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The effect of interorganizational network change on network outcomes: Empirical evidence from 7 science-industry field-networks in the Netherlands

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Abstract

This paper starts with the observation that there is a lack of contributions that explore the relation between network structure and network outcomes for networks that cannot be labelled?whole networks? but yet generate system-level outcomes. In addition, we argue that it is important to incorporate the role of network change in this relation, because this would provide levers for policy that aims at stimulating innovation in changing networks to a more productive mode. We explore a model that allows us to explore the abovementioned relation including the role of network change. Also, we accounted for different time lags after which outcomes could be generated, as the knowledge networks that were studied could be expected to need some knowledge gestation time.

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INTRODUCTION

Organizational network research has generated an abundance of insights in conditions that lead to the formation of organizational networks, as well as the impact of these networks on organizational outcomes (Brass, Galaskiewicz, Greve, & Tsai, 2004). In the past decade, it has been recognized by scholars that our understanding of this relation between networks and organizational outcomes might be incomplete and possibly even flawed without a clear understanding of the change of the underlying network structure (Ahuja, Soda, & Zaheer, 2012). After all, the benefits that an organization can reap from its network position are not only dependent on this position per se, but also on the amount of time an organization will sustain its network position. Hence, a temporal dimension is included more and more in research on the relation between networks and organizational outcomes.

The majority of the contributions that have included the temporal dimension in explaining antecedents or consequences of networks focuses on the relation between network features of organizations and organizational outcomes. With these outcomes and the management implications that can be derived from it being the main issue, the focus on network-level outcomes and the role of complete network dynamics has been considered to be of secondary importance. This point is illustrated by Table 1, in which we positioned the papers that were published in a recent Organization Science Special Issue on the topic of network dynamics. The basic models tested as well as the level of analysis of each article in this issue have been listed.

The table shows that the incorporation of network change in models that explain network-level effectiveness is a topic that is yet to be established.

INSERT TABLE 1 ABOUT HERE

A notable exception to the lack of focus on complete network evolution is the work of Human & Provan (2000). Here, the unit of analysis is shifted from the organization to the organizational network, and a description of ways in which different strategies for building network support led to the success or demise of networks is given. Contrary to other contributions, a focus on complete network dynamics is considered of primary importance in the contribution of Human & Provan (2000), as the networks being considered generate outcomes that go beyond the outcomes for individual organizations[1].

In this paper, we argue that studying the role of complete network change in the relation between network structure and network-level outcomes is also relevant for networks that do not have a clearly specified goal upfront. More specifically, we aim to investigate the role between structural as well as population change of networks that are consciously initiated by Dutch policy makers in order to stimulate innovation. With an increased interest by both policy as science in the role of networks for generating outcomes such as innovation[2], and corresponding policy measures that target the formation of interorganizational relations and networks, the question

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[1] The networks studied by Human & Provan can be characterized as 'whole' or 'engineered' networks (Kilduff and Tsai 2003; Ring, Doz, and Olk 2005). One of the distinguishing characteristics of these networks is that network members strive to achieve a common goal (Raab & Kenis, 2009). This is contrary to networks that are often mirrored with whole networks -labelled as being 'serendipitous' or 'emergent' (Kilduff and Tsai 2003; Ring, Doz, and Olk 2005). In the latter type, system-level outcomes are not considered to be relevant

[2] For example, Dutch innovation policy has evolved from a demand-push driven approach in the 1970s and 1980s to an approach that takes interaction as the starting point as from the early 1990s (Smits, 2002). The emergence of the National System of Innovations-approach in the early 1990s (see for example Edquist & Hommen, 1999) is another phenomenon that underlines this increased focus on interaction and, with that, networks

now is how these networks perform and what can be done in order to initiate network change if desired.

Current policy measures that focus on the formation of networks tend to target node and relational features. Although some of them indirectly influence features at the network level, none directly address network-level change (Meeus, Oerlemans, & Kenis, 2008). Whether or not the focus should be more on influencing the properties of complete networks depends on the answer to the question to what extent network-level dynamics affect network outcomes. It is this question that will be focused on in this paper. In our focus on the effect of different levels of complete network change on network outcomes, we will also take into account the idea of 'knowledge gestation' (Pakes & Griliches, 1984) by taking into account different time lags between the moment of network change and the generation of network outcomes.

The contribution of this paper is two-fold. First, we extend existing ideas regarding the relationship between network structure and network outcomes from the literature on whole networks to a setting in which network members do not explicitly strive to achieve a common goal, although a –more generic- goal can be identified, i.e. improving a nation's innovative output.

Secondly, we contribute to the growing body of research on network dynamics by testing the effect of network change on network outcomes. The topic of network change has been said to be embedded in various substantive research areas and therefore was obscured for quite some time (Borgatti & Foster, 2003). Recent contributions however, such as the ones in the OS Special Issue but also others (see for example Gay & Dousset, 2005; Kenis & Knoke, 2002; Koka, Madhavan, & Prescott, 2006; Madhavan, Koka, & Prescott, 1998; Powell, White, Owen-Smith,

& Koput, 2005), have developed it into a self-contained area of research. In addition to the earlier observation that a focus on complete networks is virtually absent, linking network change to network outcomes adds to the conversation by answering the question whether or not network dynamics matter for network outcomes.

THEORETICAL BACKGROUND

In order to study the effect of network stability on network-level outcomes, we specified several features that should be taken into account when focusing on complete network change. As indicated in the introduction, not much work has been done on the issue of explaining network outcomes. In as far studies exist that address the topic, the focus is on whole networks (Provan, Fish, & Sydow, 2007) rather than on emergent networks (Ring, Doz, & Olk, 2005). The networks that are studied in this paper are not explicit whole networks (they are consciously initiated rather than consciously created). Nevertheless we have used the network effectiveness model of Provan &Milward (1995) as a starting point as it is one of the few models available. This model will be applied to the context of a network in which organizational nodes potentially can exchange knowledge with each other because of sharing one or more members. The joint outcome that is generated by these nodes is the sum of all outcomes generated by each node separately.

The general conceptual framework that is used to test the effect of network stability on network outcomes is shown in Figure 1. The model is rather generic, and serves as a framework for exploring the effect of network change on network outcomes rather than testing hypotheses upfront, as our main concern in this paper is first and foremost to answer the question whether or not network change matters for network-level outcomes.

INSERT FIGURE 1 ABOUT HERE

Many contributions that describe network change focus on the development of structural indicators that are specified at the node level. From a policy perspective, network structure could be influenced by, for example, mandating relations between and assigning roles to nodes in a network. Indicators that often recur are nodal degree (Gay & Dousset, 2005; Orsenigo, Pammolli, & Riccaboni, 2001; Powell et al., 2005) and centrality (Gay & Dousset, 2005; Madhavan et al., 1998; Rosenkopf & Tushman, 1998), both of which reflect the collaborative attractiveness of an organization to others in the network. In addition, indicators such as the extent to which organizations tend to cluster together in subgroups over time, the development of the number of components in a network as well as the development of its diameter (Cantner & Graf, 2006; Gay & Dousset, 2005; Kenis & Knoke, 2002; Rosenkopf & Tushman, 1998), and the development of the level of 'hierachization' (Kenis & Knoke, 2002; Orsenigo et al., 2001) have been used.

In an attempt to distill the main indicators from this patchwork of measures, Ahuja et al. (2012) proposed five key indicators that should be taken into account when describing complete network change: degree distribution, connectivity, pattern of clustering, network density and degree assortativity. From these key indicators, we selected two indicators that are commonly used in whole network research and also complement each other (Provan & Milward, 1995; Scott, 2000): network density, which represents the general level of network cohesion (Scott, 2000), and degree centralization, which reflects the distribution of ties among nodes (Kenis & Knoke, 2002). Both features refer to the way network relations and with that the opportunities for information exchange are organized. Although density can be traced back directly to the indicators proposed by Ahuja et al. (2012), degree centralization is a result of our translation of degree distribution to a measure that summarizes this distribution at the level of the global network.

Density reflects the interconnectedness among organizations in a network. When this interconnectedness is low, information availability in the system, as well as the speed with which this information diffuses throughout the network is low (Gulati & Gargulio, 1999; Kenis & Knoke, 2002; Schilling & Phelps, 2007). The potential to gain information advantages and learn from each other's activities throughout the network that individual consortia are embedded in thus is low. High density levels, on the other hand, are more likely to be utilized by network members, as here the likelihood for information flow to occur as well as the speed of these flows is higher.

Whereas density reflects the level of cohesion in a network, network centralization reflects the distribution of ties among nodes in a network. A network that is highly centralized indicates a high concentration of information flows among a small number of organizations (Kenis & Knoke, 2002). This is an indication of the extent to which those organizations are 'in demand' by others in the network (Madhavan et al., 1998). This popularity is, in turn, explained by the dominance in the technological field of the knowledge that is developed by those central organizations (Gay & Dousset, 2005).

Network structural features are one of the three type of features that Ahuja et al. (2012) have included in their idea of 'network architecture'. Next to network structure, also the nodes that comprise the network and the ties connecting the nodes are included in this conceptualization. In addition to network structure, we also account for the network nodes by including features of the network population. This dimension is often part of a descriptive analysis of network change (e.g. Gay & Dousset, 2005; Orsenigo, Pammolli, & Riccaboni, 2001; Powell, White, Owen-Smith, & Koput, 2005; Rosenkopf & Tushman, 1998), but rarely exceeds the status of interesting descriptive statistic.

In networks, entry and exit of nodes over time takes place and with that change the population of nodes. For this reason, this is a key dimension that should be taken into account once the decision to focus on complete network change has been made. Some contributions that focus on exogenous drivers for network change have addressed this dimension and describe it in terms of the number of new entrants and the number of nodes that leave a network. The first is linked to the financing available (Powell et al., 2005), the developmental stage of the technological knowledge base (Orsenigo et al., 2001; Powell et al., 2005; Rosenkopf & Tushman, 1998) or the attractiveness of existing network members (Cantner & Graf, 2006; Gay & Dousset, 2005), whereas the latter is linked to organizational failure and mergers (Powell et al., 2005) or to being relatively disconnected to others in a network (Cantner & Graf, 2006).

Whereas the current approach regarding the population dimension of networks tends to focus on explaining new entrants and exits in terms of features of these nodes, a focus on the global evolution of networks should focus more on the role that these entrants and exits play for the network as a system. Node turnover is thought to be crucial for network vitality: both affect network stability in opposite ways: entrants add diversity to the network and render potential new relations, which in turn enlarges the partner opportunities (Meeus et al., 2008). The effect of nodes that exit a network are opposite and hence it is the combination of new entrants and exits that influence network diversity and partnering opportunities. Including this dimension in focusing on the development of complete networks over time is relevant as well from a policy perspective, as adding new or subtracting old nodes from a network affects its technological focus as well as the relational opportunities for the nodes that remain.

The concept that is of main interest in this paper is that of network change. This concept depicts the state a network is in in terms of the extent of change it has undergone in the recent past. Networks are highly stable when the structural as well as population features have not changed much in this recent past. This allows for the build-up of routines, a shared knowledge base and the development of trust which will enhance the overall network outcomes. The more network features have changed in the recent past, the more unstable the network will become. In unstable networks, nodes are likely to be less aware of each other, and will spend more time discovering opportunities and developing knowledge for themselves regardless of the existing configuration of the network, therewith missing possible opportunities for synergy. Compared to stable networks, network outcomes of unstable networks therefore are expected to be lower.

DATA AND METHODS

Empirical setting

Secondary data was collected for this study. The data were extracted from a series of consortium evaluation reports that were issued by a Dutch technology foundation, covering the time frame 1981-2004. The goal of this organization 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. Initially we obtained information on scientists and the organizations they collaborated with from 1,928 consortium descriptions. In addition, information regarding the evaluation of the outcomes that were generated by each consortium was collected.

Ahuja et al. (2012) proposed several hygiene principles that should be clarified in each network study, in order to avoid neglecting several key methodological issues when adopting a relational perspective. These principles address issues regarding the specification of network dimensions, as well as issues that address causality mechanisms. Since our primary aim in this paper is explore the link between network change and network outcomes, we will take into account practices from the first category. These practices target the specification of nodes and ties, and a specification of the relational content that flows through the ties that are inferred. In addition to these two aspects, we will also address a third aspect that has been addressed in the early 1980s. This is the issue of specifying system boundaries in terms of both time as well as focus of activities (Laumann, Marsden, & Prensky, 1983).

Node and tie specification. From a relational perspective, our dataset can be considered a 3-mode network: individual scientists are linked to industrial organizations through participation in R&D consortia. This allows for different approaches in specifying networks: scientists can be linked to each other because they work with the same industrial organization, albeit in different consortia. Likewise, organizations can be linked to each other because of collaborating with the same scientist. Lastly, consortia can be linked to each other because of sharing one or more members (a scientist, one or more organizations, or both).

The advice when projecting *n*-mode networks is to report information regarding all possible projections made in order to avoid information loss (Everett & Borgatti, 2013). Although we acknowledge that this provides the most comprehensive picture of network dynamics in our case, we also note that a trade-off should be made between being analytically complete and being analytically concise. For this reason, we decided to focus at one specific mode in this paper and specify each R&D consortium as a node, with ties being joint members. The main motivation for this approach is that each consortium can be seen as an organizational form with a distinct goal that is recognized by its members, and that receives resources from the funding organization.

Specification of relational content. Ahuja et al. (2012) state that, when direct observations of information flows through ties are absent, a plausible case should be built about the content that is inferred to be flowing through these ties. Because we make a shift in analysis from networks of consortium members to the level of the consortium, Zaheer & Soda (2009) recommend that two assumptions should be addressed here: the assumption of composition and the assumption of contagion.

The first assumption refers to explaining the logic that, when a tie is present between two consortia through a single link that connects part of one consortium to a part of the other consortium, this tie can be considered as a tie linking both consortia. Key here is to realize that the whole reason for existence of these consortia is that they were funded with the goal of increasing interaction between science and industry. The idea is that R&D is more effective when knowledge creators and knowledge users come together and interact. Thus, each consortium can be considered as a knowledge integrating device (Grant, 1996) rather than a collection of agents that each pursue their individual goals. In addition, all consortia are being precompetitive, meaning that there are no reasons yet to shield knowledge from one another. Hence, it can be expected that knowledge that comes from other consortia through joint membership, in addition to the knowledge that individual consortium members bring to the consortium themselves, will be shared by these joint members. Lavie et al. (2007) have stated that this knowledge is especially valuable for technological complementarity and compatibility: the value of a technology that is being developed in one consortium might be enhanced by making combinations with complementary designs or services that are being developed in other consortia, and by establishing compatibility with other technologies.

The assumption of contagion refers to explaining the logic that consortia can be considered as transmission points: network content flows through individual R&D consortia to other consortia that are not directly linked to each other. Although generally it can be expected that knowledge flows through networks are more diluted as the geodesic between two nodes increases, we think that at least locally R&D consortia could serve as transmission points because of the general focus on sharing knowledge and integrating knowledge. This is also one of the goals of the funding organization: by seeding relations between participants, it should be easier to find one another. Hence, knowledge from another consortium that is shared by one of the consortium members can be picked up by one of the other members as being relevant for one of consortia that this member is involved in, and shared with the members of that consortium as well.

Network boundary specification. Our arguments for specifying links between consortia only hold when the knowledge that is being shared falls within the same knowledge domain. For example, an oil company that is involved in (1) a consortium that focuses on developing new techniques for drilling and (2) a consortium that focuses on optimizing oil refinery processes does not have a large incentive to share information between both consortia, because they focus on two different steps in the oil company's value chain. For each consortium, we therefore specified 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. The classification used are based on Schmoch (2008). Since the focus of all consortia is on developing knowledge that is potentially of practical value, specifying network boundaries based on technological main fields avoids creating links between consortia that are not related in any way from a knowledge perspective. 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 consortia were only specified when consortia were active in the same technological field and in the same year.

INSERT TABLE 2 ABOUT HERE

Based on this approach, seven consortium networks were constructed. The total count of consortia 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[3], the number of time observations for each network ranges from 21 to 23 years.

Measures

Network outcomes. In the early years of the funding agency, consortium results were not evaluated systematically. As from 1989, however, a uniform evaluation method was implemented. This evaluation took place five years[4] after the consortium's start, and focused on determining to what extent products and incomes were generated. 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.

Although the ordinal nature of this scale implies that the differences between each successive category are not equal, the ordering principle that lies behind the classification scores allowed for a rough determination of network outcomes: first of all, a product of the scores on both the

[3] 1982, 1983 or 1984
[4] Publication took place one year after the evaluation

income as the product dimension was calculated for each consortium. Then, consortium outcome scores for each constructed network were summed, and divided by network size to adjust for differences in size among networks. Only outcomes of consortia that actually finished in the year of network observation were taken into account[5]. This calculation resulted in an average outcome score for each network.

Because the evaluation method was implemented in 1989, a 'sunrise' period exists in the dataset during which not all consortia that finished actually received an evaluation. As a rule, we calculated network outcomes for those networks in which at least 80% of the consortia that finished during that year received an evaluation. In these events, the sum of the product score was divided by the number of projects that received an evaluation rather than by network size.

Differences between the years in which consortia start, consortia are evaluated and evaluations are reported required some rearrangement of network outcome data in the dataset. In the end, network outcomes at t (which were measured at $t+5$ and reported at $t+6$) were linked to structural and population features at t as well. In order to investigate the laggedness of the effect of network change, 1, 2, 3, 4, 5 and 6-year lags were determined. With each lag, extra observations became available (over time, more and more consortia received an evaluation), increasing the number of observations in our analysis as the time lag increases.

Network density. Network density was calculated using the regular formula for networks that contain undirected relations (Scott, 2000).

[5] For example: in a given year and for a given field network, 4 projects finish. Project evaluations are as follows: project 1: 22, project 2: 13, project 3: 24 and project 4: 44. The sum of the product scores is ((2*2) + (1*3) + (2*4) + (4*4)) = 31. Taking into account network size, the network outcome score for this network is 7.75

Degree centralization. Degree centralization was selected for representing overall network centralization, as this measure most closely reflects the potential information transmission capacity of a node (as opposed to the more control-oriented betweenness centralization measure and independency-oriented closeness centralization measure). Degree centralization was calculated according to the procedures outlined by Freeman (1978). All degree centrality scores that were used for determining degree centralization were normalized, in order to account for differences in network size. In the event a network consisted of multiple components, degree centralization was calculated for each component individually, and a weighted average based on component size was calculated. Calculations were made using the 'sna' package (Butts, 2008) that is available in R (R Development Core Team, 2011).

New entrants. This variable was determined on a yearly basis and calculated as the proportion of new consortia in a network relative to network size. The criterion for a consortium being new to the network was that its project leader was not leading another project within the technological field in the same year or three years before. As this measure represents the proportion of entrants in an existing structure, the first year of observation (for which the score always would be 1) for a network was not taken into account.

Nodes leaving. A procedure similar to the procedure outlined for determining the new entrants variable was followed. This time, however, a consortium left the network when its leader did not lead any other consortium in the field network in the same year or three years after leaving.

Network stability. For each of the seven networks, we determined for each pair of subsequent years and for each network feature v whether or not the change from v_{t-1} to v_t was large enough in order to be classified as a change on that feature. The criterion that was used in this classification was that the absolute difference between v_{t-1} and v_t should be at least one standard deviation[6]. An example of this change determination procedure for the Medical Technology network can be seen in Figure 2.

INSERT FIGURE 2 ABOUT HERE

We then made an overview for each network that depicts in which year or years changes took place, and on which feature(s). An example of such an overview for the Medical Technology network is shown in Figure 3. This figure shows that four situations were identified: (1) no change on any of the dimensions (green) or (2, 3, and 4) one, two or three changes (yellow, orange and red respectively). As can be seen from this overview, no changes occurred in which each of the four features changed simultaneously. This holds for all 7 field networks. Changes in which three features changed were relatively rare, and were therefore lumped with changes in which two features changed. Network change was operationalized by making dummies for each of the different change intensities. Dummy codes were 00 (high network stability, none of the features changed), 01 (moderate network stability, one of the features changed and 10 (low network stability, two or more of the features changed.

INSERT FIGURE 3 ABOUT HERE

Controls. Because of the longitudinal nature of our dataset, network outcomes observed at *t* are not independent from network outcomes observed in the years before. Observations collected close in time will be closely correlated, and in order to correct for this we included the outcomes generated at *t-1* in our model explaining outcomes generated *t*. In addition, different

[6] This standard deviation is based on all scores on *v* within each of the seven networks rather than of all networks

technological fields might have differences in logics of interaction and interaction intensity, as well as in terms of the general level of output. In order to control for this, we included a dummy that accounts for these differences between technological fields. The fields Life sciences and Chemistry were classified as being science-based, whereas the other fields were classified as being engineering-based. Lastly, a variable 'Year' was included in order to control for unobserved temporal factors that might influence consortium outcomes, such as technological breakthroughs, or different levels of priority assigned to technological fields from the funding scheme over time. Although our field and time dummies could have been expanded more by using separate dummies for each field and each year, our number of observations did not allow for this. Therefore, the decision to aggregate dummies was made.

Analytical approach

OLS Regression was chosen as the analytical method and the following model was estimated: Network outcomes$_{tn}$ = β_1*Network outcomes$_{tn-1}$ + β_2*Field dummy + β_3*Time + β_4*Density$_t$ + β_5*Degree centralization$_t$ + β_6*New entrants$_t$ + β_7*Nodes leaving$_t$ + β_8*Moderate stability$_t$ + β_9*Low stability$_t$. In this equation, n indicates the lag of interest which ranged from 1 to 6. Thus, six models were estimated. Each of these models was similar in terms of the independent variables selected but different with respect to the observed network outcome variable, as these outcomes were observed in different years.

RESULTS

Correlations and descriptive statistics are shown in Table 3. From this table, several points can be made. First of all, correlations between the lagged outcomes are high compared to the correlations between other variables, but in general are moderate. Highly autocorrelated lags can lead to several issues when performing an OLS regression (Gujarati & Porter, 2009), which is not the case here. Secondly, science-based field consistently seem to generate lower outcomes compared to engineering-based fields, suggesting that there is a fundamental difference in the underlying logic of generating innovative outcomes. Third, our time variable is negatively related with degree centralization, the proportion of new entrants and the dummy that indicates low network stability, and positively related with the proportion of nodes leaving. This is an indication for the fact that network change in general is most prominent in the early stages of network development, with, naturally, mode nodes leaving as the network has matured. A fourth point that is worthwhile mentioning is that density and degree centralization are positively correlated, which is a counterintuitive finding because, to a certain extent an increase in density would automatically lead to a decrease in centralization. Scores on both variables, however, are not equally observed across their full possible range in any of the networks which is also impossible given the size of most of the networks observed[7]. Hence, the positive correlation between density and degree centralization reflects a general tendency in the networks observed that as the number of central consortia in the networks increases, the connectivity in the network increases as well. The last point that can be deducted from Table 3 is that the number of new entrants is positively correlated with the low stability dummy. This indicates that this population indicator makes a major contribution to high levels of network change.

INSERT TABLE 3 ABOUT HERE
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[7] Network size is accounted for in the calculation of our structural and population indicators and hence not reported separately in the correlation matrix. Average network size across all fields is 47.71, with a standard deviation of 32.25, a minimum observation of 3 and a maximum observation of 141

Using the dataset as reported in Table 3, linear model assumptions were checked with the 'gvlma' function that was developed by Peña & Slate (2006) and implemented in R (R Development Core Team, 2011). This is an omnibus test for the four assumptions of the linear model. All assumptions were found to be acceptable, except for the model that included the outcome measure with lag *t+5* as the dependent variable. The algorithm implemented in the gvlma function indicated that the error terms were not normally distributed, which suggest possible endogeneity issues. Visual inspection of the Q-Q-plot showed several outliers. In general, comparison of the Q-Q-plots for all models, showed some outliers which to us suggested that in terms of linear model assumptions all models are somehow close to the border of being acceptable, with the *t+5* model being a case that resides at the unfavorable end of the spectrum. In order to keep all models comparable, we decided to preserve the outliers in this model.

INSERT TABLE 4 ABOUT HERE

Results of the performed regression analyses are shown in Table 4. In this table, our observation that in general science-based fields deliver fewer outcomes compared to engineering-based fields is confirmed. Also, a negative effect can be seen of the low stability dummy 3 years after the network change has taken place. This suggests that, compared to highly stable networks, lower outcomes[8] are generated by networks that have undergone profound change. No differences were found between networks that are moderately stable and networks that were highly stable.

As for the structural indicators, weakly significant positive effects are found for degree centralization after 3 and 4 years. Density has a weak significant negative effect after 3 years, and a strong significant negative effect after 4 years. This indicates that more dense networks

[8] Note that our outcome measure was corrected for network size

generally deliver lower outcomes. We also find significant negative effects for the proportion of new entrants after 4 years, and the proportion of nodes leaving after five years. Hence, more nodes entering or leaving a network will lead to fewer outcomes after several years.

INSERT FIGURE 4 ABOUT HERE

The regression coefficients in Table 4 are standardized, meaning that the expected change in network outcomes in terms of standard deviation is shown for a standard deviation change in any of the independent variables. Because of correlated independent variables, this approach could be problematic. Hence, we also applied the procedure as described in Johnson (2000) for the regression model with the outcome lag of *t+3* for cross-validation purposes. The results can be found in Figure 4 and are in line with the coefficients reported in Table 4.

CONCLUSION AND DISCUSSION

This paper started with the observation that there is a lack of contributions that explore the relation between network structure and network outcomes for networks that cannot be labelled ‘whole networks’ but yet generate system-level outcomes. In addition, we argued that it was important to incorporate the role of network change in this relation, because this would provide levers for policy that aims at stimulating innovation in changing networks to a more productive mode. We explored a model that allowed us to explore the abovementioned relation including the role of network change. Also, we accounted for different time lags after which outcomes could be generated, as the knowledge networks that were studied could be expected to need some knowledge gestation time.

Three main findings can be derived from our results. First, network change inhibits the generation of network outcomes when change intensity is high. Hence, when three or more network features change simultaneously, the productivity of the complete network diminishes. In general, this effect shows after three years. Secondly, the negative relation that was found between network density and network outcomes suggests that more joint members between consortia will lead to fewer outcomes, especially after four years. Third, when there are high proportions of consortia entering or leaving, network outcomes are also negatively affected and generate fewer outcomes after four or five years respectively.

Although our general expectation regarding population change was that this would lead to network vitality, our results suggest that the opposite occurs. A possible explanation for this negative effect of new consortia entering the network might be that consortia that enter a network more or less at the same time somehow compete with each other. The negative effect of consortia leaving the network on the outcomes of all consortia that finish after four years might be explained by the fact that the projects leaving the network are in a mature state. By leaving the network, also experiences and skills that might be crucial for new entrants are lost, which affects the outcomes of those new entrants that finish four to five years later because of not being able to draw on more experienced.

The negative effect of network density implies that, although there is a strong focus on forming relations within the funding scheme, involving too many members that are also involved in other consortia simultaneously is detrimental to outcomes generated at the network-level. Many joint members could reflect a general lack of commitment to individual consortia: joint members are in it more for screening technological developments than for actively contributing to the consortia they are involved in. Another reason could be that many joint members cause an information overflow for the consortia they are involved in, which makes it difficult for members of individual consortia to focus.

The task for innovation policy thus is to stimulate network change up to a certain point, as too much change negatively affects the system. This implies that a system should be put in place that enables for monitoring network development in terms of the four indicators suggested in this paper. This would allow for ensuring that not too many experienced consortium members leave the network at the same time, for example by offering higher amounts of funding to experienced members, and would also allow for making sure that not too many unexperienced consortium members enter the network at the same time. In addition, one should be aware of and manage possible competitive effects between nodes that enter the network simultaneously, and take care that newcomers learn from experiences from more established projects.

Limitations and future research

Several limitations to this work can be identified. First of all, collecting complete network data is known to be a daunting and time-consuming task (Provan et al., 2007; Provan & Milward, 1995). By drawing on secondary data, we were able to construct a longitudinal dataset that allows for exploring the relation between network structure and network outcomes and the role of network change. Our total number of observations, however, might be a bit too low for performing an OLS, although this number increases as we use larger time lags. As time progresses, and the funding agency issues more evaluation reports, we will be able to increase our n.

Another drawback to our approach is that we had to make concessions in terms of knowledge regarding the relational content of the consortium interlocks that we specified as being a tie between two consortia. Although the hygiene principles as suggested by Ahuja et al. (2012) were reflected on, direct observations of relational content are absent. This issue could be resolved by participating in several meetings between consortium members in order to get a grasp of the role these interlocks play. At the same time, a strong assumption that underlies the funding scheme is that seeding relations within and across consortia is beneficial for generating outcomes. From that perspective, a focus on the link between network features and network outcomes could also be seen as a test as to whether or not this assumption is justified and, more importantly, leads to the expected outcomes.

In the current paper, yearly change intensity based on the magnitude of change of the network and population variables is taken into account. Figure 3 also suggests network volatility as a dimension of network change that should be taken into account. For the Medical Technology network change episodes of multiple years can be seen in early stages, after which change intensity lowers and change episodes become shorter. Although not reported in this paper, differences in timing as well as duration of periods of volatility differ across the technological field networks that are used for this study. An interesting and feasible future theoretical and analytical path therefore would be to develop models that take into account both change intensity and network volatility.

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APPENDIX

Table 1: Summary of the Special Issue on the Genesis and Dynamics of Organizational Networks (Ahuja et al., 2012)

Author(s)	Level of analysis	Basic model
(Gulati, Sytch, & Tatarynowicz, 2012)	organization, interorganizational network	tie formation behavior → small world change
(Shipilov & Li, 2012)	organization	tie features → tie formation
(Vissa, 2012)	individual	networking style → tie formation
(Mariotti & Delbridge, 2012)	organization	search activities → tie formation, evolution and termination
(Varella, Javidan, & Waldman, 2012)	intraorganizational network	leadership features → density
(Baum, McEvily, & Rowley, 2012)	organization	tie age → performance
(McEvily, Jaffee, & Tortoriello, 2012)	organization	tie features → growth rate
(Schulte, Cohen, & Klein, 2012)	intraorganizational network	tie formation ↔ perception of safety

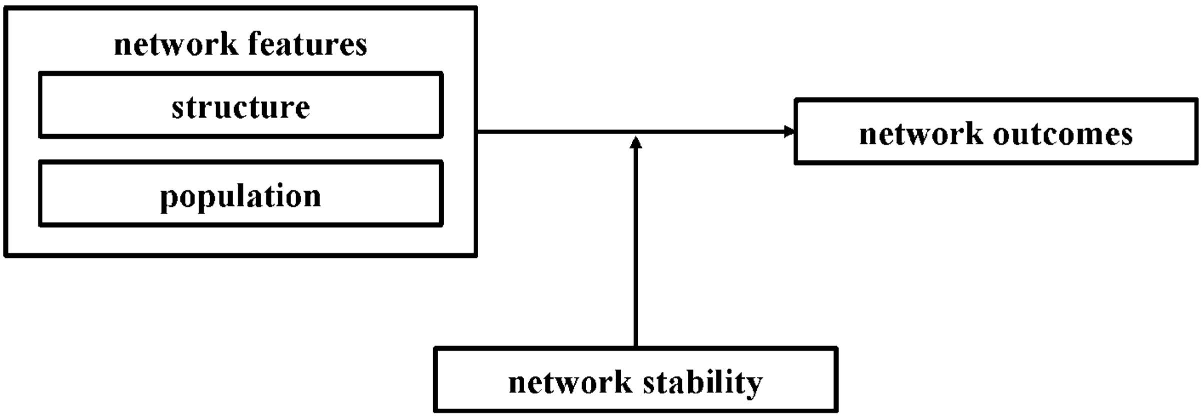

Figure 1: Conceptual model

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 applications, 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, signaling 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	Treatment	products used in diagnosis and treatment of individuals, such as operating tables, massage devices, bandages
	Measurement	development of tools for measuring bodily functions or parameters, as well as measurement parts used in treatment (e.g. sensors used in surgery robots)
	Prostheses and implants	development of replacement organs, such as artificial livers, ortheses. Sometimes, use of animal organs is explored as well
	Imaging	development of imaging techniques such as echography, x-rays, mri-scanners
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, nanostructures
	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

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

Civil Engineering	Materials engineering	development of materials used in the construction of buildings, roads, bridges
	Geotechnics	exploration of mining opportunities and development of mining techniques
	Hydraulic engineering	development of devices and constructions to control water fluids, such as dams or groynes
	Structural engineering	construction of roads and buildings, as well as elements of buildings such as locks, plumbing installations, or strong-rooms for valuables

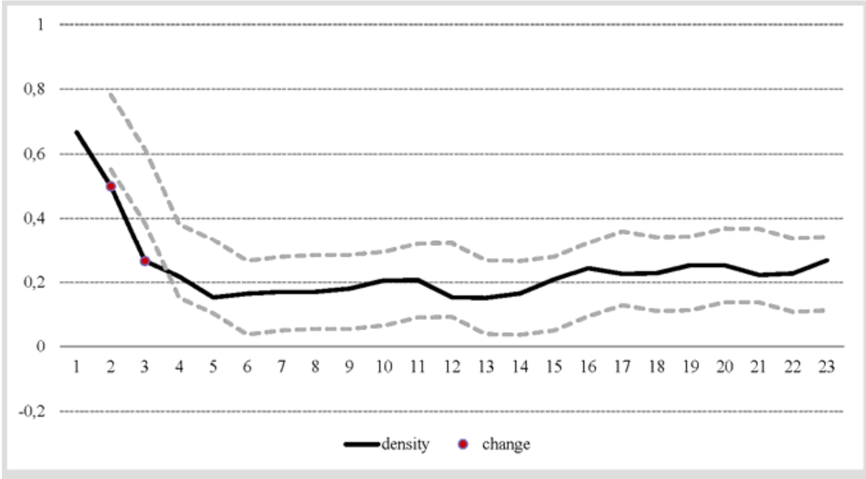

Figure 2: Change determination example for the field of Medical Technology. Shown is the development of the density score over time. When this score at *t* was larger or smaller than one standard deviation (.1149 for this example) plus or minus the score at *t-1*, the density score was labelled as being changed at *t*. These changes are marked with red dots in the graph

Change indicators		**Time**																					
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Network structure	**Density**	-	-																				
	Degree centralization	-	-	+	-																		
Network population	**New entrants**		+	-	+	-	+		-														
	Exiters				+	-		+							-			+	-				+
Overall network change intensity																							

Figure 3: Change intensity determination example for the field of Medical Technology. Changes on each indicators were grouped and mapped over time. Change intensity was determined by counting the number of changes for each *t*. Green indicates none of the indicators changed, yellow one, orange two and red three. In the analysis, orange and red were lumped together

Table 3: Descriptive statistics and correlation matrix (pairwise, maximum n=102[9])

Variable	Mean	SD	Low	High	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Network outcomes$_t$……	7.15	1.78	2	12.80	-														
2. Network outcomes$_{t+1}$….	7.26	1.77	2	12.80	.394**	-													
3. Network outcomes $_{t+2}$…	7.27	1.74	2	12.80	.266*	.392**	-												
4. Network outcomes $_{t+3}$…	7.29	1.78	2	12.80	.382**	.244*	.392**	-											
5. Network outcomes $_{t+4}$…	7.26	1.75	2	12.80	.172	.314**	.250*	.420**	-										
6. Network outcomes $_{t+5}$…	7.29	1.72	2	12.80	.290*	.195	.304**	.218*	.389**	-									
7. Network outcomes $_{t+6}$…	7.28	1.71	2	12.80	.260*	.277*	.179	.303**	.210*	.367**	-								
8. Science-based field[10]….	.29	.45	0	1	-.348**	-.333**	-.321**	-.304**	-.284**	-.251*	-.271**	-							
9. Time…………………..	11.65	6.47	1	23	.296*	.351**	.308**	.289**	.227*	.236*	.205*	.010	-						
10. Density$_t$……..………..	.25	.11	.07	.67	.174	.222	.107	-.046	-.192	-.095	.044	-.344**	-.111	-					
11. Degree centralization$_t$..	.33	.14	.08	1	.207	.008	-.084	-.028	-.086	-.162	-.084	-.102	-.222**	.586**	-				
12. New entrants$_t$………...	.17	.13	.00	.67	-.334**	-.243*	-.192	-.170	-.243	-.155	-.098	-.001	-.359**	.084	-.098	-			
13. Nodes leaving$_t$……….	.11	.08	.00	.38	.112	-.040	.082	.094	-.243*	-.361**	-.088	-.007	.273**	.133	.192*	-.264**	-		
14. Moderate stability[11]$_t$…	.42	.50	0	1	.129	.119	.244*	.128	-.060	.007	.049	-.035	-.032	.182*	-.017	-.089	.054	-	
15. Low stability$_t$……...…	.23	. 43	0	1	-.307*	-.264*	-.250*	-.343**	-.193	-.108	-.188	-.108	-.317**	.081	.072	.340**	-.092	-.474**	-

**p < 0.01; *p < 0.05

[9] Depending on the lag chosen, the number of observations differs. For this reason, pairwise correlations are shown. The number of valid cases per lag are 69 (*t+1)*, 76 (*t+2),* 83 (*t+3),* 90 (*t+4),* 97 (*t+5*) and 102 (*t+6)*

[10] The reference category consists of all engineering-based technological fields

[11] The reference category for the network stability dummies is the 'high stability' category

Table 4: Effect of network stability on network outcomes – OLS Regression Models

Dependent variable: network outcomes	**Outcome lag**					
	t+1	***t+2***	***t+3***	***t+4***	***t+5***	***t+6***
Network outcomes previous period………	.087 (.129)	.242* (.120)	.200† (.104)	.253* (.101)	.163 (.109)	.275** (.103)
Science-based field[12]…………………….…	-.304* (.126)	-.252* (.116)	-.307** (.105)	-.331** (.101)	-.271* (.107)	-.250* (.101)
Time………………………………………	.456† (.244)	.282 (.221)	.187 (.186)	.104 (.155)	.176 (.151)	.000 (.142)
Density$_t$…………………………………......	-.053 (.197)	-.152 (.181)	-.282† (.156)	-.305* (.135)	-.179 (.138)	-.083 (.136)
Degree centralization$_t$…...........................	.268 (.240)	.101 (.204)	.326† (.181)	.296† (.163)	.091 (.165)	.032 (.154)
New entrants$_t$……………………………..	-.299 (.218)	.209 (.212)	-.038 (.183)	-.390* (.167)	-.199 (.180)	.079 (.160)
Nodes leaving$_t$…………………..............	-.060 (.120)	-.057 (.119)	.112 (.109)	-.198† (.101)	-.233* (.109)	.030 (.105)
Moderate stability[13]$_t$………………………	-.014 (.114)	.162 (.114)	-.010 (.107)	-.138 (.096)	-.012 (.103)	-.070 (.103)
Low stability$_t$……………………………..	-.173 (.166)	-.096 (.153)	-.352** (.132)	-.054 (.127)	.012 (.124)	-.207 (.125)
Constant…………………………….………	-.396 (.265)	-.105 (.223)	-.148 (.173)	-.064 (.142)	-.049 (.134)	.054 (.117)
R^2	.213	.165	.265	.314	.177	.134
F	3.044**	2.650*	4.283***	5.518***	3.299**	2.733**
n	69	76	83	90	97	102

Standardized beta coefficients are shown. Standard errors are displayed between parentheses

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\dagger}< 0.1$

[12] The reference category consists of all engineering-based technological fields
[13] The reference category for the network stability dummies is the 'high stability' category

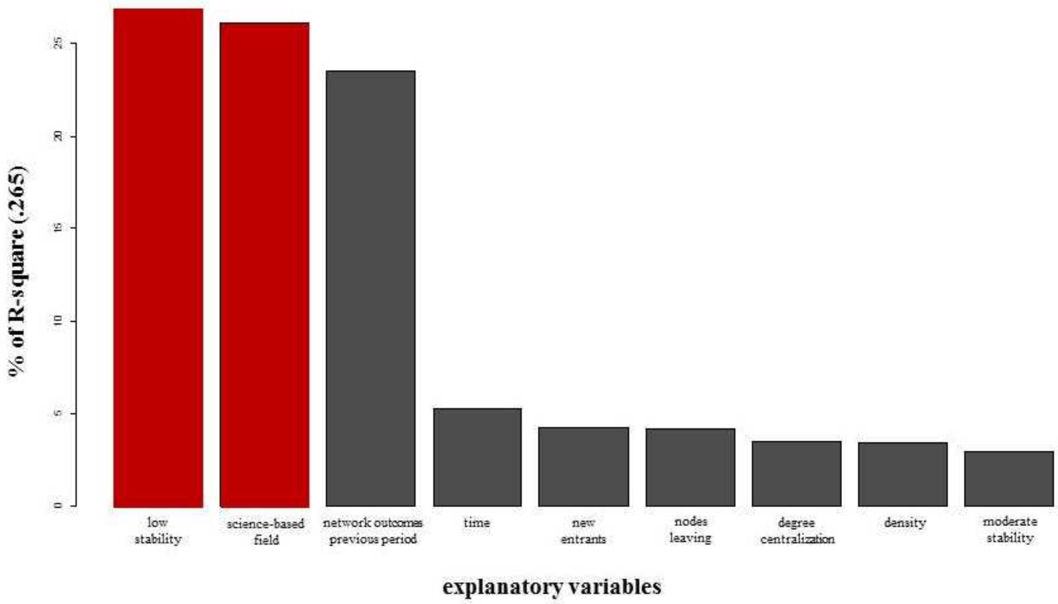

Figure 4: Relative weights of the explanatory variables at *t* in explaining outcomes *t+3*. Significant coefficients (α = 0.05) are marked red. Shown is the share of each coefficient in the total R-square, which is .265. Weights have been determined following the procedure proposed by (Johnson, 2000).