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DOI
10.1016/j.socnet.2023.02.004

Publication date
2023

Document Version
Final published version

Published in
Social Networks

Citation (APA)
Mannak, R. S., Markus, A., Meeus, M. T. H., Raab, J., & Smit, A. C. (2023). Network dynamics and its impact on innovation outcomes: R&D consortia in the Dutch water sector. *Social Networks*, *74*, 62-70. https://doi.org/10.1016/j.socnet.2023.02.004

Social Networks 74 (2023) 62–70

Contents lists available at ScienceDirect

Social Networks

journal homepage: www.elsevier.com/locate/socnet

Network dynamics and its impact on innovation outcomes: R&D consortia in the Dutch water sector

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ARTICLE INFO

Keywords:
Network dynamics
Network structure
Node turnover
R&D consortia
Innovation

ABSTRACT

In this study, we explore the relationship between inter-organizational network dynamics and innovation outcomes. We focus on node turnover and argue that both *cluster* and *broker* dynamics can range from *low* (stable) to *high* (volatile), resulting in differentiated outcomes. The data comprises 318 consortium members participating in 104 R&D consortia forged in a 23-year period in the Dutch water sector. Our analysis reveals two equifinal combinations (stable brokers – volatile clusters and volatile brokers – stable clusters) that both generate significantly higher innovation outcomes compared to networks with low, moderate, or high dynamics across the entire network.

1. Introduction

The field of Social Networks has come a long way in analyzing and understanding the evolution and dynamics of networks. By now, the field has developed a variety of analytical tools, and researchers have examined a great variety of longitudinal relational data sets (see, for example, the special issues in Social Networks (Snijders and Doreian, 2010) and Organization Science (Ahuja et al., 2012), the work around the development of Exponential Random Graph Models (Wang et al., 2013, Wasserman and Robins, 2005), and stochastic actor-oriented models for network dynamics in general (Snijders, 2017). Scholars have analyzed the coevolution of networks, individual node characteristics (Snijders et al., 2010), and the joint evolvement of groups (Hilbert et al., 2016), as well as the factors driving inter-organizational network dynamics (Amati et al., 2021; Chen et al., 2022; Gulati et al., 2012; Ingold and Fischer, 2014; Prell and Feng, 2016; Prell and Lo, 2016; Zhang et al., 2016). Accordingly, recent literature has confirmed but also responded to the critique that social networks are inherently dynamic and that earlier analyses of networks did not take that into account (Kilduff and Brass, 2010).

This study contributes to research on interorganizational network dynamics by addressing *two* important research gaps: First, most studies focus on network dynamics as such, primarily using variations of exponential graph models and stochastic actor-oriented models, which analyze network evolution based on a combination of node and tie attributes, node behavior, and network structural characteristics (for an overview of the different models and approaches see Chen et al., 2022). These studies refrain from explaining the effect of network dynamics on network outcomes (see Matous and Todo, 2017, for a notable exception). Therefore, despite the numerous studies on network dynamics, we still have limited insights into the consequences of network dynamics on outcomes both at the level of individual organizations (Chen et al., 2022) and especially at the network level. Connecting network dynamics and outcomes is therefore regarded as one of the four most promising research directions in the recent review on network dynamics and organizations by Chen et al. (2022), which we address in this study.

Second, we demonstrate the impact of exiting and entering nodes as a driver of network dynamics (Gay and Dousset, 2005; Hernandez and Menon, 2018; Sytch and Tatarynowicz, 2014; Zhang et al., 2017). While both node and tie turnover represent drivers of network dynamics, most of the work on network evolution and dynamics has been on tie turnover (Zhang and Guler, 2020). In principle, network dynamics occur in the basic building blocks of networks: in ties and nodes. Ties can be forged and dissolved (tie turnover) or change their content. Nodes can either drop out or newly enter a network (node turnover). Node and tie level changes aggregate into whole network dynamics regarding network

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https://doi.org/10.1016/j.socnet.2023.02.004
Received 24 August 2022; Received in revised form 8 February 2023; Accepted 10 February 2023
Available online 22 February 2023

structure and composition changes (Ahuja et al., 2012; Chen et al., 2022). For example, due to node turnover, clusters of nodes can change regarding their composition and their connectedness to other clusters. In this study, we focus on specific loci of dynamics of clustered nodes and the most central nodes, i.e., brokers between the clusters.

Thus far, much research has focused on a network structure that exhibits a combination of clusters and brokers between these clusters as the primary source of innovation at the individual, organizational, consortium, and country levels (Chen and Guan, 2010; Den Hamer and Frenken, 2021; Filieri et al., 2014; Fleming et al., 2007; Schilling and Phelps, 2007; Van Rijnsoever et al., 2015). A structural combination of clusters and brokers, for example, provides both information transmission capacity and knowledge access to the embedded firms, resulting in higher patenting outcomes (Schilling and Phelps, 2007). However, if clustering and brokers influence innovation outcomes while also being sensitive to network dynamics, as recently advocated by multiple scholars (Ahuja et al., 2012; Andersson et al., 2007; Tatarynowicz et al., 2016), tension emerges between demands for stability and network dynamics. This tension has been acknowledged before in the interorganizational network literature (e.g., Provan and Kenis, 2008), also in relation to innovation outcomes. While the network form of organizing was initially introduced as a flexible form, accommodating demand for speed (Powell, 1990) and novel information (Kumar and Zaheer, 2019), stability is also needed to facilitate the development of social capital (Coleman, 1990), trust, and knowledge sharing needed for innovation (Brunetta et al., 2020). Research has shown that both dynamics and stability can (co)-occur simultaneously (Quintane et al., 2013) and that this combination fosters innovation (Sytch and Tatarynowicz, 2014; Zheng and Yang, 2015). We conjecture that stability and dynamics should not be randomly distributed across the network, and some dynamics might influence innovative outcomes differently relative to others. Therefore, in our analysis, we introduce three combinations of stability and dynamics: stable brokers combined with cluster dynamics, stable clusters combined with broker dynamics, or medium dynamics in all network parts. More specifically, we argue that a natural influx and turnover of nodes in clustered loci of the network can foster innovation. In contrast, the turnover of brokers can significantly disrupt and limit all participants' information access and put the network in a state of turbulence. Therefore, we reason that broker turnover should only occur exceptionally and only under the condition of high levels of stability in clustered network loci. Thus, we contribute to the literature by developing a refined understanding of where dynamics and stability can occur in a network and how specific combinations of stability and dynamics influence innovation outcomes.

To examine this network dynamics and its impact on innovation outcomes, we use unique quantitative data over 23 years, complemented with 51 interviews. The data represents a one-mode projection of a two-mode network of organizations and R&D consortia (multimember R&D projects, subsequently referred to as consortia). Organizations cluster within a project and become brokers when they participate simultaneously in different projects. The temporality of the projects (average duration 4–5 years) causes node turnover of both brokers and clustered actors.

We address the following research question: *To what extent do broker and cluster dynamics within networks influence the innovation outcomes of research and development (R&D) consortia embedded in these networks?*

Building on Valente and Fujimoto (2010), we conducted a simulation study to exemplify how node turnover induces structural network dynamics. We simulate the case-by-case exit of all network members and compute the difference in network stability to build an instrument for network dynamics, as shown in the Supplementary Information. Then, we turn to our primary analysis exploring how node dynamics among clustered and brokering actors influence the innovation outcomes of consortia.

2. Theoretical background

Prior research has established how small-world networks foster innovation (Den Hamer and Frenken, 2021; Schilling and Phelps, 2007; Uzzi and Spiro, 2005). "Small-world" networks (Watts, 1999) are characterized by the presence of clustered organizations, with connections present between these tightly-knit clusters of organizations (Baum et al., 2003). A small world network structure is conducive to innovation because brokers enable information flows between fields of expertise, which fosters idea generation and development in the clusters (Steen et al., 2011). Small-world research has thus shown the importance of brokers and clusters for innovation outcomes but does not address how network dynamics influence these innovation outcomes. We ask: Would high turnover among brokers, in clusters, or in both brokers and clusters influence innovation outcomes generated by consortia?

To analyze the combined effects of network average broker and network average cluster dynamics on innovation outcomes, we introduce four stylized combinations of cluster and broker dynamics as visualized in Fig. 1. We define organizations participating in only one consortium at a time as *clustered actors*. In addition, we distinguish *brokers,* hub organizations participating in multiple consortia simultaneously and creating connections between different consortia. Thus, we use a structural conceptualization of brokerage, in which "brokerage occurs when one actor (the broker) is connected to two other actors (alters) who are not themselves connected" (Kwon et al., 2020, p.1095). This network structural conceptualization does not include further requirements regarding secondary structural holes (Burt, 1992), process (Marsden, 1982; Obstfeld et al., 2014), or entrepreneurial behavior (Burt, 2005). Our theoretical arguments explain how stability and dynamics occurring in clusters and brokers within the network influence the ability of consortia to generate innovation outcomes.

Prior endeavors to integrate network stability and dynamics as prerequisites for innovation have led researchers to assert that *moderate* turnover of network members generally favors the network's innovation outcomes (e.g., Sytch and Tatarynowicz, 2014). However, this conclusion leaves undisputed whether dynamics are moderate in both clusters and brokers or whether this outcome is brought about through high dynamics in clusters combined with stable brokers or vice versa. Therefore, this perspective can be refined by analyzing the combined effects of stability and dynamics of clusters and brokers separately rather than using the average turnover of clustered actors and brokers. We argue that innovation requires novel knowledge and idea generation induced by a renewal of information sources either in clusters or brokers. At the same time, innovation requires relational experience and meaningful integration induced by either stable brokers or stable clusters. In the following, we discuss the four quadrants of Fig. 1 in relation to innovation outcomes.

2.1. The rigid network

In the first type of network (Fig. 1, upper left quadrant), clusters and brokers are stable due to prolonged network membership and low inflow of novel organizations. We refer to this combination as the "*rigid network*". Through persistent connections between the same consortia, the information space becomes more homogenous and equally distributed over actors, increasing the likelihood of information being redundant. Without new entrants, consortia will suffer from a lack of novel knowledge and become over-embedded and inert (Ahuja et al., 2012; Kumar and Zaheer, 2019; Soda et al., 2021; Zheng and Yang, 2015). This inertia will likely result in low innovation potential.

2.2. The volatile network

The second combination, the "*volatile network*" (Fig. 1, lower right quadrant), is characterized by dynamic brokers and dynamic clusters. Although this combination satisfies the demand for novel skills and

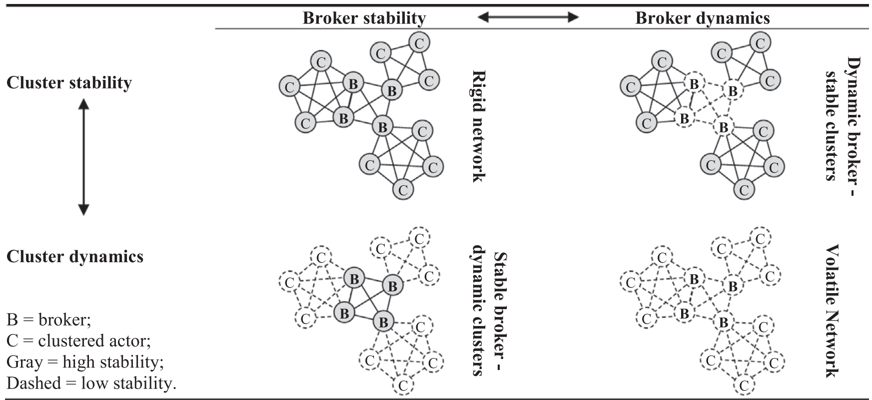

Fig. 1. Types of dynamics in networks.

perspectives, the inflow of novel knowledge might not be absorbed effectively as new actors bring in too much novelty. Such dynamics lack the trust and hamper meaningful integration required for successful collaborative innovation (Brunetta et al., 2020; Dyer and Singh, 1998; Filieri et al., 2014; Mannak et al., 2019; Zhang et al., 2017; Zheng and Yang, 2015). Therefore, when both clusters and brokers change simultaneously, it constrains the productive recombination within fixed time frames. The knowledge exchange in volatile networks limits the deployment of collaboration routines and requires too frequent revision and development of new routines, which is likely to happen at the expense of time and resources for R&D activities.

2.3. The stable broker-dynamic cluster network

This type of network (Fig. 1, lower left quadrant) combines stable brokers and dynamic clusters. This combination promotes innovation outcomes because the brokers accumulate collaborative routines that smoothen knowledge access, flow, and deployment by various consortium organizations over time. Moreover, the accumulated relational experience of the brokers expands their shared network memory (Soda et al., 2004). This network memory allows the brokers to integrate heterogeneous bodies of knowledge they are exposed to as the network evolves (Burt and Merluzzi, 2016). Thus, the advantage of stable brokers' abundant relational experience compensates for the heterogeneous knowledge influx of dynamics clusters. In this network, stable brokers can access, distribute and (re-)combine the diverse knowledge originating from the varying sets of clusters. In the absence of cluster dynamics, brokers would likely suffer from social and cognitive rigidity, "becoming entrenched and fixated in their ways of collaborating and coordinating […] diminishing their ability to generate creative ideas" (Soda et al., 2021, pp. 9–11).

2.4. The dynamic broker-stable cluster network

This type of network (Fig. 1, upper right quadrant) combines high turnover among brokers, whereas clusters are stable. High broker turnover induces new shortcuts and, thus, network restructuring. From a knowledge diversity perspective, the broker dynamics provide *novel knowledge* that rejuvenates knowledge repertoires of clusters while avoiding lock-in among clustered members (Ahuja et al., 2012; Kumar and Zaheer, 2019). At the same time, such a shakeup creates turbulence and therefore requires cluster stability to balance these dynamics. The dynamic broker-stable cluster combination offers the benefits of meaningful integration of knowledge because the clusters are characterized by high trust and supportive norms among the tightly-knit organizations (Coleman, 2009; Reagans and McEvily, 2003). Over time, repeated/-frequent interaction allows clustered actors to understand each other better, improving the participants' communication and trust (Brunetta et al., 2020; Narayan and Kadiyali, 2016).

In sum, we explore our balancing proposition that *the probability of innovation outcomes for consortia is higher in networks with broker dynamics combined with stable clusters and in networks with stable brokers combined with cluster dynamics than in rigid or volatile networks.*.[1]

3. Method

3.1. Data

We explore the research question with longitudinal network data in the Dutch water sector over 23 years (1982–2004) from 318 organizations participating in 104 consortia. The Netherlands has a long tradition of generating innovative solutions regarding delta and maritime water management and is considered one of the most innovative economic sectors in The Netherlands, with a world-renowned reputation (Van de Ven, 1993). The Dutch water sector operates in a complex technological environment. Relevant expertise about this sector resides in public universities (e.g., Delft University of Technology), public-private research institutes (e.g., the former National Institute for Integrated Water Management and Wastewater Treatment, RIZA being the Dutch acronym), and commercial corporations (e.g., DSM Research and Shell Research and Technology Centre). The innovation locus of this world-leading sector resides in interorganizational networks (Powell et al., 1996). The historical data of this industry offers unique opportunities to study dynamics in interorganizational relations over time. We acquired secondary data on consortium composition, duration, funding, and innovation outcomes from annual evaluation reports published by a Dutch technology program that facilitates demand-driven university-industry collaboration (see Raesfeld et al., 2012, for a similar approach). Each consortium funded by this policy instrument consists of a consortium leader, professors affiliated with a Dutch university, and around five to six organizations from the Dutch water sector. Funded consortia are expected to apply state-of-the-art fundamental research to advance technologies and applications in three water-related areas: maritime, delta, and water technology.

3.2. Dependent variable

Ten years after being launched, the *innovation outcomes* of consortia were evaluated by an external committee of specialists from industry and academia appointed by the funding agency. The evaluation covered

[1] A priori we do not have any theoretical expectations regarding the differences in innovation outcomes when comparing these two particular combinations. In Section 4 we compare the predicted effects of the different combinations.

the entire ten-year period, thus taking into account that it can take up to ten years for any outcomes to materialize. Our study includes innovation outcomes from 97 consortia, for which the funding agency consistently used the same coding matrix. The consortia's innovation outcomes were coded high (1) in case consortium members participated actively, a preliminary or ready-to-use product was developed, and an occasional or persistent revenue stream was foreseen or realized. Otherwise, innovation outcomes were coded as low (0). Robustness tests with a continuous operationalization or with separate outcome dimensions yielded identical results, as shown in the Supplementary Information. Examples of consortia with high innovation outcomes include a 301.370 Euro wave modeling project to predict wave drift forces on offshore constructions and ships and a 222.790 Euro project to develop an aerobic granular sludge reactor for wastewater treatment. Both R&D projects resulted in the successful application of patents and actual applications in the field.

3.3. Independent variables: network average broker stability and network average cluster stability

The network has evolved over 23 years through membership turnover, which results from entry, exit, and actors repeating their collaboration in multiple consortia over multiple years. Nodes in the network are organizations, including (representatives of) universities and other organizations in the Dutch water sector. Interorganizational relations are counted if they are part of a joint consortium in a given year. A typical consortium lasted 4–5 years. In this research setting, ties between consortium members expire when the consortium ends (as formally noted in the annual report) unless the members repeat their collaboration in a second consortium. Most organizations (64.8%) participate in only one consortium in the entire observation period, entering the network at the start of a consortium and permanently exiting when its funding expires, i.e. each year, approximately 16.7% of the organizations exit the network. Other organizations opt to stay in the network by joining a second consortium (13.5%) and/or participating in multiple consortia at the same time (21.7%). Through multi-consortia membership, brokers are in-between other network actors, with their betweenness centrality being higher than 0, with the betweenness centrality of clustered actors being 0, because clustered actors only participate in one consortium at a time. The number of brokers and clustered actors vary over time. Of the 318 actors, 69 function as a broker at some point in time, and 249 are clustered actors.

We define stability for brokers and clustered actors as the average proportion of prior years in which these actors participated in the network since 1982. Therefore, the measure for network stability is the reverse of the measure for network dynamics. To ensure comparability of scores across years, we expressed the years of network participation as a proportion of the observation period and computed the network average across all brokers or clustered actors present in the network at that time. For example, in 1984, the network contained eight brokers, of which two joined the network in 1982, five joined the network in 1983, and one joined the network in 1984, resulting in the network average broker stability of $(2 * 1 + 5 * 0.5 + 1 * 0)/8 = 56.3\%$. In other words, network average broker stability and network average cluster stability increase with the length of time in which brokers and clustered actors have each participated in the network. Corresponding to prior research on the innovation capacity of small-world networks (e.g., Den Hamer and Frenken, 2021; Schilling and Phelps, 2007), network average broker stability and network average cluster stability are measured at the network level, although a robustness test with consortium-level averages yields comparable results (see: Supplementary Information).

Fig. 2 illustrates these network dynamics, showing the network respectively in 1989 and 2000. In both years, the network structure is highly comparable regarding the clustering coefficient and average path length. However, in 1989, both the network average broker stability and network average cluster stability were high (rigid network), while in 2000, the broker stability was high, while the cluster stability was low. In 1989, one-third of the consortia achieved innovation outcomes against two-thirds in 2000.

As discussed in the Supplementary Information, we use an instrumental variable approach to address the endogeneity issue of network dynamics models. The issue is that unobserved factors may influence both network dynamics and innovation outcomes, i.e., the endogenous regressors and the error term of the dependent variable. Our instrumental variable approach addresses this issue by identifying instruments that influence the endogenous regressors without being correlated with the error term of the dependent variable, in our case, instruments observed in the time window before the consortium starts. Our approach builds on the reasoning that whole network dynamics are a cumulative function of the addition, retention, and exit of all organizations in the network. Employing a simulation study and regression analysis, we determine the weighted contribution of each organization to the next year's network average stability if the organization were to remain in the network. Next, we instrument organizational retention vs. exit by means of observed reorganizations (see Supplementary Information).

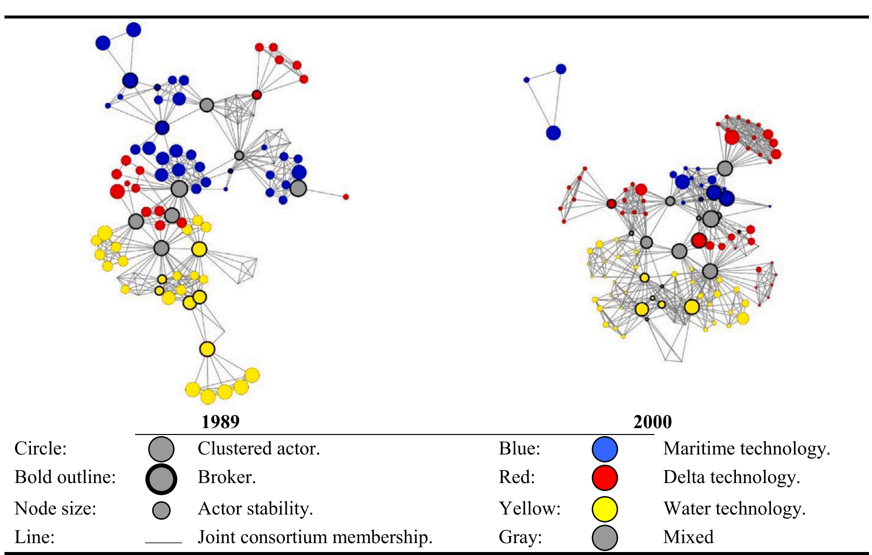

Fig. 2. Water networks in 1989 and 2000.

3.4. Control variables

In our analysis of innovation outcomes, we use the control variables sub-field (Maritime technology, Delta technology, Water technology); consortium size (number of consortium members); consortium duration (years since consortium start until consortium end); allocated funding (in €100,000 corrected for inflation, with 2004 as the reference year), researcher quality (expressed as the number of publications per research associate in the five years following consortium start), clustering coefficient, network average path length, and a two-mode network autocorrelation term (Fujimoto et al., 2011). By controlling for clustering coefficient and network average path length, our study builds on prior literature that established how small-world networks, being network structures characterized by a high degree of clustering and short average path length, drive the innovation outcomes of embedded actors (Den Hamer and Frenken, 2021; Schilling and Phelps, 2007; Uzzi and Spiro, 2005). Our study adds a dynamic component to this literature.

3.5. Analytical procedure

Our analyses show the extent to which network dynamics, in terms of network average broker stability and cluster stability, influence the innovation outcomes of consortia in the network. The consortium is the unit of analysis, with broker and cluster stability measured at the network level. All models include heteroscedasticity-robust standard errors clustered at the network level, as well as the abovementioned consortium-level and network-level control variables. We apply a two-stage instrumental variable (IV) probit model. The model has a lagged structure: network average broker stability and cluster stability are measured at t_0, with innovation outcomes measured at t_{+10}.

The results section presents the regression coefficients and several model statistics. We include a Chi-squared test for model fit showing the extent to which the whole model fits the data (i.e., the coefficients jointly differ from zero), the log-likelihood value of the model, and a likelihood ratio test showing the model improvement as compared to a model with only control variables. We include an F-test for instrument strength showing the extent to which the instruments jointly provide an adequate prediction of the instrumented variables. The instruments should be sufficiently correlated with the endogenous regressors (Bascle, 2008), being network average broker stability and cluster stability. In addition, we provide the endogeneity statistic showing whether the instrumented variables should be considered endogenous, and thus an IV model is needed. Finally, the overidentification restriction shows whether the instruments used are uncorrelated from the error term of the dependent variable (the last statistic should not be statistically significant while all the others should be). Building on Hoetker's (2007) work on logit and probit models, we also computed and visualized the marginal effects to facilitate adequate interpretation of the results. Finally, our post hoc analysis compared the computed margins using Bonferroni-adjusted chi-squared tests.

3.6. Interviews

To enrich our findings with qualitative insights into the functioning and development of the network, we conducted 51 interviews with stratified sampled respondents. The stratification was based on the actor type (13 university representatives; 38 representatives of water sector organizations), sub-field (14 Maritime technology, 15 Delta technology, 17 Water technology; 5 mixed), experience (21 repeated consortium members; 30 one-time only members), and innovation outcomes (28 from consortia achieving innovation outcomes, and 23 from consortia not achieving innovation outcomes). During the interviews, we discussed, among others, motivations for joining the consortia, experience with new entrants and repeated collaborations, innovation outcomes, and key developments in the network. All interviews were transcribed verbatim and analyzed using an open, axial, and selective coding approach. Interviews lasted, on average, 1 h and 6 min and transcripts averaged 9107 words.

4. Results

In this section, we present the results of the IV probit model. Approximately 56% of the consortia achieved innovation outcomes (Table 1). The network average broker stability varies between approximately 11% and 72%, with cluster stability varying between 15% and 49%. The variance inflation factors (VIF) indicate no sign of multicollinearity. Table 2 displays the instrumental variable model results with a probit regression transformation for the probability of innovation outcomes. All models show a significant fit to the data (Chiˆ2).

Based on likelihood ratio tests, we compared the model fit of a model with only control variables (Model 1), a model with linear terms (Model 2), and an interaction term (Model 3). Model 3 best fits the data, in line with our proposition. Model 3 fits significantly better to the data than Model 1 (Chiˆ2: 9.230; $p < .050$) and Model 2 (Chiˆ2: 4.790; $p < .050$). Model 3 also fits significantly better than a model with non-linear direct effects of broker and cluster stability (see Supplementary Information). Finally, Model 3 also fits significantly better to the data than an alternative model specification in which the locus of stability is not specified, i.e., with moderate average network stability regardless of the position of organizations (see Supplementary Information). Hence, rather than moderate average stability across the entire network, stability and dynamics should be differentiated in different parts of the network.

The results of Model 3 demonstrate that the effect of broker stability is conditional on *cluster* stability and vice versa. The results are in line with our proposition that consortia in networks with a combination of high and low stability of brokers and clusters (i.e., networks in which either brokers are stable while *clusters* are dynamic, or *clusters* are stable while brokers are dynamic) have a higher probability of innovation outcomes than networks with low, moderate, or high levels of both broker and cluster stability. We also ran a bootstrapped model with 1000 replications, which provides identical results given the limited sample size. A robustness test with a split-sample approach confirms that broker (cluster) stability only stimulates innovation under low cluster (broker) stability conditions, as shown in the Supplementary Information.

Fig. 3 provides a graphic representation of the average marginal effects of network average broker and cluster stability on the probability of innovation outcomes for consortia in the network. The surface represents the observed range of the two variables (approximately 0.125–0.500 for cluster stability and 0.125–0.750 for broker stability), and the wireframe represents the predicted effect. As indicated in Fig. 3, the probability of innovation outcomes is lowest (close to 0%) in networks that either combine low (0.125) levels of broker stability with low (0.125) levels of cluster stability (volatile network) or that combine high (0.750) levels of broker stability with high (0.500) levels of cluster stability (rigid network). The probability of innovation outcomes is highest (close to 100%) in networks that either combine low (0.125) levels of broker stability with high (0.500) levels of cluster stability (dynamic broker – stable cluster network) or that combine high (0.750) levels of broker stability with low (0.125) levels of cluster stability (stable broker – dynamic cluster network). The probability of innovation outcomes in networks with moderate cluster and broker stability is approximately 54%. Bonferroni adjusted post hoc tests on the marginal effects further support our proposition. In networks with the 'dynamic broker-stable cluster' combination and networks with the 'stable broker-dynamic cluster' combination, consortia have a significantly ($p < .050$) higher probability of innovation outcomes than they do in 'rigid', 'volatile', and networks with moderate levels of stability, equally distributed across the entire network. Thus, differentiation of network dynamics matters for the innovation outcomes of the consortia embedded in the network.

Table 1
Descriptive statistics and correlations.

	Variables	Mean	SD	Min	Max	VIF
1	Consortium outcomes	0.557	0.499	0	1	
2	Consortium size	5.608	3.002	0	22	1.260
3	Consortium duration	4.485	1.234	1	8	1.490
4	Allocated funding	3.307	2.110	0.098	12.390	1.580
5	Researcher quality	6.308	6.774	0	47	1.210
6	Network autocorrelation	0.494	0.288	0	1	1.370
7	Clustering coefficient	7.485	2.572	2.329	11.803	2.220
8	Path length	1.312	0.134	1.108	1.686	1.270
9	Broker stability	0.527	0.109	0.114	0.720	1.890
10	Cluster stability	0.270	0.100	0.149	0.486	1.580

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	1.000									
2	0.008	1.000								
3	-0.121	0.139	1.000							
4	0.015	0.290	0.443	1.000						
5	0.141	-0.063	-0.109	-0.033	1.000					
6	-0.047	0.138	0.093	0.121	-0.073	1.000				
7	-0.105	0.147	-0.048	0.034	0.166	0.338	1.000			
8	0.053	0.077	-0.138	-0.140	-0.014	0.095	0.400	1.000		
9	-0.049	-0.052	-0.102	-0.248	-0.082	-0.043	0.461	0.229	1.000	
10	-0.040	-0.275	-0.252	-0.063	-0.225	0.113	-0.065	-0.002	0.291	1.000

Note: 97 consortia

Table 2
IV-probit model of probability of innovation outcomes for consortia.

	Model 1		Model 2		Model 3	
	Innovation outcomes		Innovation outcomes		Innovation outcomes	
Intercept	-0.622	(1.092)	-2.620	(1.909)	-20.043***	(3.267)
Consortium size	0.011	(0.052)	0.006	(0.044)	-0.001	(0.044)
Consortium duration	-0.169	(0.134)	-0.228†	(0.133)	-0.070	(0.146)
Allocated funding	0.079	(0.074)	0.167*	(0.078)	0.136†	(0.078)
Researcher quality	0.041	(0.026)	0.054*	(0.021)	0.071**	(0.023)
Network autocorrelation	-0.249	(0.696)	0.556	(0.735)	0.034	(0.804)
Clustering coefficient	-0.098†	(0.058)	-0.254**	(0.079)	-0.041	(0.078)
Path length	1.579†	(0.951)	1.495	(1.030)	1.673†	(0.911)
Endogenous regressors:						
Broker stability			6.405*	(2.734)	33.979***	(5.287)
Cluster stability			-1.958	(1.786)	52.004***	(8.379)
Broker * cluster stability					-95.803***	(14.388)
Subfield dummies	YES		YES		YES	
Model fit (Chiˆ2)	22.060**		61.930***		84.070***	
Log-likelihood	-61.513		-59.288		-56.895	
Df	10		12		13	
Model improvement			4.450		9.230*	
Instrument strength:						
Broker stability			9.000***		11.070***	
Cluster stability			73.180***		79.530***	
Broker * cluster stability					21.850***	
Endogeneity of stability			8.680*		3.930	
Overidentifying restrictions			0.506		0.611	

Note: 97 consortia. Standard errors in parenthesis. Heteroscedasticity-robust standard errors clustered at the network level. † $p < .100$; * $p < .050$; ** $p < .010$; *** $p < .001$;

4.1. Qualitative findings

The qualitative findings derived from our interviews substantiate the arguments we used to explain our quantitative findings. Regarding cluster stability, respondents argue that: "the greatest advantage is that partners get used to each other and become increasingly effective and productive" (Resp. 3). Cluster stability gives consortium members time to "overcome deficiencies in the collaboration" (Resp. 9), "to become familiar with each other's backgrounds" (Resp. 2), and "to gain experience with the involvement and reliability of partners" (Resp. 3). However, to realize innovation outcomes, at some point a consortium needs "fresh blood" (Resp. 1 and 2). Respondents suggest that new entrants provide injections of novel skills and perspectives, both mitigating "group-think" (Resp. 1) and "intellectual inbreeding" (Resp. 3). At the same time, ongoing addition of new entrants to existing consortia may cause several complications for incumbent organizations, like the disruption of the "preceding learning process" (Resp. 4) and established practices related to "confidentiality" (Resp. 5) and non-disclosure agreements. From these findings, we infer that clusters should alternate between periods of relative stability and periods of membership turnover.

Given that clusters are not islands in themselves but are integrated into the broader network through brokers, we also asked respondents about the sources of network-level dynamics. Interview respondents argue that, on the one hand, socio-economic trends (23 respondents), such as the increasing need to pool scarce resources and growing habit of collaboration, and policy initiatives (21 respondents) spur collaboration. On the other hand, the network is mostly shaken up by

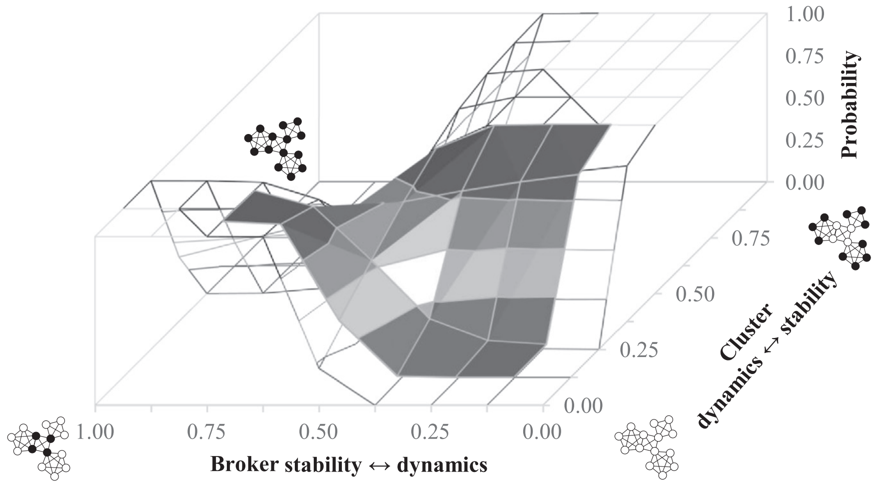

Fig. 3. Marginal effects broker stability and cluster stability on the probability of innovation outcomes. The surface represents an observed range, and the wireframe represents the predicted effect on 97 consortia.

reorganizations of research institutes (20 respondents). The latter one is particularly relevant in relation to network average broker dynamics. Since their founding, the most prominent brokers in this network achieved highly institutionalized positions in the Dutch water sector (Rijkswaterstaat: 1798, Deltares - WL | Delft Hydraulics: 1927 RIZA: 1933). Interviewees widely acknowledged that these organizations are crucial to providing stable connections between clustered organizations in the network (e.g., Resp. 2, 4, and 6). The research institutes function as "intermediaries between academic and industrial parties within the R&D consortia" (Resp. 7) and act as central brokers between consortia and subfields within the broader infrastructure of the network, so-called "spiders in the web" (Resp. 8). Respondents closely monitor the strategies and activities and activities of these brokers. "[Research Institute A] is an important player in this kind of research projects. They are involved in many projects, and they just have that networking role" (Resp. 3) or "[Research Institute B] really acts as a hub for the entire knowledge infrastructure in the Netherlands in this field. So you will have contact with them." (Resp. 10). Research institutes that fulfill a brokerage position can foster innovation outcomes for organizations in the network, using their large knowledge pool and experience.

However, the qualitative analysis also reveals the vulnerability of the network to broker dynamics. In the early 1990 s, the Dutch government imposed an organizational change to reduce the scope of activities in one of the two most important research centers and brokers in the network. This downsizing loosened its ties to organizations in various subfields and made the network vulnerable to disintegration. Two years later, the entire network collapsed due to different exogenous shocks – oil crisis, flooding risks in the Netherlands, and the dropout of Rijkswaterstaat - that disintegrated the vulnerable network. Several years later, the research center restored the scope of its activities and regained a position as a central broker, resulting in the re-integration and growth of the network. This led to a rebound in innovation outcomes, such as the development of new water treatment plants or new models to predict wave impacts on ships, offshore installations or coastal areas. The case illustrates how some organizations fulfill a major role in broker dynamics within the network and consequentially in the innovation outcomes of all consortia embedded in the network.

5. Discussion

By exploring how clusters in networks and brokers between these clusters can range from stable to dynamic, resulting in four stylized combinations of network dynamics, our study contributes to the literature on network dynamics and the explanation of outcomes in particular regarding innovation (e.g., Andersson et al., 2007; Burt and Merluzzi, 2016; Kumar and Zaheer, 2019; Leminen et al., 2020; Soda et al., 2021; Sytch and Tatarynowicz, 2014). Our findings confirm prior research, which concluded that the locus of innovation resides in interorganizational networks (Powell et al., 1996; Yaqub et al., 2020) and refine these insights by showing that neither *rigid* nor *volatile* networks promote innovation outcomes. Moreover, this study shows where and how dynamics occur in an inter-organizational network in relation to network outcomes. The study shows that it is not just average dynamics that facilitate superior outcomes but the (combination of) dynamics in clusters and brokers that matters. Therefore, identifying parts of the network where high, moderate, or low stability occurs is essential to an enhanced understanding of the network dynamics–outcome nexus (Gay and Dousset, 2005). Without this distinction, high and low levels of stability that co-occur in different parts of the network might be averaged out in the analysis, and the findings might be erroneously attributed to aggregate network dynamics. Our results reveal that, instead of moderate stability in all parts of the network, fostering innovation requires high membership turnover in one part of the network (either in the clusters or the brokers), combined with prolonged membership in another part of the network. In that sense, our results demonstrate equifinality of the effects of (combinations of) broker and cluster dynamics on outcomes. Indeed, "Stability and change co-exist and must do so. More stability in one part of a network will increase change in a different part, and vice versa." (Freytag and Ritter, 2005, p. 646). This combination seems to be particularly important for innovation outcomes because it facilitates the combination of "critical access to heterogeneous knowledge and resources" (Sytch and Tatarynowicz, 2014, p. 274) on the one hand and the trust-building and meaningful integration of knowledge on the other. Generally, this comes back to an observation that networks are characterized by "dynamic stability" (Kilduff et al., 2006).

The study also contributes to our understanding of the effect of node turnover on network evolution and especially the effect of network dynamics on network outcomes. Our results demonstrate that even in institutionalized fields, node turnover does occur and greatly impacts network dynamics and, ultimately, network outcomes. This demonstrates that although tie turnover is important for network dynamics, node turnover might have an even more radical impact on network dynamics since the related ties also disappear with a node. Therefore, node turnover should be included in the analysis of network evolution in social network studies (Zhang and Guler, 2020). For research on intra-organizational networks, for example, that means that employee turnover is crucial for understanding network dynamics as crucial boundary spanners might leave an organization influencing the functioning of an organization (e.g., Methot et al., 2018).

This study is subject to several limitations that invite future research. First, our theoretical arguments for the quantitative findings have strong validity based on prior work (e.g., Sytch and Tatarynowicz, 2014). However, we have no direct measures to investigate the underlying mechanism between network dynamics and innovation outcomes. More work is needed to understand better how network structure and dynamics contribute to changes in network composition and outcomes (Kaartemo et al., 2020; Leminen et al., 2020; Möller et al., 2020; Ter Wal et al., 2016; Yaqub et al., 2020). Second, we study a network of consortia in The Netherlands, representing a specific institutional context with specific outcomes. The Dutch context has some unique characteristics regarding innovation policy and organizations active in fundamental and applied research. Traditionally, the Dutch government has played an active role in stimulating innovation by providing subsidies and orchestrating the innovation system (e.g., Raesfeld et al., 2012). This is precisely the case within the water sector, which is of existential importance for the Netherlands. This has implications for the generalizability of our findings. Future work on network dynamics in varied contexts, including other countries, sectors, and other outcomes, is needed (Leminen et al., 2020). A third limitation is that our Dutch research context occurs in a confined geographical area. In geographical terms, The Netherlands is the same size as some large US metropolitan areas, and we only study domestic consortia. A final limitation regards the availability of measures for network dynamics. While the field has made progress in analyzing network dynamics such as relational event modeling (Vu et al., 2017) as well as ERGM and stochastic actor-oriented models for network dynamics (Snijders, 2017, Wang, Pattison and Robins 2013, Kevork and Kauermann, 2022), we still lack established measures for the level of dynamics as an important network-level characteristic. Therefore, we have developed our own measures. Future research should further develop them, for example, in the direction of time-weighted network measures.

Our study contributes to a comprehensive framework for future research to explore how network dynamics and structure interplay in various contexts. We agree with Chen et al. (2022) that this opens up a new research agenda of organizational network research, which will help us understand how networks change over time and how dynamics co-evolve with the network capacity of nodes active in a network, and the subsequent effects on outcomes. With the present article, we aim to encourage network scholars to further investigate network structure, tie and node turnover dynamics, and their impact on network outcomes.

Declarations of interest

None.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.socnet.2023.02.004.

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