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RESEARCH ARTICLE

Understanding collaboration patterns on funded research projects: A network analysis

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Abstract
This paper provides an examination of inter-organizational collaboration in the UK research system. Data are collected on organizational collaboration on projects funded by four key UK research councils: Arts and Humanities Research Council, Economic and Social Research Council, Engineering and Physical Sciences Research Council, and Biotechnology and Biological Sciences Research Council. The organizational partnerships include both academic and nonacademic institutions. A collaboration network is created for each research council, and an exponential random graph model is applied to inform on the mechanisms underpinning collaborative tie formation on research council-funded projects. We find that in the sciences, collaborative patterns are much more hierarchical and concentrated in a small handful of actors compared to the social sciences and humanities projects. Institutions that are members of the elite Russell Group (a set of 24 high-ranking UK universities) are much more likely to be involved in collaborations across research councils.

Keywords: collaboration; knowledge exchange; ERGM; research council; UK

1. Introduction

Collaboration is central to research and the creation of new knowledge, as research work does not occur in a vacuum (Akbaritabar et al., 2018). Collaboration can occur at various levels, such as between individuals and between organizations (Kenekayoro et al., 2014). Collaboration between organizations involves academic institutions, along with partners from industry and government (Mascarenhas et al., 2018). Collaborative ties between organizations allow access to greater sources of funds, expertise, and equipment in the creation of new scientific knowledge. This paper aims to provide an examination of the factors underpinning the formation of inter-organizational collaboration ties on UK research council-funded projects. Universities are argued to be core knowledge producing entities and play a key role in the development of innovative output for industry and business (Fritsch & Slavtchev, 2007; Huggins et al., 2008; Roesler & Broekel, 2017; Smith & Bagchi-Sen, 2006). Universities have been identified as central to knowledge production (Etzkowitz & Leydesdorff, 2000) and act as engines for both regional and national development of innovation capabilities (Coenen, 2007; Sánchez-Barrioluengo et al., 2019; Yusuf, 2006).

Innovation activities are becoming increasingly open and networked (Hewitt-Dundas, 2012), resulting in dyadic partnerships between organizations to develop new knowledge and to exchange ideas. This gives rise to collaboration networks, where organizations are embedded in the collaborative system. The production of academic and scientific knowledge cannot be separated from the system, context, or network in which it is generated (Newell et al., 2001); therefore, network analysis is a useful analytical tool to understand the process of knowledge production. Network analysis is a widely utilized framework to understand collaborative partnerships at a variety of levels (Durugbo, 2016), including institutional and individual levels (Newman, 2001, 2004).

In the UK, the Research Excellence Framework, or REF, is the mechanism by which the government evaluates research in universities (Khazragui & Hudson, 2015). The REF is a performance-based funding system (Watermeyer, 2016), as it acts as a mechanism for the distribution of quality-related funding by the government. Therefore, the REF often drives organizational level strategy regarding funding bids, collaborative partnerships, and target journal publication. There have been two REF exercises, one in 2014 and another in 2021. The results of REF 2021 were released in May 2022 and have been the subject of much discussion at the institution and national level. The REF 2021 results highlighted that the "golden triangle" of world's leading universities in the South of England (Imperial College London, University of Cambridge, and University of Oxford) remains amongst the highest ranked institutions (Financial Times, 2022).

After a number of government reviews, such as the Lambert Review (Lambert, 2003), there was an increased pressure for UK research councils to improve levels of impact of funded projects (Lyall et al., 2015). Therefore, when applying for Research Council UK funding, organizations and individuals must demonstrate impact, often in the form of economic, cultural, and societal benefits in their research (Watermeyer, 2016). As a result, public engagement activities, such as industry or community partnerships, are often built into research bids in order to demonstrate the reach and significance (beyond academia) of their research (Chowdhury et al., 2016; Copley, 2018; Watermeyer, 2014). Given the importance of collaborative arrangements in the distribution of public money, and the subsequent impact on national innovative performance and knowledge creation, understanding the mechanisms underpinning the formation of collaborative ties has profound policy implications (Chompalov et al., 2002).

The collaboration between universities and industry is often perceived as a vehicle for knowledge exchange and innovation creation (Ankrah & Omar, 2015). Although partnering with industry collaborators is encouraged by UK research councils, some argue that the impact of these collaborators does not always yield a positive outcome. Many argue that industry participation can result in the suppression of the dissemination of preliminary results, limiting the practice of open science and academic independence (Bölling & Eriksson, 2016; Czarnitzki et al., 2015; Nelson, 2004; Partha & David, 1994). Banal-Estañol et al. (2015) note in their examination of Engineering and Physical Sciences Research Council (EPSRC)-funded projects in top UK universities that academics benefit most when industry is involved in some projects, but not all. Collaboration is vital for universities, as it supports the development of research capacity (Aldieri et al., 2018; Kodama et al., 2013) and increasing the general productivity of a university (Lissoni et al., 2011).

The research to date has tended to focus on explaining university—industry partnerships, given the implications for impact and reaching relevant beneficiaries. However, there has been less attention given to university—university collaborative ties. Yet given the role that universities play in national innovation systems, and their role in research council-funded projects, it is important to understand the factors that give rise to these partnerships, in addition to university-industry ties. Projects funded by research councils rarely involve only one university, rather involve many university stakeholders. This paper examines collaborations between organizations on research-funded projects involving several partnership ties, including university–industry and university–university ties.

As noted by Subramanyam (1983), collaboration within scientific research may differ vastly from one discipline to another. This paper intends to provide a comparative analysis, investigating whether inter-organizational collaboration differs amongst disciplines. This paper contributes to the extant literature that attempts to understand the formation of university–industry ties, along with contributing to better understanding what determines university–university ties (which has received less attention). There is a rich and extensive literature devoted to understanding collaborative inter-organizational network ties (Lomi et al., 2014; Lomi & Pattison, 2006); this paper aims to contribute to the inter-organizational literature by taking an inter-organizational perspective to understand the formation of collaborative ties arising from arrangements on UK research council-funded projects. Additionally, much of the existing work devoted to understanding the scientific process itself, or the Science of Science (Fortunato et al., 2018), focused on single research disciplines; this work extends the analysis to various research councils covering a range of disciplines, representing a contribution to the Science of Science literature. Understanding the formation and patterns of collaboration also is of importance to key funding bodies in the UK and has the potential to shape funding allocation decisions.

This paper is structured as follows: the next section provides an overview of the relevant theory and literature, along with the research questions that this be addressed by this paper. The third section will provide an overview of the data and methodological approach used to address these research questions. This will be followed by a results section that will provide both the descriptive analysis and modeling results. The paper will conclude with a discussion of the results, along with final remarks and directions for future research.

2. Theory and literature

This section will provide an overview of the theory and literature for three key areas, more specifically, inter-organizational networks, geography and collaboration, and the role of elite status in collaboration networks.

2.1. Inter-organizational networks

There is an extensive literature on inter-organizational networks (Bergenholtz & Waldstrøm, 2011), often focusing on what gives rise to these networks and how they shape organizational behavior or performance, especially innovation performance (Gulati & Gargiulo, 1999; Powell et al., 1996).

Inter-organizational networks have been utilized in investigating patterns of innovation, more specifically how these networks promote and facilitate innovation activities. University–industry collaborations have been recognized as key for the development of innovation and economic activity (Bishop et al., 2011; Skute et al., 2019); therefore, there has been an increase of empirical work examining the collaborative arrangements and relations between academic institutions and industry actors (Bruneel et al., 2010; He et al., 2021; Isaeva et al., 2021; Olmos-Peñuela et al., 2014; Scandura, 2016; Tian et al., 2021). These works often consider the benefits of university collaboration to industry partners, along with the impact of geography and regional patterns on formation of university–industry ties, where these will often vary depending on the content of the tie.

This paper aims to understand the formation of inter-organizational collaboration arising from UK research council-funded projects and seeks to address the following research question, concerning network effects (or network factors):

RQ1: What are the factors underpinning the formation of inter-organization collaborative ties for UK research council-funded projects? How do these factors differ from each other when the funding bodies are different research councils?

2.2. Geography and collaboration

Geography often plays a role in the formation of collaborative ties on research projects, where much research crosses national borders (Bergé, 2017; Cronin et al., 2003; Gui et al., 2018). Others note that proximity more generally (which includes geographic proximity) substantially shapes and impacts collaboration, including inter-organizational collaboration (Knoben & Oerlemans, 2006). However, the extent that geography impacts collaboration, more specifically interactive learning and innovation, is extensively debated (Ben Letaifa & Rabeau, 2013; De Fuentes & Dutrénit, 2016; Ter Wal, 2014). Many note that geographic proximity has the potential to increase cooperation amongst collaborators (Katz, 1994). Much of the extant literature examining collaborative patterns notes the positive impact of geographic proximity on productivity (Adams et al., 2005; Wang et al., 2005). Broström (2010) argues that geographic proximity is very important for short-term, applied projects, where high levels of trust and cooperation are required, yet it is less important for long-term projects, where it is easier to work across large distances. In their study of EPSRC-funded research projects, D'Este & Iammarino (2010) identified an inverted U-shaped relationship between academic research quality and the collaboration distance between university and industry partners. They found that university departments with high level of research quality were more likely to attract distant partners, up to a certain point.

Boschma (2005) notes in his seminal work on proximity and innovation that geographic proximity alone does not encourage collaborative learning to occur, rather it facilitates interactive learning by strengthening other dimensions of proximity. There are many forms of proximity, including cognitive, organizational, social, institutional, and geographic proximity. Geographic proximity is the most well known and considers the impact of distance on collaborative ties. Cognitive proximity refers to organizations sharing, or having a close cognitive base, which is sufficient for the organizations to communicate, understand, and process any new knowledge creation. Organizational proximity refers to interdependencies between organizations, often in the form of existing relationships (economic, organizational relationships), which reduces the risk of uncertainty and opportunism. Social proximity consists of the socially embedded relations between actors at the micro level (within the organization), which promote trust. Institutional proximity is when organizations have a similar institutional environment, in terms of norms and values of conduct. Institutional proximity can result in a stable environment for interactive learning to occur effectively. Although these various forms of proximity are seen to have a positive impact on collaboration, Boschma (2005) does highlight potential negative impacts. More specifically, that high levels of proximity can result in the issue of lock-in, which can cause a lack of openness and flexibility.

Many have extended and examined the impact of proximity in further detail (Broekel & Boschma, 2012; Ponds et al., 2007). Gertler (2003) notes that proximity, more specifically geographic proximity, will impact tacit knowledge in a different way compared with codified knowledge flows. Gertler (2003) further highlights that tacit knowledge is a vital element of learning and innovative activity, yet it often poses challenges given it often cannot be easily codified or articulated (especially over long distances). Alpaydın & Fitjar (2021) find that when an organization is making the decision to collaborate with a university, all five types of proximity play a key role, where the importance of a particular type of proximity depends on the context of the interaction, whereas D'Este et al. (2013) find that geographic proximity and organizational proximity are perhaps the most important for the formation of university–industry collaborative ties, yet geographic proximity remains more important than organizational proximity.

Several studies have noted the importance of geographic proximity for establishing and maintaining university–industry relations in innovation networks (Laursen et al., 2008; Ponds et al., 2007; Runiewicz-Wardyn, 2022). This has been found to be of particular importance in the life sciences, where numerous empirical studies have attributed the success of industry–university relationship to geographic proximity (these include the works of Feldman, 1999; Majava et al., 2016).

When examining collaboration networks, it is expected that collaborative relations and activity are more likely to originate from, or occur within, regions where there are more firms, as there is simply more opportunity (Huggins & Prokop, 2017). However, when considering universities, regions often do not house an extensive number of universities, and Broekel & Hartog (2013a)

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suggest that this results in cross-regional collaborative ties between universities to occur. When considering university and firm collaborations, the impact of geographic distance can vary based on firm size. For example, Helmers & Rogers (2015) find that smaller firms benefit more from localized partnerships with universities. Larger firms are not evenly distributed across the country, and there are regions with a university present that are not home to large multinational corporations. Kindt et al. (2022) note that when there are fewer multinational corporations in the region, universities will take a more central role as facilitators of knowledge exchange, often working with Small and Medium Enterprises.

Given that scientific activity is reliant on collaboration, especially between academic institutions, there have been a number of policy initiatives to encourage and promote collaboration across national borders. Amongst them is the Horizon 2020 program, which is an EU initiative that aims to act as a policy tool for collaborative activity across the European Research Area (Hoekman & Frenken, 2013), that are not dampened by geographic distance or borders (Bergé, 2017).

Geographic proximity is noted to have a substantial impact in the formation of inter-organizational ties, including university–industry relations; therefore, in this study we expect that organizations (including academic institutions) that are closer to each other are more likely to collaborate.

Given the importance of proximity, and more specifically geographic proximity on collaboration (and to test our expectations), this paper seeks to address the following research question:

RQ2: What is the role of geography in the formation of collaborative ties? Are collaborative ties more likely to be London centric?

2.3. Elite status and networks

Powell et al. (2005) provide an examination of inter-organizational collaboration in the life sciences, where they find that network expansion is a result of herdlike behavior, with network partners selected by matching with the dominant choices of others, exhibiting a follow the trend pattern of network expansion. This pattern of behavior can encourage the practice of selecting prestigious organizational partners that are often the dominant choice of others in the selection of collaborative partners.

Maghssudipour et al. (2021) consider the role of status in inter-firm knowledge transfer networks in an industrial cluster. They found that status was the key driver of assortative matching in the formation of knowledge transfer ties. More specifically, they found that low-status firms were not part of the more meaningful collaborations, or "collaborative circles," rather high-status firms were likely to collaborate with other high-status firms. These findings are in line with the work of Balland et al. (2016); they find that status drives the formation of business knowledge networks. Furthermore, they find that proximity is particularly important for technical knowledge networks.

In the UK university context, status often plays a role, as universities exhibit heterogeneous characteristics in terms of their background, history, resources, and even how they approach external opportunities (Chang et al., 2016; Charles et al., 2014; Huggins et al., 2012). University characteristics are often reflected in the "mission groups" that universities belong to. There are a number of mission groups that a university can be a member of in the UK; these include the prestigious Russell Group, Million+, and University Alliance (Furey et al., 2014). The Million+ group describes itself as a university think tank and the University Alliance is a group of universities that focus on practice. The Russell Group is a set of elite UK universities with a focus on research-intensive activities and receives the largest share of government funding (O'Connell, 2015). Therefore, this paper aims to examine the roles of these Russell Group institutions in the collaboration network, and how their role differs between disciplines. The links between nonacademic organizations and universities differ by mission group; the Russell Group is more likely to partner with larger firms and non-commercial organizations, whereas the other groups have a broad range of partnerships, with lower levels of specialization (Sánchez-Barrioluengo et al., 2019). This paper aims to examine where the factors for forming collaborative ties differ between research-intensive universities, compared to other institutions. Russell Group membership has frequently been utilized as a measure of proxy for elite universities in the extant literature examining university cooperation for innovation purposes (Abreu et al., 2016; Degl'Innocenti et al., 2019; Guerrero et al., 2015; Hewitt-Dundas, 2013; Pickernell et al., 2019; Sánchez-Barrioluengo & Benneworth, 2019). For instance, Guerrero et al. (2015) use Russell Group membership as a definition of entrepreneurial universities.

Cruz-Castro et al. (2016) developed a typology to understand how Spanish universities react to European funding opportunities. The typology is based on two dimensions: firstly, the commitment (of the university along with individual academics) to act and respond to research oriented and research excellence values held by funding bodies, and secondly, their organizational capabilities. The four typologies are Committed, Operational, Hesitant, and Neglected. They find that a university with a Committed response is one that is research focused with links to international funding, whereas they note that universities with a Neglected response are typically those with low levels of research specialization yet have a strong teaching orientation.

Given the importance of status in the context of the UK research ecosystem, and in inter-organizational networks more generally, we address the following research question in this paper:

RQ3: Are elite universities, those belonging to the Russell Group, more active in collaboration on UK research council-funded projects? Are these higher capacity universities more likely to have collaborative ties? Do Russell Group members collaborate with each other?

When considering the typology developed by Cruz-Castro et al. (2016), and their findings regarding the activities of Committed organizational responses, we expect in this study, higher status universities will be more active in the collaboration networks, as they are more likely to have a committed response to research funding opportunities.

3. Data and methods

The data are extracted programmatically from the Gateway to Research website. This dataset provides detailed information on UK research council-funded projects, including funded value, collaborating organizations, individuals, and project outcomes. This dataset has been used in extant literature to tackle a variety of research questions, including understanding collaboration and knowledge exchange patterns (Sarabi & Smith, 2021; Williams et al., 2017). In this paper, the Gateway to Research dataset is utilized to construct a set of inter-organizational collaboration networks. Gateway to Research provides details on a number of different types of projects that are funded by research councils, such as studentships, research grants, and knowledge exchange programs. In this study, we focus only on research grants, as these are often the largest (in terms of funding allocated) and typically involve a range of collaborative partners. Also, by focusing on one type of award, it allows for a more reliable comparison between the different research councils.

There are several UK research councils that fund projects in various disciplines. In this paper, four research councils are examined, representing four key disciplines. These are the Arts and Humanities Research Council (AHRC), the Economic and Social Research Council (ESRC), the EPSRC, and the Biotechnology and Biological Sciences Research Council (BBSRC). The EPSRC and BBSRC are the two largest scientific research councils by the number of projects they fund. It is important to note that whilst the UK research councils are a major source of funding for UK universities, there are other funding sources available to UK universities, such as those provided by the EU. However, this study focuses on the four UK research council-funded projects and the collaboration networks that arise from these projects.

The AHRC funds research projects belonging to a range of disciplines in the arts and humanities, including history, archaeology, philosophy, and languages. They also fund more

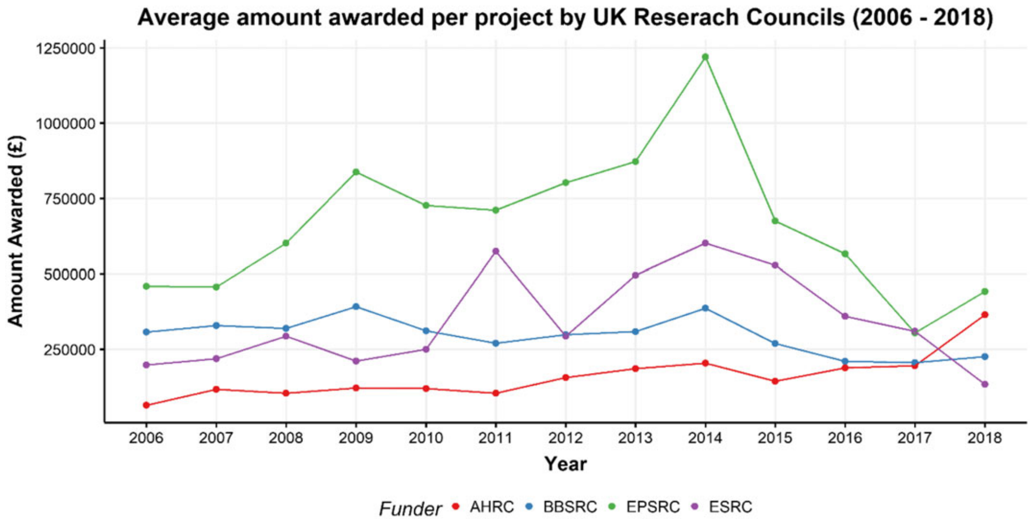

Figure 1. Average amount awarded per project by each UK research councils.

contemporary research such as the application, design, and effectiveness of digital content. The subjects funded by the ESRC overlap somewhat with the AHRC, yet they have more of a focus on social and economics questions, and subsequent policy impacts and outcomes. The EPSRC focuses on several disciplines in the sciences, such as healthcare technologies, structural engineering, manufacturing, mathematics, advanced materials, and chemistry. They are one of the largest public funders in the UK for research related to innovation activities (Owen & Goldberg, 2010). In more recent years, the EPSRC has funded a number of projects linked to industrial decarbonization. This research council emphasizes a focus on international engagement. The BBSRC state in their strategic vision statement that they aim to focus on creating environments for partnership with universities, research organizations, businesses, charities, and government to create the best possible environment for research and innovation to flourish. The discipline areas covered by the BBSRC include green energy, food security issues, industrial biotechnology, and pharmaceuticals. Much of the extant studies investigating the activities of UK research councils focuses on the ESRC and the EPSRC, with limited attention given to other councils, especially the AHRC and the BBSRC (Vick & Robertson, 2017); therefore, this paper contributes to the empirical analysis of these understudied research councils.

Universities can apply for a number of grants across all research councils, yet the success rate can vary. For instance, in the academic year 2015–16, UCL applied for 167 EPSRC research and innovation grants and fellowships, yet only 51 were awarded. Over the same period, the University of Leeds applied for 34 AHRC research grants and fellowships, yet less than half of these were awarded. Some universities have competitive internal procedures for larger grants, where expressions of interest for a grant application are put forward internally (often at a departmental level). These are then assessed by a panel and a smaller number are supported by the institution and these applications will then receive support and assistance in developing the final grant application. However, it must be noted that internal procedures for research council grant applications differ from university to university.

Figure 1 indicates the average amount awarded per project for each research council from 2006 to 2018. We observe that EPSRC, that is most closely associated with the hard sciences, provides higher levels of funding per project (although this has been decreasing since 2014). Perhaps reflecting that projects within engineering and associated areas often require expensive and specialized equipment. Although the BBSRC is also linked to the hard sciences, on average it awards

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Table 1. Russell Group universities

University of Birmingham	University of Edinburgh	University of Leeds	Newcastle University
University of Bristol	University of Exeter	University of Liverpool	University of Nottingham
University of Cambridge	University of Glasgow	London School of Economics & Political Science (LSE)	Queen Mary, University of London
Cardiff University	Imperial College London	University of Manchester	University of Oxford
Durham University	King's College London	Queen's University Belfast	University of Sheffield
University of Southampton	University College London (UCL)	University of Warwick	University of York

less funding per project when compared to the EPSRC and is somewhat comparable to projects funded by the ESRC. The AHRC awards the least per project and is perhaps the research council most associated with the social sciences. However, there has been a steady increase in the average amount awarded per project.

The Russell Group is a set of universities that claim to have higher research activities. Prior to the main analysis undertaken by this paper, we provide an exploratory analysis of features of Russell Group universities, compared to non-Russell Group universities drawing on data from the Higher Education Statistics Agency. The data include university income, revenues generated from intellectual property, number of academic staff employed, number of attendees at community engagement events, income from regeneration programs, and value of research contracts with nonacademic partners. Table 1 indicates the members of the Russell Group; we observe a number of older institutions are included, such as the University of Oxford and the University of Cambridge. A further point to highlight when discussing the Russell Group is the geographic distribution. Out of these 24 universities, 5 are based in London, with a further 5 toward the south of England, with only 4 outside of England, and the remaining 10 in the midlands and north of England. Therefore, the Russell Group is England centric, and to some extent, London centric.

Figure 2 provides an overview of Russell Group universities, compared to the remaining UK universities that are not part of the group. It provides a boxplot of the various measures of capacity (taking the average for each institution over the period 2014/15 to 2017/18) for all higher education institutions in the UK.

This indicates that the Russell Group membership is not just a measure of elite in terms of reputation in the UK higher education system, but it is also a sign of increased capabilities, with higher levels of investment and capacity on research-related activities than non-Russell Group members (Pinar & Unlu, 2019). For instance, Russell Group members tend to have higher levels of income, increased returns from intellectual property, more valuable contracts with nonacademic institutions, and higher levels of academic staff. However, there are two notable areas where Russell Group members do not clearly outperform their non-group member counterparts: community engagement events and development programs.

Data from Gateway to Research are used to construct the collaboration network. The networks represent collaboration on projects that are active anytime during the period 2015–2018; 2015 is used as the starting point, as it is the first year following the 2014 REF. The REF is taken as the starting year, as it represents a key driver of university level strategy regarding research activity, more specifically, funding bids, collaborative partnerships, and journal publication. The nodes are organizations (including both academic and nonacademic institutions), and they are linked

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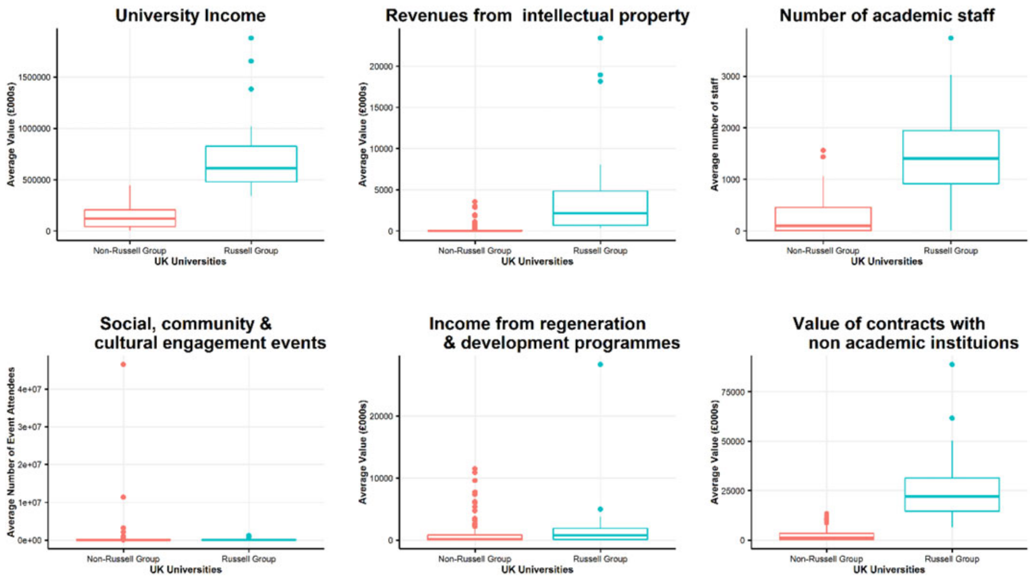

Figure 2. Boxplot of capacity indicates for UK HEIs.

if they have collaborated together on the same project; this approach has been utilized in previous research examining inter-organizational collaboration (Bellotti et al., 2016). The nonacademic institutions include firms, government organizations, NGOs, and other charities; these are both UK institutions and those based outside the UK. In the inter-organizational networks, the links are weighted by the number of research projects they have collaborated on together; these data are essentially a one-mode projection of two-mode affiliation data.

To understand patterns of collaboration, a sophisticated network model is applied, an exponential random graph model (ERGM). Network analysis is an established methodological approach to understand collaboration patterns (Broekel & Hartog, 2013b; Fan et al., 2017; Kyvik & Reymert, 2017) and the inter-organizational relations (Lomi & Pallotti, 2012). Hazir (2013) makes use of an ERGM to R&D collaboration arising from funding allocated as part of the EU's 7th Framework Program. Network analysis has been utilized in various forms in the extant literature to inform on collaborative patterns (Bellotti, 2012; Broekel et al., 2014; Sylvan Katz & Martin, 1997; Lissoni, 2010; Maggioni & Uberti, 2005), examining networks at the level of individuals, organizations, and even bibliometric data.

An ERGM is a network model that is parameterized in terms of local structural configurations (Lusher et al., 2013). ERGMs can test hypothesis at the very local level, where the model is able to identify micro configurations that represent a theoretical process, and then calculates whether this process is seen in the network more than a researcher would expect by chance. For example, a transitivity effect, which would capture the propensity for triadic closure. In the context of collaboration, if two actors share a collaborative partner, is it more likely that they would also become collaborative partners? The ERGM would allow us to test whether transitivity occurs in the network significantly more or less than by random chance (Robins et al., 2007). The ERGM takes the following form:

$$P\left(Y=y\right)=\frac{1}{k(\theta)}\exp\left(\sum\theta_Q z_Q\left(y\right)\right).$$

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where

Y is the observed network.
y is a network instance.
Q is all the network configuration types (the local structural configurations).
$z_Q(y)$ is the network statistic corresponding to configuration type Q.
θ_Q is the parameter corresponding to configuration type Q.
$k(\theta)$ is the normalizing constant to ensure that the above is a proper probability distribution.

ERGMs have been applied in a vast range of empirical settings (Kibanov et al., 2019), including knowledge exchange networks (Jiang & Chen, 2019) and co-authorship collaborations (Kronegger et al., 2012; McLevey et al., 2018). In this study, the ERGM is implemented using the ergm package in R (Hunter et al., 2008b), which is part of the statnet suite of packages for social network analysis (Handcock et al., 2008).

ERGMs are limited to binary relationships; therefore, a dichotomization process needs to be applied, as this is a weighted network, where the strength of the tie between organizations is the number of funded projects they collaborate on. Extant work has noted that applying dichotomization algorithms to networks that are one-mode projections of two-mode networks can provide additional challenges (Neal, 2014; Neal et al., 2021), in particular noting which co-occurrences are significant.

There are several dichotomization techniques and algorithms available (Baggio, 2019). The most straightforward is to simply ignore the edge weights and retain all the edges. However, this does not account for the heterogeneity of edge weights and is only useful when the density is low or there is little variation in the edge weights (which is not the case for these collaboration networks) (Thomas & Blitzstein, 2011). A further dichotomization technique is to apply a threshold, where the researcher takes a particular value (often an arbitrary value) and disregards all edges with weights less than this value (Borgatti & Quintane, 2018). Although this approach is popular, one difficulty that arises in its application is the selection of an appropriate threshold value, as a network with an uneven distribution of edge weights can increase the issues of arbitrariness and structural bias of the threshold approach (Neal, 2014). In addition to the threshold approaches, there are procedures available to assess an edge's significance and to use this as the basis for the edge reduction. Serrano et al. (2009) propose a more systematic approach to extract the key edges from a network, which they refer to as the network backbone. This is a filtering approach that retains the significantly heterogeneous links at specified significance level and disregards all other edges (considering them non-essential). This approach does not only preserve high value edges but also preserves low value edges that are important for maintaining the overall connectivity of the network. The multiscale backbone filtering procedure has become an established approach within social network analysis and network science, with applications in international trade (García-Pérez et al., 2016; Xing et al., 2021) and transport (Viljoen & Joubert, 2016) to name a few.

In this study, we extract the backbone of the network, making use of the approach outlined by Serrano et al. (2009), where we retain the significantly heterogeneous links at the 0.05 significance level. This approach (and significance level) helps retain key ties, whilst preserving the overall connectivity of the network.

In the specification of the ERGM, several network terms are specified, along with a set of actor covariates. The network terms that are specified include edges, a degree centralization parameter (geometrically weighted degree or GWDEGREE), and a clustering parameter (geometrically weighted edgewise shared partners). The edges parameter captures the baseline tendency for a collaborative tie to form in the network (it is analogous to the intercept in a regression model). The degree activity effect (also referred to as the GWDEGREE effect) allows to control for the distribution of collaborative ties in the network and test for centralization effects (Levy, 2016). A negative and significant effect would indicate that collaborative ties are concentrated in a small handful of actors, pointing toward a centralized network structure. This would suggest that there

Table 2. Lead organizations receiving the most funding from the research councils

AHRC	BBSRC	EPSRC	ESRC
University of Glasgow	University of Edinburgh	Imperial College London	University of Essex
University of Leeds	John Innes Centre	University College London	University College London
University of Oxford	University of Manchester	University of Manchester	LSE
University College London	The Pirbright Institute	University of Oxford	University of Edinburgh
University of Nottingham	University of Cambridge	University of Cambridge	University of Oxford
University of Manchester	Rothamsted Research	University of Southampton	University of Southampton
University of York	University of Nottingham	University of Bristol	University of Sheffield
Lancaster University	University College London	University of Nottingham	Cardiff University
University of Edinburgh	University of Oxford	University of Sheffield	University of Bristol
University of Cambridge	Imperial College London	University of Leeds	University of Manchester

is a tendency for preferential attachment or assortative mixing based on degree occurring in the network (Newman, 2002). In the case of inter-organizational networks, organizations with many ties tend to have more access to information about activities and partners, and therefore can better evaluate potential (and current) collaborative partners (Broekel & Bednarz, 2018; Polidoro et al., 2011), whereas a positive and significant effect would indicate that collaborative ties are spread out evenly throughout the network (Hunter, 2007). There is evidence of both disassortative and assortative mixing in inter-organizational networks, and differences are often due to inter-organizational differentiation and institutional arrangements (Amati et al., 2019).

The clustering parameter, geometrically weighted edgewise shared partners (gwesp), captures the mechanism of triadic closure in the network (Hunter, 2007). This term measures the number of triangles in the collaboration network, in consideration of the number of ties involved in multiple triads. Therefore, a positive and significant parameter provides evidence for triadic closure and clustering in the network (Broekel & Hartog, 2013b). Pallotti et al. (2013) suggest that in the context of inter-organizational collaborative ties, the presence of triads ties (and clustering more generally) can act as insurance against the disruption of knowledge and resource flows and can reduce uncertainty, as actors have access to multiple sources of information. The degree centralization parameter and the clustering parameter are included in the model specification to address the first research question posed by this paper. To examine whether degree centralization and clustering are key processes underpinning the formation of inter-organizational collaborative ties, and whether these patterns are the same across research councils.

The ERGM approach also allows for the specification of nodal attributes, to investigate the impact of actor properties on the formation of network ties. These include a node activity effect, which captures whether an actor in the network is more likely to establish collaborative ties in the network. The other is a nodal homophily effect, which captures whether actors with the same

Table 3. Descriptive network statistics

	AHRC	BBSRC	EPSRC	ESRC
Number of organizations	73	290	692	90
Density	0.0381	0.0304	0.0124	0.0727
Diameter	40	48	33	24
Average path length	3.3344	2.7902	2.847	2.4254
Degree assortativity	−0.2419	−0.2609	−0.3234	−0.3558

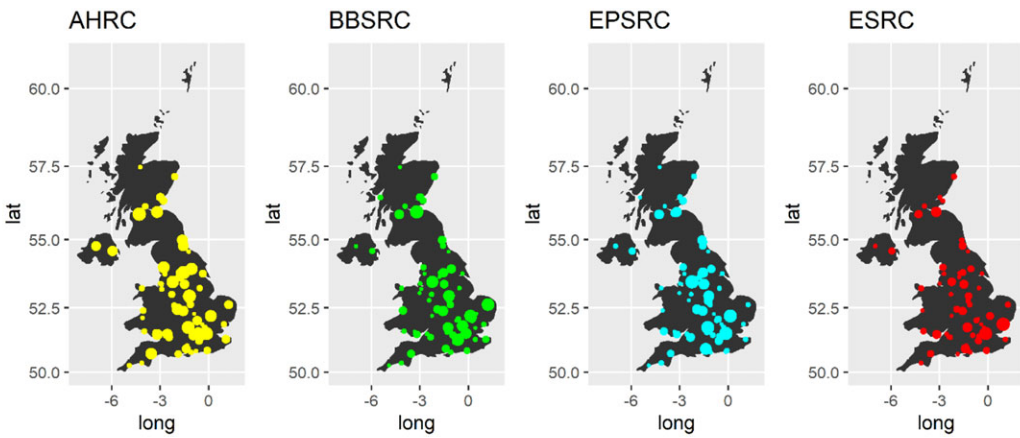

Figure 3. Map of funding levels to lead organizations.

nodal attribute are more likely to collaborate, compared to those with a different nodal attribute (McPherson et al., 2001).

Given the Russell Group is a set of self-proclaimed leading universities with a focus on research activities, we include two variables that account for whether an organization is a member of the group (or not). The first is the activity effect, which captures whether members of the Russell Group are more active in a network and are more likely to be involved in research council-funded projects. The second is a group homophily effect, this captures whether members of the Russell Group are more likely to collaborate with other leading universities that are members of this group. The use of the Russell Group parameters in the ERGM addresses the third research question posed by this paper, as they allow us to examine the activity of elite academic institutions in these various inter-organizational collaboration networks.

Additionally, a set of geography parameters are specified, capturing whether certain regions of the UK are more active, for instance are collaborative ties more likely if they involve London-based institutions? A region match term is also specified to examine whether collaborative ties are more likely to occur within the same region—are geographically proximate institutions more likely to collaborate? The regional groupings include London, the South of England (South West, South East, East of England), the Midlands (West Midlands and East Midlands), Northern England (North West, North East, and Yorkshire and Humber), Scotland, Wales, Northern Ireland, and outside the UK. The number of regional groupings has been condensed to allow for a more parsimonious modeling approach. The inclusion of these effects aids in addressing the second research question posed by this paper, more specifically to examine the role of geographic proximity in the formation of collaborative ties.

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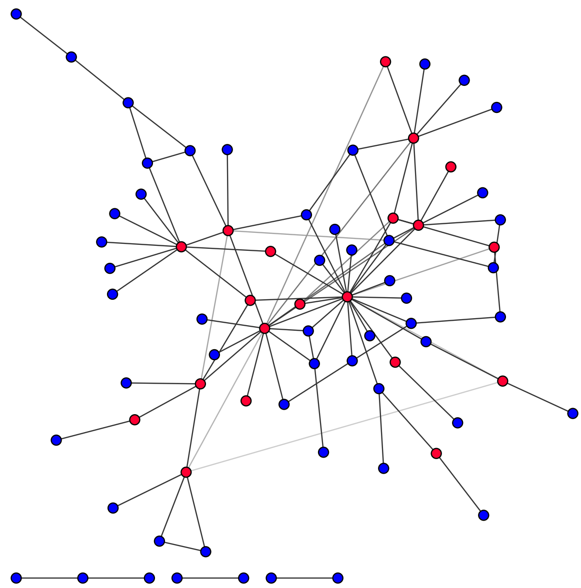

Figure 4. AHRC collaboration network.

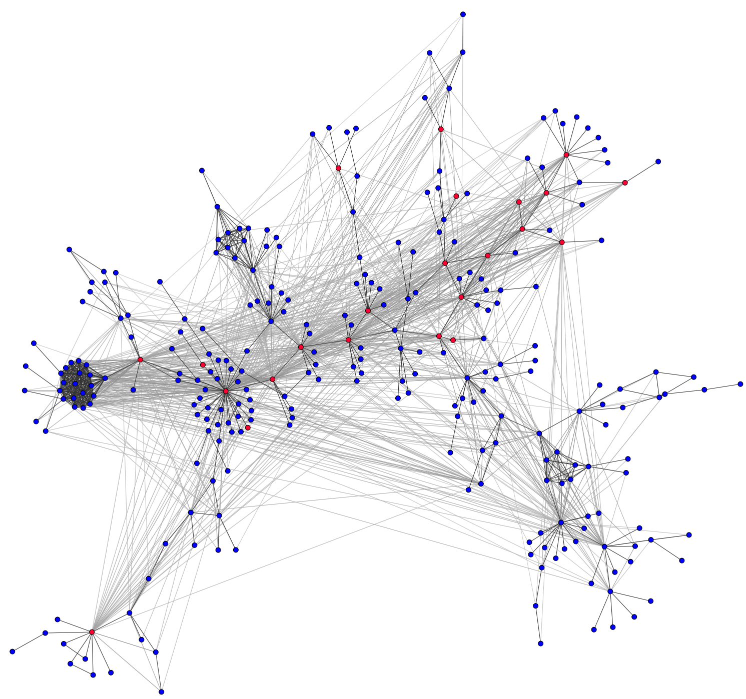

Figure 5. BBSRC collaboration network.

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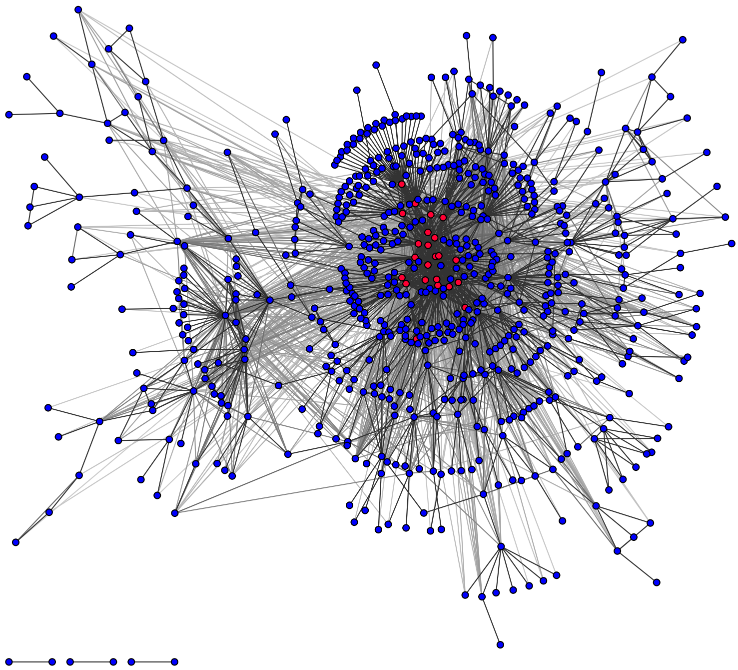

Figure 6. EPSRC collaboration network.

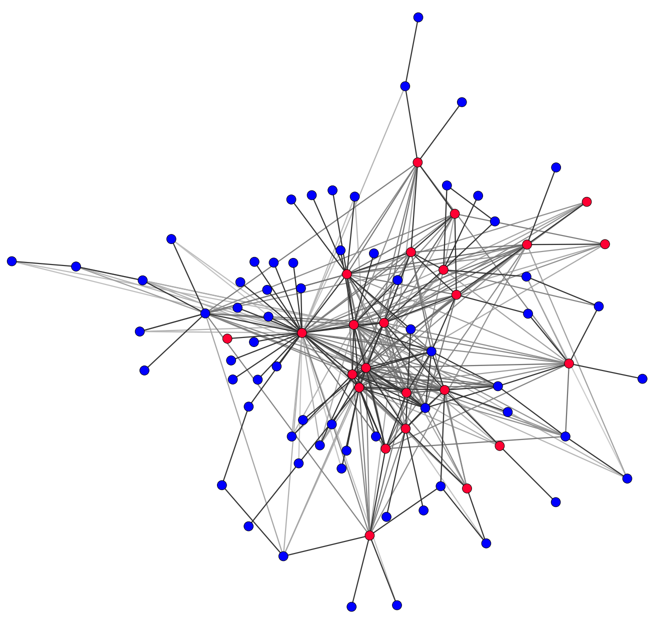

Figure 7. ESRC collaboration network.

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Table 4. Correlation results for between the observed network matrix and the optimal core-periphery matrix

	Core-periphery correlation
AHRC	0.3963
BBSRC	0.5914
ESRC	0.7420
EPSRC	0.6162

Table 5. Top organizations by eigenvector centrality

AHRC	BBSRC	EPSRC	ESRC
University College London	University of Edinburgh	Imperial College London	University College London
University of Oxford	Imperial College London	University College London	University of Southampton
University of Manchester	University of Nottingham	University of Oxford	University of Bristol
The British Library	University of Cambridge	University of Cambridge	University of Cambridge
University of Edinburgh	University of California Davis	University of Southampton	University of Oxford
University of Glasgow	University of Oxford	National Physical Laboratory	Imperial College London
Harvard University	European Bioinformatics Institute	University of Bristol	University of Sheffield
University of Cambridge	French National Institute of Agricultural Research	University of Manchester	University of Leicester
The British Museum	University of East Anglia	University of Edinburgh	University of Warwick
King's College London	University of Bristol	University of Nottingham	University of York

4. Results

Table 2 presents the top leading institutions by the level of funding they receive from each research council. There is a high level of overlap amongst the different research councils, with elite UK universities (often part of the Russell Group) obtaining the most funding across disciplines. It is no surprise that the Pirbright Institute receives a high level of funding, given that its parent organization is the BBSRC.

A descriptive analysis for each research council network is presented in Table 3 and includes a variety of network level metrics to inform on features of the collaboration networks. We observe that there are fewer organizations present in the backbone collaboration network in the AHRC

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Table 6. Percentage of total organizations in the network belonging to each region

	AHRC	BBSRC	EPSRC	ESRC
Midlands	5.48	4.48	7.23	5.56
Northern England	17.81	4.48	11.13	11.11
Northern Ireland	2.74	1.38	1.01	2.22
Outside UK	8.22	58.28	30.78	25.56
Scotland	8.22	4.83	5.20	11.11
South of England	21.92	17.93	27.02	17.78
London	35.62	7.24	15.32	22.22
Wales	0.00	1.38	2.31	4.44

and ESRC, compared to their counterparts in the sciences, where the networks are over three times the size. We can note that this is not simply a result of the level of funding awarded by the research councils, as the BBSRC awards similar levels (in terms of amount awarded) to the ESRC and AHRC.

Density is the ratio of observed ties to all possible ties in a network and acts as a measure of network connectivity (Wasserman & Faust, 1994). We observe that although the networks vary in terms of size, they have more comparable levels of connectivity, where they are all relatively low (this can also be observed in the network visualizations presented in Figures 4–7). Network diameter is the longest geodesic distance in the network, where the geodesic distance refers to the number of relationships in the shortest possible path from one actor to another (Knoke & Yang, 2008). Average path length is the average distance between any two actors in the network. These results indicate that organizations are further apart in the AHRC collaborations, especially compared to the ESRC where they are much closer.

Degree assortativity captures the correlation between degree centrality of connected actors in a network (Newman, 2002), where scores can be between −1 and 1. Degree centrality is the number of ties an actor has in the network (Freeman, 1978), in this empirical setting, it is the number of collaborative partners an organization has. A positive score would suggest that well-connected actors link to other well-connected actors, whereas a negative score, which would suggest that high degree actors are connected to many low degree actors, pointing toward a pattern of disassortativity in the network. The score is negative across research councils, indicating that there is a set of organizations with many collaborative ties that link to less connected collaborative partners. Other aspects of the network, such as centralization and clustering patterns, are presented through the use of the ERGM.

Figure 3 presents the geographical distribution of funding for each research council, the circles represent the lead organization that was funded by the research council, and the size of the node is the total level of funding they received over the time period. Across research councils, much of the funding is centered on institutions in the south of England, particularly London. Funding for the AHRC appears to be more evenly distributed compared to the other research councils. The BBSRC has higher level of funding awarded to Scottish institutions compared to the other research councils.

Figures 4–7 present the inter-organizational networks associated with each research council; networks were visualized using the Visone software (Baur et al., 2001) applying the layout outlined by Nocaj et al. (2015). This layout algorithm puts an emphasis on structurally embedded ties, highlighting these ties and using these to drive the network layout. The red nodes represent

Table 7. ERGM results

	AHRC	BBSRC	EPSRC	ESRC
Edges	−5.9508***	−6.2483***	−7.8614***	−6.0525***
	(0.6524)	(0.1690)	(0.1592)	(0.4554)
Russell Group activity	1.9382***	1.8474***	3.1882***	1.3605***
	(0.3282)	(0.0835)	(0.1227)	(0.1758)
Russell Group match	−0.0281	0.9674***	1.7414***	−0.1398
	(0.2076)	(0.0972)	(0.1264)	(0.1678)
Midlands activity	−0.5704	−0.0704	−0.1346***	−0.0365
	(0.4025)	(0.0891)	(0.0397)	(0.1492)
Northern England activity	−0.7562**	−0.3703***	−0.2895***	−0.3079*
	(0.2353)	(0.0882)	(0.0350)	(0.1231)
Northern Ireland activity	−0.9893	−1.9748***	−0.7530***	−0.6502*
	(0.6843)	(0.3844)	(0.1223)	(0.3249)
Outside UK activity	0.1534	−0.2061***	−0.3385***	−0.2090
	(0.3853)	(0.0594)	(0.0264)	(0.1676)
Scotland activity	−0.1029	0.3340***	−0.0721	−0.0182
	(0.2778)	(0.0737)	(0.0439)	(0.1306)
South of England activity	−0.3332	0.1615*	−0.1400***	0.1424
	(0.1782)	(0.0633)	(0.0260)	(0.0883)
Wales activity		−0.2704	−0.2706***	0.2593
		(0.1633)	(0.0688)	(0.1637)
Region match	1.5369***	0.5691***	0.5043***	0.8894***
	(0.2176)	(0.0748)	(0.0390)	(0.1608)
Degree centralization (gwdegree)	1.1503	−1.6575***	−1.3016***	0.8696
	(0.6169)	(0.1767)	(0.1245)	(0.4460)
Clustering (gwesp)	0.3483**	1.7554***	1.9872***	0.9132***
	(0.1214)	(0.1053)	(0.0789)	(0.1280)

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

members of the Russell Group. The networks represent the backbone, the statistically significant collaborative ties, where isolated nodes have been removed from the visualization and subsequent analysis.

The AHRC network (Figure 4) is significantly smaller and sparser than the other network, this is because the AHRC funds far less projects when compared to its counterparts in the sciences (as observed in Figure 1). The ESRC network (as seen in Figure 7) has a similar structure yet has a larger number of organizations present, whilst the BBSRC (Figure 5) and EPSRC (Figure 6) networks are much larger networks and are characterized by clusters, that is, areas of the network with higher level of connectivity. In the EPSRC network, this is the densely connected core.

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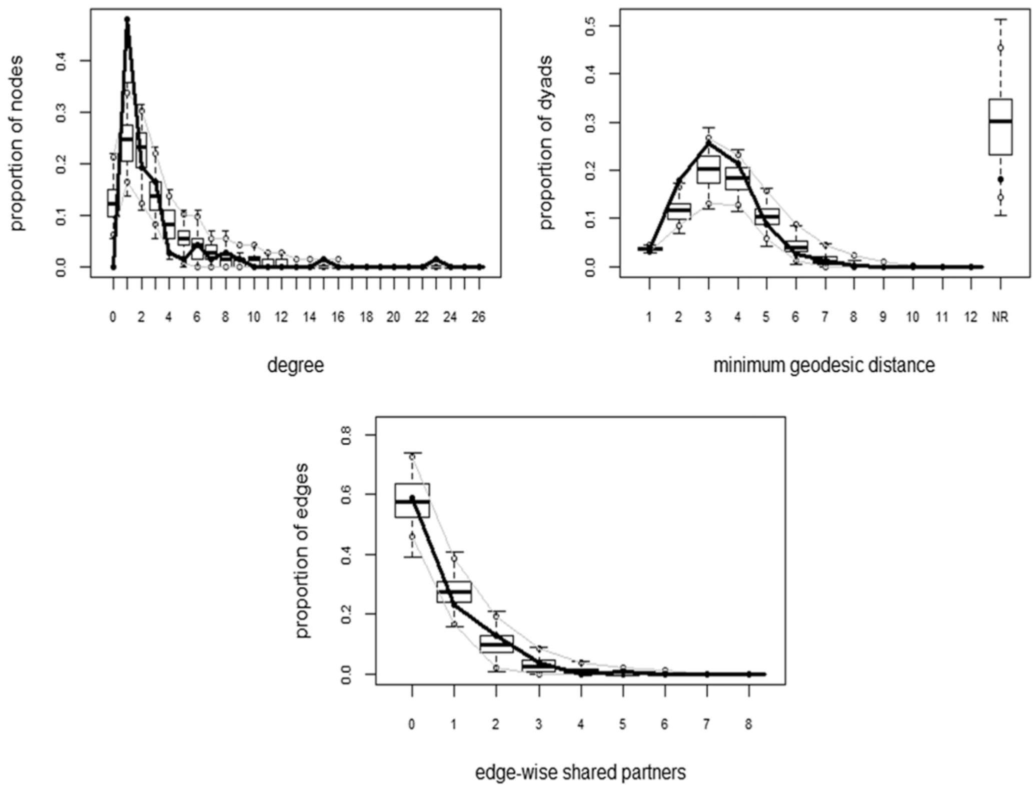

Figure 8. AHRC goodness of fit plots.

These collaboration networks consistently have a core-periphery structure, where there is a densely connected core, with disconnected actors orbiting the center (Borgatti & Everett, 2000). These structures point toward the potential for silos to emerge, which can result in constrained single loop learning (Argyris & Schoen, 1978), rather than effective inter-organizational collaboration (Cronin, 2007). Table 4 confirms the core-periphery structure that is observed in the visualizations of the inter-organizational collaboration networks (employing the core/periphery analysis procedure documented in Borgatti et al., 2018). Table 4 presents the correlation between the observed network matrix and the optimal patterns matrix for a core/periphery structure. We observe high correlations for all research councils, in particular the ESRC, yet somewhat less so in the case of the AHRC.

An examination of top institutions by their global position in the networks is also undertaken. This is operationalized through the calculation of the eigenvector centrality of organizations in the collaborative networks. Eigenvector centrality captures the centrality of an organization's collaborative partners; therefore, actors with a high eigenvector centrality will be well-connected organizations are connected to other well-connected organizations (Bonacich, 1987). Therefore, eigenvector represents an ideal metric (compared to other centrality measures) to capture the importance of an actor in the collaboration system, as it allows to identify those at the core and most active in collaborative research projects funded by each research council.

Table 5 shows the top 10 institutions by eigenvector centrality in each research council network. These are mainly Russell Group universities, and the list is similar to the lead institutions that receive high levels of funding, as presented in Table 1. However, there are some nonacademic or non-UK-based institutions holding prominent positions in the networks. In the case of the

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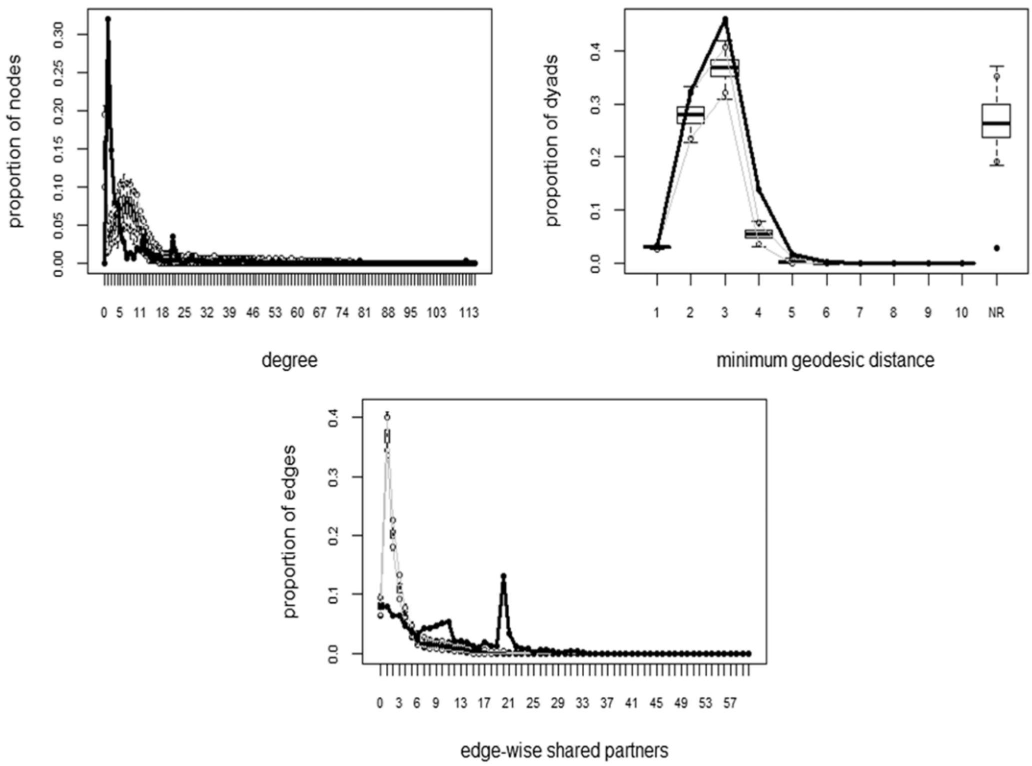

Figure 9. BBSRC goodness of fit plots.

AHRC, the British Library and the British Museum are both nonacademic institutions holding prominent positions; however, these are still considered elite institutions with close historical ties to Russell Group members. With the exception of the University of Leicester, all of the most central institutions in the ESRC network are Russell Group members. Similar patterns are observed for EPSRC; apart from the National Physical Laboratory, the most central universities are all Russell Group members.

Table 6 presents the percentage of total organizations belonging to each regional partition present in the network (these are only actors that are a part of the backbone of the network); here we expect to observe more organizations from regions with a higher population or a higher number of large cities (which are more likely to include a higher number of academic institutions). In the EPSRC and BBSRC networks, there is not only a higher level of nonacademic partners but also a higher proportion of international partners, based outside the UK. For the AHRC, we observe that there are no Welsh institutions in the backbone of the network. A potential explanation for this is that most of the employment in the creative sector that is closely aligned with the AHRC is concentrated in London and the South East (this is also observed in Table 6), with very little in Wales and Northern Ireland (Mateos-Garcia & Bakhshi, 2016). For the BBSRC and EPSRC, the majority of collaborators come from outside the UK. The BBSRC is less London centric, especially compared to the other research councils. Institutions collaborating on ESRC projects tend to be from London and the South of England; however, similar to the EPSRC and BBSRC, there is a high level of non-UK institutions. Extant work has identified that geographic proximity is important for university–industry collaborations, yet some regions contain more universities than others and therefore are potentially in a better position to establish collaborations with nonacademic partners. However, D'Este et al. (2013) find that the impact of geographic proximity in the formation

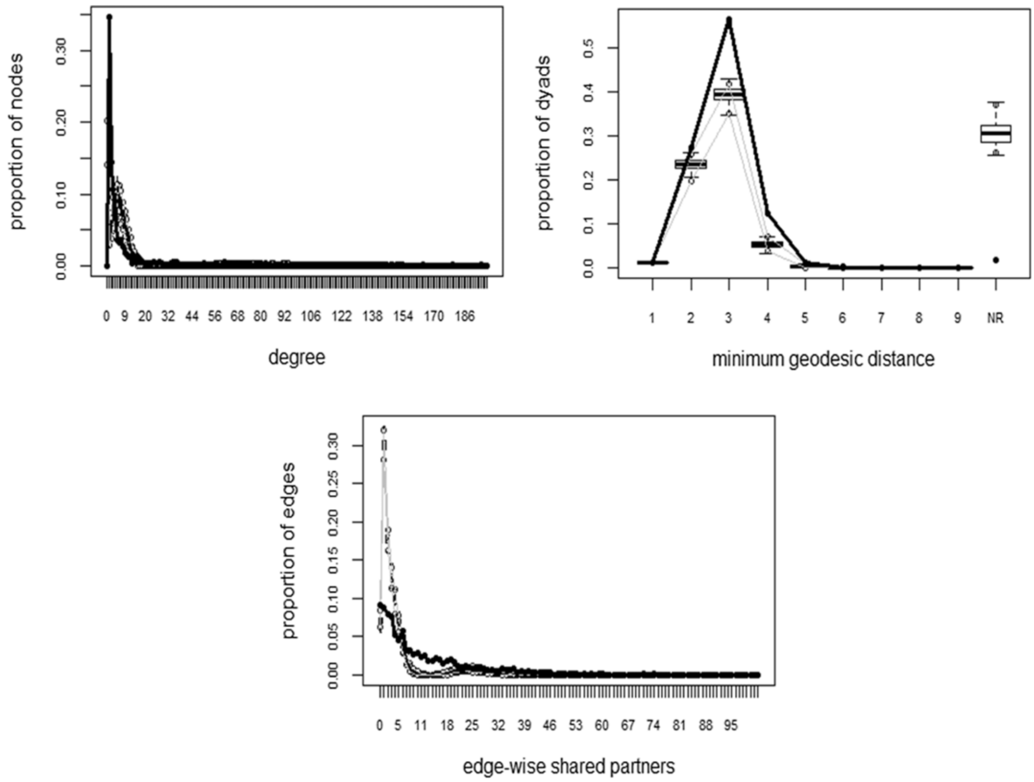

Figure 10. EPSRC goodness of fit plots.

of university–industry ties is weakened when firms are located in dense clusters (especially tech clusters).

Academic and industry partnerships are often essential for the commercialization of knowledge (Perkmann et al., 2013); therefore, it is no surprise that it is on EPSRC projects where the majority of nonacademic partnerships are observed. The field of engineering is more applied and better suited for commercialization when compared to the other research council funders (Lee & Miozzo, 2019), such as the AHRC. In university–industry collaborations, universities act as important centers for the development and creation of scientific knowledge (Dooley et al., 2016; Hemmert, 2004), acting as entrepreneurial agents allowing firms to accrue innovative performance benefits (Caloghirou et al., 2004; Etzkowitz et al., 2000; Gassmann & Zeschky, 2008; Huggins et al., 2019). Kumaramangalam (2005) notes that in the UK biotech industry, there is the potential for firm-level benefits to be accrued from participating in academic collaborations, yet these can vary drastically between firms.

The results of the ERGM are given in Table 7; the parameter estimates are provided along with the standard errors in parentheses. For the regional activity effects, the baseline region is London; therefore, the results capture whether organizations from the region are more or less likely to form collaborative ties compared to London-based institutions.

Table 7 indicates that across research councils, members of the elite Russell Group are more likely to form collaborative ties, where there is a large and strongly positive and significant Russell Group activity effect in all four models. However, there is only a significant tendency for Russell Group universities to collaborate in the sciences, as shown by the positive and significant match effect in the BBSRC and EPSRC models. Whereas in the social sciences and humanities

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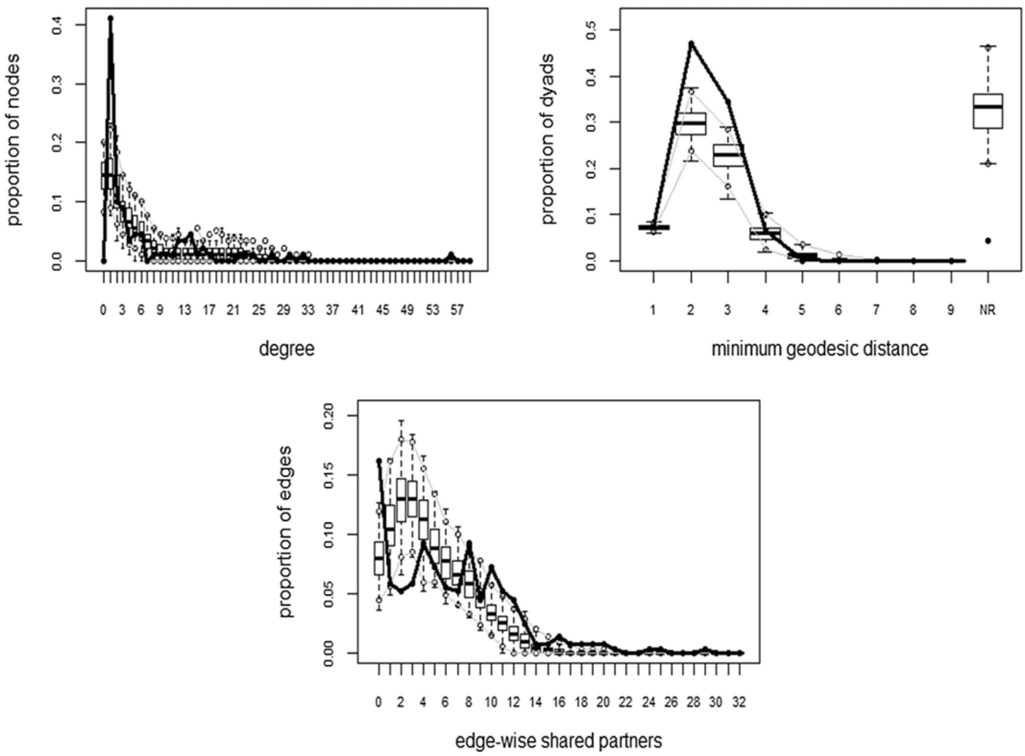

Figure 11. ESRC goodness of fit plots.

(AHRC and ESRC), there is not a significant tendency for elite Russell Group institutions to collaborate.

The ERGM results indicate that regional activity differs by research council. In the case of the AHRC, we observe that institutions from the North of England (North East, North West, and Yorkshire) are less likely to form collaborative ties than London-based institutions. For BBSRC-funded projects, there are several negative and significant effects, indicating that much of the collaboration in this discipline is London centric. There are negative and significant effects for Northern England, Northern Ireland, and outside the UK. There is a positive and significant Scotland activity effect; this suggests that Scottish institutions are more likely to be involved in BBSRC collaborative ties than their London-based counterparts. There is a weakly positive and significant South of England activity effect.

Collaborative ties on EPSRC-funded projects tend to be London centric, with a set of negative and significant regional activity results. This indicates that institutions from all other regions are less likely to form collaborative ties than London-based institutions. In Scotland, there is a range of initiatives related to EPSRC disciplines to promote knowledge exchange and collaborations (Kitagawa, 2010). For instance, there is the Scottish Universities Physics Alliance, which aims to foster physics-related partnerships in Scotland. However, there is no significant Scottish activity effect, indicating that the involvement of Scottish consortiums does not surpass London-based organizations.

In the case of the ESRC, there are only negative and weakly significant regional activity effects for the North of England and Northern Ireland. This suggests a weaker link between regional partition and collaborative activity for economics and the social sciences.

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Table 8. AHRC goodness of fit statistics

	obs	min	mean	max	MC *p*-value
Edges	100	80	99.63	121	0.94
Russell Group activity	112	83	111.15	149	0.98
Russell Group match	52	33	52.16	70	1
Midlands activity	9	3	9.02	17	1
Northern England activity	35	22	34.53	54	0.94
Northern Ireland activity	3	0	3.04	8	1
Outside UK activity	9	4	9.26	20	1
Scotland activity	17	7	16.15	28	0.84
South of England activity	48	28	48.57	71	1
Region match	51	33	50.22	69	0.98
Degree centralization (gwdegree)	112.89	100.55	112.93	129.21	0.96
Clustering (gwesp)	54.79	14.63	53.96	113.21	0.98

Table 9. BBSRC goodness of fit statistics

	obs	min	mean	max	MC *p*-value
Edges	1274	1052	1241.99	1403	0.72
Russell Group activity	791	703	780.78	849	0.84
Russell Group match	769	609	750.03	892	0.78
Midlands activity	145	95	143.89	194	1
Northern England activity	177	131	171.82	199	0.74
Northern Ireland activity	4	0	3.57	11	0.96
Outside UK activity	955	700	914.36	1103	0.74
Scotland activity	251	208	244.43	294	0.72
South of England activity	737	570	734.21	842	0.96
Wales activity	31	17	31.21	47	1
Region match	422	324	409.02	504	0.76
Degree centralization (gwdegree)	403.4	363.18	397.59	422.43	0.64
Clustering (gwesp)	1173	965	1142.38	1306	0.74

Across research councils, there is a positive and significant regional homophily effect. This indicates that even geographic distance plays an important role in the formation of collaborative ties, regardless of discipline.

The network effects of degree centralization and clustering indicate that collaborative ties are more hierarchical in the sciences, compared to the social sciences, humanities, and arts (the AHRC

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Table 10. EPSRC goodness of fit statistics

	obs	min	mean	max	MC *p*-value
Edges	2959	2383	2767.68	2994	0.04
Russell Group activity	1973	1710	1893.75	2032	0.16
Russell Group match	1458	1138	1346.77	1475	0.06
Midlands activity	521	400	468.51	529	0.1
Northern England activity	760	613	719.69	806	0.34
Northern Ireland activity	46	36	46.62	61	1
Outside UK activity	788	641	736.12	897	0.34
Scotland activity	400	296	360.97	424	0.12
South of England activity	1866	1435	1746.27	2001	0.16
Wales activity	119	73	111.35	156	0.62
Region match	810	623	748.82	852	0.1
Degree centralization (gwdegree)	949.58	846.99	915.72	954.19	0.04
Clustering (gwesp)	2942.07	2351.92	2747.74	2994.68	0.08

Table 11. ESRC goodness of fit statistics

	obs	min	mean	max	MC *p*-value
Edges	291	236	290.62	344	1
Russell Group activity	404	344	402.28	460	0.94
Russell Group match	157	135	156.3	175	0.94
Midlands activity	51	36	51.4	77	0.98
Northern England activity	94	61	91.44	121	0.86
Northern Ireland activity	7	1	7.18	18	1
Outside UK activity	35	19	35.14	55	1
Scotland activity	51	26	53.7	89	0.8
South of England activity	163	116	159.53	222	0.82
Wales activity	32	15	32.19	51	1
Region match	79	52	77.07	100	0.8
Degree centralization (gwdegree)	162.47	142.36	163.09	179.15	0.86
Clustering (gwesp)	580.68	448.76	577.76	722.32	0.96

and ESRC-funded projects). There is a negative and significant degree centralization effect for the BBSRC and EPSRC networks. This indicates that for these research councils' collaborative ties are concentrated in a small handful of organizations, rather than spread out evenly throughout the system, pointing toward a more hierarchical structure, where for the AHRC and ESRC the degree centralization parameter is non-significant.

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The clustering parameter is positive and significant across research council networks, this indicates that these networks are characterized by areas of higher density; this can also be observed in the network visualizations. Furthermore, it suggests that there is a tendency for triadic closure in the network, that if two organizations share collaborative partners, they are also likely to collaborate. This process occurs regardless of research council discipline, yet the effect is larger in the hard science (BBSRC and EPSRC), compared to the social sciences (AHRC and ESRC).

In order to assess whether the models sufficiently explain the observed networks and data, goodness of fit procedures are carried out. The goodness of fit procedure compares the salient structural features of the observed networks with a set of networks simulated from the estimated ERGM (Hunter et al., 2008a). If the model is a good fit, then the simulated networks would share characteristics with the observed networks. The results for the goodness of fit for each research council are given in Figures 8–11.

We observe that the ERGMs are able to reasonable explain degree patterns for each research council (yet less so in the case of EPSRC). The models are also able to sufficiently explain minimum geodesic distance and edgewise shared partner patterns.

In addition to the goodness of fit plots presented in Figures 8–11, Tables 8–11 give the goodness of fit summary statistics. For each effect specified in the model, it gives the observed value, along with the minimum, maximum, and mean for the effect in the set of simulated networks. Tables 8–11 also report the Monte Carlo p-values, which are the proportion of the simulated values of the effect that are at least as extreme as the observed value. Therefore, in this case a small p-value (less than or equal to 0.05) indicates cases where the model is not able to produce the particular effect or network characteristic (Luke, 2015).

The tables, in combination with the goodness of fit plots presented in Figures 8–11, show that the ERGMs for the cases of AHRC, ESRC, and BBSRC are a relatively good fit, capturing many of the network characteristics. However, in the case of the EPSRC (although it is able to reproduce many other salient characteristics), the tables indicate that the model is not able to fully explain the degree centralization patterns in the networks (with an MC p-value below 0.05). This suggests that in the case of engineering and the physical sciences, group membership and geography are not enough to explain degree patterns. This indicates further research is required to understand what other features shape degree centralization patterns in a collaboration network in the (hard) sciences.

5. Discussion and conclusion

This paper addresses three key research questions regarding the formation of collaborative ties on UK research council projects. The first research question asked what the factors underpinning the formation of collaborative ties are and whether differences emerge between research councils. The results from the ERGM provide an answer to this question, in particular the estimated degree centralization and clustering effects. In the BBSRC and EPSRC models, there was a negative and significant effect, pointing toward collaborative ties being concentrated in a handful of organizations in these networks, which contrasted to the case of the AHRC and ESRC. This provides a strong indicator that the discipline and the setting of research matter for the formation of collaborative ties. Collaboration in the humanities and social sciences follows a different process to the hard sciences (in particular engineering and biological sciences). However, the tendency for clustering and triadic closure was observed across the research council networks, although this effect was larger in the case of BBSRC and EPSRC. The presence of a connected core arising from collaboration on funded projects is not unique to these two UK research councils; Breschi & Cusmano (2004) find that a network of R&D joint ventures arising from the EU Frameworks Program (FP) is characterized by an "oligarchic core." Furthermore, Maggioni et al. (2014) find that knowledge flows arising from EU-funded research networks (as part of the fifth Framework Program) are

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characterized by a hierarchical network structure with a high level of activity concentrated in core economic regions.

The second research question asked what the role of geography is in the formation of collaborative ties—whether collaboration tend to be London centric. In addition, whether geography plays the same role across disciplines? From the ERGM results, we observe that geography had a significant effect on collaboration, with some regions being more active than others, with clear differences between the research councils. Furthermore, there was a strong tendency for collaboration to occur within the same regional partition. This indicates that distance matters when forming collaborative ties on research council-funded projects.

At the regional level, the ERGM results point toward potential policy implications, as there are far fewer collaborative partnerships being developed that involve institutions for the North of England. This points toward a need to develop either academic capabilities in the region or to better engage nonacademic institutions from the region in research-funded partnerships. There have already been some attempts to establish consortiums in Yorkshire and Humber through the White Rose Consortium (a strategic partnership between the Universities of Leeds, Sheffield, and York) (Harrison et al., 2017), yet this is a partnership of Russell Group universities and is not replicated in other areas of the North of England.

The final research question posed addresses the issue of belonging to a university mission group and collaboration participation. More specifically, it asked whether elite universities, those belonging to the Russell Group, are more active in collaboration on UK research council-funded projects. The descriptive analysis examining where funding and eigenvector centrality were concentrated provided some insights to address this question. Members of the Russell Group received the most funding from these four research councils and were amongst the most central organizations in all of the networks. The ERGM results confirmed this finding, where members of the elite Russell group were much more likely to establish collaborative ties in the networks, with a positive and significant effect in all four models. This effect was particularly large in the case of the EPSRC. This suggests that there is a need for research councils to ensure that projects are not limited to this small subset of UK institutions, to foster collaboration outside of these 24 universities, indicating that university status should be considered in research council funding allocation decisions. However, the Russell match parameter indicated that only in the hard sciences (BBSRC and EPSRC) we observed collaboration between Russell group members; the same tendency is not observed for ESRC and AHRC. This perhaps indicates potential competitive effects in these disciplines (although the effect was not negative and significant for these research councils).

There are a number of limitations to this work, which can be explored further in future research. Firstly, our examination of the network is restricted to the backbone, that is, the binary version of the network. Future work could make use of alternative modeling framework, to explicitly account for the edge weights (such as Wilson et al., 2017), this would allow for a different set research question related to exploration and exploitation collaboration on research council-funded projects to be tackled (Cronin, 2007; Gilsing & Nooteboom, 2006; Gilsing et al., 2008), and to explain the intensity of collaborative ties. However, it is key to note that these models are more computationally intensive, especially for some of the larger network presented in this case, than the standard, binary ERGMs. Future work could also explore what determine organizational-project ties (rather than inter-organizational ties), through the use of a two-mode ERGM.

A further line of future research could investigate how collaborative patterns differ from one REF period to the next (such as from REF2014 to REF2021). For instance, do universities strategically collaborate following the REF? Are they likely to collaborate with those that performed better in the previous REF? A multiplex network analysis (Nicosia & Latora, 2015) or graph matching approaches (Emmert-Streib et al., 2016) could be used in future work to address these questions. A further avenue for research could also explore the link between these collaboration networks and subsequent REF results; is holding a more central position in this collaboration network associated with a better ranking or performance in specific Units of Assessment in the REF exercise?

This work focuses on the UK setting; however, there are numerous other institutional settings that also use research funding as a key policy tool (often to encourage innovative activity). One prominent example is the Horizon 2020 program in the EU. Future research could examine the process underpinning inter-organizational networks arising from EU funding and compare and contrast to the single country case.

This research focuses on a single snapshot, using the REF as a frame; however, future work could compare and contrast two different REF cycles, to examine if any differences arise, and to better examine further political influence (such as change in government) impacts the formation of inter-organizational networks arising from collaborative arrange on UK-funded projects.

Future work could also consider this as a multiplex network (Battiston et al., 2016), where each research council collaborative partnerships are considered to be layers in the same system, rather than examining them as separate networks (Lazega & Pattison, 1999).

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