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Pinpointing effects of R&D consortium embeddedness on innovative outcomes across time and network order

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Abstract

This paper starts from the observation that, for an evaluation of policy measures that target science-industry collaborations, it is necessary to disentangle the network effect of these collaborations from the multiple relations that are usually used to construct alliance networks. Because of some specific features of science-industry collaborations, we specified hypotheses regarding the effect of an the positional embeddedness of such an constellation on its innovative outcomes in order to answer the question to what extent, if any, network features of r&d constellations affect their innovative outcomes and where and when does this effect actually occur.

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INTRODUCTION

Research on interorganizational networks and innovation has created insights in the way an organization's network position influences its innovative performance. For a large part, this research focuses at the link between networking behaviour of firms and their innovative outcomes (Pittaway, Robertson, Munir, Denyer, & Neely, 2004), but also several studies have been conducted that focus on the link between the network position of a firm and its innovative outcomes.

In Table 1 an overview can be found that is based on a literature review that was conducted by Meeus, Oerlemans & Kenis (2008). The authors took stock of the literature that, in one way or another, focuses at the relation between network features and organizational innovation and evaluated which findings were more or less robust across studies. They then evaluated current innovation policy in a specific country (The Netherlands) in terms of the extent to which this policy actually actively targeted these network features. This is relevant to do, especially when it comes down to inducing science-industry interaction which has been one of the key foci of innovation policy amongst various countries for the past decades[1].

[1] For example, Smits (2002) describes how Dutch innovation policy has shifted from a demand-push driven approach in the 1970s and 1980 to an approach that takes interaction as a starting point. The emergence of the National Systems of Innovations-approach in the early 1990s (see for example Edquist and Hommen 1999) shows that the topic has been picked up by the academic community as well

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INSERT TABLE 1 ABOUT HERE

One of the problems with evaluating innovation policy in terms of its effects on network features using the existing literature on alliances and networks is that the type of interorganizational formation used often is not too differentiated. Once coined as an intermediate form between taking full control of another (hierarchies) and arm's-length transaction (markets) (Powell, 1990), by now a vast array of different network forms of organization have been identified by organization scholars. Todeva & Knoke (2005), for example, identified 11 intermediate forms of interorganizational formations[2]. Many studies on interorganizational networks and innovation tend to lump these formations together (see for example Powell, Koput, and Smith-Doerr 1996), which makes it impossible to delineate the effect of being involved in a relational structure that is based on a specific type of tie.

This criticism has been voiced by other authors as well. Das & Teng (2002), for example, make the point that usually alliance networks are based on dyadic interorganizational formations, although some of these formations involve more than two partners, which is ignored[3]. This is problematic especially for science-industry networks, it is precisely this types of collaborations that do involve more than two partners (Corey, 1997; Das & Teng, 2002; Evan, 1993). Knowing that different exchange mechanisms can be at play once multiple partners are involved in a collaboration (Das & Teng, 2002), it can be expected that networks that are based solely on relations in multi-partner science-industry consortia might work out differently for the

[2] By taking the level of integration and formalization in the governance of relationships as a ruler, the forms are ordered and range from joint ventures and equity formations at the hierarchal end of the continuum to licensing agreements and industry standard groups at the market end of the continuum
[3] Sometimes this feature shows up as a control variable (Sampson, 2007), though

organizations involved compared to networks that lump together all types of dyadic interorganizational arrangements.

In this paper, we label multi-partner science-industry constellations as “R&D consortia” (rdcs). The basic question that is going to be answered is to what extent, if any, network features of rdcs affect their innovative outcomes, and where and when does this effect actually occur? With the ‘where’ of our question, we mean that one can benefit from its local network environment, or from its global network environment. As we will see in the theoretical framework of this paper, this basically links to the distinction between the ego network approach and the complete network approach in network studies. With the ‘when’-aspect of our question, we take into account that a unique feature of rdcs is that they take place over relatively long time periods and one can ask the question at what point in time the rdc actually benefits most from its network position. Thus, the ‘laggedness’ of outcomes relative to a certain network position at a certain moment in time will be explored.

By specifying what the effect of rdc network features is on rdc outcomes, we build forth on Meeus et al. (2008) by making clear what type of effects on rdcs policy makers should be aware of the moment when stimulating multi-partner science-industry interaction. We do so by focusing on a well-researched relation, namely the relation between positional embeddedness (centrality) and innovative outcomes. In addition, from the perspective of rdc management knowing if the outcomes of their rdc are affected by its local or global network environment is relevant to know because that gives them clues about the (im)-possibility of trying to manage their own network position: if the network effect would stem from the global network environment, there is not much they can do (the environment is faceless here) and interventions could be better left to policy. If, however, the network effect would stem from the local network environment of the rdc, rdc managers would have some levers for optimising their own network position in that local network. The time dimension adds to that an indication about the moment this network optimization, be it local (by rdc managers) or global (by policy makers) should take place.

From an academic perspective we contribute to the body of literature that focuses on science-industry interaction by showing how the networks that are induced because of stimulating this type of interaction actually works in favour of, or against the rdcs initiated. Although many citation studies have shed light on the topic (see, for example, the work of Leydesdorff et al.), isolating science-industry relations from the more general alliance networks has not been done before to our knowledge. As we will show in this paper, the insights that we generate are at odds with the general insights regarding networks and innovation that have been generated by the alliance literature.

THEORY

In this section, we will delineate the type of collaborations that we focus on in this paper and explain on which dimensions these collaborations differ compared to those studied in existing research that adopts an interorganizational relational perspective in explaining innovation outcomes. Then, based on this existing research, we will develop three hypotheses that will indicate what our expectations are regarding the relationship between network position and innovative outcomes for the type of actors that we look at in this study. Based on the existing view on the relationship between positional embeddedness and the innovative outcomes of an organization and some unique features of rdcs, two competing hypotheses regarding this relation in the situation of an rdc network will be formulated. Building on these two hypotheses, the issues of network order and timing of outcomes will be added. To provide the reader with a marker, the conceptual model that is developed in this section is provided in Figure 1.

INSERT FIGURE 1 ABOUT HERE

Setting the stage: R&D consortia

R&D consortia[4] exist because of the need for conducting joint research and development activities (Corey, 1997; Das & Teng, 2002; Evan, 1993). This form of collaboration has some distinct features that differentiate it from other forms, such as the joint venture.

First of all, whereas R&D-focused joint ventures are formed in order to contribute to the competitive advantage of the partners involved, the focus in rdcs is on pre-competitive R&D (Corey, 1997). Thus, although in both types of collaborations there is a sense of what the market is interested in, the end result that is delivered in an rdc is far less defined upfront and its end-goals are less focussed (Evan, 1993), leaving more room for search and trial and error activities. Doz, Olk & Ring (2000) propose that one of the main activities in the early stages of these collaborations is problem specification and goal-setting. Because of this, a second feature of rdcs is that they can be characterized by long exchange horizons between members (Das & Teng, 2002). Both features lead to the possibility of membership turnover during the collaboration because over time, the goal or goals of the collaboration might deviate, which as a consequence

[4] Definitions of R&D consortia range from very strict ones that exclude governmental or academic involvement (Das & Teng, 2002) to more loosely formulated definitions that allow for basically any type of partner and organizational set-up, as long as the goal is to advance technology in any field (Corey, 1997). Also, its antecedent (science-industry collaborations) is sometimes excluded (Evan, 1993) and sometimes included (Ring et al., 2005) in the scope of the definition. A reason for this variety is that R&D consortia play different roles for different national economies (Corey, 1997). We believe that, whatever differences there might be, the type of collaborations that are addressed share some features that allow for an equal treatment, at least from an interorganizational perspective. One should keep in mind though, that the empirical analysis that is presented later in this paper is based on a specific, yet important, form of science-industry collaboration and as such can be considered to one of the ways an rdc can materialize.

might lead to a less interesting proposition for existing members and possibly attract new members (Doz et al., 2000; Evan, 1993; Lavie, Lechner, & Singh, 2007).

The involvement of multiple partners is the fourth feature that distinguishes an rdc from other forms of interorganizational associations. This transcends a collection of dyadic alliances among each member, and an rdc can be considered to be a network in itself (Lavie et al., 2007). Next to membership turnover, a consequence of the participation of multiple partners is that the logic of exchange in rdcs is based on monitoring the pooling and distribution of resources by the members as a group rather than on expectations of direct reciprocity (Das & Teng, 2002). In other words: members do not expect a direct reciprocation of their contributions to the rdc, but expect reciprocity at any moment later on during the collaboration.

The presence of multiple members also leads to the involvement of members with variation in backgrounds. Depending on the main source of funding of the rdc and the nature of the organization or organizations that initiated it, industry representatives, NGOs, national labs and university researchers all can be involved (Corey, 1997; Evan, 1993; Ring, Doz, & Olk, 2005; Todeva & Knoke, 2005). Because of the pre-competitive nature of the rdc, participants can be future clients as well as future competitors (Corey, 1997; Evan, 1993). The involvement of these members in the collaboration varies as well, and depends on the amount of resources contributed to the rdc. In general, contribution of members tends to be less compared to, for example, a joint venture (Das & Teng, 2002; Evan, 1993). One reason for this is that the outcome does require not much contribution of members per se, such as setting an industry standard (Das & Teng, 2002). Another reason is that some members use the rdc to screen technological developments in their field and lie in wait in order to act on opportunities (Lavie et al., 2007). Once such an opportunity has been identified, it is likely that further development takes place in a collaborative arrangement that allows for fewer members (with that excluding potential competitors), such as an R&D joint venture.

Besides varying levels of internal involvement in the rdc, members also can display various levels of external involvement, i.e. involvement in other rdcs. Lavie et al. (2007) explain how the efficiency losses of being involved in multiple rdcs (redundant resource investments in R&D and dispersal of technological focus) of which not all are successful are outweighed by its benefits. Some of these benefits accrue to the individual member (for example getting a better grasp of technological possibilities and market needs, benchmarking of technologies, being better positioned to assess potential competitors and combining knowledge), but there also benefits for the rdc as a whole, especially in terms of information, complementarity, compatibility and facilitation of collaboration (Lavie et al., 2007).

With respect to information benefits of external involvement, members can overcome risks of the rdc getting overembedded (Uzzi, 1997) because of having ties to other rdcs that allow for external information inflow. In terms of complementarity benefits, the value of a technology being developed in a certain rdc can be enhanced by making combinations with complementary designs or services that are being developed in other rdcs. In the same vein, compatibility between designs is more likely to be established when members are externally involved in other rdcs, especially in the situation in which a dominant design is yet to emerge. Lastly, external involvement in other rdcs builds-up experience of a member, fostering trust-building, knowledge sharing and conflict resolution routines (Lavie et al., 2007).

External involvement of members leads to cross-linkages between rdcs, and with that networks between rdcs emerge in addition to the networks that form within each rdcs. These differ from networks based on dyadic alliances in that now nodes are collections of multiple organizations than individual ones, and ties reflect joint membership rather than direct ties to one another. In the remainder of this section, our attention will be on the implication of these networks for rdc outcomes. We will base this on the existing arguments used in the interorganizational literature that takes dyadic alliances as a starting point for explaining innovative outcomes, taking into account the distinguishing features of rdcs described in the above.

Networks and innovative outcomes of R&D consortia

The end-results that are to be delivered by an rdc are not much defined upfront, and some therefore claim that an rdc has delivered outcomes the moment it has advanced any technology in the field it is active in (Corey, 1997). In this paper, we will specify innovative outcomes as a product that has the potential to be used by end users. As described, there is at least a sense of what the market is interested in at the start of an rdc, and although it is inherent to an rdc that its results at the best give rise to projects in which the original concept is made ready for marketing, the extent to which the results are assessed to be adopted by its users are indicative for its innovative potential.

The main benefits that accrue from members that are externally involved in other rdcs have been specified in terms of knowledge benefits and facilitation of collaboration in the previous section. The extent to which a specific rdc has externally involved members can be reflected by the concept of positional embeddedness. Positional embeddedness indicates the extent a network node occupies a distinguishable position compared to other nodes in that network (Gulati & Gargulio, 1999). As such, it is an indication of the prominence of this node. Generally speaking, it has been consistently shown to be positively related to the generation of innovative outcomes (see Table 1 as well as Phelps, Heidl, and Wadhwa 2012). When an rdc is highly positionally embedded, compared to other rdcs in a network, this indicates that it has members that on the aggregate are involved in many other rdcs.

Generally, three arguments have been made to ground the mechanisms that are at play in the relation between positional embeddedness and innovation outcomes: a resource-based argument, a knowledge-based argument and a status-based argument (Meeus et al., 2008). The applicability of each argument for the case of networks between rdcs will now be explored.

According to the resource-based argument, centrality is taken as a proxy for the amount and quality of critical resources that are available to an actor (engaging in interorganizational relationships is only possible when these resources are available). More central actors then are more likely to have 'slack resources' which enable experimentation and innovation (Meeus et al., 2008). In the context of rdcs, many external linkages mean that few or many partners have many external links which might indicate the presence of 'slack resources', so if any contribution in the rdc has to be made, these actors might be more likely to put these on the table which facilitates innovation. However, this assumes high levels of internal involvement as well, which might be unrealistic given the level of external ties which in fact might indicate that members are spreading their risks rather than putting their resources in one technology. Instead of facilitating innovation, many external ties therefore also could hamper innovation.

According to the knowledge-based argument, innovation is more likely to occur in a rich and complex knowledge environment because of being exposed to a wide variety of cues that stimulate innovation (Meeus et al., 2008). Central nodes then are best positioned to innovate as this wide variety of cues is available to them in a timely fashion. Likewise, we saw that external involvement of members might open up windows to other rdcs, allowing for external information inflow and ensuring compatibility between different technologies that are being developed. Because sharing this is not only in the interest of the group but also in the interest of the member, the question whether or not the member will act in the benefit of the rdc is of less concern here.

According to the status-based argument, more central actors are likely to be innovation leaders rather than innovation followers (otherwise they would not be central in the first place) (Meeus et al., 2008). Being a leader also puts the actor in the position of influencing others in their adoption decisions as well as being able to assess market needs relatively accurately compared to less central actors (Phelps et al., 2012). In the cases of the rdc, this many external linkages then can turn out can turn out for the bad of the rdc. In the situation of an rdc, members with many external linkages are likely to be innovation leaders as well and their participation in an rdc might partly be to try to impose one's own technological agenda on others rather than participating in a relatively open innovation trajectory.

Applying the mechanisms that are used in the alliance literature on networks that consist of rdcs does not lead to a clear idea about the direction of the relationship between an rdcs' positional embeddedness and its innovative outcomes, and we therefore construct two competing hypotheses:

Hypothesis 1a: There is a positive relationship between the positional embeddedness of an rdc and its innovative outcomes

Hypothesis 1b: There is a negative relationship between the positional embeddedness of an rdc and its innovative outcomes

Expanding the basic hypotheses by introducing network order

In the network literature in general, there are two approaches in explaining the relationship between network position and the outcomes that a node generates because of having that position. In the first approach, the focus is on the ego-network of actors and the extent to which their ego network allows them to bridge different clusters (Burt, 1992; Lee, 2010) and reap the benefits from that, gives access to (heterogeneous) information sources (Ahuja, 2000; Uzzi, 1997) and allows actors to assess others in its direct environment before entering a partnering decision (Gulati & Gargulio, 1999). Although the complete network is always lingering in the background in the arguments that are made by these authors, their main focus is on the direct ties of and actor and its indirect ties.

The complete network is explicitly addressed by authors that use the second approach. Here, the complete network is taken into account in that the measures used are global (taking the complete network into account, such as betweenness centrality) rather than local (taking the direct network of an actor into account, such as degree centrality). Here it is argued that information benefits come with certain network positions that put an actor on certain pathways or at certain distances in the network that are advantageous compared to others (Ahuja, Polidoro Jr., & Mitchell, 2009; Gilsing, Nooteboom, Vanhaverbeke, Duysters, & van den Oord, 2008; Powell et al., 1996; Schilling & Phelps, 2007), under the assumption that information flows are substantial enough to actually reach those actors that are centrally positioned.

The question whether or not network effects occur at the global or local network is relevant for managers of an rdc. In rdc networks, rdc leaders have relative control over the first order of their network (control over with whom these partners collaborate else than the rdc leader). At the second and higher order levels the network is for the larger part out of their control and it is unlikely that they have information about who inhabits that level of the network. So when most of the effect of positional embeddedness actually stems from that higher order network, this would imply that rdc leaders do not have much control over that network effect and most of it actually happens behind their back, contrary to the situation in which this network effect stems from their first order network.

Literature that focuses on diffusion through networks, such as the spread of emotions (e.g. happiness or loneliness (Cacioppo, Fowler, & Christakis, 2009; Fowler & Christakis, 2008)) and behaviour-related medical conditions (e.g. obesity (Christakis & Fowler, 2007)) showed that at degrees of separation higher than three, the network effect disappears. Rather than degrees of separation we use the idea of network order that has been used by Uzzi (1997). Nodes that are at the first network order compared to a focal node are one step away, nodes that are at the second order compared to this focal node are two steps away, et cetera. As network order increases, the environment of the focal node is likely to become faceless and therefore it is less likely that information benefits can be obtained from nodes that are at a relative distant position from the focal node. Especially in the case of rdcs this is an important issue, since here ties are being specified as members being externally involved in other rdcs. We therefore hypothesize that:

Hypothesis 2: As the order of the network embeddedness of an rdc increases, the effect of positional embeddedness on innovative outcomes weakens.

Expanding the basic hypotheses by introducing the laggedness of network effects

In the alliance literature, the time lag between network features and outcomes is usually 1 year (see for example Ahuja 2000). In the event of rdc networks, that does not seem to be the amount of time needed to translate information. As we saw, one of the features of an rdc is that the final deliverable is not clearly defined upfront because often a first intuition or basic finding needs to be developed into a deliverable that is more or less ready to be developed for marketing purposes. Knowing that the conversion of information to knowledge is a process rather than something that occurs at one point in time (Nonaka, 1994), the question then is when an rdc actually will be able to use the information that might be transmitted through members that are externally involved.

Typically, an rdc is organized in a project form, and projects go through several stages (typically specified as the stage of problem conceptualization, planning, execution and termination (Pinto & Prescott, 1988)). Regardless of its effect, we expect information inflows through external involvement of members to be most likely to influence the outcome of the rdc in the early stages rather than the late stages, as in the early stages the decisions that will be made a relatively path-independent. In addition, because these early stages are characterized by trial and error activities, external information is more likely to have an effect compared to a situation when a product is actually in development. We therefore hypothesize that:

Hypothesis 3: As the time lag between the network embeddedness of an rdc and the generation of innovative outcomes decreases, the effect of positional embeddedness on innovative outcomes weakens.

DATA AND METHODS

Empirical setting

To be able to pinpoint the outcome effects of consortium embeddedness across time and network order, secondary data was collected for this study. This data were extracted from a series of project evaluation reports that were issued by a Dutch technology foundation, covering the time frame 1981-2004. Starting from the observation that a gap existed between science and industry, the goal of this foundation is to fund research projects that bring together scientists in the field of the natural sciences and industrial organizations to jointly work on utilizing scientific knowledge. Different technological subfields are focused at, for example instruments, pharmaceuticals, mechanical engineering and transport technology. An important feature of the scheme is that the applicant, who has to be a scientist at a research institution, has to show upfront that one or more industrial organizations see the possible utilization value of the results that are to be generated and display the willingness to commit to participate in a user committee that comes together at least twice a year. The project groups that are formed once an application is granted are suitable for this research because they focus on pre-competitive R&D, therewith involving a variety of industrial partners, and have duration of four to five years. In addition, the funding scheme requires a minimum level of interaction within these projects and members are allowed to be involved in multiple projects at the same time, which allows for linkage formation between projects.

Because the funds that are assigned to these projects stem from public sources, the results of each funded project are reported by the funding organization after five years. Initially we obtained information on scientists and the organizations they collaborated with from 1.928 project descriptions. In addition, information regarding the evaluation of the outcomes that were generated by these projects was collected. Our first step was to construct rdc-networks with this data.

Network boundary specification

The basis for specifying linkages between rdcs was that these rdcs should at least have one member in common (either an industrial organization or an academic project leader). Because in our theoretical reasoning, these external member linkages are most likely to be activated in the event compatibility issues between technologies are at stake, network boundaries should be specified that actually make activation of these links more likely in this context. One can imagine, for example, that an oil company that is involved in (1) an rdc that focuses at developing new techniques for drilling and (2) an rdc that focuses on optimizing oil refinery processes does not have a large incentive to share information between both rdcs, because they focus on two different steps in the company's value chain. We therefore specified for each rdc the technological main and subfield in which it was active. The used main- and subfields are shown in Table 2, including keywords to characterize each subfield. Since the focus of all rdcs is on developing knowledge that is potentially of practical value, specifying network boundaries based on technological main fields avoids creating links between rdcs that are not related in any way. Cross-over links between subfields were allowed for, however. The Life Sciences field, for example, consists of the subfields Biotechnology, Basic food chemistry, Pharmaceuticals and Analysis of biological materials, and any link between those subfields was allowed for. Relations between rdcs were only specified when rdcs were active in the same technological field and in the same year. Figure 2 displays the process from getting to the individual rdc information to the relational data.

INSERT TABLE 2 ABOUT HERE

INSERT FIGURE 2 ABOUT HERE

Based on this approach, seven rdc networks were constructed. Nodes were rdcs, and linkages indicate common membership between rdcs. The total count of nodes for all these networks was 1.661 (involving 1.052 project leaders and 2.126 organizations). Depending on the year in which a network emerged for the first time[5], the number of time observations for each network ranges from 21 to 23.

Measures

Innovative outcomes$_t$. The funding organization implemented a uniform project evaluation method as from the year 1989. This evaluation took place five years after the project start and focused on determining to what extent an end product that could be used independently by the end user was generated. This was assessed by expert opinion. For both dimensions, four scores were possible: (1) failure, (2) further research or development is necessary, (3) substantial realization in the near future is feasible or (4) substantially realization of results. For the operationalization of rdc outcomes this score was used.

Positional embeddedness$_{i,\ t\text{-}n}$. For each project, we calculated three different positional embeddedness scores for different combinations of network orders and time lags. First, we will describe which indicators were used for calculating positional embeddedness. Then we will explain the procedure for determining the different network orders and the way the positional embeddedness indicators were calculated.

[5] 1982, 1983 or 1984

From the three theoretical mechanisms that have been proposed to explain the relationship between positional embeddedness and innovative outcomes, three types of positional embeddedness emerge. First of all, the resource-based argument takes the amount of ties as a proxy. This corresponds with the measure of degree centrality (Ahuja, 2000; Powell et al., 1996; Shan, Walker, & Kogut, 1994). Secondly, the knowledge-based argument takes the richness of the information environment of an rdc as its starting point, which mostly resembles the betweenness centrality measure (Owen-Smith & Powell, 2004). Lastly, the status-based argument focuses on the extent to which influence on others can be exerted, which is captured by the measure of closeness centrality (Powell et al., 1996).

Determination of positional embeddedness measures for all orders i and for each time lag

Before these measures could be calculated, a procedure to determine network layers for each rdc was developed. This procedure is outlined in Figure 3. In total, 1.661 rdcs were active in a sequence of multiple years in one of the seven networks that were specified, and for each rdc and for each network year this rdc was present, we constructed its first-order network by determining its first-order neighbourhood using the igraph package in R (Csardi & Nepusz, 2006). Its second-order network was constructed by determining the neighbourhood of the first-order network, and so on. The maximum possible network diameter was nine, so this procedure was repeated for each node until its ninth-order network was determined.

INSERT FIGURE 3 ABOUT HERE

Once each matrix was constructed, the three centrality measures were calculated for each matrix according to the procedure described by Freeman (1978) and using the sna package in R (Butts, 2008). All measures were normalized to correct for network size, except for the first-order measures of degree and closeness because here normalization would always lead to a score of 1[6]. For these measures we therefore used the non-normalized scores.

Once all positional embeddedness measures were calculated, we made a selection of rdcs that (1) were five years of duration, (2) were part of a network for five years in a row, and (3) did have at least four network orders. This was done to make sure each rdc that was included in the analysis was suitable to test our ideas about the effect of positional embeddedness specified at different network orders and at different points in time. In total 251 rdcs were selected. In a further attempt to account for alternative explanations for the success of an rdc, several control variables were determined.

Control – Maximum network order. The selection of rdcs led to a sample in which each rdc has in common that they are all somewhere in the periphery of the network, as their minimum amount of layers should be 4. In terms of the higher-orders, these rdcs are not comparable anymore: some rdcs could have a maximum order of nine and thus be prone to network effects at higher orders as well. To control for effects that come from having more orders above the minimum amount, we included the maximum network order of each rdc in our models as a control.

Control – Project size. This variable was included in our analysis in order to control for differences in rdc size. These might lead to different levels of involvement of members and resources contributed, which in turn might affect the innovative output of the rdc.

[6] Degree, for example, is normalized by dividing the degree score by (network size minus one). For a node's first order network, this is always equal to the degree of that node

Control – Project leader experience. The number of previous rdcs a project leader was involved in within the scheme was included as a control as well, because once active in the funding scheme, project leaders gain experience with the funding scheme and also might start to build forth on previous project results. The accumulation of experience and results over time increases the likelihood of succeeding with subsequent projects. This variable was calculated as the number of rdcs a project leader had led in the five years before starting the rdc of interest.

Control – Relational experience project members. Generally members of an rdc (so project leaders and industrial members alike) might repeatedly be involved with one another in rdcs within the scheme, building up trust and therefore become more willing to share information (Gulati, 1995). This variable was calculated as the number of industrial members a project leader has collaborated with in the five years before the start of the rdc of interest.

Subfield dummies. We controlled for unobservable project-level effects by including subfield dummies. The rationale behind this is that technology plays an important role for the organization of an rdc. Development of new technologies, for example, may require a different set of partners compared to the development of a technology that is the further development of an already existing one. In addition, it is known that across different fields, the amount of funding and R&D investment can be markedly different (Todeva & Knoke, 2005). Table 3 shows the number of projects that belonged to a certain subfields. Also, totals for each main field are shown.

INSERT TABLE 3 ABOUT HERE

Starting year dummies. Project starting year dummies were included in order to control for temporal influences. For example, it is known that in several years the funding organization had to cut-back on their budgets, which led to a more stringent selection of projects. Table 4 shows the number of projects started in each year.

INSERT TABLE 4 ABOUT HERE

Analytical approach

To test the effect of positional embeddedness based on different network orders, different time lags regarding the outcomes generated and different operationalizations of positional embeddedness, we ran 75 OLS regression models in which all control variables mentioned above as well as one variant of the positional embeddedness measure was included. For each of the three measures, 5x5 combinations of this measure were possible: 5 network orders (1^{st}, 2^{nd}, 3^{rd}, 4^{th} and the complete network, in order to check whether or not the effect of the latter would be different from the effect of the 4^{th} order) and 5 time lags (*t-1*, *t-2*, *t-3*, *t-4* and *t-5*, indicating the fifth, fourth, third, second and first project year respectively. Except for the time and field dummies, all variables were standardized for comparison purposes.

Since we were interested in the effect of positional embeddedness determined with network of different orders and for different time lags regarding the outcome generated, our next step in the analysis was to plot significance levels of the three centrality measures for different combinations of network order and time lag. Those levels show the probability that the observed effect of positional embeddedness is zero and plotting this probability for different order-lag combinations gives an idea about the diluteness and laggedness of the embeddedness effect.

RESULTS

OLS assumptions (linearity, homoscedasticity, normality, error terms are not correlated) were checked for each model using the ‘gvlma’-function that is implemented in the package with the same name in R and developed by Peña and Slate (2006). Also, possible issues with multicollinearity were checked by calculating VIF-scores. All assumptions were satisfied for all models, except for 9 models that were specified for the time lag *t-5*, where the assumption of linearity appeared to be violated. Inspection of the component residual plots for these models showed that the relationship between the three centrality measures here could be represented as a third order polynomial rather than a linear association. We refrained from modelling this, as the general trend of this polynomial was captured by a linear relationship as well.

The dependent variable was interpreted by us as being a continuous variable, although one might argue that an ordinal logistic regression model would be more appropriate to use here. We tested these models as well and the general patterns that emerged from this did not deviate from those of the OLS models, although larger confidence intervals were reported in the ordinal logistic regression model and hence, weaker effects were found. Results of the ordinal logistic regression model are available from the authors by request.

In Table 5, descriptive statistics and correlations regarding part of the dataset used are shown. The analysis we used posed challenges in terms of reporting results. If we were to present all variables used and analyses conducted, we would have to show descriptives and correlations between 132 variables (1 dependent variable, 3 time-independent controls, 1 x 5 time-dependent controls, 48 time and field controls and 3 centrality measures x 5 layers x 5 time lags) and the results of 75 regression models that each vary in terms of the centrality measure used, the layer looked at and the time lag between the moment of observation of the centrality measure and the outcomes that are generated. Rather than doing this, we decided to show some example result tables. Table 5 therefore shows part of the dataset that was used for exploring the effect of positional embeddedness with a network of order 2 for all three centrality measures and for all 5 time lags, excluding time and field dummies.

INSERT TABLE 5 ABOUT HERE

As one can see from this table, large correlations exist within and between the centrality measures used, but as they were never included in one model together, this did not pose any problems. The same holds for the other network orders that were specified. The centrality measures reported in this table were positively skewed, with skewness values ranging from 0.95 to 1.46.

INSERT TABLE 6 ABOUT HERE

Table 6 shows the results for the OLS models estimated using the 2^{nd} order degree centrality measure for the different time lags. As can be seen from this model, the effect of this specific centrality measure is negative in all models except model 4. The results of all regression models are consistent in terms of this negative effect, supporting hypothesis 1b and rejecting hypothesis 1a. In the context of rdcs, positional embeddedness through external involvement of members thus has a negative rather than a positive influence on the innovative outcomes generated.

Table 6 suggest that for this specific network order and centrality measure, the effect of positional embeddedness on project outcomes is present 2 and 3 years before the outcome is delivered. Weak effects are seen in the year before (*t-1*) and the starting year *(t-5)*. The effect of positional embeddedness for different network orders and different time lags cannot be fully deducted from this model, because neither all network measures nor all network orders are shown here. This full picture is shown in Figure 4, Figure 5 and Figure 6 that show the significance levels of the (negative) coefficients for the degree, betweenness and closeness centrality measures, for different combinations of network orders and time lags between measuring the centrality measure and project outcomes delivered. Black areas denote significance levels between 0.01 and 0.05 and grey areas denote significance levels between 0.05 and 0.10. White lines depict significance altitude lines, increasing with 0.01 from the centre of the shaded areas to the outer regions.

INSERT FIGURE 4 ABOUT HERE

INSERT FIGURE 5 ABOUT HERE

INSERT FIGURE 6 ABOUT HERE

The reference point (the ‘origin’ in the picture) denotes the start of the project (t-5, or five years before the project ends) at network order 1 (so all projects that are directly connected to the focal project through external involvement of its members). For comparison purposes, the effect of the complete network is also shown in order to delineate between 4th order network effects and complete network effects. To provide the reader an anchor point regarding the regression results:

the results shown in Table 6 appear in the three figures as the line that shows network order 2 and cuts through all time lags.

A question that remains is the question regarding the relative effect of the positional embeddedness measures used compared to all other variables included in the analysis. For all significant embeddedness effects found, we ran new OLS models, this time without the embeddedness measure included. In Table 7 the increase in R^2 for models with the embeddedness measure compared to the models without the embeddedness measure is reported. From this table it can be deducted that in general, the explanatory power of network effects in explaining innovative outcomes of rdcs is low, with increases in explanatory power ranging between 0% and 2%. Relative large values can be found at network orders 2 for all embeddedness measures, 2 to 3 years before the projects' end.

INSERT TABLE 7 ABOUT HERE

CONCLUSION AND DISCUSSION

This paper started with the observation that, for an evaluation of policy measures that target science-industry collaborations, it is necessary to disentangle the network effect of these collaborations from the multiple relations that are usually used to construct alliance networks. Because of some specific features of science-industry collaborations, especially that they tend to consist of more than two partners, we specified hypotheses regarding the effect of the positional embeddedness of an rdc on its innovative outcomes in order to answer the question to what extent, if any, network features of rdcs affect their innovative outcomes and at which network order and when this effect actually occurs?

With the analysis conducted in this paper, we were able to show that, although the network effect is marginal, rdcs are negatively affected by their positional embeddedness in rdc networks and this effect is the strongest for the 2nd network order. Contrary to our expectations, the effect of positional embeddedness is not the strongest in early stages of the rdc but instead, it occurs almost as from the start (second year) until the end of the rdc when the measure of betweenness centrality is used. For the degree and closeness centrality measures this effect is weaker and more closely located towards the end of the project. This indicates that information-rich environments are the most prominent explanatory factor in these networks, and negatively influence the outcomes of an rdc throughout its course. The weaker negative effects of having members with high degrees in terms of external involvement as well as the potential to impose its technological agenda on others tends to take place later on during the project.

We will now discuss the main findings and explore possible reasons for the general negative effect of having a high level of positional embeddedness in rdc networks. Regarding the negative effect of degree, the reason we gave for this was that rdc members that have many ties to other rdcs might actually be spreading their risk rather than devoting their resources to one technology. This actually challenges an assumption that is made by Lavie et al. (2007) who acknowledge this effect, but expect that conflicts of interest that might emerge because partners seek to support multiple technologies are effectively dealt with. Our expectations regarding the negative effect of high-status members trying to influence the technological agenda of the rdc and with that limiting the open focus that is needed in these types of collaborations were also confirmed by our findings.

Unexpected was the effect of the betweenness centrality of an rdc on its performance. Contrary to our expectations, being in a rich and complex knowledge environment by an rdc because of external involvement of one or more of the members does not stimulate the generation of innovative outcomes, but rather seems to be detrimental to it. Members that are involved in many consortia at the same time might be not too committed to any of these consortia. At the same time they generate a burden to other members because their involvement implies costs of coordination and adjustment. Hence, less effort can be given to the trial and error processes that are needed in order to develop a basic idea that can be built forth on. Another explanation might be that the high score on the betweenness centrality measure is a proxy for a project member that is rather generalist in its technological interest and therefore is not contributing much to the rdcs involved in, but acting like a spectator instead.

Based on these findings, the implication for rdc managers is that in general, partnering with industrial members that are involved in many other rdcs should be avoided, because this is indicative for a member that will not be too involved in the rdc that one is starting. Rather, one should try to involve members that are willing to be actively involved in the project. This can be achieved, for example, by letting members pay a fee for joining the rdc, which is a construction that is used in R&D consortia (Corey, 1997; Evan, 1993). This forces member to focus their efforts and to be more picky about which rdc to join and which rdc not to join. For policy makers, the implication is that networks are not beneficial for all activities, or, that existing networks are too dense because of many members being involved in many rdcs at the same moment. Authors have suggested that the most effective network structures are networks that look like ‘small worlds’: densely connected clusters, connected to each other through bridges (Schilling & Phelps, 2007).

Future research

By specifying what the effect of rdc network features is on rdc outcomes, we have built forth on Meeus et al. (2008) by showing what the effects are in rdc networks policy makers as well as rdc managers should be aware of. From an academic perspective we contribute to the body of literature that focuses on science-industry interaction by showing how the networks that are induced because of stimulating this type of interaction work against the rdcs initiated. Nevertheless, this research is a first step towards getting more insights in the way rdc networks work and several future research steps will be undertaken in order to proceed further on this path.

First of all, by focussing on positional embeddedness, we ignored the role that the structure of the overall network plays. From the alliance literature, we know that the features of these complete networks (such as clustering and reach, see Schilling & Phelps, 2007) affect rdc outcomes as well. In addition, there are many rdc-level features, such as member diversity, proximity, and member involvement that are known to affect rdc outcomes. We will therefore work further and develop a multilevel model that takes all levels into account. The focus on the network position of an rdc must therefore be seen as a first step in the direction of the development of such a model, and with this research we were able what type of network specification and time lag actually matters most in explaining rdc outcomes.

Another path that will be explored further that of exploring what happens with rdcs that are not positioned in the network such that they have at least 4 network orders around them. In this paper, we focused on rdcs that are relatively peripheral in the networks they are embedded in. For those players, being central does not seem to pay-off, but one might find other effects in the centre of the network. Further analysis will reveal if this is actually the case.

Lastly, several cases with low outcomes and high positional embeddedness scores will be further investigated to try to reveal what actually happened there. The database that was draw on contained descriptions about the projects in terms of how the research process unfolded as well, and these descriptions might get more in-depth information about what might have happened why the rdc was not that successful. In addition, we expect this to enhance our interpretation of the different embeddedness measures used.

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APPENDIX

Table 1: Summary of main findings literature review on the relation between network features and organizational innovation (Meeus et al., 2008)

Level of analysis	Feature	Effect on firm innovation
Alter features	*Type of alter*	
	Rivals	Negative
	Universities	Positive
	Institutional partners	Positive
	Venture capitalists	Positive
	Performance of alter	
	Innovative performance	Positive
	Network position of alter	
	Number of indirect partners (weighted with their innovativeness)	Positive
Relational features	Tie strength	Mixed findings
	Prior ties	No effect
	Repeated ties	Positive
Positional features	Centrality	Positive
	Maintaining structural holes	Positive
Complete network features	Network range	Positive
	Density	Mixed findings
	"Small worldedness"	Mixed findings

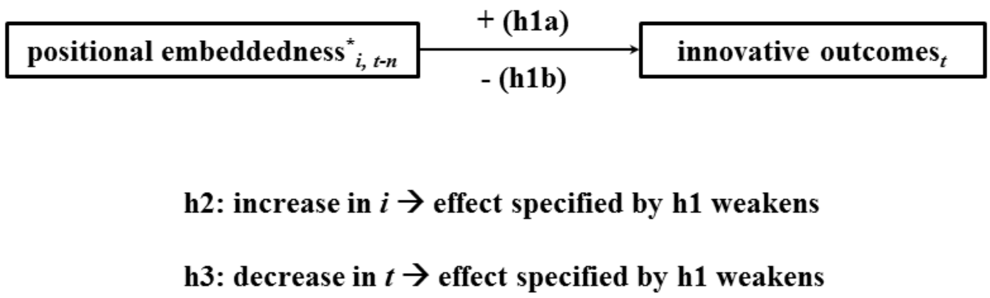


Figure 1: Conceptual model. The subscripts for the positional embeddedness variable should be read as follows: of a node in network with order *i* at time *t-n*

Table 2: Overview of main- and subfields used in classifying each project and keywords characterizing each subfield

Main field	Subfield	Subfield keywords
Electrical Engineering	Electrical machinery, apparatus, energy	generation, conversion and distribution of electric power, electric machines, electronic elements such as resistors, magnets, capacitors, lamps or cables
	Audio-visual technology	consumer electronics
	Basic communication processes	oscillation, modulation, resonant circuits, impulse technique, coding/decoding
	Computer technology	arrangements for controlling programmes, methods and arrangements for data conversions, e.g. image data processing, recognition of data, speech analysis
Instruments	Control	elements for controlling and regulating electrical and non-electrical systems, test arrangements, traffic control, signalling systems
	Measurement	measurement techniques and applications, e.g. measurement of mechanical properties such as oscillation, speed, length
	Optics	optical elements and apparatus, laser technology, optical switching
Medical Technology	Medical technology	sophisticated (e.g. ortheses, MRI-scanners) and less-sophisticated products(e.g. operating tables, massage devices, bandages)
Life Sciences	Analysis of biological materials	analysis of blood for medical purposes, using biotechnological methods
	Biotechnology	non-pharmaceutical oriented biotechnology
	Food Chemistry	seed and crop optimization, food innovation
	Pharmaceuticals	medicinal preparations containing (non-)organic active ingredients

Table 2 (continued): Overview of main- and subfields used in classifying each project and keywords characterizing each subfield

Main field	Subfield	Subfield keywords
Life Sciences	Analysis of biological materials	analysis of blood for medical purposes, using biotechnological methods
	Biotechnology	non-pharmaceutical oriented biotechnology
	Food Chemistry	seed and crop optimization, food innovation
	Pharmaceuticals	medicinal preparations containing (non-)organic active ingredients
Chemistry	Basic materials chemistry	paints, petroleum, gas, detergents
	Chemical engineering	apparatus and processes for the industrial production of chemicals
	Environmental technology	filters, waste-disposal, water cleaning, gas-flow silencers, exhaust apparatus
	Macromolecular chemistry, polymers	chemical aspects of polymers
	Materials, metallurgy	metals, ceramics, glass, processes for the manufacture of steel
	Microstructure and Nanotechnology	micro-structural devices or systems, nano-structures
	Organic Fine Chemistry	cosmetics, non-pharmaceutical oriented organic chemistry
	Surface technology, coating	metal coating, electrolytic processes, crystal growth and apparatus for applying liquids to surfaces
Mechanical Engineering	Engines, pumps, turbines	non-electrical engines for all types of application, especially those for the automobile industry
	Thermal processes and apparatus	steam generation, combustion, heating, refrigeration, cooling, heat exchange
	Transport	transport technology and applications, mainly automotive-oriented
Civil Engineering	Civil engineering	mining, construction of roads and buildings, as well as elements of buildings such as locks, plumbing installations, or strong-rooms for valuables

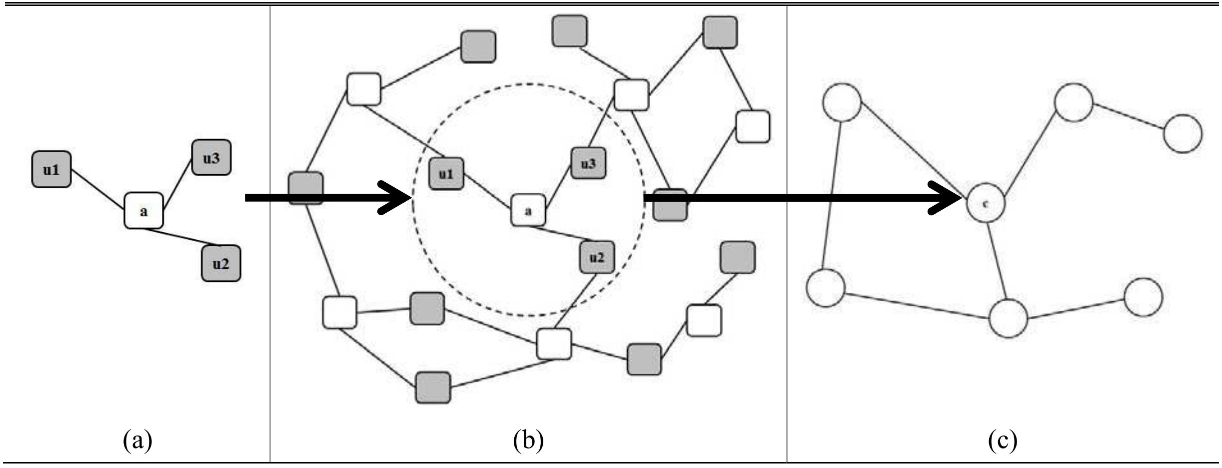
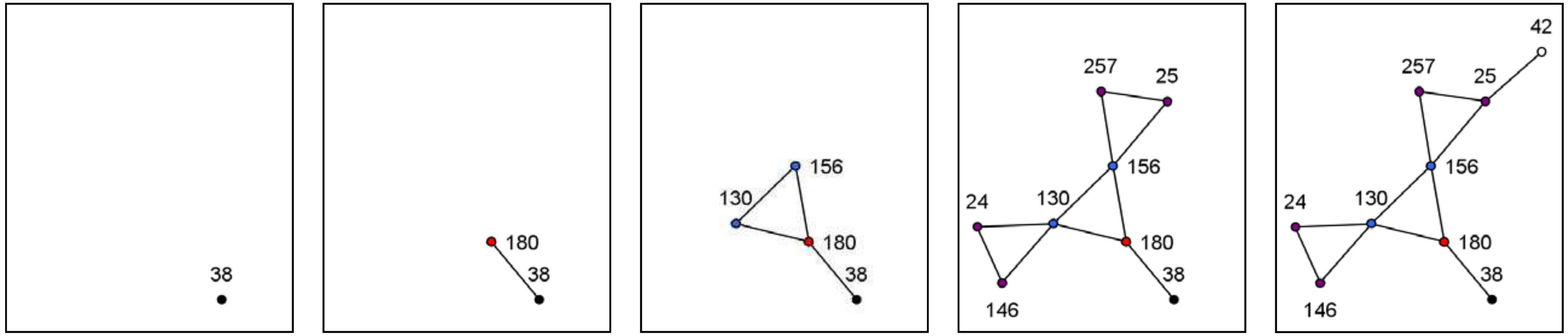


Figure 2: Overview of tie specification. Single rdcs (a) are connected with one another through members that are involved in multiple rdcs ((b), especially the links between u1, u2 and u2 with nodes other than a). Taking the rdc as an organizational unit ((b), the dotted circle which represents c in picture (c)), a network between rdcs emerges (c)



0th order	1st order	2nd order	3rd order	4th order

Figure 3: Visual representation of network order determination. For reference: nodes in the network that are shown here are specified at the level of c in step (c) in Figure 2. The reference here is the rdc that got the grant number 38 in the 1983 Electrical engineering network (diameter = 4). Node colors represent the network order a specific node belongs to. The implemented procedure was as follows: for each node, the 0th order network was determined (that is, the network in which the node of interest is isolated from all other nodes). From this network, the neighborhood (all nodes that directly link to the node in the already specified network) was determined to get at the 1st order network. In turn, the neighborhood of this 1st order network was determined in order to get at the 2nd order network. This was done using the 'nei'-function that is available in the igraph package (Csardi & Nepusz, 2006) which is distributed in the R statistical environment (R Development Core Team, 2011). The algorithm was applied to all rdcs in all networks. Based on the maximum observed diameter of 9, in total 72,198 iterations took place. Once each matrix was determined, the three centrality measures were calculated for each of them using packages that are part of the 'statnet' suite (Butts, 2008)

Table 3: Count of main- and subfields. Subfields dummies were included in all analyses

Main field	Subfield	Count	Subtotals
Electrical engineering	Audio-visual technology	4	
	Computer technology	3	
	Basic communication processes	2	
	Electrical machinery, apparatus, energy	7	16
Measurement	Measurement	36	
	Optics	7	
	Control	3	46
Medical technology	Medical technology	10	10
Life sciences	Food chemistry	61	
	Biotechnology	21	
	Pharmaceuticals	36	
	Analysis of biological materials	13	131
Chemistry	Basic materials chemistry	4	
	Chemical engineering	11	
	Organic fine chemistry	12	
	Surface technology, coating	1	
	Environmental technology	5	
	Macromolecular chemistry, polymers	3	
	Materials, metallurgy	4	
	Microstructure and nanotechnology	1	41
Mechanical engineering	Thermal processes and apparatus	1	
	Engines, pumps, turbines	1	
	Transport	1	3
Civil engineering	Civil engineering	4	4
		TOTALS	**251**

Table 4: Count of starting years. Starting year dummies were included in all analyses

Starting year	count
1989	11
1990	13
1991	5
1992	4
1993	10
1994	31
1995	35
1996	39
1997	25
1998	24
1999	26
2000	28
TOTALS	**251**

Table 5: Descriptive statistics and correlation matrix for all networks with order 2

Variable	Mean	SD	Low	High	1	2	3	4	5	6	7	8	9	10
1. Project outcomes$_{t}$………...…………	1.896	.852	0	3	-									
2. 2nd order degree centrality$_{t-1}$………....	.238	.114	.054	.714	-.082	-								
3. 2nd order degree centrality $_{t-2}$………..	.239	.109	.043	.667	-.096	.830**	-							
4. 2nd order degree centrality $_{t-3}$………..	.241	.118	.063	.674	-.132*	.744**	.896**	-						
5. 2nd order degree centrality $_{t-4}$………..	.246	.124	.064	.756	-.160*	.700**	.810**	.911**	-					
6. 2nd order degree centrality $_{t-5}$………..	.250	.126	.051	.667	-.154*	.628**	.711**	.782**	.885**	-				
7. 2nd order betweenness centrality$_{t-1}$…..	.046	.077	.000	.500	-.075	.294**	.189**	.170**	.157*	.135*	-			
8. 2nd order betweenness centrality $_{t-2}$…..	.042	.062	.000	.327	-.050	.226**	.291**	.226**	.183**	.142*	.678**	-		
9. 2nd order betweenness centrality $_{t-3}$…..	.040	.060	.000	.333	-.085	.228**	.277**	.329**	.265**	.222**	.521**	.705**	-	
10. 2nd order betweenness centrality $_{t-4}$…	.042	.072	.000	.571	-.116	.170**	.170**	.216**	.280**	.295**	.273**	.424**	.594**	-
11. 2nd order betweenness centrality $_{t-5}$…	.049	.090	.000	.600	-.058	.054	.073	.121	.155*	.180**	.152*	.261**	.366**	.572**
12. 2nd order closeness centrality$_{t-1}$……..	.570	.041	.514	.778	-.060	.992**	.803**	.711**	.673**	.605**	.268**	.203**	.204**	.155*
13. 2nd order closeness centrality$_{t-2}$……..	.570	.038	.511	.750	-.079	.827**	.996**	.892**	.807**	.703**	.177**	.272**	.260**	.155*
14. 2nd order closeness centrality$_{t-3}$……..	.571	.042	.516	.754	-.110	.732**	.886**	.995**	.902**	.761**	.155*	.207**	.310**	.200**
15. 2nd order closeness centrality$_{t-4}$……..	.573	.044	.516	.804	-.141*	.689**	.798**	.898**	.994**	.874**	.139*	.162*	.245**	.272**
16. 2nd order closeness centrality$_{t-5}$…….	.575	.045	.513	.750	-.143*	.611**	.690**	.756**	.872**	.994**	.129*	.136*	.216**	.314**
17. Maximum network order$_{t-1}$…………	4.594	.700	4	7	-.044	.073	-.019	-.139*	-.180**	-.134*	.015	-.055	-.156*	-.180**
18. Maximum network order$_{t-2}$…………	4.614	.697	4	7	-.108	.015	.086	-.062	-.146*	-.117	-.003	.114	.006	-.007
19. Maximum network order$_{t-3}$…………	4.582	.636	4	6	-.139*	.039	.065	-.011	-.097	-.092	-.117	.026	.047	-.015
20. Maximum network order$_{t-4}$…………	4.614	.631	4	6	-.186**	-.127*	-.049	-.043	.047	.045	-.061	.050	.078	.072
21. Maximum network order$_{t-5}$…………	4.586	.672	4	7	-.145*	-.147*	-.077	-.060	.035	.089	-.158*	-.082	-.056	.136*
22. Project size………...………………	3.841	1.786	1	10	.107	.086	.091	.100	.084	.032	.114	.166**	.212**	.159*
23. Project leader experience…………..	1.124	1.788	0	11	.192**	.013	-.024	-.028	-.022	-.038	-.097	-.119	-.102	-.016
24. Relational experience project members...	.892	1.923	0	13	.108	.042	-.024	-.007	-.009	-.039	-.113	-.112	-.096	-.066

**$p < 0,01$; *$p < 0,05$, n=251

Table 5 (continued): Descriptive statistics and correlation matrix for all networks with order 2

Variable	11	12	13	14	15	16	17	18	19	20	21	22	23
1. Project outcomes$_{t}$……….......………													
2. 2nd order degree centrality$_{t-1}$………....													
3. 2nd order degree centrality $_{t-2}$………..													
4. 2nd order degree centrality $_{t-3}$………..													
5. 2nd order degree centrality $_{t-4}$………..													
6. 2nd order degree centrality $_{t-5}$………..													
7. 2nd order betweenness centrality$_{t-1}$..…													
8. 2nd order betweenness centrality $_{t-2}$…..													
9. 2nd order betweenness centrality $_{t-3}$…..													
10. 2nd order betweenness centrality $_{t-4}$…													
11. 2nd order betweenness centrality $_{t-5}$…	-												
12. 2nd order closeness centrality$_{t-1}$……..	.053	-											
13. 2nd order closeness centrality $_{t-2}$…….	.067	.808**	-										
14. 2nd order closeness centrality $_{t-3}$…….	.116	.705**	.890**	-									
15. 2nd order closeness centrality $_{t-4}$…….	.156*	.670**	.802**	.898**	-								
16. 2nd order closeness centrality $_{t-5}$…….	.181**	.592**	.686**	.741**	.868**	-							
17. Maximum network order$_{t-1}$…………	-.090	.083	-.025	-.142*	-.185**	-.137*	-						
18. Maximum network order$_{t-2}$…………	.038	.019	.093	-.065	-.149*	-.112	.619**	-					
19. Maximum network order$_{t-3}$…………	.051	-.035	.066	-.011	-.100	-.091	.353**	.690**	-				
20. Maximum network order$_{t-4}$…………	.022	-.124*	-.048	-.046	.051	.062	.177**	.314**	.523**	-			
21. Maximum network order$_{t-5}$…………	.117	-.143*	-.075	-.063	.034	.099	.100	.178**	.295**	.593**	-		
22. Project size……….....………………	.199**	.075	.086	.100	.087	.038	-.193**	-.172**	-.165**	-.126*	-.082	-	
23. Project leader experience…………..	.029	.025	-.008	-.011	.005	-.020	-.190**	-.151*	-.012	-.085	-.027	.141*	-
24. Relational experience project members...	-.064	.042	-.018	-.002	.006	-.027	-.062	-.085	-.102	.048	-.004	.116	.609**

$^{**}p < .01$; $^{*}p < .05$, n=251

Table 6: Effect of 2nd order degree centrality on project outcomes for the degree centrality measure and the 2nd network order – OLS Regression Models

Dependent variable: project outcomes	Model 1	Model 2	Model 3	Model 4	Model 5
2nd order degree centrality$_{t-1}$………………	-.134† (-1.936)				
2nd order degree centrality$_{t-2}$………………		-.0177* -2.548			
2nd order degree centrality$_{t-3}$………………			-.150* -2.108		
2nd order degree centrality$_{t-4}$…………..….				-.090 (-1.275)	
2nd order degree centrality$_{t-5}$………...…….					-.139† (-1.902)
Maximum network order$_{t-1}$……….…..…..	-.038 (-.545)				
Maximum network order$_{t-2}$……….…..…..		-.014 -.208			
Maximum network order$_{t-3}$……….…..…..			-.006 (.092)		
Maximum network order$_{t-4}$……….…..…..				.064 (.899)	
Maximum network order$_{t-5}$……….…..…..					.078 (1.085)
Project size………………………………..	.010 (.156)	.021 (.323)	.018 (.271)	.019 (.287)	.027 (.410)
Project leader experience…………………	.020 (.239)	.019 (.226)	.020 (.236)	.022 (.260)	.026 (.317)
Relational experience project members…..	.045 (.586)	.046 (.598)	.047 (.612)	.046 (.586)	.054 (.696)
Year dummies included............................	*yes*	*yes*	*yes*	*yes*	*yes*
Subfield dummies included……………...	*yes*	*yes*	*yes*	*yes*	*Yes*
Constant…………………………………..	-1.081** (-2.938)	1.132** (2.823)	1.169** (2.891)	1.121** (2.761)	1.130** (2.815)
R^2	.187	.195	.188	.180	.179
F	2.477***	2.556***	2.48***	2.406***	2.398***
n	251	251	251	251	251

Standardized beta coefficients are shown. t-values are displayed between parentheses

***p < .001; **p < .01; *p < .05; †< .1

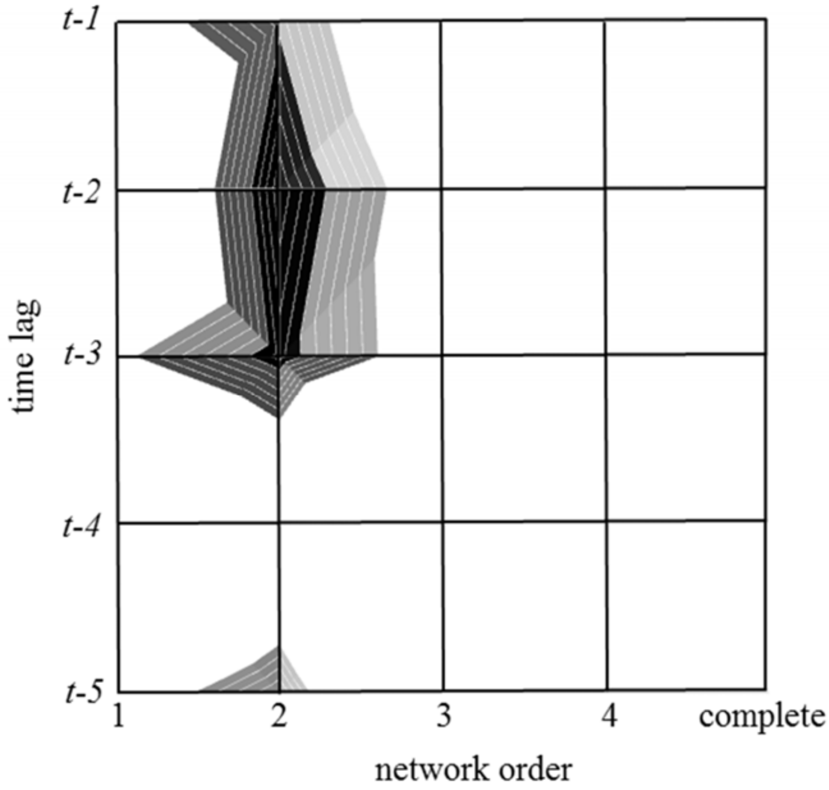


Figure 4: The effect of positional embeddedness on innovative outcomes for the degree measure. Shown are significance levels of the degree measure given a combination between network order and time lags. Colors indicate significance cut-off points: black shows the area where α is in between 0.01 and 0.05 and grey shows the area where α is in between 0.05 and 0.10. White lines show a stepwise increase in α with 0.01 as from the center

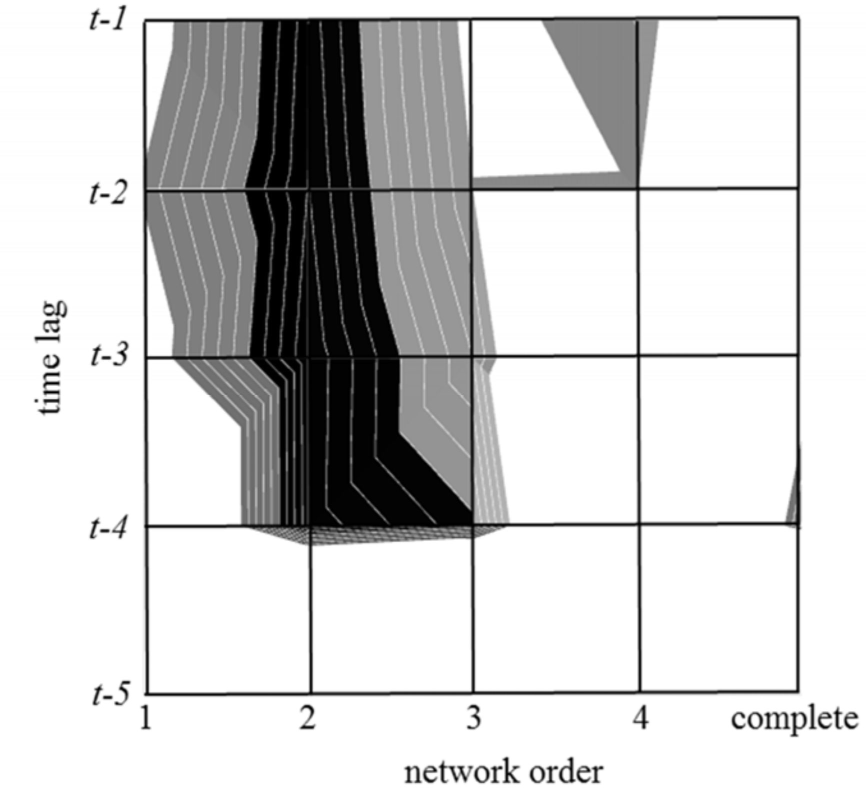


Figure 5: The effect of positional embeddedness on innovative outcomes for the betweenness measure. Shown are significance levels of the degree measure given a combination between network order and time lags. Colors indicate significance cut-off points: black shows the area where α is in between 0.01 and 0.05 and grey shows the area where α is in between 0.05 and 0.10. White lines show a stepwise increase in α with 0.01 as from the center

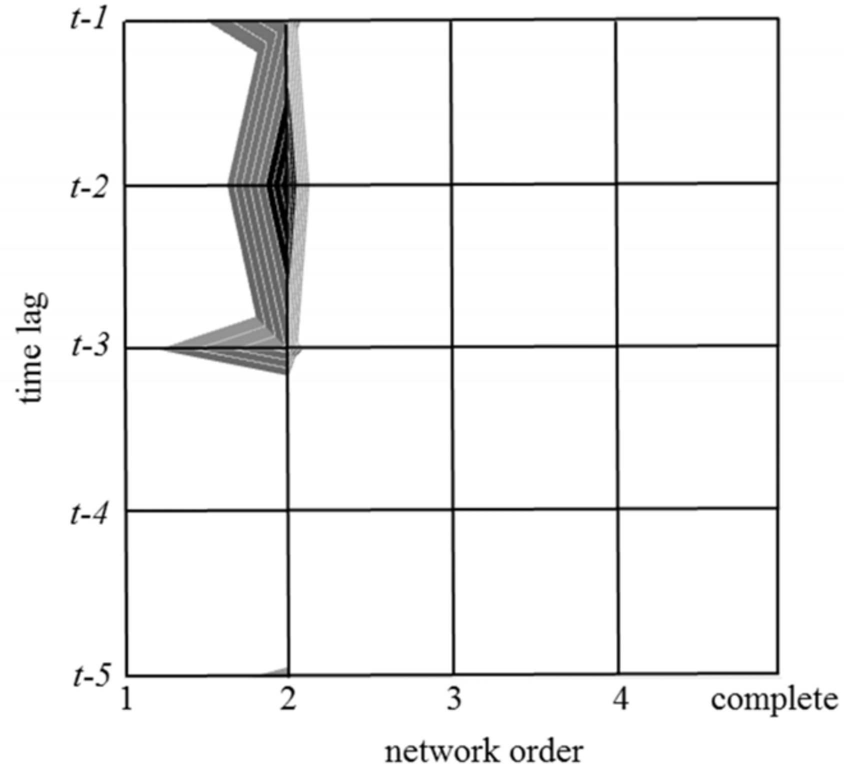


Figure 6: The effect of positional embeddedness on innovative outcomes for the closeness measures. Shown are significance levels of the degree measure given a combination between network order and time lags. Colors indicate significance cut-off points: black shows the area where α is in between 0.01 and 0.05 and grey shows the area where α is in between 0.05 and 0.10. White lines show a stepwise increase in α with 0.01 as from the center

Table 7: Relative effects of positional embeddedness given a combination network order and time lag. Shown is the change in R^2 when the embeddedness measure is added to the OLS compared to the model in which this is not the case

Measure	Network order. time lag	ΔR^2
Degree	2.1	0.0100
	2.3	0.0132
	2.4	0.0209
	2.5	0.0105
Betweenness	2.1	0.0081
	4.2	0.0067
	cn.2	0.0073
	2.3	0.0115
	3.3	0.0081
	4.3	0.0067
	cn3	0.0000
	2.4	0.0203
	3.4	0.0209
	4.4	0.0174
	cn.4	0.0160
	4.5	0.0068
Closeness	2.1	0.0074
	2.3	0.0093
	4.2	0.0174
	2.5	0.0091