend previous works by materialising the conceptualisation of IS as a network. Thus, from our conceptualisation, the IS consists of diverse nodes both in terms of typology and geographic dispersion, interacting to share information and collaboration. This modelling allows us to consider the effectiveness of the IS in terms of the network structure and properties, which, applying the potential of the social network analysis, allows us to determine the ability to achieve the objectives of the research and development policy. Secondly, we consider that the effectiveness of innovation systems is related to the position of the node in the network, concluding that the effectiveness of the IS depends on the heterogeneity and geographic diversity of the nodes as well as their positions.

The second group of theoretical contributions is rooted in the research and development policies. A correct evaluation of the research and development policy must analyse the topology and the structural properties of the network. First, the cohesion of the IS allows us to assess the viability of potential collaborations. A correct evaluation of the *dynamics of the R&D policy* requires the analysis of the cohesion of the network, for example, in terms of transfer of information and knowledge and regional cohesion. Secondly, we consider the centrality of the IS, which determines the existence of research and innovation trajectories. We conclude that a correct evaluation of *R&D policies in terms of competitiveness* must involve an analysis of the centrality of the IS, considering the technological trajectories and their competitiveness. Lastly, the IS connectivity allows us to analyse the *transversality* between the different technological trajectories, as a way of promoting synergistic effects between them. Moreover, unlike the cohesion between nodes that affects the number of contacts, the connectivity of the nodes allows us to consider access to knowledge transfer from the point of view of proximity to the core of the network, influencing the dissemination of information in quality rather than quantity.

From the policy-making point of view, we have pointed out that belonging to research consortia provides some benefits for the institutions and firms that participate in the European programs. First, the EU finances and supports the development of technological projects, which benefits the institutions and companies that belong to that consortium, and the institutions and companies further obtain social capital by establishing relationships with other partners, who in turn have participated in previous projects acquiring knowledge and information. Second, it is necessary to know the structural properties of this network, because these play a key role in the diffusion of information and the establishment of collaborations for future projects. Lastly, we provide some indicators of how the position in the network allows the node to access a different type of information, which will have a differential impact on its ability to carry out research and innovation.

Finally, like any other, our study is not free of limitations. The main limitations are that our exploratory analysis is based on a sample of EU programs. Subsequent studies should expand the sample, covering a variety of technological areas, studying the network topology. First, future research should expand the sample to various research topics of the EU Framework Programs to analyse the adequacy of the centrality measures in other programs. Second, our study shows a highly centralised topology with a single technological trajectory. Future works should investigate other types of innovation and research networks with different technological trajectories. This would allow us to consider the adequacy of our indicators for other types of networks. In particular, the betweenness centrality could provide information on the transversality of the programs, in terms of collaboration between the various lines and transfer of information between them, which is an objective within the innovation and research policies. Additionally, further studies will be necessary in order to quantify the network indicators and the structural properties of the network.

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Table 1.

Summary statistics of all FP7 projects (KBBE), all members

Variable	Median	Mean	Std. Dev.	Min.	Max.
Project Members	17	18.307	6.946	4	38
Project Duration	48	45.187	9.599	18	69
Project Funding €	2.997,449	3.428,522	2.133,814	495,655	8.999,828
Org, funding €	3.237,885	3.428,522	1.576,069	495,655	8.999,828
Country Funding €	3.483,347	3.428,522	4.755,541	996,036	8.944,185

Table 2.

The main characteristic of the Agri-food network (2008-2014)

Network-level indicators	Value
Number of nodes	1514
Number of edges	29529
Number of projects	222
Density	0.026
Diameter	5
Size of largest Clique	38
Number of Maximal Cliques	6209
Mean distance	2.356
Mean Clustering	0.251

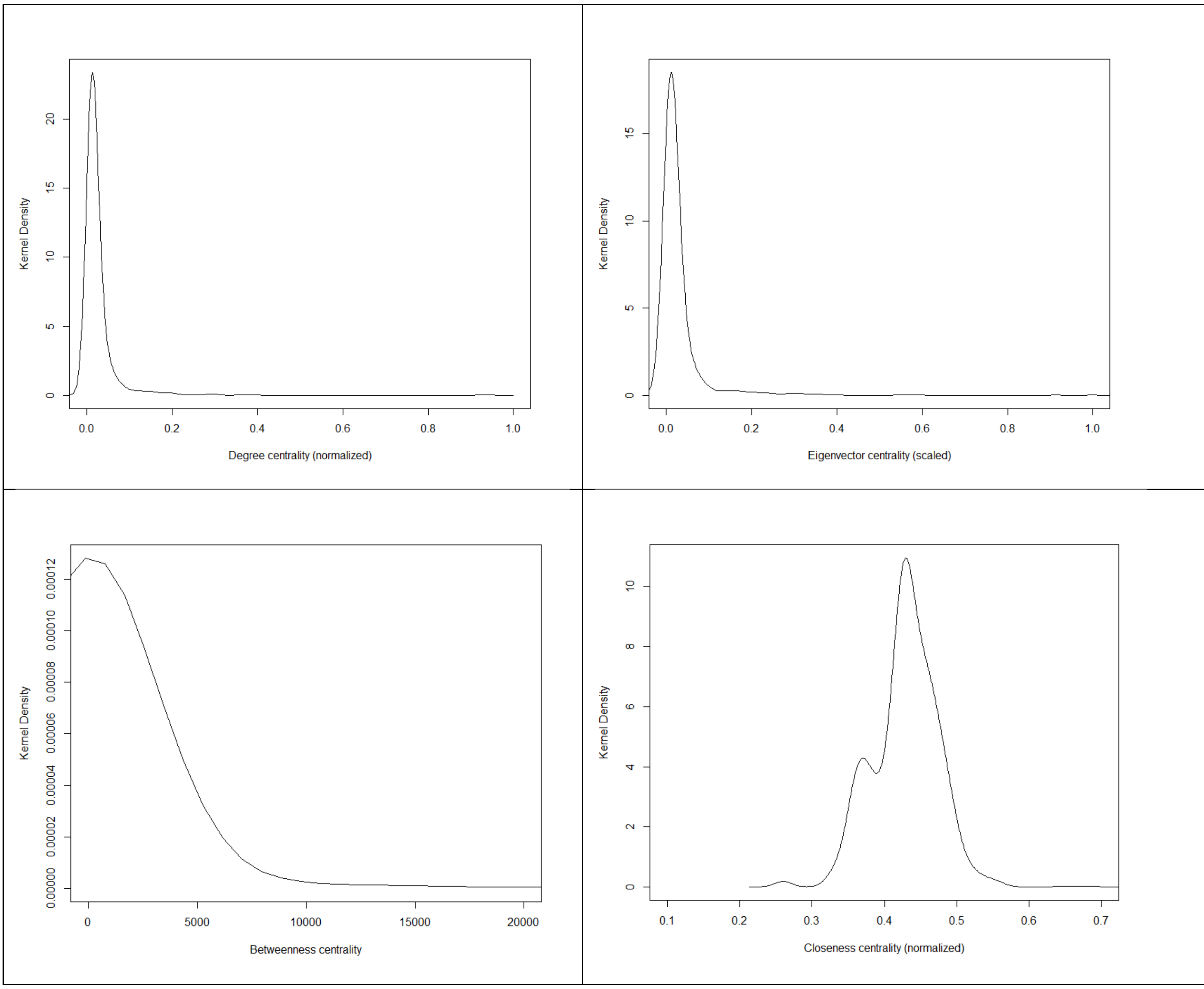

Fig. 1. Densities of centrality measures on the node level

Table 3.
Positional indicators of the nodes in the network*

Name	Type	Country	Degree	Betweenness	Eigenvector	Closeness	Projects	Number Partners/ projects
STICHTING DIENST LANDBOUWKUNDIG ONDERZOEK	NGO	NL	0,947786	0.293294	0.913798	0,020993	80	16,9
INSTITUT NATIONAL DE LA RECHERCHE AGRONOMIQUEFR	REI	FR	0,918705	0.209683	1	0,01933	75	17,6
THE SECRETARY OF STATE FOR ENVIRONMENT FOOD AND RURAL AFFAIRS	REI	GB	0,289491	0.033337	0.306912	0,006615	29	19,4
INSTITUTO NACIONAL DE INVESTIGACION Y TECNOLOGIA AGRARIA Y ALIMENTARIA	REI	ES	0,310641	0.032074	0.355767	0,006643	25	22,3
EIDGENOESSISCHES DEPARTEMENT FUER WIRTSCHAFT BILDUNG UND FORSCHUNG	REI	CH	0,399868	0.028719	0.590113	0,007801	28	20,6
AARHUS UNIVERSITET	REI	DK	0,362194	0.019537	0.574473	0,007058	24	18,9
AGENCIA ESTATAL CONSEJO SUPERIOR DE INVESTIGACIONES CIENTIFICAS	REI	ES	0,294779	0.051484	0.295185	0,006914	25	17,3
SVERIGES LANTBRUKSUNIVERSITET	REI	SE	0,366821	0.026011	0.545839	0,006941	30	15,9
DANMARKS TEKNISKE UNIVERSITET	REI	DK	0,296761	0.049143	0.259176	0,00705	17	21,9
WAGENINGEN UNIVERSITY	REI	NL	0,293457	0.023368	0.300549	0,00619	30	14,3

* Normalised values (range from 0 to 1).

Table 4.
Number of nodes by countries in the Agro-food network

Type of Institution	Number of Nodes
REI	808
SME	489
LEN	161
NGO	66
IND	5

Table 5.
Positional indicator by countries in the Agri-food network*

Institutions Typology	Degree	Betweenness	Closeness	Eigenvector
REI	0,0338	0,0012	0,0003	0,0401
SME	0,0146	0	0,0003	0,0123
LEN	0,0181	0,0002	0,0003	0,0186
NGO	0,0278	0,0045	0,0003	0,0261
IND	0,0194	0,0005	0,0003	0,0176

*Normalised values (range from 0 to 1).

Table 6.
Top ten countries in terms of institutions

Country	Number of Nodes
ES	145
GB	141
DE	134
IT	124
FR	109
NL	71
BE	66
GR	39
DK	38
CH	35

Table 7.
Positional Indicator by countries in Agri-food network*

Countries	Degree	Betweenness	Closeness	Eigenvector
ES	0.02424	0.0008	0.00064	0.02356
GB	0.02919	0.00068	0.00074	0.03019
DE	0.0237	0.00027	0.00062	0.02642
IT	0.02752	0.00068	0.00071	0.03024
FR	0.03456	0.0025	0.00084	0.03882
NL	0.03626	0.00477	0.00089	0.04153
BE	0.02683	0.00069	0.00068	0.03352
GR	0.02515	0.00077	0.00067	0.02319
DK	0.04587	0.00257	0.00105	0.0525
CH	0.03091	0.00108	0.00075	0.03672

*Normalised values (range from 0 to 1).