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Network dynamics in collaborative research in the EU, 2003-2017

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Abstract

A key objective of the EU Framework Programmes for Research and Innovation is the creation of cross-country research networks. We make use of Social Network tools to describe the evolution of the EU research network across countries on the basis of unique data covering collaborative projects launched during the first four years of implementation of Horizon 2020 and its predecessor programmes, the Sixth and Seventh Framework Programme. We describe the positioning of all EU-countries in the collaborative research network, the positioning of the older member EU-15 and the newer member EU-13 countries in particular, and to what extent the network has been subject to change during the period 2003-2017. EU-15 and EU-13 countries have become more integrated, and some organizations fulfil a bridging function in the EU research network. EU-13 countries are more heavily engaged in parts of the programme on lower complexity research activities.

Keywords: collaborative research network, European Union, Horizon 2020, Framework Programme, social network analysis, bridging, complexity

JEL: D85, O33, O38

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[1] The views expressed in this document are solely those of the authors and do not necessarily represent the official views of the European Commission.

1. Introduction

A key objective of the European Research Area is to stimulate research collaboration and knowledge diffusion in the European Union through the Framework Programmes (FP) that represent one of the largest transnational efforts worldwide funding thousands of collaborative research and innovation (R&I) projects (European Commission 2017, 2018). The FPs offer collaboration opportunities for researchers. The majority of the budget of the current FP, Horizon 2020, is spent on supporting such collaboration through collaborative R&I projects. To fully reap the benefits of collaborative R&I, it is important that the research network remains open and easily accessible to new participants. In this context, a good understanding of the way countries and organizations collaborate within the FP is crucial.

The main objective of the paper is to present the Horizon 2020 research network making use of Social Network Analysis tools. This collaborative research network across countries is constructed on the basis of unique data covering collaborative projects[2] launched during the first four years of implementation of Horizon 2020. The data is drawn from the Common Research Data Warehouse (CORDA)[3]. It includes data on the Horizon 2020 programme[4] as well as full data on the implementation of its predecessor programmes, the Sixth and the Seventh Framework Programme for Research and Technological Development (FP6 and FP7)[5]. We describe the positioning of all EU-countries in this collaborative research network, and in particular the positioning of the older member EU-15 versus newer member EU-13 countries that joined the EU after 2004. Our findings show that the two groups of countries have become more integrated during the period 2003-2017, and that some organizations fulfil a bridging function in this overall research network. However, the EU-13 countries tend to focus more on parts of the programmes that deal with low complexity research activities.

We structure the paper as follows. First, we briefly review the literature on research collaboration in the EU. Then, we analyze the research collaboration network under Horizon 2020, with particular attention to the positioning of EU-15 and EU-13 countries. Moreover, we take a dynamic perspective, including data on FP6 and FP7, to assess how the EU research collaboration network has changed over time. Finally, we conclude.

2. Collaborative research networks in the EU

Knowledge is a crucial asset for economic development. Countries engage in research to produce new knowledge to gain competitiveness (Foray 2004). To an increasing extent,

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[2] Data include all evaluated calls for collaborative projects. Projects under Public-Public Partnerships, EIT's Knowledge and Innovation Communities (KICs), and direct actions of the Joint Research Centre are not included.

[3] This database is maintained by the Common Support Centre of DG Research and Innovation (European Commission).

[4] Year of signature of the contract. Cut-off date for Horizon 2020 is 1/1/2018.

[5] Projects with incomplete data on signature date, duration and participant identifier were removed from the analysis (about 99.1% of the initial dataset of collaborative projects).

knowledge production is the outcome of a collective activity in which agents interact and recombine existing knowledge in novel ways. This is especially true for production of complex knowledge that requires inputs from other agents (Jones 2009). This is reflected in a persistent increase of collaborative research over time (Wuchty et al. 2007; Tijssen 2008; van der Wouden and Rigby 2017). Collaborative research is promoted by public policy because it would tackle the problem of fragmentation of research, provide savings in the cost of research, contribute to avoiding duplication of research effort, and facilitate knowledge spillovers and cross-fertilization of ideas between firms and between firms and other organizations, such as universities (Katz and Martin 1997). There is some evidence that such spillover effects do indeed exist, for instance on inventive output (see e.g. Czarnitzki and Fier 2003; Hoekman et al. 2013; Wanzenbock et al. 2014; Broekel 2015; Hazir et al. 2016).

The European Union is very active in promoting collaborative R&I projects through its Framework Programmes, such as Horizon 2020. While the main objective is to reduce the spatial barriers to research collaboration, the question is whether this leads to a level playing field among countries and contributes to reducing spatial disparities across Europe, as targeted by Cohesion policy through the Structural Funds. Studies (e.g. Moreno et al. 2005; Autant-Bernhard et al. 2007; Maggioni and Uberti 2009) have expressed concerns in this respect, claiming there is a natural tendency of research activity to concentrate in space when national barriers are removed and freedom of movement of knowledge and researchers is established.

Network theory would predict that the structure of knowledge networks is often skewed, that is, some countries or regions are highly connected, while others are poorly or not connected at all (Powell et al. 2005; Giuliani 2007; Maggioni et al. 2007; Huggins and Thompson 2014). This may be due to features of countries (such as absorptive capacity), forms of proximities between countries (e.g. geographical proximity) that reduce search and coordination costs, and network positions of countries (like being a hub in the overall network) (e.g. Singh 2005; Breschi and Lissoni 2009; Boschma and Frenken 2010; Ponds et al. 2010; Balland 2012; Balland et al. 2013; Ter Wal 2014; Cassi and Plunket 2015; Stuck et al. 2016; Tsouri 2018). Countries prefer to collaborate with other countries that show research excellence (Hoekman 2012), are close geographically (Scherngell and Barber 2009), have been engaged in previous collaborations (Breschi and Lissoni 2009), share similar knowledge (Nooteboom et al. 2000; Gilsing et al. 2007) and common institutions (like language), and form a hub in the network (Vicente et al. 2011). All these factors tend to contribute to a self-reinforcing tendency in the spatial evolution of knowledge networks (Barabasi and Albert 1999; Glückler 2007).

This has led to recurrent concerns that FP funding runs the risk of reproducing or even deepening already existing divides in research excellence across countries in the European Union (e.g. Breschi and Cusmano 2004; Autant-Bernhard et al. 2007; Paier and Scherngell 2011; Wanzenbock et al. 2014). Another obstacle to full integration of the knowledge network in the EU is that countries may lack the absorptive capacity. This implies it remains a challenge to reconcile the pursuit of excellence through R&I policy and inclusive growth and income convergence across countries and regions in the EU (Farole et al. 2011; Hoekman 2012). In this respect, serious concerns have been voiced that the older EU member states (EU-15) continue to take up the lion share of FP funding. Although the newer EU-13 member states are participating in the FP to an increasing extent (Radosevic and Yoruk 2014), they are not in terms of their relative participation rate compared to EU-15, and the effect on innovation has been modest (Radosevic and Ciampi Stancova 2018). This spatial imbalance of research and innovation performance is persistent over time, also despite massive efforts by the EU through Cohesion Policy and its Structural Funds to tackle such disparities.

Having said that, research also shows that FP funding is more evenly distributed across regions in the EU than often expected, and that there are some signs of a positive impact of FP funding in lagging regions (Hoekman et al. 2013). De Noni et al (2018) has identified a positive effect of collaboration of lagging-behind European regions with especially knowledge-intensive regions on their innovative performance. In this respect, it is crucial to know which countries take up a bridging position in the overall knowledge network, connecting different parts of the network that enable the diffusion of knowledge across countries (Burt 2004; Fleming et al. 2007; Morrison 2008; Graf 2011; Breschi and Lenzi 2015; Broekel and Mueller, 2018). The question is whether EU-13 countries are capable of acting as gatekeepers, and if so, which organizations have taken up that role.

The degree and nature of participation of countries in the EU network may also depend on the complexity of research that is involved in FP projects. However, little is known about how complexity affects the structure of the knowledge network of the EU. Sorenson et al. (2006) showed that the diffusion of more complex knowledge requires more proximate actors. Hidalgo and Hausmann (2009) argued that the more complex knowledge is, the fewer countries will actually participate in the production of such new knowledge, which they define as non-ubiquitous knowledge. Balland and Rigby (2017) provided empirical evidence for this, showing that the more complex technologies are more spatially concentrated. We will test whether a functional spatial division of labour actually exists within the European research space by looking at the participation of EU countries. We hypothesize that the EU-13 countries participate in those programmes that are associated with lower complexity, as compared to EU-15 countries that might participate more in higher complexity programmes.

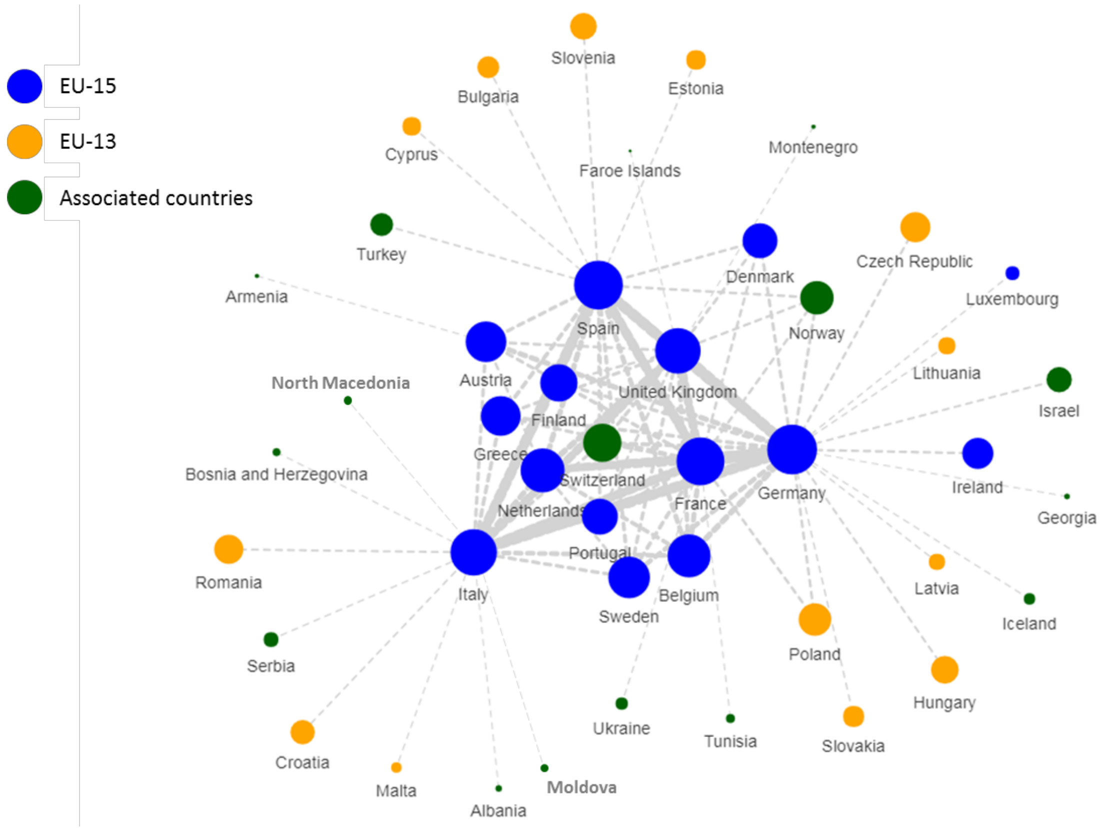
With the use of unique and recent data, we describe the structure of the collaborative research networks under the Horizon 2020 programme, employing sophisticated network tools. We will focus particular attention on the position of EU-13 countries, as compared to the EU-15 countries. We examine the extent to which EU-13 countries have been successful in participating in the EU collaborative research network, how that has changed over time since the launch of the 6th FP in 2003, whether EU-13 countries have gained access to gatekeepers in the overall network, and to what extent they participate in projects on complex activities.

3. The Horizon 2020 network

Since 2014, Horizon 2020 has been funding a large number of collaborative projects, involving a massive network of collaborations between R&I stakeholders. Over 2014-2017, Horizon 2020 funded more than 7,500 collaborative projects among 23,664 participants from

149 countries, resulting in almost 1.5 million of one-to-one opportunities to collaborate[6]. The strongest connections are represented as a country-country graph in Figure 1.

Figure 1 The H2020 Collaboration Network



Note: This graph represents the backbone of Horizon 2020. Nodes are countries, and links represent strong[7] connections based on Horizon 2020 projects. EU-15 countries are represented in blue, EU-13 countries are represented in orange, Associated Countries (AC) are represented in green. Non-associated third countries (TC) countries are not represented on the graph.

Source: Author's calculations based on CORDA data.

The figure shows two types of connections: (i) the single strongest connection of each country to another country, and (ii) the top 40 strongest connections in the network. Centrality can be defined as the importance of a country in the network. This importance as such can have different meanings, hence different definitions, with the most straightforward definition being based on the number of connections of a country's participants in the whole network. The size of the nodes is proportional to the centrality of the country. The figure shows that the core of the network is mainly composed of EU-15 participants. Germany, France, the UK, Italy, and Spain appear to be key players in the network of participations to Horizon 2020.

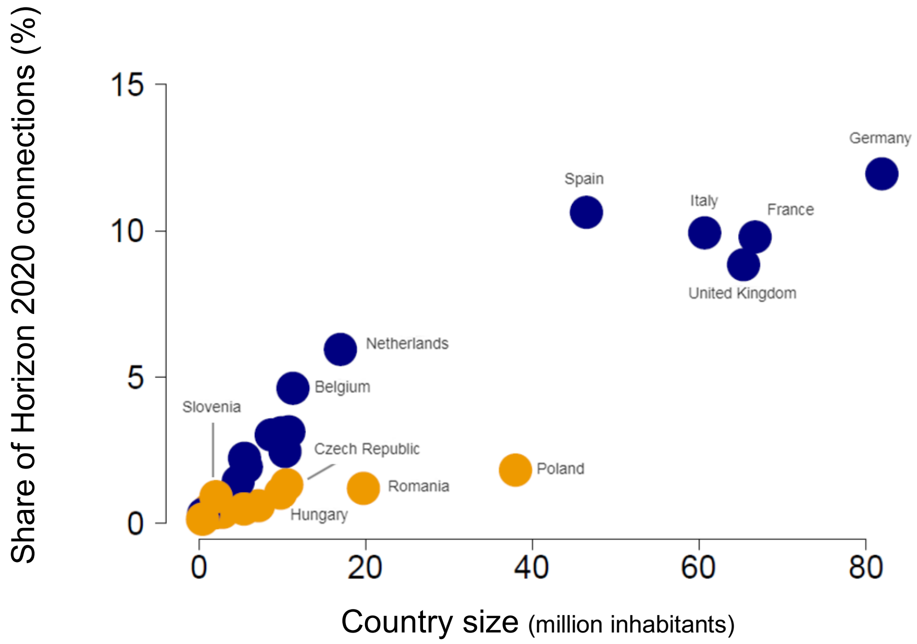
[6] Before Horizon 2020, FP6 and FP7 funded respectively 5,912 and 12,493 collaborative projects, which correspond to 1,305,305 and 1,989,450 collaborations between participants.

[7] Links displayed on this graph with N actors combines the N-1 links of a maximum spanning tree (MST) and the N-1 strongest links of the original graph. The MST represents the backbone of a weighted network and is based on three rules. First, only N-1 links from a network with N actors are kept. Second, rule #1 should be satisfied while keeping the strongest links. If xij = 1, xjk = 2, and xki = 3, the algorithm will remove xij. Third, rule #1 and #2 should be satisfied without creating any isolate in the network.

EU-13 participants have a substantial number of collaborations with the largest players in the network, which are participants from EU-15 countries. As a result, German participants are frequent partners of several EU-13 countries, such as Czech Republic, Hungary, Latvia, Lithuania and Slovakia. Croatia, Malta and Romania present strong ties with Italy, while Bulgaria, Cyprus, Estonia and Slovenia tend to connect with Spanish participants. Important collaborators of Polish participants are French participants.

It is important to understand which countries occupy central positions in the network. Overall, as shown in the interim evaluation of Horizon 2020 (European Commission, 2017), the most connected countries are also the largest ones (Figure 2). The most connected country is Germany, with around 12% of the collaborations within the network involving German participants, followed by Spain (11%), Italy (10%), and France (10%). Overall, 79.3% of the collaborations involve participants from EU-15 countries against 9.8% for EU-13 countries (and respectively 6.6% and 4.2% for associated and third countries). Poland is the EU-13 country with most connections (1.8% of all connections).

Figure 2 Country size and share of connections under Horizon 2020



Source: Author's calculations based on CORDA data.

While size effect appears to be important, Figure 2 also shows that some countries with similar size perform differently in terms of collaborations: although population in Romania and the Netherlands are close, Dutch participants are responsible for a much higher share of connections in the Programme (6%) than Romanian participants (1.2%). On the other hand, smaller countries like Slovenia present almost as many connections as countries with a population that is five times larger or more like Hungary, Czech Republic and Romania. The graph also highlights a significant gap between Poland and Spain, with Spanish participants being involved in almost four times more collaborations than Polish participants despite the fact that both countries have a large population.

The position of countries can be more precisely assessed with different centrality measures. Centrality can be defined as the importance of a node (here a participant) in the network. This importance as such can have different meanings, hence different definitions. Using data on Framework Programmes' project participations, a network of participants was constructed, represented by an $n \times n$ matrix $X = (x_{ij})$, where x_{ij} represents the number of connections between participant i and participant j $(i, j = 1, \ldots, n)$.

The positions of participants are analysed in this global network using four different metrics: degree centrality, eigenvector centrality, network hubs, and EU15-EU13 gatekeeping position. Degree centrality refers to the number of direct connections of a given node, and is computed as follows: $\boldsymbol{Degree_i = \sum_j x_{i,j}}$ Eigenvector centrality takes into account the centrality of participants a participant is connected to. Eigenvector centrality takes into account the whole network structure, and is equal to the leading eigenvector of the column stochastic $n \times n$ matrix $X = (x_{ij})$ - whose leading eigenvalue is 1: $\boldsymbol{Eigen_i = \sum_j X_{i,j} x_j}$

As shown in Figure 3, centrality measures show that participants from EU-15 countries tend to be more central than participants from EU-13 countries, associated countries and third countries in Horizon 2020. There are, however, important variations, with some EU-13 participants being more central than many EU-15 participants. Both in terms of degree centrality (number of direct connections) and eigenvector centrality (tendency to be linked to nodes that are themselves central), participants from EU-15 countries appear to be on average more central than participants from other country groups[8]. The average degree centrality of EU-15 participants is 50, compared to 41 for EU-13 participants, 42 for participants from associated countries and 28 for participants from third countries, indicating more direct connections for EU-15 participants. The influence of a country in the network can also be measured by examining whether participants are linked to other important participants (i.e. participants with many connections). This is measured by the eigenvector centrality[9] that is also significantly higher on average for EU-15 participants (5.33) than EU13 countries (3.52).

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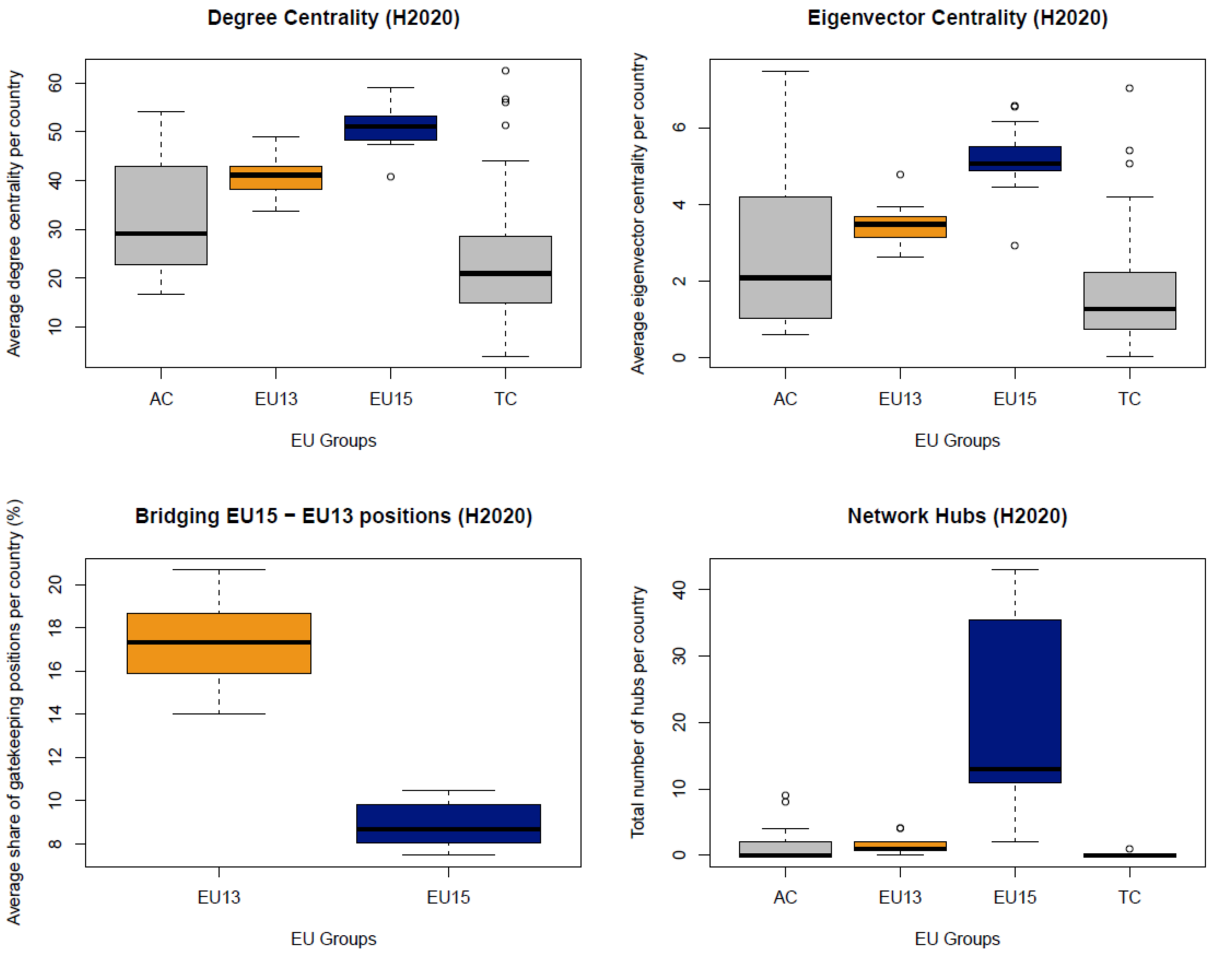
[8] The interim evaluation of Horizon 2020 (European Commission 2017) also shows highest centrality measures for EU-15 countries in Horizon 2020 compared to other country groups. The approach used for country analysis in this interim evaluation relies on connections at country level after aggregation of participants, not average statistics of participants within a country as in this analysis. As a consequence, differences in centrality measures seem to be exacerbated at participant level in this paper, especially the difference between EU-15 countries and EU-13 countries.

[9] The maximum value for the eigenvector centrality of a participant is 1. To avoid very small values when we average eigenvector centrality of participants at the country level, we multiply eigenvector centrality by 1,000.

Figure 3 Centrality measures in Horizon 2020[10]



Note: All network measures are first computed at the participant-level, and then summed up/averaged at the country level. The boxplots in this figure show the distributions of these measures at the country level (thick line = median, limits of the box = interquartile interval, upper and lower whiskers = greatest and lowest values excluding outliers). Degree centrality, for instance, represents the distribution of the average degree centrality of participants at country level. AC = associated countries, TC = third countries.

Source: Author's calculations based on CORDA data.

EU15-EU13 gatekeeping positions are derived from betweenness centrality and reflect the number of times a participant i connects an EU-15 participant j with an EU-13 participant k (i.e. the number of times i lies on the shortest path between EU-15 and EU-13 participants). Let's $\sigma_{j,k}$ be the total number of shortest paths from node *j* (EU13) to node *k* (EU 15), and $\sigma_{j,k}$ *(i)* the total number of shortest paths from node *j* (EU13) to node *k* (EU 15) that passes through *i*. The EU15-EU13 gatekeeping position can be computed as $\boldsymbol{GatekeepingEU13-EU15_i} = \sum_{j\#i\#k} \frac{\boldsymbol{\sigma j,k\,(i)}}{\boldsymbol{\sigma j,k}}$. We present the *share* of EU15-EU13 gatekeeping positions that is obtained by dividing $\boldsymbol{GatekeepingEU13-EU15_i}$ by $\boldsymbol{Gatekeeping_i}$ (overall gatekeeping). Network hub is a dummy variable (0/1) that takes value 1 if a participant belongs to the top 2% of both the degree and eigenvector centrality distribution.

[10] These measures are based on the network of participations without any threshold in the number of connections between two participants. See Annex for centrality measures based on connections in at least 2 projects.

As shown in Figure 3, while EU-15 participants more frequently play a role of hub in the network, critical intermediaries between EU-13 and EU-15 participants are more represented by EU-13 organisations. Most network hubs (participants having a significantly larger number of connections in the network) are EU-15 participants. However, key gatekeeping positions are much more present in the EU-13 compared to the EU-15. This means that EU-13 organisations very often act as a bridge between EU-15 organisations and EU-13 organisations. This result is not surprising because EU-15 countries participate more than EU-13 countries. Hence, the likelihood to have one EU-13 participant in a project with a majority of EU-15 participants is higher than the other way around. This highlights that EU13 organisations have a 'broker' or 'gatekeeper' role for linking a large number of organisations that would not be connected otherwise. Slovakia, Latvia, Malta and Estonia are the top 4 countries in which participants have the strongest gatekeepers profile between EU-13 and EU-15 participants.

As shown in Table 1, higher education institutions are the real hubs of the network in general. They present significantly higher centrality measures compared to other types of participants, in particular a very high average degree centrality of 144 compared to 87 for research organisation, 42 for public bodies and 29 for private companies. Many higher education institutions also play the role of hubs in the network: 233 hubs universities under Horizon 2020, which is more than all other types of participants together. Research centres seem to be the second more central type of organisation, followed by public organisations.

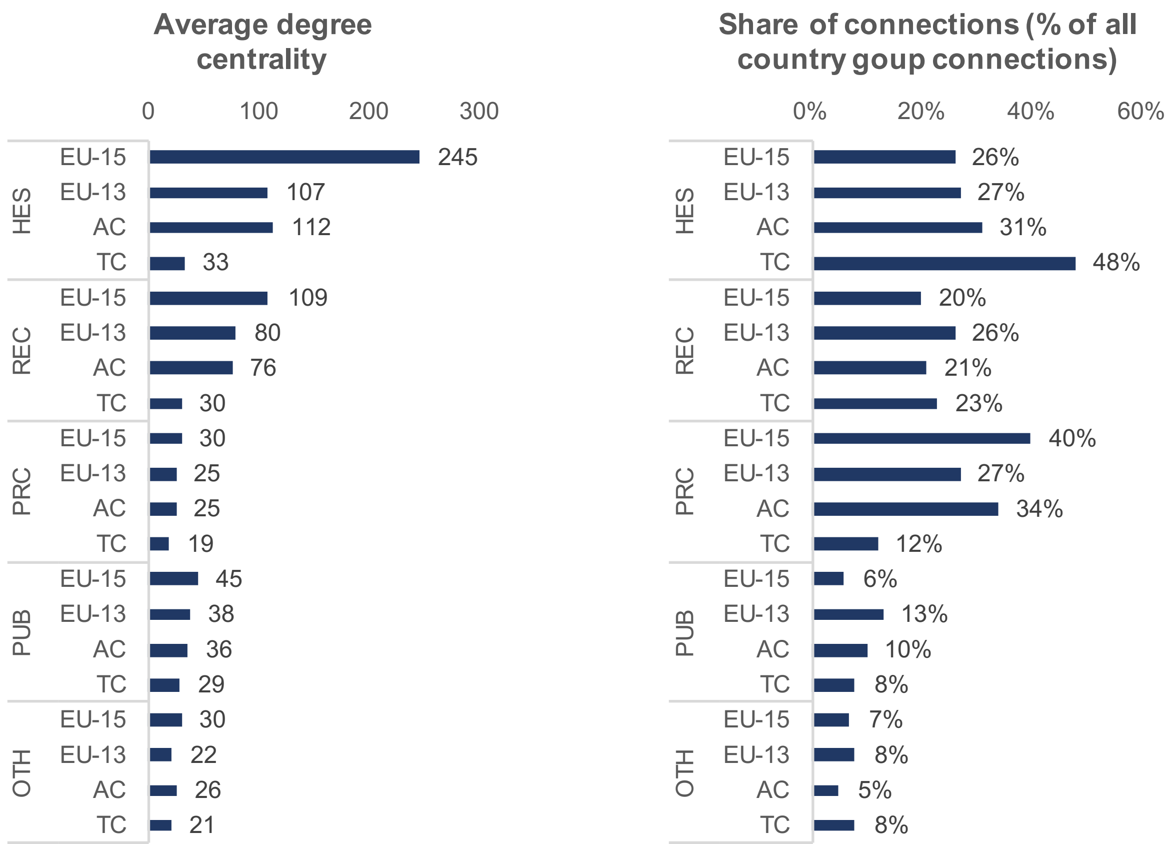
Table 1 Network statistics by type of organisation (Horizon 2020)

Type of organisation	Average Degree centrality	Average Eigenvector centrality	Average share of gatekeepers EU-13-EU15	Total number of Hubs
Public bodies	41.5	3.1	0.13	9
Higher education	144.4	19.5	0.11	233
Research organisations	87.4	11.1	0.11	93
Private companies	29.1	2.3	0.08	25
Other	28.3	1.7	0.11	3

Source: Author's calculations based on CORDA data.

On the other hand, private companies report low centrality measures, which means that they are not as central as other types of organisations. This contrast with their significantly large number of connections compared to other types of organisations. Figure 4 illustrates this. The figure shows that 40% of the connections of EU-15 include private companies. The private sector is actually the most important sector in terms of number of collaborations for all country groups, except for third countries where higher education institutions are responsible for almost half the connections within the network. However, private companies are also characterised by a larger number of one-shot collaborations. As a consequence, they present particularly low average centrality measures compared to other types of organisations, especially compared to higher education institutions. Another important observation is that the centrality of private companies in the whole network is similar between EU-15 countries, EU-13 countries and associated countries, while the centrality of higher education institutions in the EU-15 countries is significantly larger than in other country groups.

Figure 4 Centrality by type of organisation and by country group (Horizon 2020)

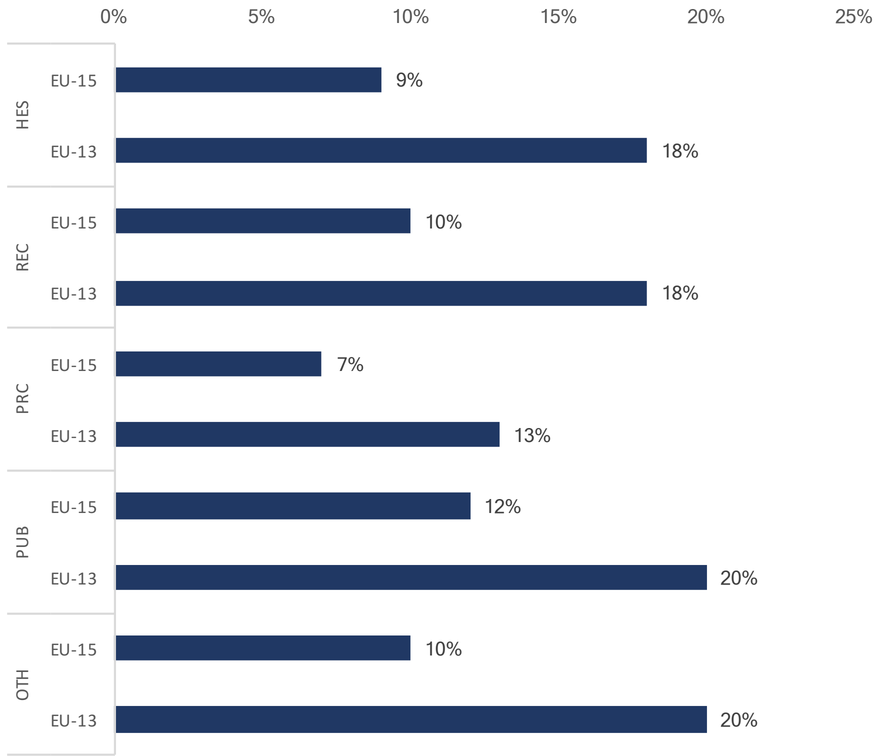


Note: REC = research organisations, PUB = public bodies, PRC = private sector, HES = higher education institutions, OTH = other participants. AC = associated countries, TC = third countries.

Source: Author's calculations based on CORDA data.

When looking at collaborations between EU-13 and EU-15 participants (Table 1), participants acting as intermediaries (gatekeepers) are more frequent within public bodies (13%) compared to other types of organisations. Only 8% of companies play this bridging role. Hence, while the interim evaluation of Horizon 2020 (European Commission, 2017) showed that EU-15 companies can represent significant numbers of connections with EU-13 participants, corresponding to massive bridges with EU-13 participants, this broker role is not as frequent for them as for other types of participants. As mentioned above, this bridging role is much more frequent within EU-13 participants. Figure 5 shows the differences in this role by type of participant for EU-13 and EU-15 countries. EU-13 participants are almost always twice more active in this gatekeeping role than EU-15 participants, regardless of the type of organisation. At the bottom, only 7% of EU-15 private companies are bridging EU-15 and EU-13 participants. The most active gatekeepers are EU-13 research organisations, public bodies and higher education institutions (20%). The top EU-15 participants that present the largest numbers of collaborations with EU-13 participants in Horizon 2020 are Fraunhofer (DE), CNR (IT), CNRS (FR), CEA (FR) and VTT (FI). The top 5 EU-15 participants that present the highest share of collaborations with EU-13 participants in their collaborations are ENEA (IT), NERC (UK), CINECA (IT), UoA (EL) and JUELICH (DE).

Figure 5 Bridging EU-15 - EU-13 positions (share of gatekeeping positions by type of organisation and country group)



Note: REC = research organisations, PUB = public bodies, PRC = private sector, HES = higher education institutions, OTH = other participants.

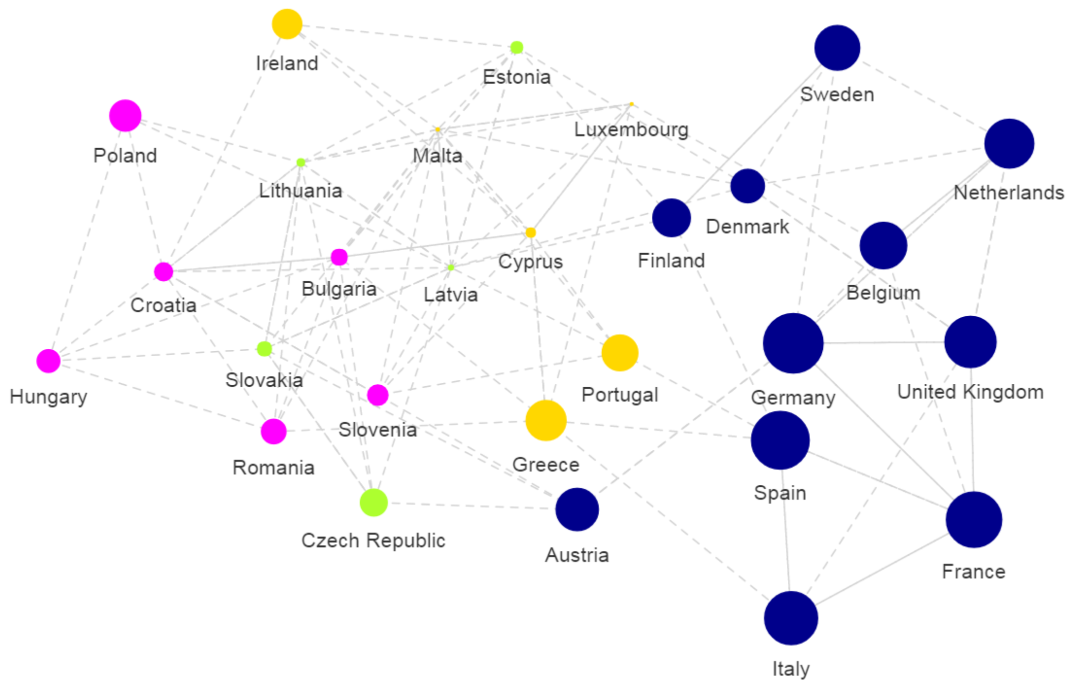
Source: Author's calculations based on CORDA data.

The large number of connections between EU-13 countries and a few EU-15 countries can be partly explained by the larger number of participations of these EU-15 countries in Horizon 2020. A normalisation process can be implemented to control for this. Figure 6 shows the country relatedness network, which expresses collaboration preferences between countries. To compute this relatedness, the number of connections between two countries is divided by the number of connections expected by chance[11], i.e. based on the amount of participations of both countries (Hidalgo et al., 2007; Balland et al., 2018). In Figure 7, the top four strongest

[11] Relatedness is computed using the EconGeo software, implemented as a R package (Balland, 2017).

connections of each country are represented. As a result, participants appear to show very specific preferences in their cross-country collaborations. Several clusters of countries can be observed[12]. Countries in a cluster of strong preferences are represented by the same colour. Participants from Baltic countries, Czech Republic and Slovakia tend to collaborate more with each other than what would be expected statistically (green cluster). Cyprus, Greece, Ireland, Luxembourg, Malta, and Portugal form another group of preferred connections (yellow cluster). These two groups bridge to some extent the other two clusters, which are formed respectively by large EU-13 countries (pink cluster) and large EU-15 countries (blue cluster). Overall, these preferences suggest that different forms of proximity, including cultural and geographical proximities tend to shape the structure of the Horizon 2020 network.

Figure 6 The H2020 Country-Relatedness Network (between EU15 and EU13 countries)



Note: Colours based on community structure (Blondel et al, 2008). The top four strongest connections (after normalisation) of each country are represented. A plain link indicates that the connection is in the top four connections of both countries. A dashed link indicates that the connection is in the top four of one of both countries. The size of the nodes is proportional to country centrality without normalisation.

Source: CORDA data.

As shown in Table 1, higher education institutions are the real hubs of the network in general. They present significantly higher centrality measures compared to other types of participants, in particular a very high average degree centrality of 144 compared to 87 for research organisations, 42 for public bodies and 29 for private companies. Many higher education

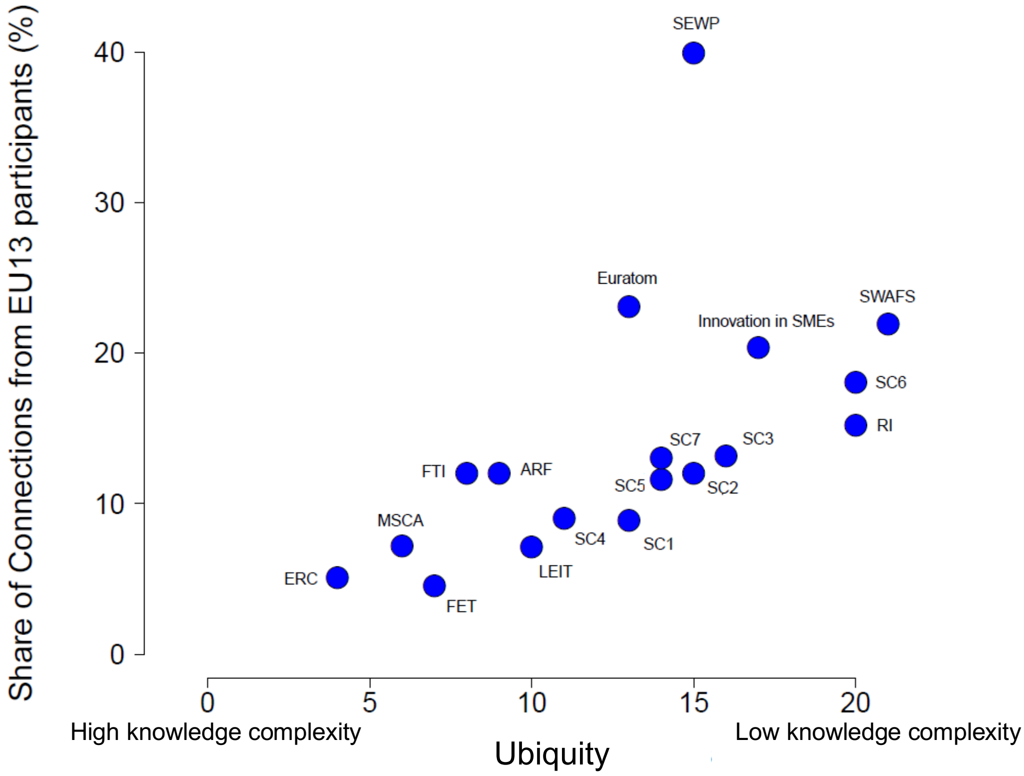
[12] Communities within the network are based on the multi-level modularity optimisation algorithm for finding community structure as described by Blondel et al. (2008).

institutions also play the role of hubs in the network: 233 hubs universities under Horizon 2020, which is more than all other types of participants together. Research centres seem to be the second more central type of organisation, followed by public organisations.

Not all countries participate in the same proportion in the different parts of the Programme. This proportion directly affects the importance or centrality of a specific country in the different programme parts (see Annex for definition of the acronyms and for the number of connections by country and by programme part). Following Hidalgo and Hausmann (2009), we measure the so-called ubiquity of a programme as the number of countries that have a relative comparative advantage in a specific programme part. Relative comparative advantage is a measure of specialisation, i.e. a participant participates more than what could be expected by chance. The country–project FP networks are operationalized as a n x k two-mode matrix M = (Mc,i), where Mc,i reflects whether a country c has a relative comparative advantage (RCA) in the participation of programme part i (c = 1,. . ., n; i = 1, . . ., k). A country c has RCA in programme part i at time t if the share of projects i in the country's portfolio is higher than the share of projects i in the entire FP portfolio. Ubiquity is the 2-mode degree centrality of programme parts (Ki,0) and is given by the number of countries that exhibit RCA in a particular programme part: $\mathbf{Ubiquity_i} = \sum_\mathbf{c} \mathbf{M_{c,i}}$.

Figure 7 shows that there is a pattern that can be observed when linking the ubiquity of the programme parts (parts that are more ‘common’ amongst countries) with the proportion of connections from EU-13 participants. Ubiquity has been shown to reflect the underlying knowledge complexity of products and technologies (Balland and Rigby 2017), and could therefore be interpreted as a measure of how difficult it is for a country to be a leader in a specific programme part. The figure shows that EU-13 and EU-15 participants are not central in the same programme parts. As expected, EU-13 participants are much more central in programme parts with a lower level of knowledge complexity (i.e. presenting high level of ubiquity), while EU-15 participants dominate more complex programme parts.

Figure 7 Ubiquity of programme parts and EU-13 centrality (Horizon 2020)

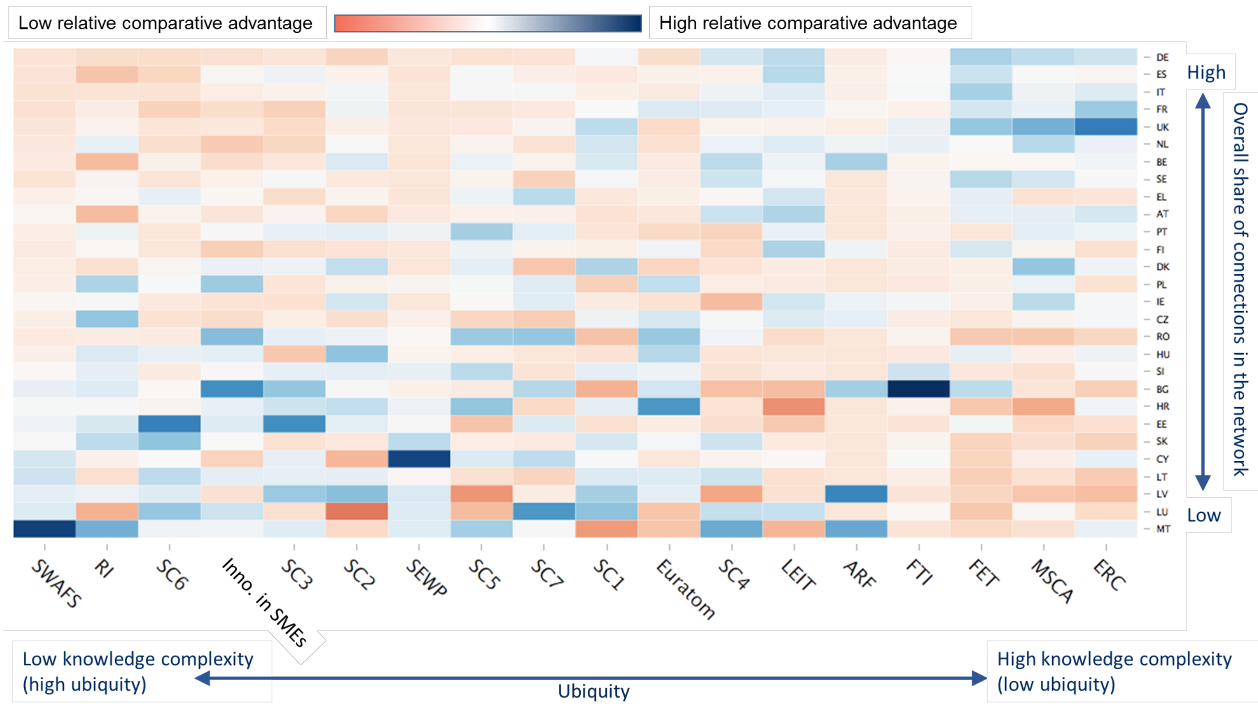


Note: Acronyms for programme parts in Annex. Some programme parts like ERC or MSCA only present a minority of projects with collaborations.

Source: Author's calculations based on CORDA data.

The level of knowledge complexity reflects the fact that only few countries have a relative comparative advantage in the participation of a programme part. Figure 8 shows the relative comparative advantages of countries by programme parts when countries are ranked by decreasing overall centrality (share of connections) from top to bottom, and programme parts are ranked with increasing complexity from left to right. The pattern of colours indicates that high relative comparative advantages (blue) can be found in the top right and bottom left parts of the matrix, while lower relative comparative advantages (red) dominate the top left and bottom right parts. This reflects the idea that countries that are less central are also countries that have a lower relative comparative advantage in more complex programme parts and higher comparative advantage in less complex programme parts.

Figure 8 Relative comparative advantage of countries by programme part (Horizon 2020)



Note: Acronyms for programme parts in Annex. Blue indicates high comparative advantage and red indicates low comparative advantage. Darker blue or red indicate respectively higher or lower values.

Source: Author's calculations based on CORDA data.

4. Is the Horizon 2020 network more open?

As shown in the previous section, the size of countries in Horizon 2020 is a key determinant of their central position in the network. However, it is important to examine how the situation has evolved over time, between FP6 and FP7, and between FP7 and Horizon 2020.

On average, participants are slightly less central in the network in FP7 and Horizon 2020 compared to FP6. The average centrality degree of participants was 50 in FP6, while it became about 46 in FP7 and 47 Horizon 2020. This might signal the entry of smaller players, and indicate that the network tends to be opening to less connected participants. To confirm this intuition, we need to turn to other network indicators.

One such network indicator is the transitivity coefficient which measures the likelihood for a participant to be connected to a collaborator of a collaborator. As shown in Table 2, participants appear to be more likely in Horizon 2020 than in FP7 to collaborate with partners of their own partners, i.e. the transitivity of collaborations has increased. This signals that participants rely more on information they receive from their own partners to create new collaborations, which could be reflected by higher clustering behaviours within the network.

Table 2 Evolution of the network

Framework Programme	Average degree centrality	Transitivity	Assortativity	Inequality	Average path length
FP6	50.22	0.17	-0.1	0.66	2.79
FP7	46.01	0.12	-0.11	0.67	2.79
Horizon 2020	47.06	0.16	-0.08	0.65	2.81

Source: Author's calculations based on CORDA data.

Another network indicator is the assortativity coefficient. It measures the extent to which nodes in a network associate with other nodes in the network, being of a similar or opposing sort. The assortativity of the network is determined for the degree (number of direct neighbours) of the nodes in the network. If the assortativity coefficient is negative, the hubs tend to be connected with non-hubs, and vice versa. Table 2 shows that the assortativity coefficients are negative in all 3 Framework Programmes: participants acting as hubs (with high degree centrality) seem to connect more likely with other types of participants (non-hubs, with low degree centrality). This suggests key actors in the network have maintained a certain level of openness to other participants throughout the different programmes.

Network Gini coefficients measure the level of structural inequality in a network. It ranges from 0 (perfect equality, with all participants having the same number of connections) to 1 (perfect inequality). Table 2 shows that the network inequality coefficients are stable over time: the degree distribution has remained relatively similar between the Framework Programmes, with coefficient being 0.66, 0.67, and 0.65 respectively for FP6, FP7 and Horizon 2020. These coefficients suggest that few organisations have many connections, while most organisations have only a few, which is a general tendency of real-world complex networks. This aspect of the network has not been reinforced over time.

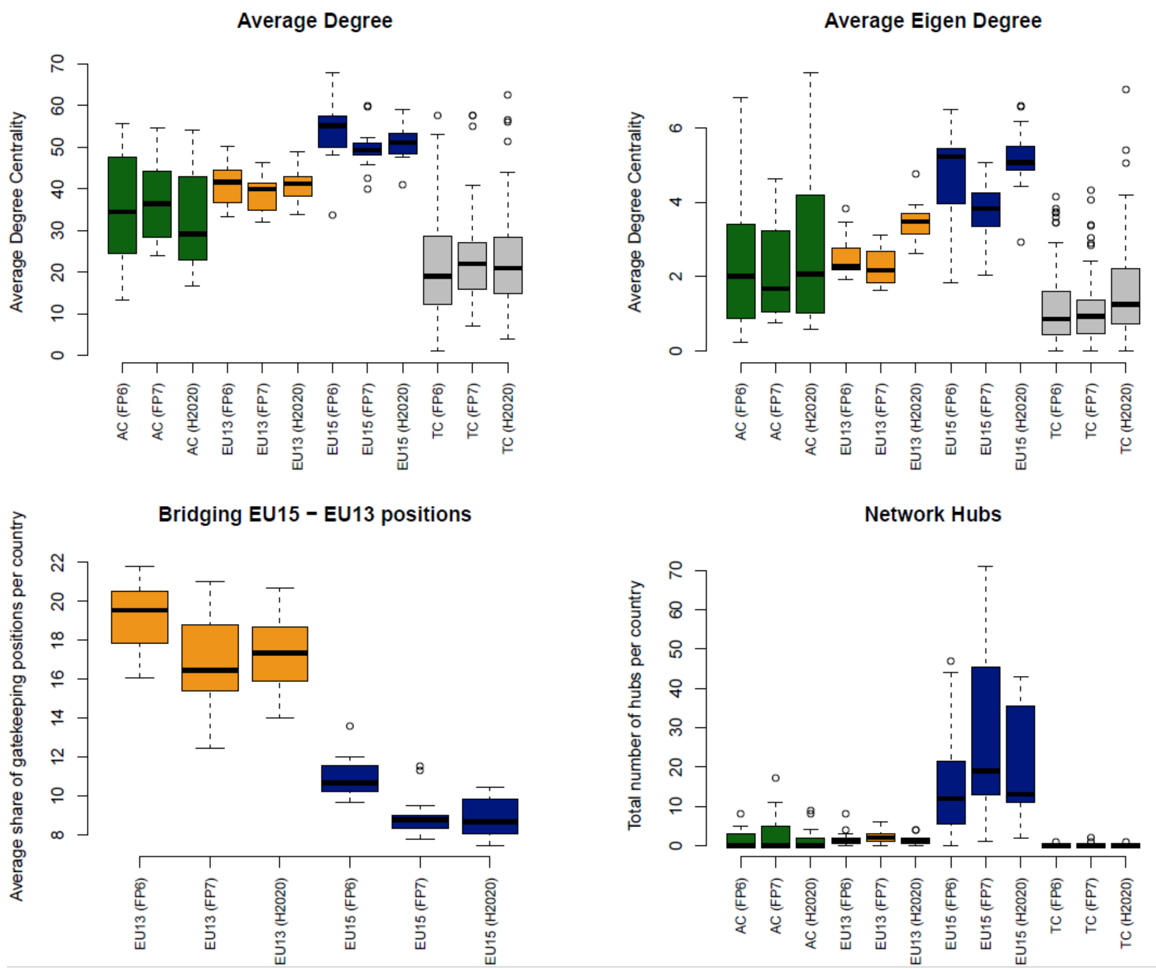
Average path length measures the average number of steps along the shortest paths for all possible pairs of network nodes. It is a measure of information flow efficiency in a network. Table 2 shows the average path length between participants has remained close to 3, meaning that on average a participant can be connected to any other participant in the network within 3 connections ("degrees of separation"). This measure is relatively small, indicating a highly-connected network in general. The average path length has not changed much over time.

Has the position of country groups changed? The centrality of country groups[13] has remained stable over time. Figure 9 shows little change in the ranking between country groups of average centrality measures between FP6 and Horizon 2020. Between FP6 and FP7, EU-13 and EU-15 participants seem to have become less central in the network, while the central position of participants from associated countries and third countries was reinforced. However, between FP7 and Horizon 2020, the centrality in the network of both EU-15 and

[13] For this analysis, the composition of country groups does not vary over time. Country groups are defined based on the situation in Horizon 2020.

EU-13 countries improved. Based on the number of hubs, the position of EU-15 countries appears to be less dominant in Horizon 2020 compared to FP7.

Figure 9 Evolution of centrality measures



Source: Author's calculations based on CORDA data.

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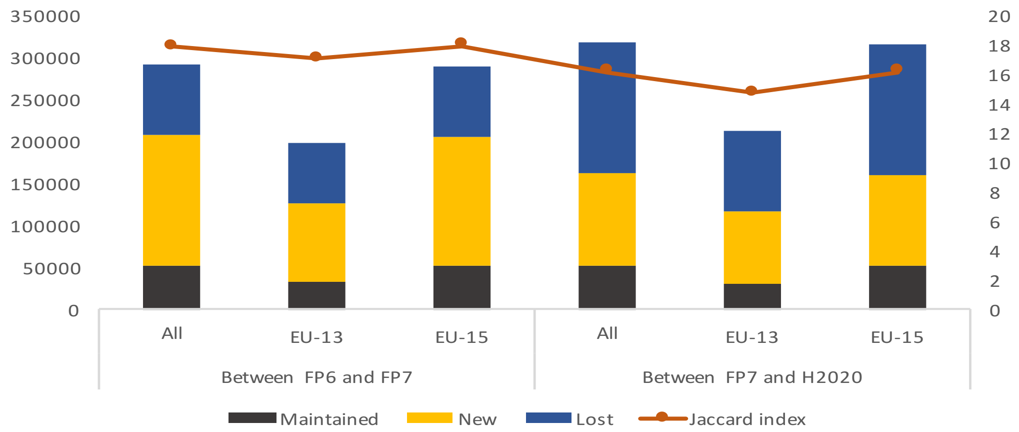
In order to look at the potential opening of the network over time, it is important to assess the persistence of collaborations. A network that is structured in "closed clubs" will be characterised by a large amount of persistent collaborations, compared to new or lost collaborations. This is proxied by the Jaccard index that measures the structural distance between networks from one period to the next (Ripley et al., 2016). It is computed by using information on the number of new ties (Nnew), the number of lost ties (Nlost), and the number of ties maintained (Nmaintained) from one period to the next:

$\frac{Nmaintained}{Nnew+Nlost+Nmaintained}$. This index is used here to assess the similarity of the connections between FP6 and FP7, and between FP7 and Horizon 2020. A Jaccard coefficient of 1 indicates perfect stability (no changes from one FP's network to the next), while a Jaccard coefficient of 0 indicates that none of the connections made in one FP is repeated in the next one. As shown in Figure 10, the network of participations to the FP's seems to be very dynamic over time. Jaccard indexes for FP6, FP7 and Horizon 2020 are quite low[14], which indicates that partners are highly likely to change over time. Between FP6 and FP7, about 1,226,970 new connections between partners were created, while 166,508 connections were maintained, and 772,822 were lost. Between FP7 and the first four years of Horizon 2020, 909,444 new connections were made, against 195,474 maintained and 1,198,004 lost. Because of this large ratio of new and lost connections in Horizon 2020 to maintained connections, Jaccard indexes are especially low in Horizon 2020, and suggests a more dynamic network compared to previous Framework Programmes.

Figure 10 Persistence of connections in the network (maintained, new and lost connections between FP's)



Note: Left axis: number of connections. Right axis: Jaccard index (x100). All = all projects, EU-13 = all projects with at least 1 EU-13 organisation, EU-15 = all projects with at least 1 EU-15 organisation

Source: Author's calculations based on CORDA data.

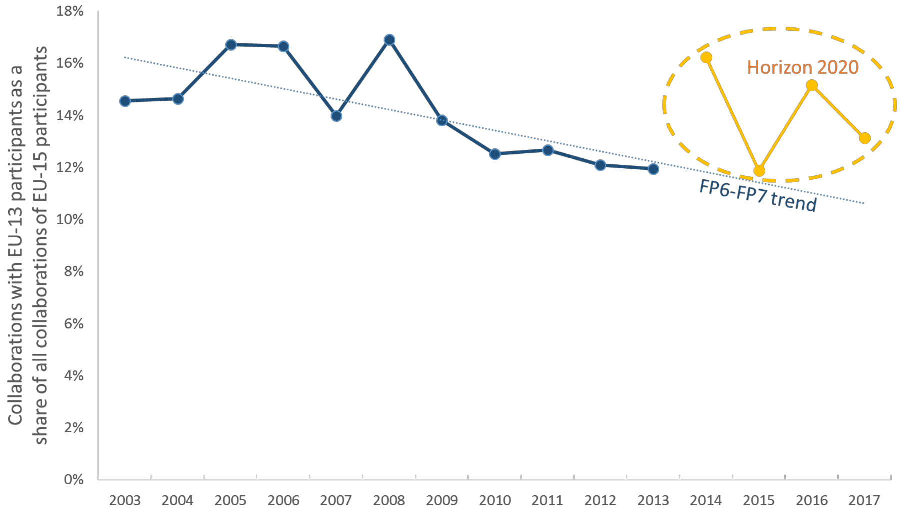
Jaccard indexes are lower for EU-13 than for EU-15 countries, showing that EU-13 countries participants have to some extent a higher propensity to be involved in new collaborations than participants from EU-15 countries. This effect is especially striking in Horizon 2020: participants from EU-13 countries have managed to generate a relatively large amount of new collaborations compared to EU-15 participants. However, both country groups seem to have more new collaborations between FP7 and Horizon 2020, than between FP6 and FP7.

In particular, are EU15-countries opening up to EU-13 countries? As shown in Figure 11, while EU-15 participants seem to have been closing to some extent their collaborations to

[14] Compared to other types of network in Ripley et al. (2016).

EU-13 participants between FP6 and FP7, they appear to have opened up to EU-13 participants with Horizon 2020. In FP6, the percentage of connections between EU-15 participants and EU-13 participants was 14.4% of all collaborations from EU-15 participants. While this percentage decreased to 13.3% during FP7, it increased again to 13.7% in Horizon 2020. Hence, while the opening of EU-15 countries to EU-13 countries seems to have worsened during FP7, the situation has improved with Horizon 2020. In parallel, the share of collaborations between EU-13 participants with each other has been stable since FP6.

Figure 11 Connections with EU-13 participants as a percentage of all connections of EU-15 participants

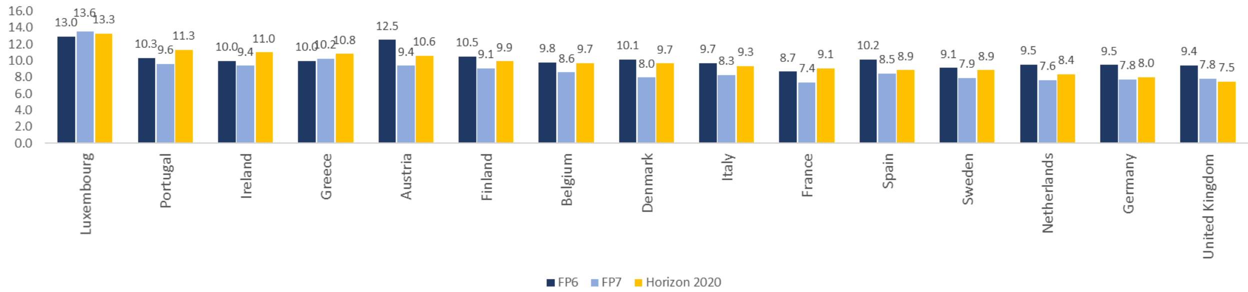


Source: Author's calculations based on CORDA data.

The evolution of these collaborations between EU-15 and EU-13 countries is detailed for each EU-15 country in Figure 12[15]. While there is a general decrease in collaborations with EU-13 participants between FP6 and FP7, almost all EU-15 countries collaborate more often with EU-13 participants in Horizon 2020, compared to FP7. The only exceptions are Luxembourg and the United Kingdom which are also respectively the countries with the largest (13.3%) and the smallest share of connections (7.5%) with EU-13 participants. Since FP6, this trend has been continuously negative only for the UK and continuously positive only for Greece.

[15] The patterns in Figures 11 and 12 are qualitatively similar. But due to collaborations within country groups, the aggregated values do not numerically correspond to the average of countries.

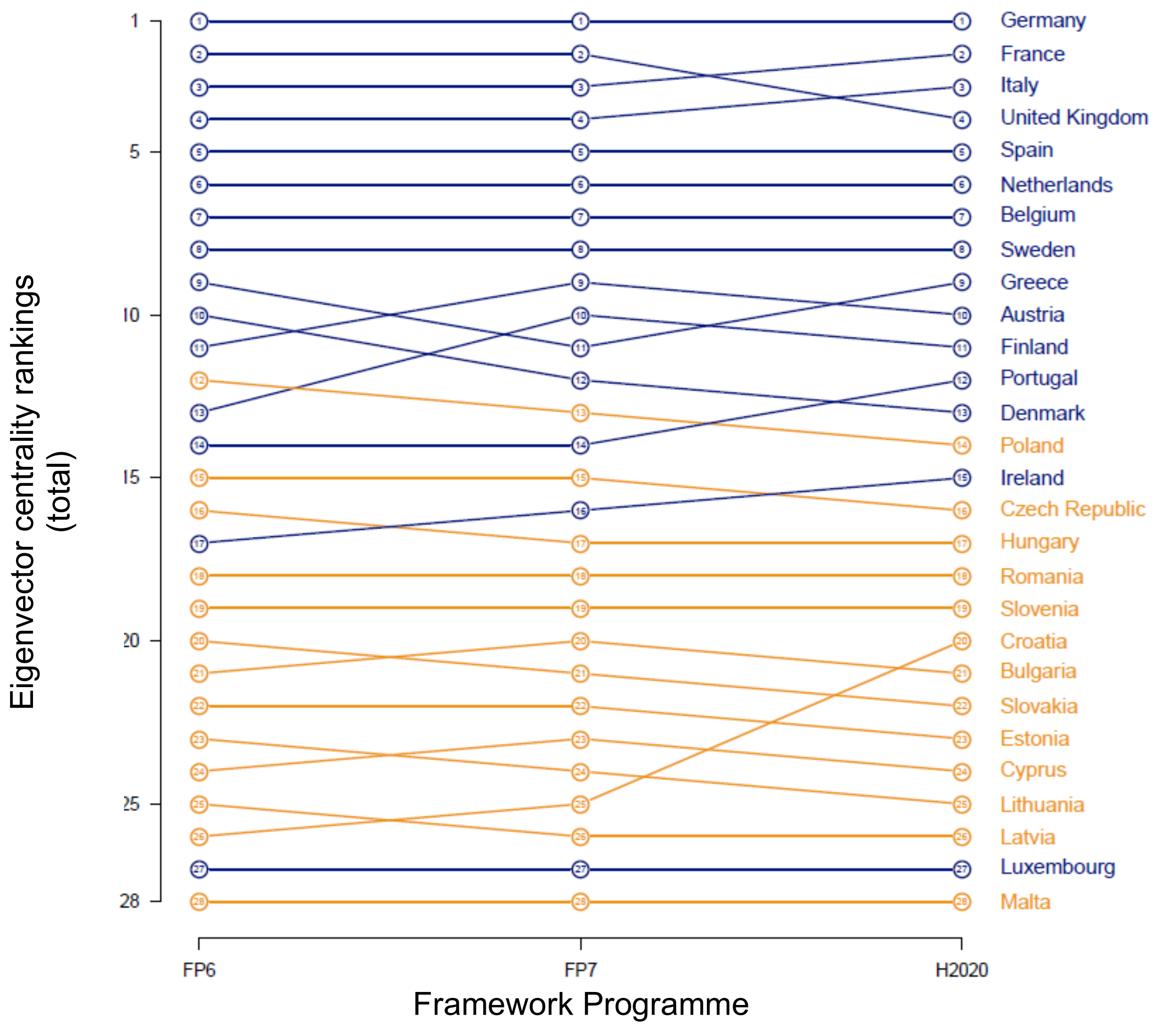
Figure 12 Connections with EU-13 countries as a percentage of all connections



Source: Author's calculations based on CORDA data.

How has the position of EU countries evolved over time? We present network indicators computed at the participant level, and averaged or aggregated at the country level. Only EU countries are analysed. When examining the position of specific countries in the network, we suggested before that country size is an important determinant in the average number of its participants' connections. This is also reflected in Figure 13, with the evolution of country rankings based on eigenvector centrality measures. Germany is both the largest participant in the FP and the most central country in the network. After Germany, France and Italy are the most central countries in Horizon 2020. While the UK was more central than France and Italy in FP6 and FP7, its central position worsened in Horizon 2020. Greece, Portugal and Ireland have improved their centrality in the network between FP7 and Horizon 2020 according to this ranking. The chart also confirms that participants from EU-15 countries tend to be more central than their EU-13 counterparts: the bottom of the chart is occupied by a majority of EU-13 countries, with only Croatia having significantly improved its position since FP6.

Figure 13 Network positions of participants by EU country



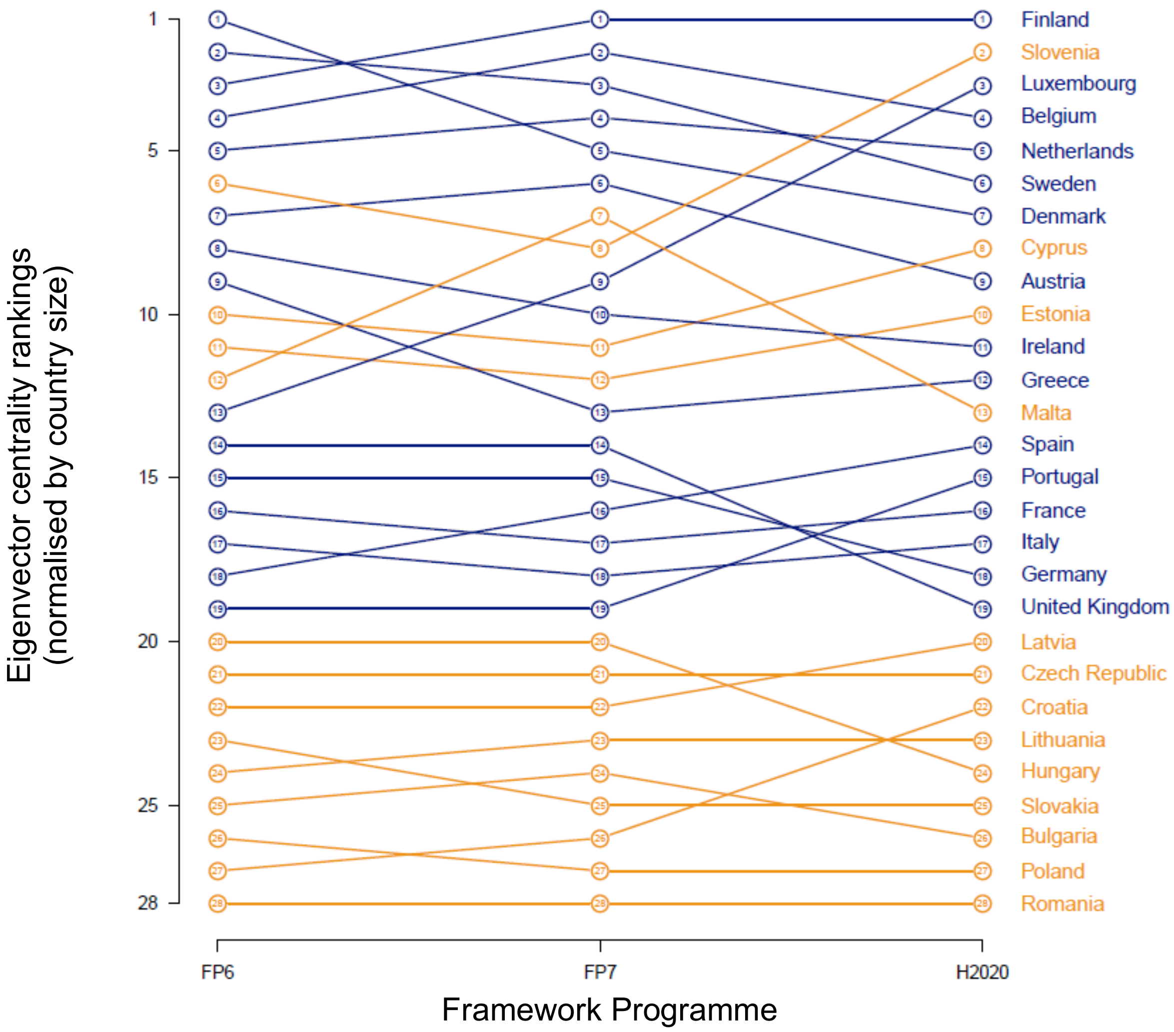
Source: Author's calculations based on CORDA data.

However, these measures are absolute and are significantly influenced by country size[16]. Normalisation for size leads to an overall different picture. Figure 14 presents the evolution of eigenvector centrality coefficients by country between FP6 and Horizon 2020 when normalising by country population. Different trends can be observed. The most central country, relative to its size, is actually Finland. Some EU-13 countries also appear to be very central in the network for their size: Slovenia is now the second most central country in the network after normalisation for size effect. This was not the case in previous programmes: Slovenia was ranked 5th in FP6 and 8th in FP7 in terms of centrality. Luxembourg, the Netherlands, Belgium, Sweden and Denmark are next in terms of size-normalised centrality measure. Among EU-13 countries, Cyprus and Estonia also present strong centrality after normalisation. Hence EU-15 and EU-13 groups are not homogenous groups, with some EU-13 countries being more central, relative to their size, than most EU-15 countries. The

[16] To ensure robustness, other variables describing country size have been tested, such as the national population of researchers (source: Eurostat). This does not affect the key messages from the analysis. However, using population reduces data noise over time and ensures reliability in the evolution of the ranking (see Box 5).

position of the UK and Hungary dropped significantly between FP7 and Horizon 2020[17]. Still, several EU-13 countries are consistently found at the bottom of the ranking.

Figure 14 Network positions of participants by EU country normalised by population



Source: Author's calculations based on CORDA data (Framework Programme) and World Bank (country population).

5. Conclusion

Using unique and very recent FP data, we have described the dynamics of the research network across EU countries during the period 2003-2017, on the basis of collaborative research projects that have been implemented under the Sixth, Seventh and part of the Eight Framework Programme for Research and Innovation.

[17] The position of Malta also decreased significantly over the same period, but it follows a significant increase in FP7 and the position of small countries is more volatile in the ranking.

A key feature of the network is the dominance of the largest EU-15 countries. This observation is expected as country size correlates with the number of participations in the Framework Programme and the number of collaborations between participants. However, when normalizing for size, some other EU-15 countries pop up as most central (like Finland) but also some EU-13 countries (like Slovenia and Estonia) appear to be central in the network. Still, other EU-13 countries remain at the bottom of the ranking.

We found different components of the networks based on the strongest connections. There are two major clusters of large EU-15 countries and large EU-13 countries that are connected to some extent by two other clusters (one cluster consisting of Baltic countries, Czech Republic and Slovakia, the other cluster representing strong collaborations between Cyprus, Greece, Ireland, Luxembourg, Malta and Portugal). Most network hubs are found in the EU-15 countries, but some EU-13 organizations fulfil a key bridging function, especially Slovenia and some Baltic countries. The most active gatekeepers are EU-13 research organizations, public bodies and higher education institutes, rather than private organizations.

Our findings also show there is a spatial division across countries with respect to the nature of their participation. As expected, EU-15 countries appear to be more engaged in programme parts that are considered to be more complex, while EU-13 countries participate in parts of the programme that are less complex. In general, countries that are less central in the network are also countries that have a relative lower comparative advantage in more complex programme parts and a relative higher comparative advantage in less complex programme parts.

The collaborative research network looks pretty stable during the period 2003-2017. The core and periphery of the EU network have not changed much over time. Having said that, there are also signs of dynamics in the research network. Countries like Slovenia, Luxembourg, Croatia, Portugal and Cyprus show striking increases in terms of size-normalised centrality from FP7 to Horizon 2020, while the UK and Hungary dropped positions. Between FP6 and FP7, EU-15 participants have been reducing their collaborations to EU-13 participants to some extent, but this trend has reverted in Horizon 2020. Moreover, the network of participations to the FP's appears to be dynamic over time and tends to be opening to less connected participants. Participants in EU-13 countries show a higher propensity to be involved in new collaborations than EU-15 countries.

Overall, the analysis shows that the research network is reproducing existing divides in research excellence across EU countries but that there is also a tendency of dynamics and more openness in the network, in particular between FP7 and Horizon 2020. There is still room for improving the connectivity and centrality of several countries, especially countries with lower R&I performance. This calls for continuous emphasis and effort, in particular for these countries, to ensure the openness of the programme's networks to their entities. This could be achieved through support activities such as organising information/networking campaigns, boosting national capacity building, offering further opportunities to entities for accessing successful R&I projects and established networks, or by supporting matchmaking between potential participants informed by analytics and network affinities.

There are a number of limitations in our paper that needs to be taken up by future research. First, the next step is to determine the main drivers behind the evolution of the collaborative research network in the EU we presented. Our study suggests that size of the country, geographical and cultural proximity, and network centrality have an effect on the propensity of EU countries to participate in research collaborations over time, but these suggestions need to be thoroughly tested through a systematic study on the dynamics of the EU network. Second, it remains an open question what are the effects of the dynamics in the EU network in terms of innovation and economic development in the respective countries. There are studies that tend to show a positive effect (e.g. Hoekman et al. 2013), but in the case of Horizon 2020, it is still too early to get an accurate assessment. Third, future research should assess whether participation of countries in more complex parts of the FP programme yields more benefits, as one would expect (Balland et al. 2018). Finally, there is a challenge to involve more lagging countries in the EU research network, and how FPs can make them benefit from the often wide presence of MNE's in peripheral countries (Radosevic and Ciampi Stancova 2018).

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7. Annex

Figure A1. Centrality with alternative threshold (one-off connections discarded)

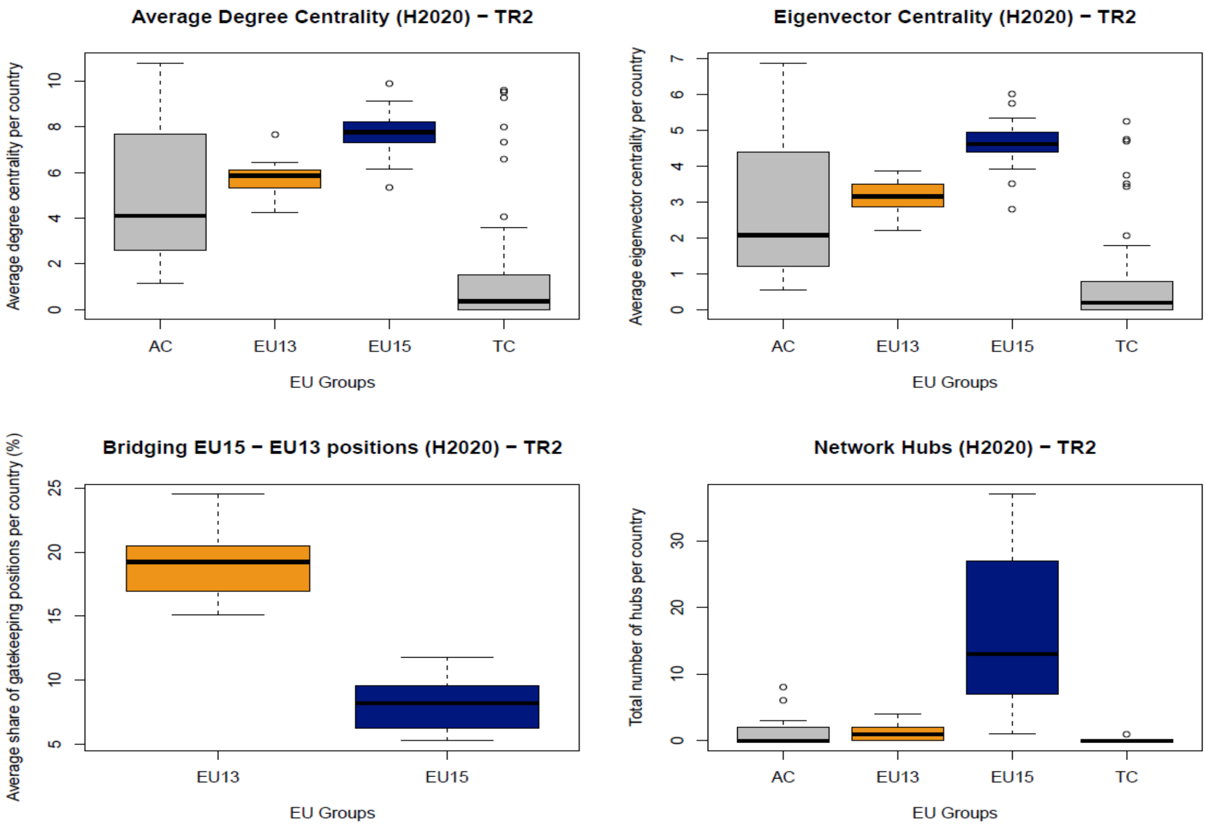

Table A1. Programmes parts in Horizon 2020

Acronym	Programme part
ERC	European Research Council
MSCA	Marie Skłodowska-Curie actions
RI	Research infrastructures (including e-infrastructure)
LEIT	Leadership in enabling & industrial technologies
ARF	Access to risk finance
Innovation in SMEs	Innovation in SMEs
FTI	Fast Track to Innovation
SC1	Health, demographic change & wellbeing
SC2	Food security, sustainable agriculture and forestry,
SC3	Secure, clean & efficient energy
SC4	Smart, green & integrated transport
SC5	Climate action, environment, resource efficiency & raw materials
SC6	Inclusive, innovative & reflective societies
SC7	Secure societies
SEWP	Spreading excellence & widening participation
SWAFS	Science with and for society
Euratom	Euratom

Figure A2. Share of country participations by programme part (%)

	ERC	FET	MSCA	RI	LEIT	ARF	Inno. in SMEs	FTI	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SEWP	SWAFS	Euratom
AT	3.58	2.77	3.27	2.14	4.25	0	2.84	1.76	2.35	2.27	3.66	4.26	3.27	4.58	3.34	2.76	5.77	2.48
BE	3.89	3.13	4.17	3.33	4.76	27.5	3.41	3.64	6.44	6.76	4.95	6.85	5.9	6.72	5.3	1.99	5.49	4.25
BG	0.09	0.79	0.43	0.9	0.27	3.57	2.44	5.76	0.23	0.7	1.19	0.32	0.59	0.95	1.31	1.17	1.83	1.41
CY	0.45	0.09	0.38	0.55	0.42	0	0.24	0.52	0.51	0.25	0.68	0.46	0.65	0.79	1	10	1.97	0.38
CZ	1.03	0.55	1.11	2.58	1.46	3.57	0.93	0.52	1.51	1.08	1.46	1.37	1.05	1.32	0.59	2.49	1.97	2.92
DE	15.4	18	15.86	11.6	16.3	5.05	9.81	12.7	13.6	8.98	12.6	16.4	11.1	10	10.2	10.26	9.2	6.19
DK	1.74	1.13	3.07	2	1.62	0	3.69	0.76	3.45	3.33	2.83	1.64	2.7	3.18	0.79	1.25	2.82	0.69
EE	0.18	0.39	0.31	0.8	0.27	0	1.05	0	0.38	0.69	1.24	0.38	0.36	2.43	0.89	1.64	1.37	0.49
EL	1.34	2.98	2.18	3.83	3.82	0.15	4.37	2.44	2.64	3.4	2.93	3.11	3.91	6.54	6.79	1.51	5.03	3.39
ES	7.11	13.1	9.87	8.12	14.4	8.47	14.45	11.9	9.11	11.3	14.5	10	12.5	7.36	11.3	3.5	8.84	12.09
FI	0.85	2.54	1.99	2.86	3.25	4.9	1.01	0.76	2.2	2.08	2.21	1.63	2.85	2.6	2.63	1.72	2.94	3.67
FR	16.4	11.5	10.36	11.3	10.7	11.7	7.14	7.32	10.7	12.5	8.23	12.4	9.53	6.13	9.31	4.8	5.84	21.58
HR	0.49	0.05	0.2	0.75	0.13	0	1.06	0.4	0.74	0.95	0.98	0.47	1.04	0.89	0.37	2.57	1.4	2.53
HU	0.89	0.93	0.83	1.59	0.76	0	1.98	0.2	0.81	1.97	0.79	0.84	1.06	2.1	0.92	2.23	1.61	2.93
IE	1.16	0.85	1.97	1.92	1.83	3.57	1.36	2.04	1.34	2.26	1.46	0.78	1.71	1.75	2.45	0.98	2.85	0.96
IT	10.6	14.8	9.97	10.3	11.2	7.28	11.53	12.1	9.38	12	11.9	11.3	11.4	10.2	12.6	6.39	7.17	9.53
LT	0.04	0.05	0.25	0.36	0.25	0	0.71	0.2	0.5	0.49	0.53	0.51	0.33	1.07	0.2	0.9	1.63	0.77
LU	0.09	0.03	0.28	0.2	0.41	0	0.76	0.32	0.59	0.05	0.3	0.45	0.21	1.09	1.01	1.83	1.16	0
LV	0	0.07	0.19	0.51	0.25	3.71	0.3	0	0.64	0.72	0.73	0.14	0.16	0.84	0.36	2.23	1.21	0.7
MT	0.13	0.03	0.1	0.31	0.06	1.19	0.24	0	0.03	0.11	0.22	0.27	0.25	0.27	0.18	0.8	1.72	0
NL	5.68	4.32	8.18	8.77	6.86	13.4	2.26	11.3	8.92	7.07	5.38	7.07	6.61	5.59	4.84	4	6.44	3.54
PL	0.72	1.03	1.84	3.35	1.42	0	5.53	0.4	1.11	1.93	1.87	1.65	2.15	3.09	3.04	4.16	2.85	4.85
PT	2.1	1.03	2.64	3.35	2.52	0	3.74	1.56	1.99	3.29	3.47	1.61	4.11	2.72	4	10.24	3.69	1.02
RO	0.27	0.1	0.6	1.31	0.74	0	3.85	0.88	0.58	1.47	1.67	1.25	2.02	1.45	2.92	3.26	1.39	3.81
SE	2.32	4.37	3.87	3.86	3.09	0	4.07	2.68	3.57	3.03	4.01	4.42	3.46	3.44	1.7	1.99	2.36	3.27
SI	0.72	0.41	0.64	1.35	0.72	0	1.35	2.76	1.18	1.24	1.35	0.74	1.47	1.16	0.78	4.46	1.95	1.58
SK	0.09	0.09	0.32	0.85	0.38	0	0.73	0.4	0.69	0.46	0.48	0.67	0.5	1.71	0.46	4.06	1.09	0.73
UK	22.6	14.9	15.11	11.2	7.92	5.94	9.16	16.7	14.8	9.59	8.41	8.94	9.09	10	10.8	6.82	8.41	4.23

Source: Author's calculations based on CORDA data.

Figure A3. Share of country participations by programme part (%) with countries organised by decreasing overall centrality (from top to bottom) and programme parts organised by decreasing ubiquity (from left to right)

	SWAFS	RI	SC6	Inno. in SMEs	SC3	SC2	SEWP	SC5	SC7	SC1	Euratom	SC4	LEIT	ARF	FTI	FET	MSCA	ERC
DE	9.2	11.6	10	9.81	12.6	8.98	10.26	11.1	10.2	13.6	6.19	16.4	16.3	5.05	12.7	18	15.86	15.4
ES	8.84	8.12	7.36	14.45	14.5	11.3	3.5	12.5	11.3	9.11	12.09	10	14.4	8.47	11.9	13.1	9.87	7.11
IT	7.17	10.3	10.2	11.53	11.9	12	6.39	11.4	12.6	9.38	9.53	11.3	11.2	7.28	12.1	14.8	9.97	10.6
FR	5.84	11.3	6.13	7.14	8.23	12.5	4.8	9.53	9.31	10.7	21.58	12.4	10.7	11.7	7.32	11.5	10.36	16.4
UK	8.41	11.2	10	9.16	8.41	9.59	6.82	9.09	10.8	14.8	4.23	8.94	7.92	5.94	16.7	14.9	15.11	22.6
NL	6.44	8.77	5.59	2.26	5.38	7.07	4	6.61	4.84	8.92	3.54	7.07	6.86	13.4	11.3	4.32	8.18	5.68
BE	5.49	3.33	6.72	3.41	4.95	6.76	1.99	5.9	5.3	6.44	4.25	6.85	4.76	27.5	3.64	3.13	4.17	3.89
SE	2.36	3.86	3.44	4.07	4.01	3.03	1.99	3.46	1.7	3.57	3.27	4.42	3.09	0	2.68	4.37	3.87	2.32
EL	5.03	3.83	6.54	4.37	2.93	3.4	1.51	3.91	6.79	2.64	3.39	3.11	3.82	0.15	2.44	2.98	2.18	1.34
AT	5.77	2.14	4.58	2.84	3.66	2.27	2.76	3.27	3.34	2.35	2.48	4.26	4.25	0	1.76	2.77	3.27	3.58
PT	3.69	3.35	2.72	3.74	3.47	3.29	10.24	4.11	4	1.99	1.02	1.61	2.52	0	1.56	1.03	2.64	2.1
FI	2.94	2.86	2.6	1.01	2.21	2.08	1.72	2.85	2.63	2.2	3.67	1.63	3.25	4.9	0.76	2.54	1.99	0.85
DK	2.82	2	3.18	3.69	2.83	3.33	1.25	2.7	0.79	3.45	0.69	1.64	1.62	0	0.76	1.13	3.07	1.74
PL	2.85	3.35	3.09	5.53	1.87	1.93	4.16	2.15	3.04	1.11	4.85	1.65	1.42	0	0.4	1.03	1.84	0.72
IE	2.85	1.92	1.75	1.36	1.46	2.26	0.98	1.71	2.45	1.34	0.96	0.78	1.83	3.57	2.04	0.85	1.97	1.16
CZ	1.97	2.58	1.32	0.93	1.46	1.08	2.49	1.05	0.59	1.51	2.92	1.37	1.46	3.57	0.52	0.55	1.11	1.03
RO	1.39	1.31	1.45	3.85	1.67	1.47	3.26	2.02	2.92	0.58	3.81	1.25	0.74	0	0.88	0.1	0.6	0.27
HU	1.61	1.59	2.1	1.98	0.79	1.97	2.23	1.06	0.92	0.81	2.93	0.84	0.76	0	0.2	0.93	0.83	0.89
SI	1.95	1.35	1.16	1.35	1.35	1.24	4.46	1.47	0.78	1.18	1.58	0.74	0.72	0	2.76	0.41	0.64	0.72
BG	1.83	0.9	0.95	2.44	1.19	0.7	1.17	0.59	1.31	0.23	1.41	0.32	0.27	3.57	5.76	0.79	0.43	0.09
HR	1.4	0.75	0.89	1.06	0.98	0.95	2.57	1.04	0.37	0.74	2.53	0.47	0.13	0	0.4	0.05	0.2	0.49
EE	1.37	0.8	2.43	1.05	1.24	0.69	1.64	0.36	0.89	0.38	0.49	0.38	0.27	0	0	0.39	0.31	0.18
SK	1.09	0.85	1.71	0.73	0.48	0.46	4.06	0.5	0.46	0.69	0.73	0.67	0.38	0	0.4	0.09	0.32	0.09
CY	1.97	0.55	0.79	0.24	0.68	0.25	10	0.65	1	0.51	0.38	0.46	0.42	0	0.52	0.09	0.38	0.45
LT	1.63	0.36	1.07	0.71	0.53	0.49	0.9	0.33	0.2	0.5	0.77	0.51	0.25	0	0.2	0.05	0.25	0.04
LV	1.21	0.51	0.84	0.3	0.73	0.72	2.23	0.16	0.36	0.64	0.7	0.14	0.25	3.71	0	0.07	0.19	0
LU	1.16	0.2	1.09	0.76	0.3	0.05	1.83	0.21	1.01	0.59	0	0.45	0.41	0	0.32	0.03	0.28	0.09
MT	1.72	0.31	0.27	0.24	0.22	0.11	0.8	0.25	0.18	0.03	0	0.27	0.06	1.19	0	0.03	0.1	0.13

Source: Author's calculations based on CORDA data.

Figure A4 Centrality rankings for EU countries

Country	Eigenvector centrality (x1000)			Eigenvector centrality ranking			Eigenvector centrality normalised by size			Ranking after normalisation		
	FP6	FP7	Horizon 2020	FP6	FP7	Horizon 2020	FP6	FP7	Horizon 2020	FP6	FP7	Horizon 2020
Austria	1956.6	2811.4	3084.2	11	9	10	238.7	335.7	355.2	7	6	9
Belgium	3391.9	4607.7	4641.6	7	7	7	324.4	422.2	410.9	4	2	4
Bulgaria	378.1	483.9	509.0	21	20	21	49.2	65.4	71.2	25	24	26
Croatia	129.8	262.2	524.3	26	25	20	29.2	60.1	125.3	27	26	22
Cyprus	202.3	292.6	418.0	24	23	24	198.4	264.0	358.6	10	11	8
Czech Republic	1174.9	1252.6	1391.7	15	15	16	115.1	119.9	131.8	21	21	21
Denmark	2037.0	2167.7	2064.9	10	12	13	376.3	391.1	361.9	1	5	7
Estonia	268.3	337.0	444.2	22	22	23	197.5	253.3	337.7	11	12	10
Finland	1734.9	2681.9	2677.0	13	10	11	331.2	500.0	487.9	3	1	1
France	9100.2	10914.0	12897.3	3	3	2	144.6	167.9	193.3	16	17	16
Germany	12843.0	15873.5	14554.3	1	1	1	155.7	195.1	177.6	15	15	18
Greece	2296.2	2625.3	3123.7	9	11	9	209.3	237.2	288.9	9	13	12
Hungary	1162.4	1208.6	1002.9	16	17	17	115.1	121.0	102.1	20	20	24
Ireland	893.0	1249.7	1508.2	17	16	15	216.5	275.2	318.7	8	10	11
Italy	7523.7	9791.4	11057.9	4	4	3	130.2	165.2	182.2	17	18	17
Latvia	175.9	204.0	305.2	25	26	26	78.1	97.0	155.1	22	22	20
Lithuania	222.5	266.9	344.8	23	24	25	66.5	86.3	119.6	24	23	23
Luxembourg	78.5	149.7	248.7	27	27	27	170.0	293.9	431.1	13	9	3
Malta	77.4	137.4	116.8	28	28	28	192.3	331.1	259.6	12	7	13
Netherlands	4712.2	6787.2	6770.5	6	6	6	289.2	408.8	398.5	5	4	5
Poland	1846.1	1673.7	1850.5	12	13	14	48.4	43.9	48.7	26	27	27
Portugal	1280.0	1667.9	2212.2	14	14	12	122.0	158.3	213.9	19	19	15
Romania	529.0	827.7	925.3	18	18	18	24.7	40.7	46.8	28	28	28
Slovakia	379.6	347.1	459.2	20	21	22	70.6	64.4	84.6	23	25	25
Slovenia	489.0	662.1	891.7	19	19	19	244.5	324.2	432.0	6	8	2

Spain	5318.2	8393.9	10921.5	5	5	5	122.8	181.2	234.9	18	16	14
Sweden	3351.9	3915.7	3778.0	8	8	8	371.8	417.8	382.7	2	3	6
United Kingdom	10139.5	12414.3	11004.3	2	2	4	168.4	197.8	168.4	14	14	19

Source: Author's calculations based on CORDA data.