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Closed clubs: Cumulative advantages and participation in Horizon 2020

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Abstract

This study presents an analysis of 2 216 European higher education institutions (HEIs) from 27 countries. It investigates determinants of participation in the European Union's Framework Programme for research and innovation (EU FP), Horizon 2020, and empirically assesses how cumulative advantages affect the chances of applying for and receiving funding in collaborative projects. Having a strong, influential network position in collaborative EU research is found to affect participation in H2020 greatly – suggesting 'closed clubs', to the detriment of less influential HEIs. Greater access to resources and capabilities significantly moderates the effect of network position on EU FP participation. Results indicate that these organizational factors are central in the feedback process whereby large, well-reputed institutions accrue further advantages.

Keywords

Higher education institutions; Horizon 2020; Matthew effect; social network analysis; research funding

1. Introduction

Newcomers to European research, seeking funding without well-developed networks and with no prior experience, are likely to fail (Enger & Castellacci, 2016; Ortega & Aguillo, 2010b). Competition for funding in the European Union's current Framework Programme for research and innovation (EU FP), Horizon 2020 (H2020), is becoming fiercer because of reduced national research budgets across Europe (European University Association, 2014, 2016). Recent studies report continued success for a few endowed higher education institutions (HEI) in applying for collaborative projects, resulting in persistent oligarchic networks that would appear to constitute 'clubs' closed to those less fortunate (see Lepori, Veglio, Heller-Schuh, Scherngell, & Barber, 2015; Ortega & Aguillo, 2010b).

This article investigates whether HEIs accrue cumulative advantages from EU FP participation, in turn leading to proposals being approved for funding not because of quality, but because of the institutions' oligopolistic role in networks. Here the assumption is that HEIs with influential positions in EU FP networks will accumulate further advantages, like increased resources and stronger research capabilities. Through mutual reinforcement, this 'cocktail' of advantages will strengthen the disproportionate allocation of EU FP funding through what Merton (1968) has dubbed the 'Matthew Effect'.

In 1984, the first EU FP was launched, with the objective of strengthening scientific and technological collaboration across Europe. Since then the multi-annual research programme has grown substantially in size and budget (Breschi, Cassi, Malerba, & Vonortas, 2009). With the inclusion of European Research Council grants in 2007, the current programme now attracts basic and applied research and innovation (Luukkonen, 2014; Nedeva & Wedlin, 2015).

Research on EU FPs has focused on convergence between national and EU policies (see Gornitzka & Langfeldt, 2008; Hakala, Kutinlahti, & Kaukonen, 2002; Laredo, 1998; Luukkonen & Nedeva, 2010), impact from participation (see Di Cagno, Fabrizi, & Meliciani, 2014; Luukkonen, 2000) and organizational characteristics associated with participation (see Geuna, 1998; Lepori et al., 2015). Most attention, however, has been devoted to the collaborative nature of EU FP projects (see Breschi & Cusmano, 2004; Must, 2010; Ortega & Aguillo, 2010a, 2010b; Paier & Scherngell, 2011; Pandza, Wilkins, & Alfoldi, 2011; Piro, Scordato, & Aksnes, 2016; Protogerou, Caloghirou, & Siokas, 2013). The main observation is the continued participation of certain organizations over time, which form 'oligarchic networks' (Makkonen & Mitze, 2016, p. 1211) that in practice control access to projects and related resources.

Due to limited data, these studies of EU FP participation have only been able to identify those who are granted funding, not whether any of the non-successful observations actually applied for funding. Not controlling for self-selection (the decision not to apply) results in biased estimates – and that is problematic when assessing cumulative advantages with perhaps major effects on policy and research. This article employs a two-step empirical analysis that accommodates self-selection. We distinguish between two stages – application, and participation (i.e. a successful application) – and control for those that are not applicable. The approach is similar to Enger and Castellacci (2016) (on Norwegian HEIs and public research organizations) and Barajas and Huergo (2010) (on Spanish firms).

We use a sample with research and education statistics on 2 216 HEIs in 27 countries (for the academic year 2013/2014), which we match with application data for the first full two years of H2020 (2014–2015), covering both funded and rejected applications for collaborative projects. We conduct a descriptive social network analysis of our sample of HEIs participation in the former FP, the seventh (2007–2013). From this, we identify the influence of each institution in a network, relative to others.

This article contributes to a better understanding of the dynamics in research funding systems. Results show that a stronger influential position in collaborative EU FP networks affects the number of applications and funded projects that a given HEI achieves in H2020, with cumulative advantages for HEIs with well-developed collaborative networks. Increased access to resources and capabilities significantly moderates the effect network position has on EU FP participation. Results suggest that these organizational factors are part of feedback processes whereby some accrue advantages, while others are left behind.

The paper is structured as follows. Section 2 presents the theory and proposes hypotheses. Section 3 presents the data, variables and choice of empirical models. In section 4, we discuss the results, and in section 5, we summarize the main findings and address policy implications.

2. Theory and hypotheses

2.1 Cumulative advantage

Cumulative advantage theory has been broadly applied to describe differences in performance between individuals, groups and organizations (see Cole & Cole, 1973; Merton, 1968, 1988; Perc, 2014; Price, 1965, 1976; Viner, Powell, & Green, 2004). The theory focuses on feedback processes as the underlying mechanism behind differences, where an initial event affects subsequent behaviour, which in turn influences the occurrence of new events. Outcomes of such minor events gradually cumulate to major advantages for some and disadvantages for others (Fox, 1983). The acquired comparative advantage is not the result of *one* single event, but rather a sequence of events involving feedback (Gulbrandsen, 2000, pp. 59-60). These feedback processes can provide advantages for those who are well placed, while depriving those who do not benefit from the events, leading to cumulative disadvantages (Merton, 1988).

The first to hypothesize the theory of cumulative advantages was Merton (1968) under the heading 'the Matthew effect'. Drawing on observations of cumulative advantages in the rewards system of science, Merton (1988, p. 609) described the Matthew effect as the accrual of peer recognition to scientists of considerable repute, concomitant with less recognition to peers of equal ability but limited repute. The skewed distribution of reputation will not only accumulate recognition but also more resources, increasing the inequality gap (Fox, 1983).

Although some scholars view this process as positive, serving to raise productivity and reward those who are successful (Cole & Cole, 1973), Merton (1988) was more concerned with its potential negative consequences: that advantages are allocated on the basis of reputational differences more than 'actual' merit or quality – contrary to his 'Ethos of Science', particularly 'universalism' (Merton, 1973). While much of the literature has focused on the individual level, Merton (1968) argued that similar effects could be observed among groups and institutions. Institutions or departments that demonstrate scientific excellence gain recognition, thus improving their position for allocation of resources and attracting scientific talent.

The Matthew effect has been adopted in various areas in addition to the sociology of science – e.g. in economics and unemployment (Heckman & Borjas, 1980), concerning lock-in effects and increasing returns (Arthur, 1989) and in education (Stanovich, 1986). Graph theorists have applied the same understanding of cumulative advantage theory and feedback processes to explain the growth of networks, for instance in analysing research collaboration (Newman, 2001). Barabási and Albert (1999) proposed that networks evolve on the basis of 'preferential attachment'. New 'nodes' (e.g. a researcher, organization) joining a network (a community) will not randomly attach to any pre-existing nodes (partner, co-author) but will opt to connect to nodes that are already well connected to others (reputed, networked). Over time, well-connected nodes gain even more links, at the expense of less connected counterparts, becoming hubs that dominate the networks and the control of resources (Perc, 2014).

Testing assumptions of cumulative advantage quantitatively has proven challenging. However, Abbasi, Hossain, and Leydesdorff (2012) have demonstrated that such well-connected nodes can be identified through measures of 'network centrality', hence, a technical measure of being well-connected and decisive for the position of other nodes in a network. Nodes with the highest measures of centrality will tend to be those to which other nodes preferentially attach. The network belonging to these nodes grows larger, while others shrink. In essence, this offers an operationalization of preferential attachment, enabling us to account for cumulative network effects in EU FP participation and how this influences participation.

We assume that an HEI's network position in collaborative projects under the previous EU Framework Programme (FP7) will strongly affect the propensity to apply and be granted funding for collaborative projects under Horizon 2020. HEIs with poor or no networks will have less chances of engaging in EU FP collaborative projects. Thus, we hypothesize:

> H1: An influential network position will positively affect the probability of participating in Horizon 2020.

HEIs with influential network positions will have experience from EU FP projects, involving various events that feed back to the institution and underpin their path of continued participation. First, these institutions will become familiar with the formalities of proposal writing, coordinating partners, and other administrative aspects that lower the costs of future participation; those lacking such experience must invest significant time in learning these practicalities. Second, there is a behavioural aspect: the positive experience of success in the competition for EU funding reinforces similar behaviour in the future. As noted by Fox (1983, p. 297), cumulative advantage requires prior positive reinforcement. Success and accumulation of advantages also entail a symbolic effect, attracting the attention of others while anticipating further accomplishments. By contrast, previous failure might induce reluctance to apply – self-selecting not to apply. Third, with their network of potential partners, influential HEIs will find it easier to establish new collaborative projects, and their dominance and previous performance in EU FP projects make them more attractive to others. Any newcomers must compete to be part of these networks, which further strengthens the consortiums, perhaps increasing the chances of obtaining funding.

2.2 Organizational resources and capabilities

Although the Matthew effect has been studied primarily at the individual level (see Laudel, 2006b; Van Looy, Ranga, Callaert, Debackere, & Zimmermann, 2004; Viner et al., 2004), the same process of accumulating advantage can be observed at the institutional level. According to Merton (1988, p. 616), the individual and the institutional level interact in accumulating advantages and disadvantages. Having observed the many Nobel Laureates at prestigious US universities, Merton (1968) described how institutions with demonstrated scientific excellence receive a disproportionate amount of resources compared to those that have not yet made their mark. In turn, such skewed allocation of resources attracts both eminent scholars and ambitious young talent. Those who find their way into these institutions have better chances of acquiring cumulative advantages than their peers in less endowed institutions. The reward system and allocation of resources ensure that the individual and the institution reinforce each other, making it difficult for newcomers. This is a potent effect because the diversity of the resources is also likely to increase, with the addition of new types of advantages as well as strengthening of pre-existing capacities (Van Looy et al., 2004).

Much of the literature on participation in EU FPs has examined the underlying dynamics. While some explain participation as influenced by compatibility between policies (see Gornitzka & Langfeldt, 2008), others have hypothesized that participation is best explained by organizational capabilities and resources (see Lepori et al., 2015). However, we argue that these organizational level factors are as much a result as a source of cumulative advantage.

The few studies dealing with this level of analysis have indicated skewed distribution of participation, without concluding as to whether allocation of funding is non-meritocratic (Geuna, 1996, 1998; Lepori et al., 2015; Nokkala, Heller-Schuh, & Paier, 2011). Large and highly reputed HEIs are generally most successful in applying for funding in EU FP projects (Henriques, Schoen, & Pontikakis, 2009). According to Geuna (1996; 1998), Lepori et al. (2015), Enger and Castellacci (2016) and Nokkala et al. (2011), participation may be explained by various factors at the organizational level: scientific reputation, size, research orientation, prior participation, and access to funding sources.

These factors are essentially resources and capabilities that organizations accumulate over time through various feedback processes. This is not necessarily a result of prior FP participation but may stem from other competitive and non-competitive arenas as well. Regardless, continued feedback is likely to reinforce the network position of the organization, in addition to the factors themselves, gradually securing even stronger collaborative links. If these collaborative links are involved in EU FP projects, then the HEI is likely to accrue even more projects, whereas organizations without such success will lag behind: poorly performing institutions will accrue cumulative *dis*advantages. Their lack of successful projects will limit access to the resources and capabilities needed to challenge the already established networks.

These organizational factors, we hypothesize, serve to moderate the effect that the network position of influential HEIs has on the propensity to participate in EU FP projects. We distinguish the factors in terms of two categories, depending on their nature and moderating effect on participation.

First, HEIs with greater *resources* (funding, staff) will have stronger networks compared to those with fewer resources. For example, HEIs with influential network positions will typically be involved in coordinating (leading) FP projects – a comprehensive undertaking that requires not only a broad network for contacting and inviting the best possible partners, but sufficient resources to oversee project activities and deliverables. A high level of resources may also offer certain scale effects. Large HEIs may benefit from having designated and experienced administrative staff able to provide researchers with time to focus on their network and project proposals, rather than the formalities involved in participation. By contrast, having a less influential position goes together with having fewer resources. Thus, we hypothesize:

> H2: A large pool of resources will positively moderate the effect of influential network position on the probability of participating in Horizon 2020 collaborative projects.

As with resources, *capabilities* (scientific reputation, productivity) represent a comparative advantage in the effect that the network position of an HEI has on EU FP participation. Studies at the individual level have demonstrated the influence of scientific reputation on grant funding in conjunction with the Matthew effect (Laudel, 2006a; Viner et al., 2004). We argue that capabilities and the influential position of the HEI will coevolve and reinforce mutually, leading to increased participation and oligarchic structures. There is a symbolic value attached to HEIs with greater capabilities. Having an excellent scientific reputation indicates to peers that a high level of quality can expected from collaboration with such an HEI, thereby attracting similar institutions seeking to sustain the 'quality' of their own networks and increasing their chances of involvement in the best applications to EU FP projects. Such symbolic value works both ways. To newcomers with a less influential network position, holding outstanding capabilities will increase their chances of gaining access to a more established consortium, and eventually grant funding. Thus, we hypothesize:

H3: Strong capabilities will positively moderate the effect of influential network position on the probability of participating in Horizon 2020 collaborative projects.

3. Data and methods

3.1 Data

Ideally, research on EU FP participation should consider multiple levels of analysis, from the country to the individual level. However, detailed data at the level of the individual or the research group are not available for cross-country comparisons. Taking HEIs as the unit of analysis together with country-level factors enables us to collect and analyse detailed data covering almost the entire HEI population in the countries under study.

Our empirical analysis is based on the European Tertiary Education Register (ETER) database[1] (Lepori et al., 2016). The data contain detailed organizational-level statistics on research and education, and have been used previously for similar types of analyses (Lepori et al., 2015). We extracted a dataset on 2 216 HEIs from 27 countries: the EU28 (excluding Hungary, Luxembourg, Romania, Slovakia and Slovenia) and EU-associated countries (Iceland, Liechtenstein, Norway and Switzerland) for the academic year 2013/2014. The database covers more HEIs than in our sample, but due to unacceptable amounts of missing data on important indicators, we omitted several countries. Even so, our sample provides almost complete coverage of HEIs that grant first degrees (undergraduate level) in their countries, and provides a representative sample of HEIs eligible for participation in Horizon 2020. The countries with the highest number of HEIs in our dataset are Germany (390), France (316), Poland (280), Italy (176), and the UK (150); the remainder average 43 HEIs per country.

We matched the ETER data with data on project applications in the eighth European framework programme, Horizon 2020, which we extracted from the EU Commission's external data warehouse, ECORDA. The data are similar to publicly available information on previous framework programmes from the Community Research and Development Information Service (CORDIS: cordis.europa.eu), but differ in two important respects. Detailed and updated information on participation in the current programme, H2020, are not yet available. Second, the data in CORDIS do not contain information on applications that have been rejected. By contrast, ECORDA holds updated information on unsuccessful as well as successful applications for H2020. However, there is restricted access to member states' public research

[1] Access data from: eter-project.com. See Lepori et al. (2016) for details.

authorities. To comply with rules on confidentiality, data on unsuccessful applications must be presented in aggregated form. For other studies using ECORDA, see (Barajas & Huergo, 2010; Breschi et al., 2009; Must, 2010; Ortega & Aguillo, 2010b).

Our dataset contains all applications for collaborative projects in H2020 for the first two full years of operation (2014–2015) that match the 2 216 HEIs in the ETER dataset. All other applications – from companies, public authorities, public research organizations or other HEIs not in the dataset – were excluded. We extracted and matched altogether 95 581 applications for participation in collaborative projects, 10 818 of which received funding. Totalled by each organization, 1 165 HEIs had applied for participation in at least one project in H2020, and 770 were granted funding for at least one.

Unlike the case in previous studies of the organizational drivers for EU FP funding (Geuna, 1998; Lepori et al., 2015; Nokkala et al., 2011) these application data offer detailed insights into not only the funding process but also the application process. Earlier studies have operated with information about which institutions actually received funding, not whether a given institution applied. One recent study (Enger & Castellacci, 2016) used similar data to the present work, but on a different sample of institutions from Norway. It found that using EU FP application data make it possible to distinguish three groups: (1) those that do not apply, (2) those that apply but are unsuccessful, (3) and those that apply and are granted funding. With the EU FP application data for H2020 and the ETER data, we can identify who has applied and who has been successful, enabling a two-step analysis of the participation process. Not controlling for this would otherwise bias the results.

To provide an adequate measure of the influential network position of each HEI, we collected data on project applications that received funding in the previous, seventh, FP (2007–2013). Concentrating on collaborative projects, we matched the data with the HEIs in our sample and kept the observations at the project level, making it possible to construct a network matrix of which HEIs collaborated in FP7 (see sub-section 3.2.1 below).

3.2 Variables

The dependent variable in step one is a count variable, measured as the number of *applications* for collaborative projects by each organization to H2020. For the second step, we use an outcome variable measured as the number of successful applications to H2020 (*participation*). Figure 1 displays the mean distribution of applications by country, while Figure 2 shows participation, i.e. successful applications.

Figure 1 Mean number of applications to H2020, by country

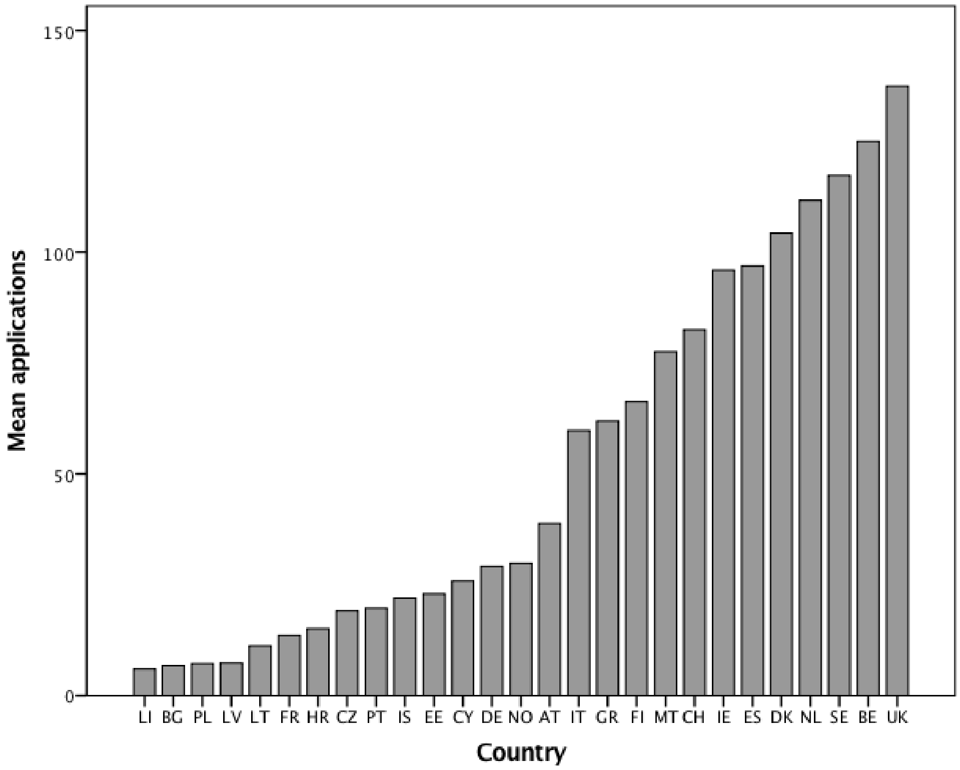
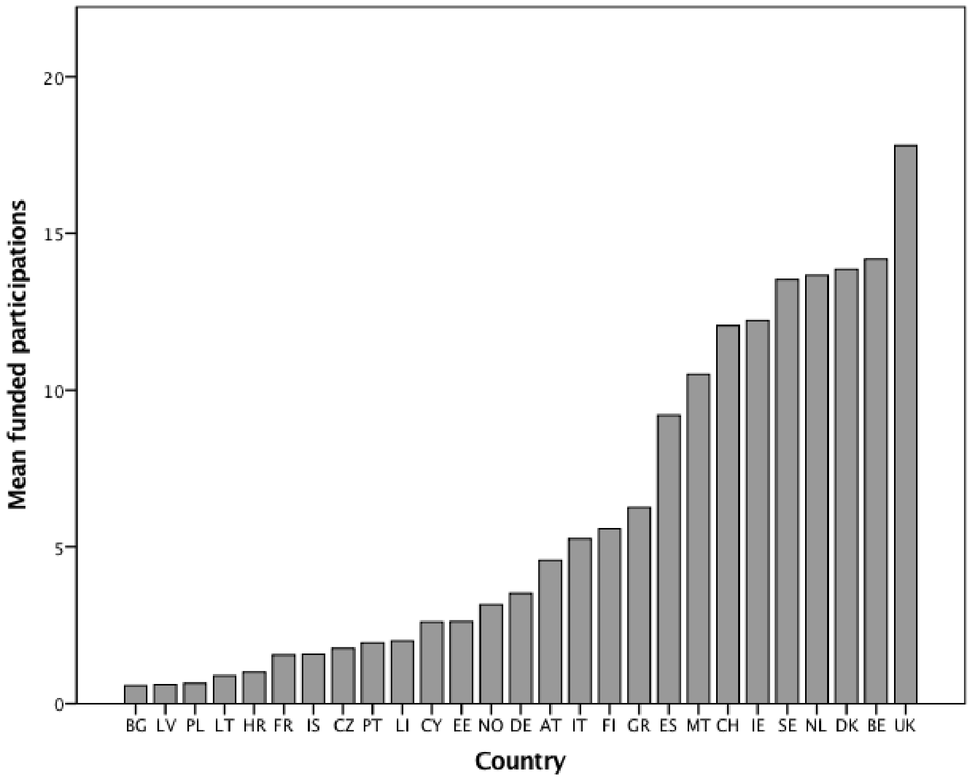


Figure 2 Mean number of H2020 projects participated in, by country



As indicators for *resources* and *capabilities,* we include a battery of variables shown to affect EU FP participation (Enger & Castellacci, 2016; Geuna, 1996, 1998; Lepori et al., 2015; Nokkala et al., 2011).

The variables or indicators characterized as *resources* are as follows: First, the *size* of the institution, measured as the number of full-time equivalents (FTE) of researchers (administrative staff excluded). With greater size, organizations will have better infrastructure and a higher number of researchers able to take part in research activities (see also Enger & Castellacci, 2016; Lepori et al., 2015). Second, *funding* is necessary for HEIs to uphold their main activities of research and teaching. In addition to nurturing the scientific activities of grantees, funding acquired through competitive grants is likely to be directed internally in ways reinforcing the comparative advantages of the institution, thereby ensuring further funding. Thus, we include a measure of *external funding,* previously argued to affect EU FP participation (Nokkala et al., 2011). Measured as the percentage share of third-party funding by total HEI revenues, this variable is partially endogenous, as EU funding is included. However, for most HEIs this constitutes only a small portion of their external funding (Lepori et al., 2016). Third, with greater *research orientation,* organizations will have more resources directed towards conducting research compared to other activities, such as teaching. Extracted from ETER, it is the ratio of total number of graduating PhD students divided by the total number of graduating first-degree students. A higher ratio indicates stronger research orientation, and is a common indicator used in determining the research orientation of an HEI (Bonaccorsi, Daraio, Lepori, & Slipersæter, 2007). All three indicators are from ETER.

We use two main variables to indicate *capabilities*. Geuna (1996; 1998) and Lepori et al. (2015) suggest that the skewed participation can be explained largely by the *scientific reputation* of the institution (commonly measured in terms of number of citations).[2] It seems logical to expect that highly reputed organizations will be in demand as partners to new project constellations. Moreover, EU evaluators may prefer to grant funding to projects whose participants can exhibit solid scholarly track records. *Scientific reputation* is the average number of citations per publication noted for each HEI (2013–2015) divided by size. We adjust the variable by academic FTE (size) since the measure is otherwise highly size-dependent. On the other hand, *productivity,* measured as the number of publications by academic FTE, indicates the scholarly productivity of the HEI. We assume that this may have symbolic effects similar to those of scientific reputation. Our bibliometric data are from Elsevier's SciVal

[2] Nokkala et al. (2011) achieves similar results using university rankings as a proxy for reputation.

database (scival.com).[3]

We control for several factors, the first of which is the scholarly orientation of the HEIs. Here we create three dummy variables based on the distribution of number of undergraduate students by academic fields. From the total number of students, we can calculate the percentage of students in a given field, and sort them into three general disciplinary fields: *physical sciences and engineering* (PE); *social sciences and humanities* (SH); and *life sciences* (LS).[4] HEIs with a higher percentage of students in, for example, PE compared to the others receive 1, otherwise 0. The same goes for the other fields.

Second, we control for the type of HEI. An HEI formally classified as a university (*UNI*) is entitled to award doctoral degrees and can be expected to display a strong research orientation. By contrast, a university of applied sciences (UAS) is not formally recognized as a 'university' by the ETER project; it has a stronger focus on applied sciences and technical education (Lepori et al., 2016).

Third, since the dataset is a cross-country sample, we control for several country-level variables. Results for these must be interpreted with caution, as they represent only 27 countries. Recent reports by the European Commission (European Commission, 2015, 2016) indicate that some countries participate less than others. The EU's new member states (the *EU 13*, which have joined since 2004) struggled to participate during the former FP – a trend likely to accumulate negatively in H2020 as well. Thus, we control for if the HEI is located in new member state (here: Croatia, Cyprus, Estonia, Latvia, Lithuania, Malta, and Poland). We also include dummies for individual *countries* and whether the HEI is located in an *EU-associated country*. Finally, we include *HERD* – higher education research and development expenditures per inhabitant in purchasing power parities for 2013. This is a measure of the national investment in higher education R&D, normalized by size of the country and corrected for price differences, extracted from EUROSTAT (eurostat.com).

Table 1 provides descriptive information on the variables included in our analysis, and Table 2 reports the correlation coefficients. In Table 1, the dependent variables are over-dispersed, with a high number of zeroes. Of the total sample of 2 216 HEIs, 1 165 were found to have applied for at least one collaborative project in H2020, while 770 HEIs achieved

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[3] Because of the set threshold for listing HEIs in the database (minimum 500 publications), we have observations for only 802 HEIs. We set scientific reputation and publications for missing HEIs at 0, similar to Lepori et al. (2015) and Enger and Castellacci (2016).
[4] In the ETER database, number of undergraduate students is noted by 11 different scientific fields. These fields are classified as either PE, SH or LS based on European Research Councils classification of scientific categories (See European Commission, 2015, p. 32, Table 4.01)

funding for at least one project. In Table 2, the dummy *PE* correlates with the *SH* dummy above 0.7. To avoid collinearity we excluded PE from the regressions, using it as the reference group for SE and LS. Further, *productivity* correlates highly with *scientific reputation.* The two variables are important indicators for capabilities and Hypothesis 3, and we cannot justify excluding either. To avoid multicollinearity, we have regressed these variables separately in both steps. We further tested for multicollinearity, and found no violations of the variance inflation factor or the tolerance.

Table 1 Descriptive Statistics

	N	Mean	SD	Min	Max
Application (count)	2216	43.132	117.113	0	1238.000
Participation (count)	2216	4.882	15.417	0	218.000
Size[a]	1656	568.772	910.650	0	6979.830
Research orientation[b]	2135	0.021	0.084	0	2.966
External funding[c]	1266	9.291	11.555	0	93.385
Scientific reputation[d]	2216	0.001	0.011	0	0.331
Productivity[e]	2216	1.023	3.214	0	65.55
HERD[f]	2180	116.653	60.416	5.900	283.300
Centrality (categorical)	2216	1.656	0.815	1	3
Social sciences and humanities (dummy)	1797	0.789	0.408	0	1
Physical sciences and engineering (dummy)	1797	0.134	0.341	0	1
Life sciences (dummy)	1797	0.077	0.267	0	1
University (dummy)	2216	0.421	0.494	0	1
University of applied sciences (dummy)	2216	0.288	0.453	0	1
Associated country (dummy)	2216	0.042	0.201	0	1
EU 13 (dummy)	2216	0.207	0.405	0	1

Note: [a] Full-time equivalents of researchers; [b] ratio of total number of graduated PhD students / total number of graduated first-degree students; [c] share of third-party funding / total HEI revenues, in percentage; [d] average number of citations per publication / size; [e] number of publications / size; [f] higher education research and development expenditures per inhabitant, in 2013 purchasing power parity.

Table 2 Correlation matrix

	Applications	Participation	Size	Research orien-tation	Scientific reputation	HERD	External funding	Associated country	EU 13	Social sciences and humanities	Physical sciences and engineering	Life sciences	Univer-sity	Centrality	Produc-tivity
Applications	1	0.867***	0.579***	0.369***	0.027**	0.134***	0.390***	0.010	-0.143***	-0.022	0.069***	-0.054**	0.400***	0.567***	0.619***
Participation		1	0.513***	0.355***	0.021**	0.139***	0.386***	0.020	-0.130***	-0.031	0.070***	-0.042*	0.346***	0.497***	0.554***
Size			1	0.283***	0.010**	0.125***	0.313***	0.023	-0.182***	-0.059**	0.123***	-0.062**	0.617***	0.684***	0.316***
Research orientation				1	0.099***	0.121***	0.306***	0.025	-0.164***	-0.020	0.052**	-0.037	0.300***	0.348***	0.396***
Scientific reputation					1	0.032	0.099**	0.043**	-0.059***	-0.050**	0.054**	0.007	0.085***	0.094***	0.771***
HERD						1	0.186***	0.257***	-0.583***	-0.072***	0.070***	0.021	-0.063***	0.119***	0.100***
External funding							1	0.026	-0.147***	-0.108***	0.146***	-0.024	0.210***	0.361***	0.372***
Associated country								1	-0.107***	0.008	-0.024	0.019	-0.051**	0.011	0.041*
EU 13									1	-0.004	-0.038	0.049**	-0.075***	-0.201***	-0.155***
Social sciences and humanities										1	-0.760***	-0.559***	0.079***	-0.045*	-0.029
Physical sciences and engineering											1	-0.114***	-0.051**	0.117***	0.055**
Life sciences												1	-0.056**	-0.080**	-0.026
University													1	0.605***	0.557***
Centrality														1	0.668***
Productivity															1

Note: Significance levels: *****1%, **5%, *10%.

3.2.1 Preferential attachment and network analysis

To find a suitable measure of the influential position of each HEI, we utilize graph theory and its applications, known as *social network analysis* (SNA) (Scott, 2012; Wasserman & Faust, 1994). This tool describes the composition and interactions in a network where each network may consist of a set of individuals or organizations connected to some or all others in the network (Scott, 2012).

Our network is defined by several HEIs (or nodes) linked by a relational tie if they have been partners on the same project, which is represented by a line (edge). We have used undirected and weighted networks – thus, we disregard the direction of the interaction, but not how many connections each has with others (self-interactions were removed, i.e. a single project where an institution had more than one participation). We constructed the network by matching the HEIs from our sample with funded research collaborations at the project level in FP7. In total, 968 HEIs participated at least once in a collaborative project, of 17 023 projects.

The common approach to understanding a social network and the interaction between the nodes involves evaluating the location of each node in terms of its strategic position to others, e.g. one university acting as a gatekeeper. These strategic positions are best measured with 'centrality', which quantifies and determines the importance of a node relative to others in a network (Scott, 2012). Centrality, first introduced by Bavelas (1950), was later refined by Freeman (1978), who defined the concepts of network centrality that are most used today. In preferential attachment, pre-existing and most connected nodes can be characterized by high measures of centrality (Abbasi et al., 2012; Barabási & Albert, 1999). We compute two measures of network centrality: betweenness and eigenvector, which both capture the importance of each node relative to others. 'Betweenness centrality' as proposed by Freeman (1978) reflects the number of times a certain node lies between other nodes in a network. The more edges that pass through the node compared to others, the greater the importance. Nodes with high betweenness centrality control interactions in the network and serve as gatekeepers. Eigenvector centrality, however, recognizes that not all edges measured by betweenness centrality are of equal importance. Eigenvector is based on the idea that a node is more central if it is in relation to other nodes which themselves are central (Ruhnau, 2000). Thus, it measures and indicates the most prestigious nodes in a network (Newman, 2008).

Using Gephi software (gephi.org), we extracted the various measures and matched them to each HEI in the dataset. Measures were normalized (ranging between 0 and 1) for comparability. The continuous measures of centrality proved to correlate strongly with several variables (close to 0.8). To avoid potential collinearity we reduced the two variables to one single variable, by principal component analysis. We then created a categorical variable, where those not participating (no centrality) received 0 by default (n=1 248), while those that did participate were separated at median, yielding 1 for low centrality if the HEI held centrality below median (n=484); and 2 if scoring above median (high centrality, n=484). Table 3 shows the distribution of HEIs by groups and network centrality. Figure 3 offers a more graphic representation of research collaboration between the HEIs in FP7. The size of the node indicates higher betweenness centrality relative to others, and stronger colouration indicates higher eigenvector centrality. We find a concentration of important institutions (scoring high on centrality) in the UK, Switzerland, Netherland, Denmark, Sweden and Belgium.

Table 3 Network centrality

	Whole network	High centrality	Low centrality
Number of HEIs	968	484	484
Mean betweenness centrality	0.042	0.082	0.002
Mean eigenvector centrality	0.225	0.417	0.033

Note: Network centrality measures are normalized, ranging between 0 and 1.

Figure 3 Network collaboration in FP7

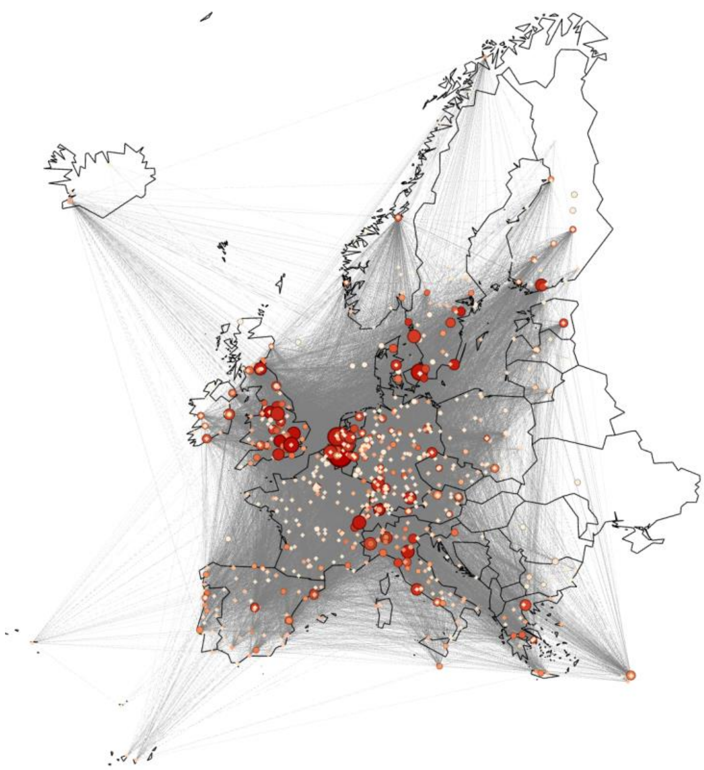

Table 4 displays a cross-tabulation of the network centrality variable by several dummy variables, clearly showing that higher centrality coincides with increased applications and participation.

Table 4 Cross-tabulation of network centrality groups

Variable (dummies)		Network centrality		
		No (n=1248)	Low (n=484)	High (n=484)
Applied	Yes	19.1 %	91.5 %	99.8 %
	No	80.9 %	8.5 %	0.2 %
1–10 applications	Yes	17.3 %	50.4 %	2.3 %
	No	82.7 %	49.6 %	97.7 %
11–50 applications	Yes	1.7 %	36.8 %	21.2 %
	No	98.3 %	63.2 %	78.8 %
More than 50 applications	Yes	0.1 %	4.3 %	76.3 %
	No	99.9 %	95.7 %	23.7 %
Applied for coordinator[a]	Yes	8.3 %	65.5 %	98.8 %
	No	91.7 %	34.5 %	1.2 %
Funded participation[b]	Yes	27.3 %	53.0 %	97.1 %
	No	72.7 %	47.0 %	2.9 %
One participation funded[c]	Yes	21.0 %	24.8 %	3.3 %
	No	79.0 %	75.2 %	96.7 %
More than one funded[d]	Yes	6.3 %	28.2 %	93.8 %
	No	93.7 %	71.8 %	6.2 %
Funded coordinator[e]	Yes	5.0 %	18.5 %	81.4 %
	No	95.0 %	81.5 %	18.6 %
Associated country	Yes	4.0 %	4.3 %	4.5 %
	No	96.0 %	95.7 %	95.5 %
EU13	Yes	27.7 %	15.3 %	8.2 %
	No	72.3 %	84.7 %	91.8 %
University	Yes	18.5 %	52.3 %	92.6 %
	No	81.5 %	47.7 %	7.4 %

Note: [a] At least one application as coordinator; [b; c; d] HEIs that have *not* applied are left out of the cross-tabulation. Number of observations for groups that have applied H2020: no centrality (n=238); low centrality (n=443); high centrality (n=484); [e] At least one participation as coordinator.

3.3 Model

We divide the empirical model into two steps. The first step estimates the probability that the HEI will apply for participation in one or more projects under H2020. The second step estimates the probability of successful application. The explanatory variables are the same for each step. In the second step we exclude those HEIs that have self-selected not to apply for EU FP participation (n=1 051). The number of observations in each regression is smaller than the total sample of 2 216 HEIs due to missing data on some explanatory variables. Because of the potential bias of omitting key variables, these cannot be excluded. In step two, there is a natural reduction of number of observations, as non-applicants are excluded.

The dependent variables are occurrence counts. Count outcomes are discrete, non-continuous, and violate the basic assumptions of more traditional linear regressions, i.e. ordinary least squares-models (Cameron & Trivedi, 2013, p. 2). An alternative would be to dichotomize the outcome variable and use a logistic regression, but this might restrict the interpretation, because some HEIs are more active in applying and achieving funding for collaborative projects, not just one project (see Table 4). The descriptive statistics in Table 1 indicate that both dependent variables are over-dispersed, with several observations at 0 and the remainder spread out. The standard deviation is also large compared to the mean. We use a negative binomial regression model (NBREG) that accommodates for over-dispersion and leads to more conservative estimates, reducing the chances of committing a type-I error (Cameron & Trivedi, 2013). In all regressions, we include a likelihood-ratio test of alpha that confirms that there is over-dispersion and that NBREG is a better model than a regular Poisson regression[5]. At step one, due to the large proportion of zeroes in the dependent variable (many HEIs do not apply at all), we use an NBREG model that accommodates for the inflation of zeroes (ZINB). A Vuong test confirms that the ZINB is better suited at step one compared to a standard negative binomial model.

Tables 5 and 6 display the results for steps one and two. To avoid collinearity, we study the two indicators *productivity* and *scientific reputation* separately, which explains why there are eight and not four regression models.

[5]The NBREG reports McFadden's Pseudo R^2 (Table 6). It is not equivalent to the R^2 found in OLS regression and must be interpreted with caution.

4. Results

With the first hypothesis, we assumed that the more influential position (network centrality) of a given HEI, the greater will be the propensity to apply for and be awarded funding in H2020 projects. From Table 5, which shows the results for step one, we observe in the first models (models 1 and 5) that HEIs with high and low levels of centrality display a significantly greater propensity to apply, compared to HEIs with no centrality. This indicates learning effects from prior participation that lower the threshold for applying. However, for the second step in Table 6 (models 1 and 5), only HEIs with high levels of centrality have a significantly greater propensity to succeed in obtaining H2020 funding compared to the group with no centrality. Estimates are positive, but non-significant, for those with low levels.

Table 4 shows similar tendencies. Only 19 per cent of the HEIs with no centrality get access to at least one collaborative project that results in an application to H2020, and 73 per cent of these end up with no funding. For the groups with low and high levels, respectively 91.5 and 99.8 per cent of the HEIs apply for at least one project, and 53 and 97 per cent succeed in achieving funding for at least one application. Thus, the lower the level of centrality, the fewer are the applications and funded projects. A high level of centrality appears to be associated with coordinating a project application as well. Among HEIs with high centrality, 99 per cent apply for at least one project as a coordinator, which indicates network position is important for taking on such a role. That this group of HEIs accounts for the majority of successful project applications (both in general and as coordinators) would help to explain why this group is significantly more likely to participate than the other two.

These results confirm Hypothesis 1. The propensity to apply, and especially to submit a successful application, is skewed in favour of those with high levels of network centrality. Based on the mechanism of cumulative advantage, and judging from our observations, participation in FP projects will accrue more in favour of those better connected, than for those with less influence. This becomes evident from the results in the second step, as high network centrality significantly affects the propensity to participate. There is a symbolic value attached to being very influential in a network that may contribute to accumulating advantages. First, within the organization itself, previous success from collaborative projects will reinforce similar behaviour: the organization or institution will continue to draft FP applications. Externally, other peers will recognize the importance of these HEIs regarding FP projects, and that their own success will depend on accessing consortiums controlled by these ‘oligarchic’ HEIs. The leading HEIs, in turn, will benefit from attracting other well-connected HEIs into their network. As a result, stable participation patterns or ‘closed clubs’ in EU FPs will start to form.

Dominant networks as such may not necessarily be a problem, especially if they produce the qualitatively best proposals. But there may be grounds for concern if these networks grow stronger and encompass other research and innovation sectors as well,[6] with the result that organizations are granted funding not because they submit the best proposals, but because they have the best-developed networks. In other words, success in applying for funding will hinge, not on who has the best ideas, but about who knows whom – which will make it increasingly difficult for newcomers.

Interestingly, in recent debates at the national level (European Commission, 2016, 2017) concern has been expressed about the participation-divide in H2020 between older EU member states (EU15), and the ‘new’ member states (the EU13). Calling for improved policy incentives, some argue that researchers in EU13 states struggle to obtain funding from H2020, not because of lower levels of skill or competence, but because they lack access to the dominant collaborative networks. Our results do show significantly negative estimates in all models regarding the EU13 states. On the other hand, participation among EU13 states appears to be heterogeneous.

We now turn to the second hypothesis. Based on Merton’s (1988) discussion of the Matthew effect at the organizational level and recent studies of EU FPs, we assume that increased resources, together with a more influential network position, will affect the chances for a successful application, otherwise referred to here as *participation*. The results show that only one of the resource-indicators in our dataset – size – significantly moderates the effect of network centrality on the propensity to apply (Table 5, models 2, 4, 6 and 8), and to submit a successful application (Table 6, models 2, 4, 6, and 8). The other indicators, *external funding* and *research orientation*, do not significantly moderate the effect of a stronger network, but they do affect the propensity to apply and succeed, in all regressions. That we find no moderating effect of these factors does not mean that they do not play a role in accumulating advantages for a HEI, only that they do not reinforce the network effect on participation – an effect that, we argue, leads to oligarchic networks. That these indicators, including size, affect participation echoes the results of previous studies of EU FPs (Geuna, 1998; Lepori et al., 2015; Nokkala et al., 2011).

[6] Breschi and Cusmano (2004) demonstrated oligarchic networks among industry participants.

Table 5 Propensity to apply H2020. Dependent variable: applications (count); model: zero inflated negative binomial regression

	Model 1 - Baseline	Model 2 - Resources	Model 3 - Capabilities	Model 4 – Full model	Model 5 - Baseline	Model 6 - Resources	Model 7 - Capabilities	Model 8 – Full model
Low centrality	**0.405 (4.59)*** **	-0.643 (-1.08)	0.304 (3.20)***	-0.878 (-1.47)	**0.344 (4.16)*** **	-0.739 (-1.32)	0.242 (2.49)**	-0.476 (-0.82)
High centrality	**1.280 (11.30)*** **	-1.701 (-2.78)***	1.326 (9.98)***	-1.962 (-2.79)***	**0.976 (8.99)*** **	-1.865 (-3.31)***	0.679 (4.82)***	-1.644 (-2.85)***
Size	**0.854 (21.42)*** **	0.540 (6.17)***	0.823 (19.47)***	0.533 (6.18)***	**0.759 (21.27)*** **	0.440 (5.28)***	**0.766 (21.70)*** **	0.501 (5.60)***
External funding	**0.019 (6.00)*** **	**0.017 (5.42)*** **	**0.018 (5.69)*** **	**0.017 (5.38)*** **	**0.014 (4.99)*** **	**0.012 (4.53)*** **	**0.014 (4.91)*** **	**0.012 (4.51)*** **
Research orientation	**1.288 (3.53)*** **	**1.402 (4.22)*** **	**1.591 (4.17)*** **	**1.353 (3.81)*** **	**0.635 (2.07)** **	**0.777 (2.74)*** **	**0.569 (1.87)* **	**0.724 (2.53)** **
Sci. reputation	**8.023 (1.85)* **	**9.708 (2.23)** **	-15.887 (-1.58)	-17.458 (-1.77)*				
Productivity					**0.574 (10.15)*** **	**0.561 (10.30)*** **	0.063 (0.36)	0.242 (1.35)
Social sci. and humanities	-0.379 (-5.23)***	-0.433 (-6.04)***	-0.393 (-5.43)***	-0.433 (-6.08)***	-0.315 (-4.64)***	-0.362 (-5.41)***	-0.315 (-4.69)***	-0.357 (-5.35)***
Life sciences	-0.195 (-1.53)	-0.309 (-2.46)**	-0.208 (-1.65)*	-0.318 (-2.54)**	-0.269 (-2.26)**	-0.368 (-3.16)***	-0.276 (-2.35)**	-0.358 (-3.09)***
University	0.670 (7.61)***	0.684 (7.92)***	0.702 (7.98)***	0.711 (8.23)***	0.362 (4.17)***	0.376 (4.42)***	0.422 (4.71)***	0.413 (4.69)***
HERD	-0.002 (-2.28)**	-0.002 (-2.30)**	-0.002 (-2.20)**	-0.001 (-2.18)**	-0.002 (-2.20)**	-0.002 (-2.26)**	-0.002 (-2.20)**	-0.002 (-2.27)**
Associated country	-0.151 (-0.98)	-0.202 (-1.35)	-0.139 (-0.91)	-0.166 (-1.10)	-0.222 (-1.59)	-0.264 (-1.94)*	-0.149 (-1.05)	-0.217 (-1.57)
EU13	-1.273 (-8.35)***	-1.228 (-8.18)***	-1.263 (-8.40)***	-1.213 (-8.14)***	-0.964 (-6.77)***	-0.933 (-6.67)***	-0.951 (-6.75)***	-0.932 (-6.70)***
Sci. reputation * Low centrality			**33.244 (2.98)*** **	**33.128 (3.01)*** **				
Sci. reputation * High centrality			0.800 (0.06)	**32.044 (1.97)** **				
Size * Low centrality		**0.197 (1.89)* **		**0.219 (2.12)** **		**0.206 (2.10)** **		0.146 (1.40)
Size * High centrality		**0.485 (4.80)*** **		**0.509 (4.66)*** **		**0.469 (4.99)*** **		**0.399 (3.99)*** **
Productivity * Low centrality							**0.445 (2.54)** **	0.280 (1.54)
Productivity * High centrality							**0.597 (3.34)*** **	**0.371 (1.99)** **
Log likelihood	-3198.7	-3185.2	-3191.6	-3180.6	-3155.7	-3140.7	-3149.8	-3142.9

Note: Coefficient with z-scores in parentheses. Significance levels: *****1%. **5%, *10%. A constant is included in all regressions, together with country dummies. 'No centrality' as reference category. LR-test of alpha in all models: p<0.001. Vuong test of ZINB vs. standard negative binomial in all models: p<0.001. Observations = 1 038

Table 6 Propensity to participate in H2020. Dependent variable: participation (count); model: negative binomial regression

	Model 1 - Baseline	Model 2 - Resources	Model 3 - Capabilities	Model 4 – Full model	Model 5 - Baseline	Model 6 - Resources	Model 7 - Capabilities	Model 8 – Full model
Low centrality	0.169 (0.99)	-1.335 (-1.07)	-0.016 (-0.08)	-1.851 (-1.46)	0.109 (0.66)	-1.911 (-1.57)	0.065 (0.31)	-1.711 (-1.39)
High centrality	**1.212 (6.61)*** **	-2.488 (-2.20)**	1.136 (5.21)***	-3.175 (-2.68)***	**0.879 (4.90)*** **	-2.7151 (-2.50)**	0.551 (2.31)**	-2.754 (-2.51)**
Size	**0.995 (17.87)*** **	0.464 (2.47)**	0.981 (16.30)***	0.426 (2.32)**	**0.915 (20.64)*** **	0.367 (2.02)**	**0.909** (20.46)***	**0.390** (2.07)**
External funding	**0.022 (6.15)*** **	**0.020 (5.72)*** **	**0.022 (6.08)*** **	**0.020 (5.80)*** **	**0.016 (5.07)*** **	**0.015 (4.72)*** **	**0.015 (4.97)*** **	**0.014 (4.66)*** **
Research orientation	**1.734 (4.25)*** **	**1.758 (4.53)*** **	**1.826 (4.33)*** **	**1.630 (4.00)*** **	**0.943 (2.86)*** **	**1.006 (3.09)*** **	**0.883 (2.67)*** **	**0.944 (2.90)*** **
Sci. reputation	2.647(0.29)	5.146 (0.62)	-36.497 (-1.29)	-37.848 (-1.52)				
Productivity					**0.686 (9.12)*** **	**0.671 (8.93)*** **	0.256 (0.80)	0.474 (1.49)
Social sci. and humanities	-0.537 (-5.91)***	-0.562 (-6.22)***	-0.533 (-5.87)***	-0.562 (-6.24)***	-0.479 (-5.83)***	-0.499 (-6.08)***	-0.474 (-5.80)***	-0.494 (-6.05)***
Life sciences	-0.269 (-1.54)	-0.320 (-1.85)*	-0.244 (-1.39)	-0.337 (-1.92)*	-0.410 (-2.56)***	-0.442 (-2.77)***	-0.407 (-2.54)**	-0.438 (-2.75)***
University	0.742 (5.26)***	0.767 (5.53)***	0.740 (5.29)***	0.778 (5.62)***	0.228 (1.58)	0.280 (1.95)*	0.357 (2.30)**	0.383 (2.50)**
HERD	-0.003 (-2.46)**	-0.003 (-2.54)**	-0.003 (-2.45)**	-0.002 (-2.42)***	-0.002 (-2.41)**	-0.002 (-2.45)**	-0.002 (-2.39)**	-0.002 (-2.46)**
Associated country	-0.253 (-1.19)	-0.300 (-1.44)	-0.248 (-1.17)	-0.287 (-1.37)	-0.236 (-1.28)	-0.268 (-1.46)	-0.182 (-0.97)	-0.223 (-1.20)
EU13	-1.502 (-7.72)***	-1.474 (-7.54)***	-1.504 (-7.70)***	-1.446 (-7.36)***	-1.105 (-6.02)***	-1.091 (-5.91)***	-1.089 (-5.97)***	-1.078 (-5.88)***
Sci. reputation * Low centrality			**55.328 (1.85)* **	**50.001 (1.86)* **				
Sci. reputation * High centrality			31.460 (1.01)	**55.029 (1.91)* **				
Size * Low centrality		0.285 (1.32)		0.344 (1.59)		**0.369 (1.75)* **		0.341 (1.58)
Size * High centrality		**0.625 (3.20)*** **		**0.703 (3.54)*** **		**0.612 (3.26)*** **		**0.581 (2.99)*** **
Productivity * Low centrality							0.246 (0.75)	0.019 (0.06)
Productivity * High centrality							0.502 (1.55)	0.264 (0.82)
Pseudo R^2	0.26	0.26	0.26	0.27	0.28	0.28	0.28	0.28
Log likelihood	-1579.6	-1571.9	-1576.9	-1569.2	-1541.9	-1535.5	-1539.5	-1533.9

Note: Coefficient is reported with z-score in parentheses. Significance levels: *****1%, **5%, *10%. A constant is included in all regressions, together with country dummies. 'No centrality' as reference category. LR-test of alpha in all models: $p<0.001$. Observations = 699

At step 1 (Table 5), size, or the number of researchers, moderates the effect of network centrality in almost all regressions, except for the group with low centrality in the final model (model 8). The coefficients are by far the strongest for interactions between size and high centrality. Similar results appear with the estimates at the second step (Table 6), where the interactions emerge as significant and strong, although non-significant for the group with low centrality (except in model 6). The comparative advantage generated by these interactions may achieve special influence in a demanding FP activity where ample resources and a broad contact network are essential. Coordinating FP projects is a resource-intensive task, requiring multiple researchers, administrative support, and not least a broad network of potential partners that can be handpicked. Moreover, a coordinator must be an attractive partner to other peers as well. Because similar HEIs will seek to maximize their chances for funding, they will tend to connect with others who are similar or more connected than they themselves are. Table 4 shows that 81 per cent of the HEIs holding the most central network positions are granted at least one role as a coordinator, compared to 19 per cent of the HEIs characterized by less centrality.

Continued success in the competition for H2020 participation is supported by a feedback loop. From increased funding follows mutual reinforcement of size and network, in addition to various other advantages. More funding enables organizational growth, with more employees, in turn facilitating a stronger network position. As both affect participation, the feedback loop continues. Conversely, in the absence of success, this feedback loop will serve to distance others from opportunities to participate.

Two specific indicators – *scientific reputation* and *productivity* – characterize certain HEI capabilities. HEIs with greater scientific capabilities will be more experienced and competent to play an active role in collaborative EU FP projects. Although this is important, we have argued, under hypothesis 3, that there is also a symbolic value associated with greater capabilities, which, together with an influential network position, will greatly affect participation in collaborative FP projects.

Turning to the results for the first step, application, we see from Table 5 that both indicators affect applications, positively and significantly (models 1 and 5). However, when interacting these with network centrality, we observe for productivity in the full model (8) that there is a significant interaction only with the group holding high centrality. There is significant interaction for the group with low centrality as well (model 7), but the significance is lost when regressed in the full model. By contrast, reputation is significant for both low and high centrality (model 4). The coefficients are strong, with the interaction for low centrality being the strongest. Other institutions and organizations will regard these HEIs as highly attractive collaborative partners, because of their strong research capabilities combined with an influential network position. The symbolic effect ensures that such HEIs are seen as particularly attractive – in effect, securing those already well situated with more.

Turning to the results at the second step in Table 6, we observe that productivity is still a significant factor affecting participations (model 5). However, there is no significant interaction effect together with network centrality, although the coefficients are positive (models 7 and 8). Reputation is non-significant as a single variable in the baseline (model 1). Nevertheless, when interacted with network centrality, similar results emerge as in step one. This shows a significant interaction (at 10 per cent level) together with low centrality (in models 3 and 4), and with high centrality in the full model (model 4).Whereas productivity characterizes scholarly output as such, reputation symbolizes peer-recognition of the output, and is likely to be more valued when selecting a partner. For the HEIs it secures similar or even more highly reputed partners, simultaneously improving their network position. When the European Commission is to decide which projects to fund, proposals involving researchers holding strong scientific reputation combined with experience from past projects would seem to be safe bets. However, evaluators of the Commission might be blinded by these characteristics, so that qualitatively better or more innovative proposals from less-known newcomers get rejected in favour of better-known consortiums – in much the same way as peer recognition at the individual level has been shown to influence the allocation of funding (see Viner et al., 2004).

5. Conclusions

This study set out to investigate whether higher education institutions (HEIs) gain cumulative advantages from EU FP participation, and if this leads to proposals being approved for funding because of the dominant role of these HEIs in networks. We hypothesized that HEIs that already hold influential positions in EU FP networks would further increase their chances of successful applications through the moderating effect of resources and capabilities at the organizational level. Through mutual reinforcement, these advantages would strengthen the disproportionate allocation of EU FP funding, through the 'Matthew Effect'.

Results show that, first (H1), a higher level of network centrality (influential position in collaborative EU FP networks) has a strong positive effect on the number of H2020 applications an HEI submits and gets approved. This supports our assumption that already well-established nodes in a network (HEIs with many influential connections) continue to lead and dominate the networks participating in EU FP projects. Secondly (H2), the number of researchers (size) significantly moderates the effect a stronger network has on the propensity to apply and participate. The interaction effect is by far strongest together with HEIs holding the most influential networks: indeed, these HEIs are responsible for coordinating the majority of H2020 projects. Since this is a task that requires strong networks as well as considerable resources, it indicates why the interaction effect is strongest, and significant, for this group. Finally (H3), an increased level of capabilities correlates significantly with the propensity to apply and gain funding. High scientific productivity, combined with an influential network position, significantly affects the propensity to apply, although not necessarily to succeed in getting H2020 funding. Further, scientific reputation correlates significantly with the propensity to apply but not to be accepted for funding. However, when interacted with network centrality, there is a significant moderating effect on both outcomes. This indicates that this capability is central in reinforcing the effect network position has, on applications, and on grant funding.

The Matthew effect has been documented in several fields, including in scientific practice by Merton (1988) and others (Viner et al., 2004). Our results suggest that the participation of European HEIs in H2020 is in no way unaffected by this process. It is difficult to say whether this has led to non-meritocratic allocation of funding, as we lack detailed insights into the decisions taken by the Commission. However, it is clear that grant funding is strongly affected by the position an institution holds in a network – and conversely, a less influential position, combined with less resources and capabilities, reduce an HEI's chances for submitting an application and getting it approved by the Commission.

Merton (1988, p. 617) asked: '[…] why have not Harvard, rich in years – 350 of them – and in much else, and Columbia […] garnered just about *all* the American Nobel laureates rather than a "mere" third of them within five years after the prize?' The same applies to EU FP participation. Why have not Oxford, Cambridge, and KU Leuven taken complete control of all funding? The answer lies in *countervailing processes* (Merton, 1988), which close off the seemingly endless accumulation of advantages. Participation is regulated and limited by several factors – some natural, others induced by policy. For example, there might simply not be enough researchers at the institution, or that funding from other sources and teaching activities requires rerouting of attention and resources. Debates on how to remedy the low participation among research institutions from EU 13 states have concerned policies aimed at halting the accumulation of advantages and sustained oligopoly. If EU 13 participation is low because these institutions lack the requisite competence, then policy-makers will need to take action at the national level, perhaps with increased support from the EU's structural funds. However, if this is due to closed clubs which limit the possibilities for institutions with poor networks, then other measures are called for. Indeed, the EC programme 'Spreading excellence and widening participation' in H2020 aims at mobilizing and helping qualifying research institutions from poorly-performing countries. If applied correctly, such schemes may serve to counteract the accumulation of advantages. However, judging from current debates (European Commission, 2016, 2017), and the finding that EU 13 HEIs in our sample have on average lower capability levels, perhaps a combination would be advisable.

The results have several policy implications. The first concerns the EU Commission. Along with existing schemes for incentivizing EU 13 researchers, it should assess the need for other measures aimed at restricting closed clubs, especially if proposal quality is compromised. Relevant measures might include networking activities to motivate collaboration between newcomers and established participants, for instance through mobility grants or a 'marketplace' where project partners could be recruited. Second, at the national level, in order to strengthen the capacities and networks of domestic research organizations, policy-makers could allocate more funding to collaborative research activities through national research councils – taking care not to crowd out EU research. Finally, HEIs themselves should work to gain access to well-connected and established EU FP consortiums. Their strategic focus should also be directed towards competing for external sources of funding – not necessarily EU funding, but funding that can serve to boost capacities and networks through collaboration.

H2020 has been running for only a few years now. Future empirical investigations should exploit the possibilities provided by longitudinal data and assess the long-term consequences of cumulative advantage on participation. Further, the EU Commission currently registers application data with reference only to the host institution, not the research group or at the individual level. Should this practice change, future studies could provide valuable insights into the participation process, and the implications for policy.

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