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The role of social capital towards resource sharing in collaborative R&D projects: Evidences from the 7th Framework Programme

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Abstract

This study examines the role of Social capital dimensions towards resource sharing within R&D cooperation projects funded by the 7th Framework Programme (FP7). Data were collected in a survey of 553 FP7 project participants and analysed using two different social network analysis (SNA) methodologies: Logistic regression quadratic assignment procedure and exponential random graph models. Results showed that all Social Capital dimensions helped to explain partners' resource sharing, although to a different extent. Prior ties were often significant, whilst shared vision and commitment were very frequently positive contributors to resource sharing. Trust was rarely significant, and occasionally detrimental, to partners' resource sharing. Therefore, the FP7 provided a collaborative but opportunistic environment for public and private actors. The novelty of this study derives from the combination of social capital theory with SNA to study intra-project partner relationships, contributing to a better understanding on the diversity of partner relationships within R&D projects.

Keywords: Social capital; Resource sharing; R&D projects; Framework programmes; LRQAP; ERGMs

1. Introduction

The European Commission has made substantial efforts, since 1984, to improve Europe's international competitiveness through successive Framework Programs for Research and Technological Development (FPs). These programmes funded many networks in the form of Research Joint Ventures (RJVs) composed of public and private international institutions. Despite the over €40,000 M of funding attributed between 2007 and 2013 (European Commission, 2015), past research on RJVs mostly addressed the composition and size as well as the frequency and diversity of institutional participation (see, for example, Pandza et al. (2011)). The relationships among project partners received little attention in previous studies. Some works have used social network analysis (SNA) to understand collaboration patterns within FP-funded RJVs, but only analysing the coparticipation in RJVs, and not the patterns of de facto internal cooperation (Breschi and Cusmano, 2004; Ortega and Aguillo, 2010; Protogerou et al., 2013; Vonortas and Okamura, 2013). Notwithstanding these contributions, understanding partner relationships is critical for comprehensively understanding R&D cooperation, because inter-organizational contracts and agreements represent only a fraction of the overall set of ties in R&D cooperation (Bekkers and Freitas, 2008; Brennecke and Rank, 2016). As Wang (2016) observed, knowledge resides within and is created by individuals, but it can also be viewed as a social and collaborative process. In fact, network interactions at the individual level among scientists and university researchers have been described as a leading source of new knowledge (Liebeskind et al., 1996), thus suggesting a predominantly social process around resource sharing and

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knowledge creation (Wang, 2016). Moreover, effective relational mechanisms are linked with greater resource sharing among partners (Yli-Renko et al., 2001), which signals interactive cooperation, and increases the likelihood of R&D success. This is particularly important in fast-paced high-technology sectors, such as the Biological Sciences, where both firms and universities frequently depend on network partners to access sources of innovation (Fontes, 2005; Powell et al., 1996).

Based on the rationale above, Social Capital, i.e. the actual and potential resources embedded in relationships (Nahapiet and Ghoshal, 1998), is likely to play a relevant role in predicting collaboration patterns within FP-funded RJVs, as previously described for networks composed only by firms (Brennecke and Rank, 2016; Lee et al., 2015; Molina-Morales and Martínez-Fernández, 2010). Accordingly, the major drivers of resource sharing might not be the number and diversity of RVJ partners (Beers and Zand, 2014), but rather the commitment, trust, prior ties and shared vision embedded in the relationships among partners (Molina-Morales and Martínez-Fernández, 2010; Pérez-Luño et al., 2011). Instead of researching the role of Social Capital towards Resource Sharing within FP-funded project networks, past studies either focused on inter-project networks and their implications in knowledge diffusion across Europe (Avedas, 2009; Protogerou et al., 2013; Vonortas and Okamura, 2013), or on Social Capital as a driver of innovation without studying the actual network of interactions (Nieves and Osorio, 2013; Pérez-Luño et al., 2011). Therefore, the novelty of this study results from the combination of Social Capital theory with SNA to study intra-project partner relationships and their impact on Resource Sharing in FPs. Ultimately, this study could contribute to a better understanding on what promotes effective R&D collaboration, leading to greater success of FPs. Accordingly, the following research question is addressed:

> To what extent do Social Capital dimensions (structural, cognitive and relational) impact Resource Sharing among participants of FP-funded R&D projects?

By using SNA, this study contributes to a better understanding on the diversity of partner relationship within R&D projects, using data collected in a survey of over 550 FP7 participants. Results showed that Social Capital dimensions increase the odds of Resource Sharing among partners. Prior Ties were often significant, whilst Shared Vision and Commitment were very frequently positive contributors to Resource Sharing. Trust was rarely significant, and occasionally detrimental, to partners' Resource Sharing. Consequently, Framework Programmes are potentially providing a collaborative but opportunistic environment for public and private actors.

2. Theoretical framework

2.1. Social capital for studying R&D cooperation networks

Social Capital theory has helped in understanding how relationships impact resource exchange (Adler and Kwon, 2002; Bourdieu, 1986; Inkpen and Tsang, 2005), value creation (Li et al., 2013; Nieves and Osorio, 2013), and innovation performance (Abbasi et al., 2014; Molina-Morales and Martínez-Fernández, 2010; Pérez-Luño et al., 2011). Most definitions of Social Capital converge to the idea that actors influence and are influenced by their networks, drawing upon the notion that relationships represent a form of capital that can be leveraged to reach individual and collective goals (Adler and Kwon, 2002; Hartmann and Herb, 2015; Inkpen and Tsang, 2005; Nahapiet and Ghoshal, 1998). Over time, consensus emerged regarding the major variables to measure Social Capital, namely: network ties, trust, norms and obligations as well as shared codes and languages (Nahapiet and Ghoshal, 1998). These variables are relational and therefore should be measured between pairs of actors. For instance, it makes little sense to ask a participant his/her overall level of trust in a 5-member network. Trust should be reported at the tie level with each member, since it is not an attribute of a single actor, such as native language, affiliation, or years of experience in FPs. In this particular case, Trust is a directed tie, meaning that A may trust B, but the opposite may not be true. Therefore, in order to properly measure Trust and all the other variables that form Social Capital, research must focus on each tie between every pair of actors, therefore requiring a study of the whole network of actors. Additionally, and just like financial or physical resources, Social Capital is a resource of limited availability. Consequently, partners in R&D networks are likely investing selectively in relationships that allow achieving their goals in the RJV, not necessarily sharing the same relationship engagement with all members. Hence, the study of Social Capital in R&D cooperation networks should be able to measure the availability of these social resources, embedded in partner relationships, and explain the extent to which that availability affects or describes the network of close collaboration and sharing of human, physical and technical resources among partners.

2.2. Social capital dimensions and resource sharing

Nahapiet and Ghoshal (1998) classified Social Capital into three dimensions: Structural, Cognitive and Relational. Tsai and Ghoshal (1998) confirmed the existence of causal relationships between Social Capital dimensions, resource exchange and value creation. This was inferred based on research in a network of subsidiaries from a multinational company, and has since then been extended to other contexts (Atuahene-Gima and Murray, 2007; Hartmann and Herb, 2015; Molina-Morales and Martínez-Fernández, 2010). The present research extends Tsai and Ghoshal's (1998) work into the study of RJV funded by the European Commission.

2.2.1. Resource sharing

Tsai and Ghoshal (1998) dealt simultaneously with resource exchange and combination among firms, by assuming exchange as a requisite for combination. The resulting output of those two activities would be the creation of new resources (Nahapiet and Ghoshal, 1998). However, resource exchange (or transfer) could in theory imply delivery from A to B, where A loses the resource to B. Nonetheless, for some resources, such as tacit knowledge or access to infrastructures, 'exchange' does not prevent its sender from accessing it; instead, 'exchange' actually means 'sharing', as more actors have access to the same resource and can work with it for individual and collective benefit. For that reason, the present study employs the notion of resource sharing, instead of the joint activities of exchange and combination.

2.2.2. Structural dimension and resource sharing

The structural dimension is partially based on the 'appropriable organization', i.e. the existence of a network, with a given density, pattern of ties and hierarchies created for one purpose, which may be used for another purpose (Nahapiet and Ghoshal, 1998). These pre-existing ties can act as channels for information and resource sharing (Allen et al., 2007; Liao and Welsch, 2003; Scott and Carrington, 2011) and potentially affect upfront the resources that a member is capable of accessing. Tsai and Ghoshal (1998) defined this dimension based on social interaction between firms' members outside their work environment, i.e., their history of social ties. However, many scholars studying R&D cooperation, or University–Industry (U–I) links, have found that prior ties can predict current or future collaborations (Defazio et al., 2009; Pinheiro et al., 2015), partly because there is an enhanced perception of the potential cooperation value (Petruzzelli, 2011). Moreover, the strength of those prior ties might have a role on resource sharing. Strong ties, such as those resulting from institutions involved in past joint R&D projects with very frequent interactions, facilitate knowledge sharing but limit the access to novel sources of information. On the other hand, weak ties, such as those resulting from socially interacting in scientific workshops and conferences, facilitate the search of information, but impede tacit knowledge sharing (Geenhuizen, 2008; Hansen, 1999). Moreover, the combination of strong and weak ties has been suggested to have a positive interaction effect (Michelfelder and Kratzer, 2013). Accordingly, based on the above rationale, the following hypotheses are presented:

H1. R&D consortium members with prior ties have greater odds of sharing resources between them when they participate in the same RJV.

H1a. R&D consortium members whom have socialized in events prior to the RJV have greater odds of sharing resources between them.

H1b. R&D consortium members whom have collaborated previously in R&D activities have greater odds of sharing resources between them.

2.2.3. Cognitive dimension and resource sharing

The cognitive dimension refers to shared representations, interpretations, and systems of meaning among parties (Nahapiet and Ghoshal, 1998), which can be linked to resource sharing (Pérez-Luño et al., 2011; Tsai and Ghoshal, 1998). These complex codes shared between different but cooperative institutions have been tested and validated in the area of U–I links (Pérez-Luño et al., 2011; Plewa et al., 2005). A greater compatibility and alignment concerning the objectives of R&D projects involving academic and private partners led to greater integration and more radical innovations (Pérez-Luño et al., 2011; Plewa and Quester, 2007). Notwithstanding, whilst the research goals and milestones are defined by all members in the project application phase, those goals are not expected to be equally important to all R&D consortium members. If that is not the case in intra-corporate networks managed by the same headquarters (Inkpen and Tsang, 2005), in FP-funded RJV goals and vision diversity should be even more pronounced. All taken, when RJV partners align in their collective goals, it could be expected a greater tendency to share resources. Accordingly, the following hypotheses are presented:

H2. R&D consortium members that share collective goals have greater odds of sharing resources between them, within their RJV.

H2a. R&D consortium members that share similar interests and objectives have greater odds of sharing resources between them.

H2b. R&D consortium members that share a common vision for the project's success have greater odds of sharing resources between them.

2.2.4. Relational dimension and resource sharing

The relational dimension of Social Capital comprises the relationships that partners build among each other through mechanisms of trust, friendship, relational norms, obligations and mutual identification (Liao and Welsch, 2003; Nahapiet and Ghoshal, 1998). Tsai and Ghoshal (1998) focused on measuring Trust and Trustworthiness (through reliability and promise keeping), but the majority of research on U–I links focuses on measuring Trust and Commitment (Frasquet et al., 2012; Pérez-Luño et al., 2011; Plewa and Quester, 2007). These past studies showed a positive and significant role of Trust and Commitment on cooperation and innovation, although Trust is not always a positive predictor of cooperation (Chow and Chan, 2008; Pinheiro et al., 2015). In line with the stream of literature on U–I cooperation, this study expects to find that Trust and Commitment positively contribute for partners' Resource Sharing, leading to the following hypotheses:

H3. R&D consortium members have greater odds of sharing resources with partners they trust within the RJV.

H4. R&D consortium members have greater odds of sharing resources with partners to whom they feel highly committed.

3. Research design

3.1. Consortia selection

In order to select FP7 (7th Framework Programme) projects involving R&D cooperation, the following criteria were adopted:

1. Project contract type: “Collaborative project”, “Large-scale integrating project”, “Research for SMEs”, or “Research for SME associations/groupings”. This criterion ensured a selection of projects with greater and more immediate societal impact, in which both R&D institutions and end-users worked closely to develop technology-based products and markets;
2. Projects with begin-date between January 2008 and March 2012, thereby focusing on on-going or recently concluded projects. On-going projects were in collaborative work for at least 18 months prior to data collection (on average, 31 months), whilst the remaining projects had finished less than 36 months prior to data collection (on average, 11 months);
3. Projects with a research purpose related to (i) the Biological Sciences, and (ii) funded by calls from the FP7-Health, FP7-Environment, FP7-KBBE, FP7-NMP and FP7-SME programmes. These two sub-criteria were chosen because Biological Sciences comprise the research foundations of many knowledge areas, with direct implications in activities concerning environment, health, food/beverage, agriculture and pharmaceutics, as well as other less conventional bio-sectors, like plastics or fuels development;
4. Projects having at least one Portuguese partner.

The first three criteria returned over 1000 projects. The need for the last criterion is exclusively quantitative, i.e. it reduces the size of the sample into a manageable one. The final dataset was composed of 69 RJVs, which included 849 institutions from 55 countries, 30 of which were outside the European Union. The geographical constraint in the fourth criterion does not implicate a meaningful change in diversity of the countries and institutions involved in the projects selected for the present study, when compared to the whole Programme (European Commission, 2015).[1] Moreover, Portuguese members accounted for 8.5% of the analysed networks. Therefore, it is not predictable that results are consequently biased towards a subset of initiatives within the Programme and conclusions should be applicable to the ensemble of the FP7-funded networks. Some of the 849 institutions were partners in more than one project, totalling 1149 participations. In accordance with the European Commission’s guidelines, at least three member-states were included in each consortium, whilst 94% of the RJVs included at least five different nationalities, thus representing very international networks.

3.2. Data collection

For each of the 69 RJVs, the contacts of project personnel were collected from the CORDIS database, research papers and posters acknowledging the project funding, as well as the project’s website when available. However, in the case of universities and research institutions, preference was given to senior researchers and professors.

RJV personnel were contacted from June to December 2013, and were invited to fill in a web survey on behalf of their organization addressing the patterns of collaboration with members of their consortium. Survey data were collected from individuals who were more likely to represent decision makers acting on behalf of their institution. On the majority of cases, the project website identified these key researchers. For most of the questions in the survey, respondents were presented with the list of their consortium members from which they could pick the members with whom they had a specific relationship. To reduce potential bias caused by social desirability, respondents were informed that their responses were completely confidential, and that the analysis would not allow for individual identification.

The survey yielded a total of 882 valid responses across all RJVs, with project response rates ranging from 15% to 100%. However, network hypotheses require a high level of response rate in order to minimize errors associated with missing data (Kossinets, 2006). Accordingly, only projects with at least 60% response rate on all survey questions were used for subsequent analysis. On large projects, with 20 or more participants [twice the average size of cooperative RJVs (European Commission, 2015)], projects were included if they had at least 50% response rate on all survey questions. This decision reduced the number of projects under study to 43, with a total of 708 participations. Within this set, 487 institutions provided a single response to the survey, and 66 institutions provided multiple responses, as more than one senior researcher from the same project filled the survey. For these cases, the union of their responses was used in order to obtain a single response. The match between each pair of responses from the same institution was calculated using the Sokal–Michener similarity measure (Choi et al., 2010), revealing a degree of 77% ± 10% of similarity among respondents. Therefore, the final dataset included responses from 553 participations.

3.3. Measures

3.3.1. Resource sharing (exchange and combination)

Resource sharing is an expected intrinsic activity of R&D projects and a key motive for R&D collaboration (Spanos et al., 2015). For this study, the focus was on both tangible and intangible assets that consortium members accessed whilst collaborating, using the following four questions: (1) “Within [acronym of the RJV], I shared human resources (students, post-docs, etc.) with the following partners”, (2) “Within [acronym], I shared samples and materials (strains, cell lines, collections, chemicals, drugs, etc.) with the following partners”, and (3) “Within [acronym], I had access to facilities / technologies from the following partners”. In order to capture collaboration ties involving information and advice sharing, as well as other resources not mentioned in the previous questions, the following was asked: (4) “Within [acronym] consortium, I worked closely with the following partners”. Similarly to Tsai and Ghoshal (1998), the present work deals simultaneously with resource exchange and combination, assuming that partners share resources with each other in order to combine them in their own activities. The four matrices were combined into a single measure of Resource Sharing

[1] With the exception of Portugal, on average, the relative frequency of participation of each EU-28 country varied by 1% when compared to the whole 7th Framework Programme (European Commission, 2015).

following a minimum rule. Accordingly, if one institution reports at least one tie in any of the four matrices, then the tie exists in the combined matrix. The Sokal–Michener similarity between the four resource matrices was assessed prior to the combination and averaged at 78% (67% of the correlations with a p-value ≤ 0.05), calculated in UCINET (Borgatti et al., 2002) using the QAP correlation procedure with 100,000 permutations of each pair.

3.3.2. Structural dimension: prior ties

Plewa et al. (2013) and Pinheiro et al. (2015) suggested that relationships among R&D partners evolve over time and encompass increasing dependencies in terms of shared resources. These collaborative relationships tend to grow from simple service provisions, where the outcomes interest mostly one of the partners, towards more complex externally funded projects with mutual goals. Moreover, prior ties in University–Industry (U–I) collaborations have been shown to lead to the achievement of higher innovative outcomes (Petruzzelli, 2011), simultaneously requiring resource sharing among partners. Similarly, at the level FP-funded projects, Defazio et al. (2009) found that the structure of prior relationships among consortium participants positively impacts current collaboration patterns, as measured by a greater output of publications.

Based on these contributions, the measures proposed by Tsai and Ghoshal (1998) were adapted to account for prior ties, and adjacency matrices were constructed for each project based on the following two questions: (1) “Prior to [acronym] consortium, I spent time (at conferences, workshops, courses, business fairs or alike) with people from the following institutions”, and (2) “Prior to [acronym] consortium, I worked in R&D with the following institutions”. For both questions, the matrices were symmetrized based on the maximum rule, since ”spending time with” and ”working with” can be considered undirected relationships. The similarity between these matrices across all projects averaged at 80% (in 95% of projects, p-value ≤ 0.05).

3.3.3. Cognitive dimension: shared understanding of collective goals

The cognitive dimension in the work of Tsai and Ghoshal (1998) used non-relational measures that required conversion in order to be analysed using social network methodologies. Those authors realized that better conceptualizations of that dimension were appropriate. Accordingly, two adjacency matrices were constructed for each project based on the following two questions: (1) “I share similar interests and objectives with the following partners”, and (2) “I shared a common vision on the key success factors for [acronym] with the following partners”. These questions were based on the works of Plewa and Quester (2007) and Pérez-Luño et al. (2011), which have found that a shared vision on the cooperation success factors, as well as similar objectives, lead to U–I cooperation. For both questions, the matrices were not symmetrized, since each response represents a perception that is not necessarily common. The similarity between these matrices across all projects averages at 76% (in 93% of projects, p-value ≤ 0.05).

3.3.4. Relational dimension: trust and commitment

The relational dimension tested by Tsai and Ghoshal (1998) focused on measuring Trust and Trustworthiness (through reliability and promise keeping). The first is a relational measure based on ties between partners, whilst the second is a perceived attribute of each partner. However, much of the research on U–I links focuses on Trust and Commitment between partners (Frasquet et al., 2012; Plewa and Quester, 2007), which are both relational measures and have shown to be essential for organizational cooperation. Accordingly, two adjacency matrices were constructed for each project based on the following two questions: (1) “I believe the following partners will never take advantage of me, even if given the opportunity”, and (2) “Within [acronym] consortium, I had a high level of commitment with the following partners”. The measure of reliability was adapted from Tsai and Ghoshal (1998), whilst the measure of commitment was adapted from Pérez-Luño et al. (2011). For both cases, the matrices were not symmetrized, since Trust and Commitment are directed relationships. The similarity between these matrices across all projects, which averaged at 64%, was very often non-significant (only in 19% of projects, p-value ≤ 0.05).

3.4. Research models

In order to test the proposed hypotheses, three models were devised using the measures defined in the previous section. Our models are based on the structural model presented by Tsai and Ghoshal (1998) to test the role of intra-firm Social Capital dimensions towards “Resource Exchange and Combination” in a network setting. The structure of the models we estimated is displayed below in Table 1. Models 1 and 2 used a single measure for each Social Capital dimension to estimate the probability of Resource Sharing, whilst Model 3 used both measures of each dimension to estimate the same dependent matrix. Models 1 and 2 used only the “Time Spent” variable from the Structural dimension (as a proxy for social interactions among partners) and the “Shared Vision” variable from the Cognitive dimension, given their resemblance to the measures used by Tsai and Ghoshal (1998) as well as other authors in more recent studies on Social Capital and innovation (Molina-Morales and Martínez-Fernández, 2010; Pérez-Luño et al., 2011). For the Relational Dimension, Model 1 used the “Trust” variable, whilst Model 2 used the “Commitment” variable, as explained in the previous section. This configuration of models will allow us to infer on the potentially uneven coefficients of Trust and Commitment towards intra-project resource sharing. Further models, similar to 1 and 2, using the “Prior work” and “Shared objectives” variables were not tested

Table 1
Description of the three research models.

Social capital dimensions	Model variables	Model 1	Model 2	Model 3
Structural dimension	Time Spent	+	+	+
	Prior work			+
Cognitive dimension	Shared Vision	+	+	+
	Shared objectives			+
Relational dimension	Trust	+		+
	Commitment		+	+

given the very high similarly between variables in both dimensions (see Appendix A1). This high similarity could also signal co-linearity issues in Model 3, which will be analysed in the following section.

4. Data analysis and results

4.1. Data imputation procedure and network reduction

Survey research data is often impaired by non-response, making attempts to analyse the data more challenging. In our research, we also encountered cases where an institution involved in a particular project did not answer one or more questions in the survey, resulting in missing data.

The complexity of social network surveys makes them prone to non-response, as it demands both concentration and perseverance from the respondent in order to deal with the repeated rosters that are needed to acquire data on social relations. However, inference drawn from statistical analysis using dyadic data is more sensitive to missing data than in the case of rectangular data structures, and existing methods to deal with missing data in network science are not as definitive as in other fields.

The easiest solution to handle missing data is to simply exclude all the actors for whom we have no responses. However, this may cause serious bias in the results and lead to invalid inference (Bearman et al., 2004; Ghani et al., 1998). Although some network aggregate measures (e.g. centrality) are robust to missing data (Borgatti et al., 2006; Kossinets, 2006), network structure is still quite sensitive to it (Krebs, 2002; Rumsey, 1993; Stork and Richards, 1992), especially if the missing data is not generated at random. This treatment of missing data that excludes all missing actors is referred to as "complete cases" (CC) analysis, as it involves, for each relational matrix, the row and column-wise deletion of all actors for whom we have no information. Importantly, when using QAP regressions or exponential random-graph models, treating missing data by using CC analysis presents two important obstacles: (1) smaller samples and (2) loss of information, which impair model convergence, leading to biased parameter estimates and unreliable regression coefficients.

A possible solution to these issues is data imputation: it increases the sample size and facilitates model convergence, allowing us to estimate exponential family graph models, as well as reduce permutation coefficient dispersion in QAP regressions. However, if the imputed data creates artificial network structures that would not be present if the respondents had answered the question, it will both underestimate the uncertainty around parameter estimates and induce bias. To deal with this relevant issue, we use two missing data treatments: CC analysis and an imputation method based on the preferential attachment algorithm (PA), which leverages information from the observed degree distribution in the network to generate tie probabilities between missing actor i and actor j and impute missing values based on those probabilities (Barabási and Albert, 1999).

We used a multiple imputation algorithm based on the concept of preferential attachment (Barabási and Albert, 1999). As proposed by Huisman and Steglich (2008), this procedure states that the probability of an edge between missing actor i and actor j will be proportional to the indegree of actor j, therefore preserving the degree distribution of the network. In short, for each actor with missing links, the algorithm randomly draws an outdegree d_i from the observed outdegree distribution. After determining the observed outdegree d_i^{obs} for each actor i with missing links, it draws, without replacement, $j=(d_i - d_i^{obs})$ actors from the set J_i, which comprises all actors j whose tie from i is missing, using preferential attachment probabilities $\pi(k_j)$, that are proportional to the outdegree of each actor $j \in J_i$.[2] In a last step, the algorithm imputes the missing X_{ij} to be equal to 1 for the sampled actors, and 0 for all others.

In simulation studies performed by Huisman and Steglich (2008), the preferential attachment algorithm (PA) is benchmarked against other methods to overcome missing data, both based on imputation and likelihood estimation. The results show that PA offers larger samples that overcome convergence problems of ERGMs, whilst also presenting some bias in estimates, but only significant for large percentages of missing data. To reduce bias and attest to the robustness of our results, we used a three step approach. First, we only included in the analysis projects in which at least 60% of the participating institutions answered the survey (and 50% for very large projects — see Section 3.2). Second, we used both preferential attachment and complete cases methods to treat missing data and compared the results of both ERGM and LRQAP estimation. For the ERG models, we compared complete cases with preferential attachment-imputed matrices for all complete cases projects in which we achieved convergence (note that complete cases lead to smaller sample sizes which induce difficulties in ERG model fitting). Third, we compared both direction and significance of coefficients between LRQAP and ERG models on PA-imputed matrices.

Alternative approaches to imputation involve likelihood-based estimation, such as the ERGM-based procedures that use MCMC methods to estimate the unobserved (missing) network ties, as proposed by Gile and Handcock (2006), Handcock and Gile (2010), Koskinen (2007), Robins et al. (2004) and Wang (2016). Within the ERGM framework, some types of missing data can be handled via a latent missing data approach proposed by Handcock and Gile (2010). However, for the smaller projects in our data, the unit non-response type of missing data we had did allow for good model convergence using this approach. In light of that, and to maintain the same data structures over the two estimation procedures (ERGM and LRQAP), we decided to use both complete case analysis and preferential attachment imputation. The results of the performed robustness tests can be found in the Appendix.

4.2. Logistic regression quadratic assignment procedure

LRQAP, short for Logistic Regression Quadratic Assignment Procedure, is a nonparametric regression technique developed for modelling network data with a binary dependent variable.

[2] $\pi(k_j) = \frac{k_j}{\sum_j k_j}$, where k_j is the indegree of actor j. See Huisman (2009) for a more detailed description.

LRQAP is part of the QAP routines, which have been described as robust in their ability to control for varying and unknown amounts of row and column autocorrelation (i.e., lack of independence among observations), a characteristic of network data (Kilduff and Krackhardt, 1994; Krackhardt, 1988; Scott and Carrington, 2011). These procedures are based on row and column-wise permutations that keep the data structure intact, except for the order of the objects which is randomly permuted (Dekker et al., 2007). The model fit and regression coefficients of the non-permuted data (or observed data) are compared to the same indexes obtained with thousands of permutations, allowing to determine how frequently the indexes of the observed data models are larger or equal (in absolute value) to the indexes obtained with all random permutations. In the present study, QAP routines were performed with 100,000 permutations.

The network data in all variables of the present study are binary, so LRQAP is an adequate technique for analysis. However, LRQAP does not control for collinearity, i.e. dependence among independent variables. Since all models in the present study include at least three variables, collinearity might bias the results, especially in Model 3, which has six independent variables. In order to control for collinearity, the same models were analysed using MRQAP (Multiple Regression QAP), which is capable of handling collinearity without increasing Type I errors (Dekker et al., 2007). According to Borgatti et al. (2013), MRQAP routines are aimed at valued data, but they can be cautiously used with binary data. In such cases, the model fit (R^2) and significances of the regression coefficients (p-values) are valid for interpretation (and comparable to those obtained with LRQAP), whilst regression coefficients are not interpretable. Accordingly, results from MRQAP and LRQAP were compared to assess (i) if the model fits were similar, and (ii) if both routines signalled the same independent variables as significant or non-significant to Resource Sharing. This comparison resulted in a robustness test for LRQAP regarding the models in this study and the detailed findings are presented in the Appendix. A short version with the main results is presented in the following section.

4.3. Results from LRQAP analysis

In the 43 R&D projects analysed, all independent variables except Trust were very frequently correlated with Resource Sharing (the dependent variable) — correlation data available in the Appendix. Based on this information, the logistic regression fits of the three research models (M1, M2 and M3) were compared in order to understand if the change or addition of independent variables between models was improving the data fit. Since the model fits were normally distributed (p-value $\geq$ 0.084 in Kolmogorov–Smirnov test), an ANOVA test was performed to asses their differences (F-value = 21.282; p-value = 0.000) and a post-hoc Tukey-B test showed that each model was statistically different from each other at $\alpha = 0.05$ (mean of each group: M1 = 0.191; M2 = 0.302; M3 = 0.365).

A robustness test to LRQAP modelling was performed by comparing its results to the same models ran in MRQAP (detailed in the Appendix). The test found (i) no statistical differences in the research model fits at $\alpha = 0.05$, and (ii) match levels of 96% (M1), 98% (M2) and 79% (M3) achieved in selecting the same variables as significant or non-significant. These results mean that, for Models 1 and 2, MRQAP and LRQAP analyses provided very similar information. However, Model 3 is likely introducing Type I errors due to collinearity among independent variables, given the substantially reduced match level. As a consequence, those results will not be further presented nor discussed, limiting the study's ability to answer H1b and H2a.

Taking into account the 43 projects under study, Fig. 1 represents how often each independent variable had a significant and positive (in green), significant and negative (in red) or non-significant regression coefficient (in black) towards Resource Sharing. The median change in Odds Ratio (O.R.) towards Resource Sharing (when that binary variable was one) can be found adjacent to each significant graph slice. The median value is reported because Ratios do not follow normal distributions.

Fig. 2 shows the distribution of all 100,000 permutations for each network variable in Model 1, along with the estimated regression coefficients (represented by the dashed lines). It should be noted that Fig. 2 represents a single but illustrative instance of the results summarized in Fig. 1.

Based on Fig. 1, it is observable that the Structural Dimension of Social Capital (variable "Time Spent" in Models 1 and 2) contributed positively to Resource Sharing in 40–50% of projects (green slice). In that respect, the odds of members sharing resources were roughly 3 times larger when partners had spent time in social events prior to their consortium. The variable being significant in about half of the projects moderately supports H1a.

The Cognitive Dimension of Social Capital, measured through Shared Project Vision, contributed positively to sharing resources between members in the vast majority of projects and it contributed negatively to one project. In this single latter case, sharing a common vision with a partner was very detrimental to Resource Sharing. Overall, the odds of members sharing resources were 3 to 5 times larger among partners whom shared a common vision for the project's key success factors, when compared to partners whom did not have similar understandings of collective goals. These results support H2b.

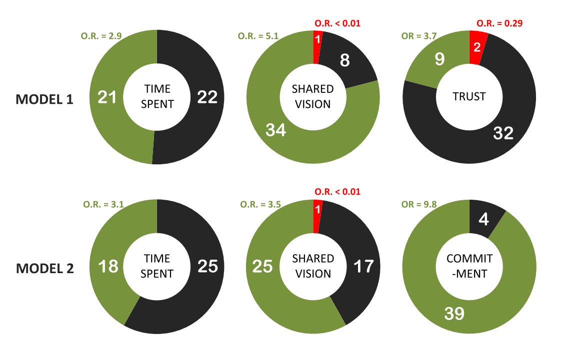


Fig. 1. Summary results of the LRQAP models for all 43 projects.

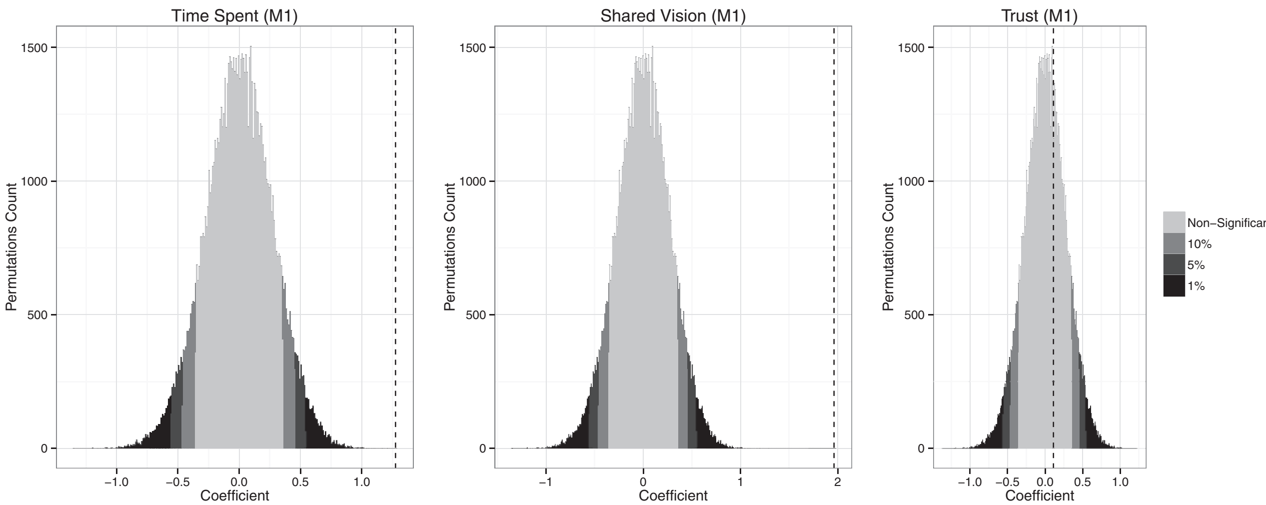


Fig. 2. Distribution of LRQAP permutations for three network variables in Model 1, for project ENV-06. The dashed line indicates the logistic regression coefficient for each of the variables.

The Relational Dimension of Social Capital was measured through partners' Trust and Commitment. In 21% of projects, Trust was a positive predictor of Resource Sharing, as hypothesized. Therefore, there were higher changes for that outcome tie to occur when partners shared a Trust tie. However, in two projects, Trust was found to be a negative predictor of Resource Sharing. In such cases, partners had much lower odds for sharing resources if they trusted each other, contradicting H3. Moreover, in the remaining 32 projects, Trust did not help describing the dependent variable. Therefore, the results from 79% of projects do not support H3. This means that Trust was not significant for partners' Resource Sharing choices. Regarding the study's last hypothesis (H4), Commitment was found to be a predictor of Resource Sharing in nearly every project (91%). R&D consortium members had nearly 10 times greater odds of being involved in Resource Sharing with whom they reported being highly committed. As a result, H4 was supported.

4.4. Exponential random graph models

Take graph Y as a simple representation of a social network, comprising a set of vertices V (commonly referred to as nodes or actors) and a set of edges E (commonly referred to as links or connections), such that $Y=(V,E)$. Let Y be understood as a random variable and y as a single realization of Y. Then, if y denotes the adjacency matrix of the network, $y_{ij}=1$ when there is an edge between vertices i and j, and $y_{ij}=0$ otherwise. In the networks we will analyse, when the ties between institutions are undirected (symmetric), $y_{ij}=y_{ji}$.

By defining Y as a random variable, we know it comprises the set of all possible networks with the same number of vertices as the observed realization y. In the case where ties are directed (asymmetric), the set of all possible networks reflects both the direction and the number of nodes of the observed network y.

Therefore, Y contains all possible networks ranging from an empty network, where there are no edges E between vertices V, to a full network, where all vertices V are tied by an edge E (Desmarais and Cranmer, 2012a). Note that for an undirected graph, the total number of possible realizations of the network is equal to $2^{\binom{V}{2}}$.

Let $g(y)$ be a scalar-valued network statistic in the observed network y, and θ the exponential random graph (ERG) parameter estimated for this statistic (equivalent to β in the context of standard regression analysis). The number of θ parameters to be estimated is a function of the network statistics $g(y)$ that are chosen to capture the network tie-formation processes.

These network configurations (or statistics) chosen to specify the model should be motivated by theory, as they reflect the local regularities and processes that give rise to the patterns that compose the observed network (Lusher and Robins, 2013). The underlying theoretical proposition of the ERG modelling approach is the idea that global patterns observed in the network emerge from decisions made at the individual level, which are themselves influenced by *endogenous* and *exogenous* factors. If we can capture what factors are driving the decision of institutions to connect with others, on different levels, we can produce an empirical distribution of networks that will exhibit the same global patterns that are present in the observed network.

The exogenous factors capture the propensity actors unveil to select their connections based on personal attributes, i.e. their propensity to match their attributes with other nodes in the network. This tendency is commonly referred to as *homophily*. For example, institutions from the same country may tend to collaborate more often due to physical proximity and language similarity. The network configurations that emerge from this selection process are dyadic independent, as they only consider factors that are exogenous to the network structure, and could very well be captured in a traditional regression framework.

The endogenous factors capture dyadic dependent processes in the network, and are crucial for the occurrence of particular patterns of ties at the global network level. For example, a tendency for transitivity will generate clique-like clusters in particular areas of the network, where the density of ties is higher. We could not observe the global affect of transitivity (emergence of clusters or cliques) if the actors did not themselves have a tendency for closure (transitivity). For an overview of all the network configurations that can be modelled, see Handcock et al. (2010) and Snijders et al. (2006).

After selecting the endogenous and exogenous configurations, the vector of p-sufficient statistics $g(y)$ is calculated globally in the network. However, it simply reflects individual tie formation choices at the local level that, when aggregated, gives rise to the observed macro-structure (Stadtfeld, 2012). In the Resource Sharing networks, the number of ties observed for all projects, as a share of the total possible number of ties, is quite high (around 0.5, which means half of all possible ties do exist). This is a measure of density, a global feature of the network, but that can be nonetheless explained by the choices of individual institutions: if we assume there are diminishing marginal returns to collaborations, due to time and resource constraints, institutions will select an optimal number of partners to collaborate with. This statistic will control for the propensity for the occurrence of ties, similar to the intercept in standard linear regression models, and it takes the following form:

$$g_1(y) = \sum_{i,j} y_{ij} \tag{1}$$

Based on the chosen network statistics and respective parameters, the ERGM yields the probability of occurrence of graph y conditional on the subgraph counts of the local network processes that constitute the network statistics, relative to the rest of the possible networks in the sample space Y. This probability is proportional to $\exp(\sum_{k=1}^{p}\theta_k g_k(y))$, which means that the direction of the network statistics g_k will be determined by the sign of the parameter θ_k: if a triangle parameter is large and positive, than the graphs in the sample space with more triads become more likely under the model, ceteris paribus. If we also take into account the configuration of a 2-path, where in a set of three vertices, two vertices have a common neighbour but no tie between them, then by including both the triangle and the 2-path configurations in the model we are able to assess the partial effect of a tendency for transitivity (triangle) given the propensity for actors to share a partner (2-path). We can then draw inference on whether there is an unusual tendency for transitivity at the local level in the network. Thus, the probability of observing y in the sample space, given the network statistics specified, is given by:

$$P(Y=y) = \frac{\exp\left(\sum_{j=1}^{p}\theta_k g_k(y)\right)}{\sum_{y*\in Y}\exp\left(\sum_{j=1}^{p}\theta_k g_k(y)\right)} \tag{2}$$

The normalization requires evaluating the probability at every possible realization of graph y in the sample space Y. Essentially, the ERGM will produce a distribution of graphs in which the configurations of the observed network are central. From here we can simulate a graph from the model and compare it to the observed network, to assess the goodness of fit. The estimation of these models directly from Maximum Likelihood is computationally demanding given the size of Y even for small networks.[3] To approximate the maximum likelihood estimates θ_k, we use MCMC-MLE, a Markov-Chain Monte Carlo simulation method. To understand the inner workings of the algorithm, see Desmarais and Cranmer (2012b).

4.4.1. Model selection

The ERGM modelling offers us two main advantages: (1) it allows for estimation of binary networks; (2) it estimates the effect of exogenous attributes on the presence or absence of ties whilst controlling for processes that are endogenous to the tie formation mechanism. The main disadvantage is that it assumes that the proposed model captures the true tie formation process, which makes model selection a crucial step in estimating ERGMs. Our theoretical framework established the causal relationship between the three dimensions of Social Capital and the phenomenon of resource sharing between R&D institutions, therefore, each of the dimensions will be introduced in the models as edge/dyad covariate configurations. This term requires an exogenous whole network from which it calculates the sum of the covariate values for each edge that appears in the network (for directed networks) or for each dyad in the network (undirected networks). In terms of the network covariates, the models estimated via exponential random graph modelling are identical to those estimated via LRQAP.

Other exogenous effects included were homophily and assortative mixing. Collaborative ties require ease of communication between the actors, so we deemed it necessary to control for all factors that would facilitate resource sharing between certain institutions and make it harder for others. The uniform homophily measures included counts the number of ties between two nodes that share the same attribute. In the two models run, we included "country", and "role" as attributes, in order to control for homophily and selection processes based on similarities of these attributes.[4] The statistic is given by the following expression:

$$U_q(y): \quad \sum_{i<j} y_{ij}\cdot I\{x_{qi} = x_{qj}\}, \tag{3}$$

where x_{qi} is the attribute value for actor i for attribute q.

The assortative mixing configuration captures the tendency for certain attributes to share more ties in common than others. Due to the predominance of particular countries in the FP projects under study, we included parameters for each combination of institutions from France, UK, Italy and Germany, as they were more likely to collaborate between themselves. The statistic that captures this effect is given by:

$$M_{q,a,b}(y): \quad \sum_{i\in X_{qa}, j\in X_{qb}, i<j} y_{ij}, \tag{4}$$

where X_{qa} is the set of all actors who have the value a for attribute q, and X_{qb} the set of all actors who have the value b for attribute q.

[3] For example, the sample space of a graph (undirected) with 20 nodes is composed of 68,719,476,736 possible realizations of the observed graph.

[4] The "role" attribute corresponds to a segmentation of members based on the tasks performed within each RJV, namely a group that performs R&D tasks, a group aiming to embed the new knowledge into market solutions and a group of mediators between the other two roles.

This resembles a set of dummy variables, each representing a particular pairing of countries.

The endogenous process of tie formation is a function of the type of interaction under study and has important implications to the overall network structure. Processes like transitivity (the tendency for a dyad to form a tie if they both share ties to common partners), if unaccounted for, can give rise to erroneous inference on the causal effect of a tie in network X on a tie in network Y, when the presence or absence of the latter is driven by (in)transitive tendencies in network Y.

In order to control for endogenous tie formation in the *Resource Sharing* network, we include in both models six configurations: a count of mutual ties; a count of intransitive triads; a geometrically weighted in-degree distribution; a geometrically weighted out-degree distribution, a geometrically weighted distribution of edgewise shared partners (triangle, $v(y)$), and a geometrically weighted distribution of dyadwise shared partners (2-path, $w(y)$). The degree statistics are important to unveil popularity effects within the network (who shares resources with most partners, or who receives the most resources).

The remaining statistics capture the tendency for closure in the network: is shared collaborative tie leading to new ties within a project? Can certain institutions bridge potential collaborations between their partners? And does it trump the effect of the dimensions of social capital? In essence, it sheds some light on whether redundant connections or sparse networks accurately reflect resource sharing between institutions. The edge and dyad-wise statistics are calculated by the expressions below:

$$v(y,\alpha_1): \quad e^{\alpha_1}\cdot\sum_{n=1}^{V-1}\{1-(1-e^{\alpha_1})^n\}\cdot\sum_{i,j} y_{ij} I\left\{\sum_n y_{in}y_{nj}=n\right\} \tag{5}$$

where n is the number of shared partners for the edge i,j and parameter α_1 controls the geometric rate of decline in the effect of triad closure on the tie probability for an increasing number of shared partners; and the dyad-wise statistic is given by

$$w(y,\alpha_2): \quad e^{\alpha_2}\cdot\sum_{n=1}^{V-1}\{1-(1-e^{\alpha_2})^n\}\cdot\sum_{i,j} I\left\{\sum_n y_{in}y_{nj}=n\right\} \tag{6}$$

where n is the number of shared partners between the dyad i,j and parameter α_2 controls the geometric rate of decline in the effect of 2-paths on the tie probability for an increasing number of shared partners between the dyad.

The iterative process taken in the exponential random graph algorithm evaluates the observed network statistics by deleting and adding ties to the network until it is evaluated at all possible realizations that constitute the sample space. Adding and deleting ties between nodes means that the ERGM can only handle binary edges, such that the weight carried by an existent tie is equal to 1. This is a problem when the adjacency matrix of the observed network (dependent variable) has valued edges, where a higher value indicates a stronger link between the vertices. Therefore, in order to estimate the ERGMs we dichotomize the shared resources network by coercing all edges $>k$ to be equal to 1, where $k=1,\ldots,m$.

The two models estimated are composed of endogenous, exogenous and network covariate configurations listed in Table 2.

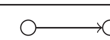
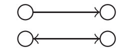
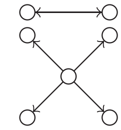
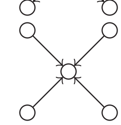
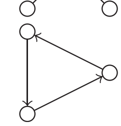
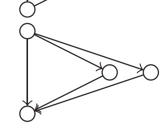
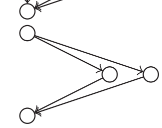
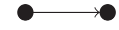
4.5. Results from ERGM analysis

The heterogeneity of the projects in terms of their size is one of the main obstacles to a direct comparison of the results across RJVs. The larger the network, the more opportunities for collaboration arise, but the more difficult it becomes to form close-knit groups where all institutions share resources with every other. As the network density decreases, the average geodesic increases and the information flow in the network slows down. At the same time, the emergence of particular network structures, such as cliques and other closure-type formats, are also less likely to emerge by chance than in smaller networks, which gives us some leeway in the interpretation of these network effects.

The joint distribution of network density for all projects follows a normal distribution, with both median and average network density around 0.5, and consequently decreasing with network size (see Fig. 3). Theoretically, this should not affect how well the endogenous effects capture the tie-formation process at the individual level. However, the networks size will

Table 2
Network configurations included in both ERGM models, estimated for all 43 FP-7 projects; "gw" stands for "geometrically weighted".

Covariate network	Model 1	Model 2
Time	Yes	Yes
Shared Vision	Yes	Yes
Trust	Yes	No
Commitment	No	Yes

Endogenous effects	All models
Arc	
Reciprocity	
Out-degree (gw)	
In-degree (gw)	
Intransitive triads	
ESP (gw)	
DSP (gw)	
Exogenous effects	
Homophily(country)	
Homophily(role)	
Assortative mixing (country)	UK, FR, IT, DE

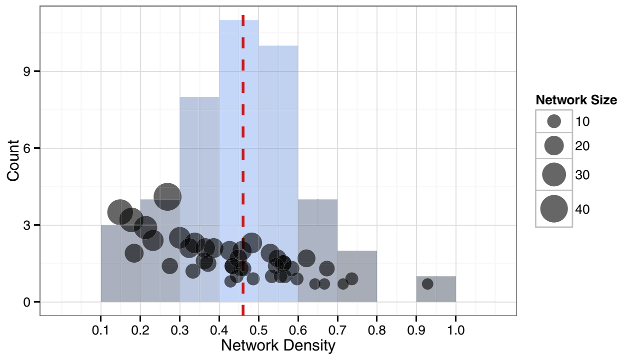


Fig. 3. Histogram of network density, where bars represent counts of FP projects (N = 43) and circles represent the size of resource sharing networks. The dashed line indicates the average network density for the 43 FP projects.

affect the number of parameters we are able to estimate, and models are adjusted appropriately to account for that.

An aggregate perspective on the performance of each configuration is present in Table 3. Overall, the results from the ERGMs confirm the results obtained using the LRQAP permutation tests in both proportion of significant coefficients and direction of the effect. Therefore, the effect of structural, cognitive and relational dimensions of Social Capital on Resource Sharing in R&D networks is robust to the inclusion of endogenous network effects, such as homophily, popularity and transitivity. The results for each of the dimensions are broke down by project in Fig. 4, for both models.

The ERGM coefficients reported are the log odds of a tie, which means that spending time together prior to the RJV in NMP-04 (Model 1) will increase the odds of sharing resources by a factor of $\exp(1.25) = 3.49$, given no change in the values of the other statistics. The effect of this structural component of Social Capital receives moderate support in Model 1, and little support in Model 2, when "commitment" was included as a covariate network. The cognitive dimension hypothesis receives strong support in Model 1, but also loses relevance in Model 2. In terms of the relational dimension of Social Capital, it shows a strong positive effect on the probability of Resource Sharing through reported "Commitment" within the project, rather than through "Trust", which was only significant in 15% of the projects.

The endogenous effects did not fare well in terms of significance, which can be attributed to the sheer number of parameters that needed estimation and the low number of nodes in certain networks. Nonetheless, the results suggest that Resource Sharing dynamics in R&D projects is not driven by popularity or activity (degree statistics), by a tendency towards role or country homophily, or by particular patterns of assortative mixing (particular country-dyads being more likely than others), but rather by closure and mutuality. The intransitive triad parameter was negative in almost all instances where it achieved statistical significance, which suggests that intransitivity is not a local configuration that will produce the global patterns of ties at the network level. In other words, if institution A collaborates with B, and B collaborates with C, then A is likely to collaborate with C as well.

The closure effect is reinforced by the positive and statistically significant coefficients of the geometrically-weighted edge-wise shared partner's statistic. For those projects where closure was not a significant predictor of tie formation, the dyad-wise shared partner statistic was significant and in part driven by the low tendency to reciprocate ties in most networks (notice that the coefficient for the mutuality statistic was only a significant predictor of tie formation in less than 1/3 of the networks). In some networks there is a significant tendency to reciprocate ties, which will close several triadic structures and form close-knit groups, but in others, reciprocation does not happen and intransitive structures are more likely to emerge.

Table 3
Summary of ERGM results in terms of significance and direction of the estimated coefficients. For each model, the columns indicate the % of projects for which the coefficient was significant, and for this subset, what % was positive and negative, respectively. AIC values of model fit display the median value for all projects.

Configuration	Model 1				Model 2			
	N	Significant	Positive	Negative	N	Significant	Positive	Negative
DSP (gw)	40	35.0	92.9	7.1	40	32.5	84.6	15.4
ESP (gw)	33	21.2	100	0.0	33	24.2	87.5	12.5
In-degree (gw)	40	10.0	25.0	75.0	39	7.7	33.3	66.7
Out-degree (gw)	35	8.6	0.0	100.0	35	11.4	0	100
Intransitive triads	39	69.2	3.7	96.3	38	65.8	0	100
DE-ITA	11	0.0	–	–	11	9.1	0	100
DE-UK	10	0.0	–	–	10	20.0	50	50
ITA-UK	14	7.1	0.0	100	14	7.1	0	100
Mutuality	41	29.3	100	0.0	41	26.8	100	0
Homophily (country)	27	7.4	50.0	50.0	26	3.8	100	0
Homophily (role)	39	7.7	33.3	66.7	39	2.6	0	100
Time Spent	41	61.0	100	0.0	41	41.5	100	0
Shared Vision	41	70.7	100	0.0	41	51.2	100	0
Trust	40	15.0	83.3	16.7	–	–	–	–
Commitment	–	–	–	–	40	87.5	100	0
		$AIC_{\bar{\mu}}$	229			$AIC_{\bar{\mu}}$	215	

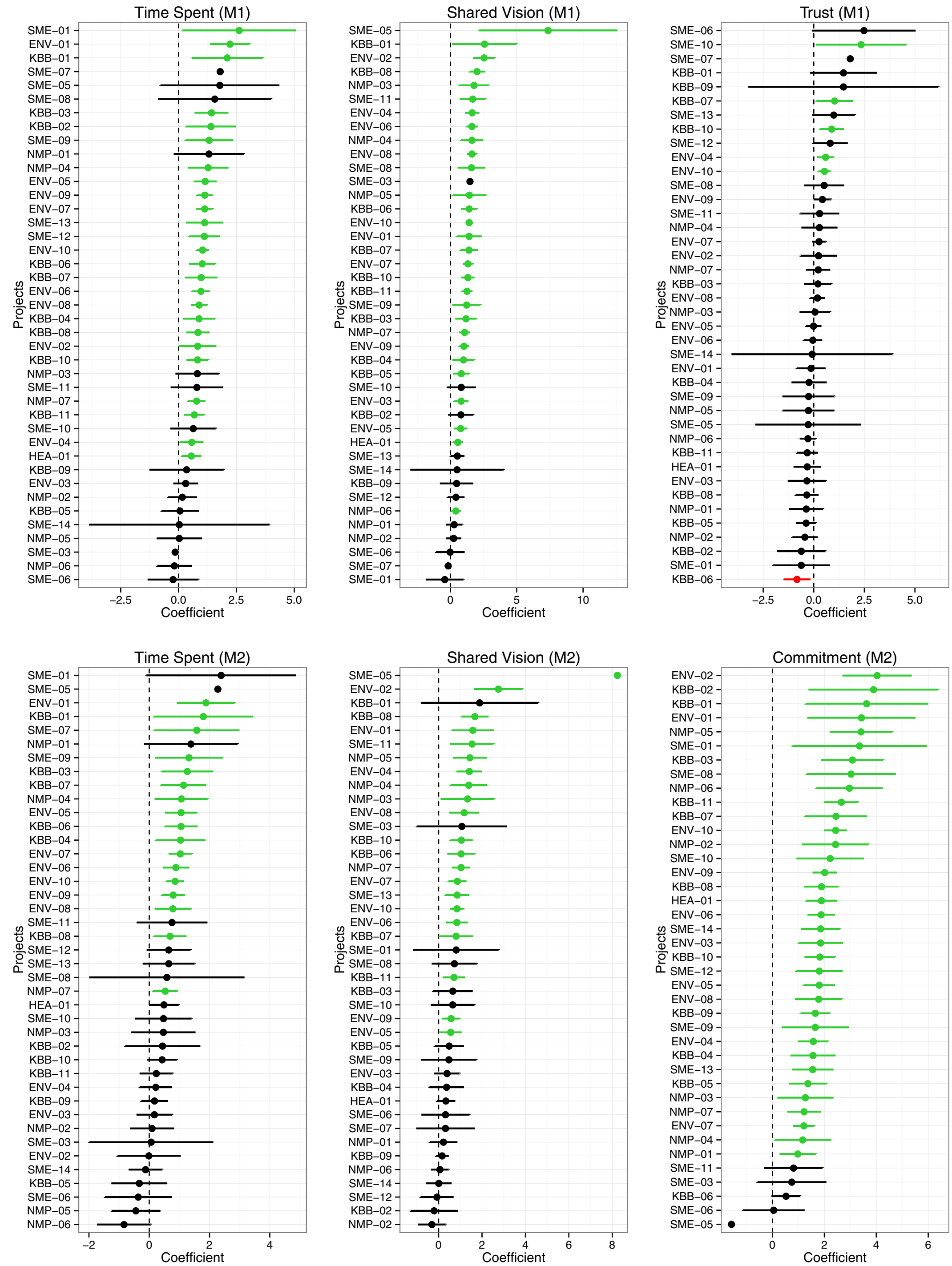


Fig. 4. ERGM coefficients of the three edge covariate networks for all projects, for models 1 and 2. Bars and dots are coloured if significantly different from zero (green for positive, significant and red for negative, significant), otherwise black. For some projects, the standard errors were so large that the confidence bar was excluded from the plot. Projects are named according to their funding programme: SME = FP7-SME; ENV = FP7-ENVIRONMENT; KBB = FP7-KBBE; NMP = FP7-NMP and HEA = FP7-HEALTH. Within each funding programme, projects are numbered sequentially as an ascending function of the number of members. Projects SME-02 and SME-04 were excluded from the results due to non-convergence of ERGM models.

5. Discussion

The present study aimed at examining the role of Social Capital dimensions (structural, relational and cognitive) towards Resource Sharing within R&D cooperation networks (defined as RJVs) funded by the European Commission. The novelty of this study results from the combination of Social Capital theory with social network analysis (SNA) to study intra-project partner relationships. Results showed that all Social Capital dimensions helped to explain Resource Sharing among partners, although to a different extent. Firstly, the structural dimension was measured using Prior Ties as suggested by the literature on University–Industry (U–I) links (Defazio et al., 2009; Santoro and Bierly, 2006). In about half of the 43 projects studied, Prior Ties significantly increased the odds of partners being involved in resource sharing. Secondly, the cognitive dimension was measured through a Shared Vision of the project success, and in 50–75% of the projects it increased the involvement of the partners in Resource Sharing. These results are consistent with other works (Chiu et al., 2006; Partanen et al., 2008), despite that those did not use SNA. Thirdly, the relational dimension was measured using two variables originating from Relationship Marketing but broadly used in the literature of U–I links: Trust and Commitment (Morgan and Hunt, 1994). The present research found that, unlike previously suggested (Blomqvist and Hurmelinna-Laukkanen, 2007; Partanen et al., 2008; Pérez-Luño et al., 2011; Plewa and Quester, 2007), Trust does not contribute positively to Resource Sharing. On the other hand, Commitment was the strongest and most prevalent predictor of Resource Sharing among all variables measured in Social Capital. These results regarding Commitment and Trust align significantly with the work of Benavides-Espinosa and Ribeiro-Soriano (2014) on International Joint Ventures.

The findings here reported were simultaneously and independently verified by two different methodologies within SNA: Logistic Regression Quadratic Assignment Procedure (LRQAP) and exponential random graph models (ERGM). Both arrived at the same conclusions, which reinforce the validity of our results. The first conclusion is that the European Commission Framework Programmes provide a unique collaborative environment that very often is not based on inter-partner Trust, even though Trust has been deemed as a critical condition for R&D cooperation (Frasquet et al., 2012; Pérez-Luño et al., 2011). In some networks, Trust was even detrimental to the choices underlying partners' Resource Sharing. Overall this indicates that resources were mostly shared among partners that did not rely on each other. Accordingly, it can be assumed that relational governance mechanisms are not standard among different types of cooperation projects. In particular, Framework Programmes are potentially providing a collaborative but opportunistic environment for public and private actors. The second conclusion is that the high Commitment and Shared Vision observed in these projects could derive from high-stakes outcomes (high-risk & high-gain), which force partners to carefully invest their resources (technical, physical, time, money, among others) to avoid inefficiencies that could negatively impact on their organizations. Further identification of the motivations of each individual partner for getting involved should help defining what drives their commitment and their vision for the project success.

There are two important shortcomings in the present research design. One the one hand, considering the overall size of the FP7 only a small number of projects were analysed, even though the participation of the majority of EU-28 countries in this study closely resembles the distribution observed in the whole Programme (European Commission, 2015). On the other hand, by using binary variables, important variation was lost regarding the degree of interaction between members. That information might have allowed a deeper insight into the conclusions hereby presented. For that purpose, each respondent should have reported the level of their interaction with N-1 consortium members for each dimension included in the analysis, which would have become cumbersome, eventually jeopardizing the utilization of all the data.

6. Conclusions

This research advanced knowledge by proposing a set of relation-oriented measures for analysing Social Capital in R&D cooperation projects through SNA. Past studies have consistently approached these relational constructs through non-relational measures, thus disregarding the network effects that ultimately impact the collaboration choices within each RJV (Pérez-Luño et al., 2011; Plewa and Quester, 2007). Collaborative ties are necessarily autocorrelated when conceptualized in a traditional regression framework: if we were able to look at the temporal evolution of the Resource Sharing network, it would become clear how the emergence of some ties is endogenous to the pre-existing structure in the network. In other words, particular types of relations have a tendency for clustering and closure. Therefore, institutions choose to share resources with other institutions with which they share a common partner, and not according to physical proximity, perceived trust or language similarities (Defazio et al., 2009; Pinheiro et al., 2015; Plewa et al., 2013). Nonetheless, even when controlling for endogenous and attribute-based tie formation, the Social Capital dimensions were clearly the strongest predictors of Resource Sharing within R&D cooperation networks.

Based on the conclusions of the present study, managers of FP-funded projects, as well as the European Commission, should be aware of the importance of Commitment and a Shared Vision towards close collaboration among project partners. This study shows that these two variables frequently and positively affect Resource Sharing. This in turn should impact the effectiveness of R&D collaboration in each project, which, in turn, should necessarily contribute the success of FPs in the long run. Importantly, this study provides further support to the notion that for any project network, the distribution of ties should be shaped in a manner that a priori provides a structure enabling success. The absence of this pattern of relations may not be enough to completely jeopardize the predicted outcomes of a project, but will limit them to the minimum that can be achieved by that particular group of collaborating partners. These types of consequences were previously analysed and reported for inter-firm networks (Cross et al., 2002). Accordingly, modelling the network ties of FP projects that were recognizably very successful should unveil ideal patterns of ties that lead to success, putatively allowing future improvement of the Programmes' financial support efficacy.

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Appendix A

A.1. Sokal–Michener similarities

Given the binary nature of the variables in this study, the correlations were calculated using the QAP simple matching routine available in UCINET (Borgatti et al., 2002), along with 100,000 permutations. Table 4 shows the average matching score across the 43 projects for each pair of variables as well as how often the observed correlation was significant at $\alpha = 0.05$ — using imputed data matrices. It should be noted that all independent variables except Trust were frequently correlated with the dependent variable (Resource Sharing).

A.2. LRQAP robustness test

As explained in Section 4.2, QAP routines are robust to unknown and varying amounts of row and column autocorrelation. However, unlike the Semi-Partialling MRQAP proposed by Dekker et al. (2007), LRQAP does not control for collinearity, increasing the likelihood of Type I errors when models are multivariate. In order to test whether collinearity was affecting the data analysis, LRQAP models were compared to the results obtained in MRQAP. This test focused on answering two questions:

1. How similar are MRQAP and LRQAP regression model fits?
2. How often do MRQAP and LRQAP models signal the same independent variable as significant or non-significant?

To answer the first question, the model fits ran through group comparison techniques. Since LRQAP and MRQAP model fits were normally distributed (p-value ≥ 0.084 in Kolmogorov–Smirnov test, except for one case of p-value = 0.039), an ANOVA test was performed to assess their differences along with a post-hoc Tukey-B test (Table 5). Results showed that, pairwise, each respective model is not significantly different in MRQAP and LRQAP, thus suggesting that both techniques provide similar information. The similar pairs are highlighted in Table 5.

To answer the second but even more critical question, the significances of the model coefficients (i.e., the p-values) from MRQAP were compared to those obtained in LRQAP. The objective was to determine how often these techniques would be in agreement regarding the significance of an independent variable. For this purpose, an agreement is achieved when either of these two scenarios occurs, given a significance value of 95%:

- both MRQAP and LRQAP signal the same independent variable as significant;
- both MRQAP and LRQAP signal the same independent variable as non-significant.

Table 6 presents the level of agreement across 43 research projects regarding MRQAP and LRQAP match towards signalling the same independent variable as significant or as non-significant. Accordingly, as example, for Model 1 (M1), MRQAP and LRQAP agreed, in 93% of the projects, whether Trust was either significant or non-significant to Resource Sharing. This does not mean that Trust had a significant impact towards Resource Sharing in 93% of the projects, but rather a higher level of agreement between routines, therefore offering similar findings for the role of Trust.

Considering the levels of agreement displayed in Table 6, especially for M1 and M2 (average of 96% and 98%, respectively), both LRQAP and MRQAP analyses provide highly comparable results. Since MRQAP routines were controlling for collinearity, only a very small amount of bias can be assumed in LRQAP's M1

Table 4
Average of Sokal–Michener similarity measures among model variables (values in parentheses indicate the percentage of projects with significant correlation at α=0.05).

Sokal–Michener similarities	1	2	3	4	5	6
1. Prior Ties: Time Spent						
2. Prior Ties: Work in R&D	**0.73** (84%)					
3. Trust	**0.52** (9%)	**0.59** (12%)				
4. Commitment	**0.59** (65%)	**0.67** (60%)	**0.64** (28%)			
5. Shared Vision	**0.62** (60%)	**0.61** (58%)	**0.60** (21%)	**0.70** (81%)		
6. Shared objectives	**0.63** (65%)	**0.68** (67%)	**0.61** (21%)	**0.74** (93%)	**0.72** (91%)	
7. Resource Sharing	**0.63** (60%)	**0.63** (67%)	**0.57** (21%)	**0.72** (88%)	**0.68** (77%)	**0.68** (81%)

Table 5
ANOVA test and pairwise group comparisons (Tukey-B test) of MRQAP and LRQAP regression fits for Models 1, 2 and 3 with imputed data.

ANOVA Model fit (R2)	Tukey's B test results	N	Subsets for α=0.05		
			1	2	3
	M1 (MRQAP)	43	0.1884	–	–
	M1 (LRQAP)	43	0.1907	–	–
F-value = 16.705	M2 (MRQAP)	43	–	0.2931	–
p-value = 0.000	M2 (LRQAP)	43	–	0.3021	0.3021
	M3 (MRQAP)	43	–	0.3490	0.3490
	M3 (LRQAP)	43	–	–	0.3652

Table 6
Level of agreement between MRQAP and LRQAP towards signalling the same independent variables as significant or as non-significant (α=0.05 /imputed data models used).

Model	Time Spent	Prior Work	Shared Objectives	Shared Vision	Trust	Commitment
M1	98%	–	–	98%	93%	–
M2	98%	–	–	95%	–	100%
M3	93%	91%	95%	63%	67%	67%

and M2 modelling. However, it should be noted that M3 showed a much lower agreement level (average of 79%), especially in variables with directed ties (last 4 columns). These results indicate that LRQAP was not capable of avoiding significance errors likely due to a high level of collinearity. Therefore, it was decided that the study, and consequent discussion, should only focus on Model 1 and Model 2, to avoid conclusions based on potential Type I errors from LRQAP analysis in Model 3.

A.3. Assessing the level of agreement in LRQAP's imputed data and non-imputed data models

The multiple imputation procedure, described in Section 4.1, aimed at creating a dataset without missing values, a requirement to analyse networks using ERGMs and some QAP routines. However, a test was required to assess the level of agreement between model analyses with imputed and non-imputed data, as to verify if similar findings are returned in those analyses. Consequently, this test focused on answering two questions:

1. How similar are LRQAP model fits using imputed and non-imputed data?
2. How often are LRQAP analyses with imputed and non-imputed data presenting the coefficients of the same independent variables:
   - as significant or non-significant (level of agreement)?
   - with the equal direction (positive/negative), for each significant coefficient?

Answering the first question required comparing the two groups of LRQAP model fits: imputed and non-imputed. A paired samples t-test was used, since the imputation procedure was assumed as a "treatment" and LRQAP model fits were normally distributed(Kolmogorov–Smirnov test: p-value = 0.074 for imputed and p-value ≥ 0.200 for non-imputed data). The test indicates a mean difference of 0.131 in R^2, with imputed models having significantly smaller fits (p-value = 0.000). This was caused by the data imputation procedure, which was based on conserving tie distribution probability among non-respondents and not on increasing fit towards imputed models.

To address the second question, the level of agreement between LRQAP routines with imputed and non-imputed data was analysed, as performed previously in Appendix A2. Table 5 presents how often LRQAP routines agree on whether a coefficient is significant or non-significant (columns from "Prior Ties: Time Spent" to "Commitment") and how often does the direction of the coefficient change when both routines agree that a coefficient is significant (last column).

As per Table 7, the average level of agreement per model was 88%, 91% and 67%, respectively. Similarly to the results in the previous Appendix, M1 and M2 provide very similar information, without a single change in the direction of the significant coefficients. The level of agreement in M3 is very reduced, at it was caused by the larger amount of missing values in Model 3, which limited LRQAP's ability to avoid Type I errors in non-imputed data modelling.

Table 7
Level of agreement between LRQAP routines with imputed data and non-imputed data towards signalling the same independent variables as significant or as non-significant. *The value in parentheses is the total number of significant coefficients in both routines at $\alpha = 0.05$.

Model	Time Spent	Prior Work	Shared Objectives	Shared Vision	Trust	Commitment	Δ in direction*
M1	84%	–	–	91%	88%	–	0% (n = 58)
M2	91%	–	–	84%	–	98%	0% (n = 77)
M3	71%	76%	79%	60%	52%	67%	3% (n = 69)

This assessment reinforced the decision of focusing solely on results from M1 and M2 (similarly to the previous Appendix) and showed that, despite the significant differences found in model fit, the imputation procedure did not change severely the results obtained from LRQAP analyses.

A.4. ERGM goodness of fit

We used two similar approaches to test the goodness-of-fit of the ERG models we estimated. Here we illustrate some of the results visually from Model 2 using project ENV-06.

The two procedures stem from the same principle: using the coefficients estimated in the ERG model, we simulate 100 networks and compare the distribution of particular properties in these networks with the distribution of the observed properties in our network. Fig. 5 plots the distribution of the minimum geodesic distance (the shortest geodesic path between two nodes) of the observed network of resource sharing for ENV-06 over a box plot distribution for the 100 simulated networks. Overall, the model does a good job in identifying the proportion of nodes that can be reached by each value of the minimum geodesic distance, encapsulating the observed distribution within its range.

We were also interested to see how well the model would capture node-level properties of betweenness and eigenvector centrality or transitivity. Fig. 6 plots the values for each of these measures found in the 100 simulated networks against the values in the observed network of resource sharing for ENV-06. Again,

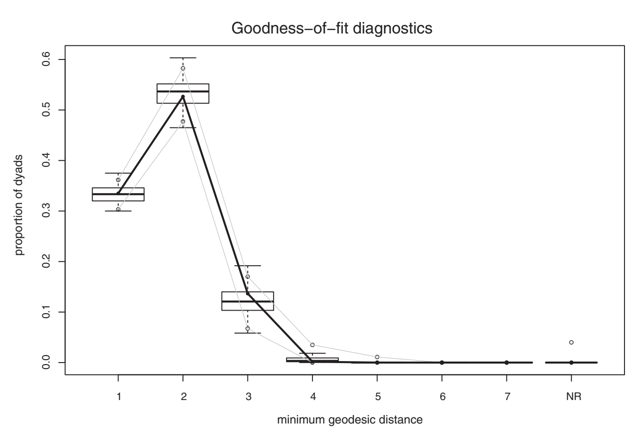

Fig. 5. The plot compares the observed data to 100 simulated networks (generated from the ERG for Model 2 and its estimated coefficients) for the minimum geodesic distance, for the project ENV-06.

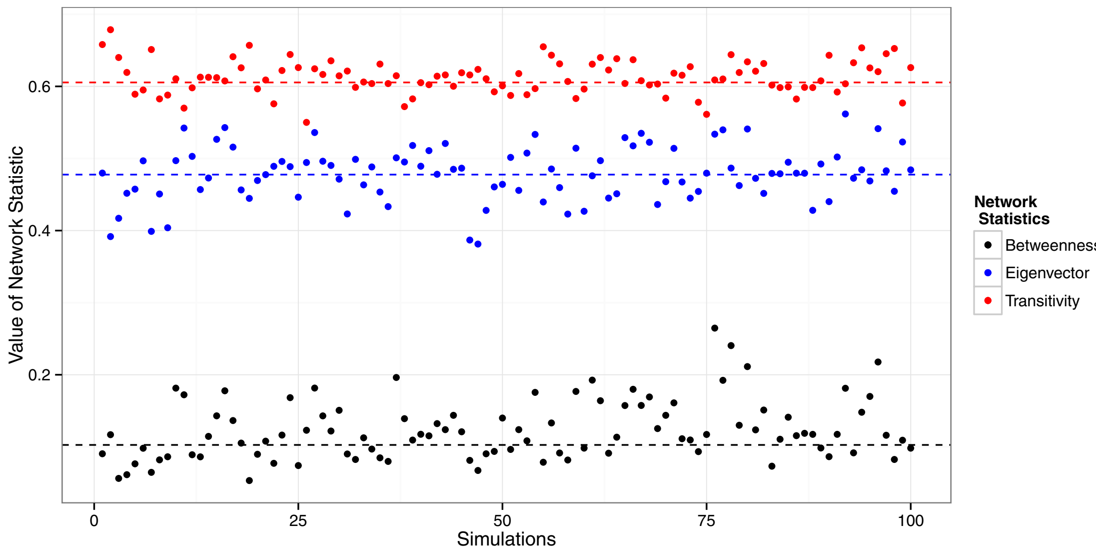

Fig. 6. Statistics of 100 simulated networks produced by the ERGM Model 2 estimated for the ENV-06 project, plotted against the observed values for said statistics in the original network of resource sharing.

the model does a good job in predicting structural properties of the network. Not surprisingly, transitivity values bounce very closely around the observed value in the ENV-06 network of resource sharing since we included a count of intransitive ties as a configuration in Model 2.

We ran the same tests for all projects included in our analysis. Although Model 2 seems to be a better fit in some case than others, it performed well for all projects.

A.5. Robustness check: multiple imputation v. row/column-wise deletion

On the main concerns of using multiple imputation of network data is the possibility of generating different local and aggregate patterns of tie formation that did not occur in reality, which we sought to avoid by using a preferential attachment algorithm in order to preserve the degree distribution of the network. In addition to this, we re-ran all the models using only complete cases to assess the robustness of the results obtained with imputed data.

Therefore, we performed row and column-wise deletion of any institution that, within a project, had missing values across the rows and the columns. The summary of the ERGM results for non-imputed networks is shown in Table 8, which can be compared directly with Table 3. The variation in network size (smaller networks) affected not only the estimation of configurations related to homophily (smaller probability of homophilous pairs), but also the statistical significance of some

Table 8
Summary of ERGM results in terms of significance and direction of the estimated coefficients. For each model, the columns indicate the % of projects for which the coefficient was significant, and for this subset, what % was positive and negative, respectively. AIC values of model fit display the median value for all projects.

	Model 1				Model 2			
Configuration	N	Significant	Positive	Negative	N	Significant	Positive	Negative
DSP (gw)	38	18.4	71.4	28.6	37	21.6	37.5	62.5
ESP (gw)	34	14.7	100	0	34	11.8	100	0
In-degree (gw)	38	2.6	0	100	37	0	–	–
Out-degree (gw)	13	7.7	0	100	13	7.7	0	100
Intransitive triads	13	38.5	0	100	13	15.4	0	100
DE-ITA	3	0	–	–	3	0	–	–
DE-UK	3	0	–	–	3	0	–	–
ITA-UK	2	0	–	–	2	0	–	–
Mutuality	38	28.9	100	0	38	18.4	100	0
Homophily (country)	1	0	–	–	1	0	–	–
Homophily (role)	6	0	–	–	6	0	–	–
Time Spent	37	51.4	100	0	37	29.7	100	0
Shared Vision	38	81.6	100	0	37	51.4	100	0
Trust	35	17.1	100	0	–	–	–	–
Commitment	–	–	–	–	33	87.9	100	0
		$AIC_{\tilde{\mu}}$	105			$AIC_{\tilde{\mu}}$	86	

effects. However, we are able to compare the direction of the effect the significant configurations with those in the ERGM ran on imputed models.

Overall, the comparison suggests that the imputed networks do mimic the local patterns of tie formation that exist in the networks of complete cases. The direction of the effects is identical in both imputed and non-imputed networks for edge-covariate configurations (such as our matrices of Trust, Commitment, Shared Vision and Time Spent), only differing slightly in one project for "Trust" and in two endogenous configurations, but maintaining the overall tendency in the direction of the effect for both models, which lends support to the multiple imputation method and the results from the ERGM estimation.

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