Understanding the formation and evolution of collaborative networks using a multi-actor climate program as example

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Abstract. The mechanisms governing the composition of formal collaborative network remain poorly understood, owing to a restrictive focus on endogenous mechanisms to the exclusion of exogenous mechanisms. It is important to study how endogenous network structure and exogenous actor behaviour influence network formation and evolution over time. Current efforts in modelling longitudinal social networks are consistent with this view. The use of stochastic actor-based simulation models for the co-evolution of networks and behaviour allows the joint representation of endogenous and exogenous mechanisms, specifically the structural, componential, functional, and behavioural mechanisms of network formation. In this paper we study the emergence of collaborative networks in the Knowledge for Climate (KvK) research program. Endogenous mechanisms (transitivity and centrality) play a key role in the evolution of the KvK network. The results also reveal the influence of exogenous mechanisms: actors tend to collaborate with other actors from the same type of organizations (componential) and patterns of collaboration are affected by the nature and differences in roles (functional). Our analysis reveals a gap between actors from different sectors and a gap between actors working on global problems and those working on local problems. This is particularly visible in the fact that organizations active in hotspots projects, which focus on developing practical solutions for local and regional problems, are significantly more likely to form new ties than those active in theme projects.

1 INTRODUCTION

Networks have become a central concept in many fields, particularly in the areas of communication and organization. Among the various types of networks, collaborative networks are of special importance [1]. Collaborative networks are undergoing dramatic changes driven by scientific, economic, political, societal, cultural, and communicative processes collectively known as globalization [2].

These changes are particularly visible in science itself. In addition to the rise of international collaboration, scientific research is increasingly carried out in interinstitutional and international collaborative teams. Team science has evolved as a way to organize scientific research aimed at understanding and solving the most complex problems that confront humanity [3,4]. The rise of team science has created an urgent need to understand the fundamental configurations and interaction rules that govern the formation of collaborative networks as well as the behavioural patterns that emerge.

Understanding collaborative networks in science requires that we take into account two aspects of their evolution: complexity and history. Complexity arises from the fact that the actors in collaborative networks are largely autonomous, geographically distributed, and heterogeneous in terms of their operating environment, culture, social capital, and goals [1], have a set of attributes and preferences, and follow rules of interaction. They collaborate with each other to seek complementarities that allow them to participate in a competitive socioeconomic environment and achieve scientific excellence [5]. The history of networks relates to the fact that 'networks from nowhere' do not exist. Understanding the evolution of networks necessitates longitudinal analysis.

One way to analyse the formation of a complex social network is to simulate its emergence from the behaviour of individuals in the network. Simulation requires empirical data to verify the results.

We contribute to the understanding of the evolution of scientific networks and the empirical basis for future simulations by studying the Knowledge for Climate (KvK) research program, a €90 million multi-actor program aimed at developing useful knowledge for practical solutions to climate adaptation and mitigation.[3] Climate change is one of today's grand challenges and network effects are prevalent in climate science. The core of the program is formed by so-called hotspot projects in which government, industry, and science collaborate to develop real options for coping with climate issues at the local and regional level (e.g. in the port of Rotterdam and around Schiphol Airport).

The mechanisms underlying the processes of network evolution are not yet fully understood [6,7]. A deeper understanding of network evolution requires studying mechanisms that extend beyond the well-accepted drivers. The sociological literature on network formation and stability suggests four general mechanisms that may generate and sustain social ties that are potentially important for the KvK networks being studied, namely structural, componential, functional and behavioural mechanisms [8]. Our interest in both endogenous and exogenous mechanisms of network formation is linked with the recent theory on the co-evolution of social networks.

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The use of stochastic actor-based simulation models for the co-evolution of networks and behaviour allows the joint representation of endogenous and exogenous mechanisms and making the distinction between social selection and social influence processes, as elaborated by Snijders et al. [9,10,11,12]. Thus, we add to the empirical foundations of network simulation.

In section 2 we introduce the mechanisms of network formation and evolution. Section 3 describes the network data obtained from the KvK research program and outlines our approach to the analysis of structure, behaviour, and their dynamics. The results of the empirical study are presented and interpreted in section 4. Finally, in section 5, we present our conclusions and discuss our findings in light of the theoretical and practical relevance.

2 MECHANISMS OF NETWORK FORMATION AND EVOLUTION

The evolution of a network is driven simultaneously by endogenous effects that derive from network structure and actor positions, and exogenous effects that derive from the attributes and behaviours of individual actors. The combination of endogenous network effects and exogenous actor covariate effects constitutes the so-called objective function. This objective function captures the theoretically relevant information that the actor has at his disposal in the decision to establish a new tie or not [12].

Utilizing insights from the sociological literature on network formation, we have identified four general mechanisms that generate and sustain social ties that are potentially important for the KvK networks [8].

- *Structural mechanisms (endogenous)*. The structural dimension addresses the structure or composition of the actors attached to the network. One of the principal features in most networks is the tendency toward transitivity or transitive closure. This means that collaborative partners of collaborative partners tend to become collaborative partners themselves. A second feature is that popular or active organizations will become even more popular or active in the collaborative network over time. Thirdly, The number of organizations with which an organization indirectly collaborates (i.e. the number of alters at geodesic distance two) is also considered to measure the effect from indirect relations. The tendency to keep other organizations at distance two can also be interpreted as negative measure of triadic closure.
- *Componential mechanisms (exogenous)*. It has been argued that the identity of organizations constitutes an important aspect of form [13]. Individuals with the same type of affiliations tend to recognize each other's configurations of characteristic, processes, and resources [14]. The homophily principle, which suggests that collaborative partners are selected based on the similarity of characteristics, has been shown to be a crucial network mechanism in many contexts [15]. A second componential mechanism is geographic distance to the network centre and between individual nodes. The existing literature finds that geographical distance matters and that being geographically close stimulates and facilitates collaboration [16].
- *Functional mechanisms (exogenous)*. This dimension considers the extent to which participants possess valuable and complementary competencies that help ensure the success of the collaboration [17]. Competencies represent the organization's knowledge, skills and capabilities. The individuals of the organizations active in the KvK program network play different roles, ranging from purely formal, non-substantive roles (e.g. legal representative, contract signee), programme functions (e.g. programme administrator, project supervisor), substantive roles in projects (e.g. project member, hotspot member), and leaders of projects, consortia, and hotspots. Theories of status variation address the greater capacity of high-status actors to attract others, compared with low-status actors [18,19].
- *Behaviour mechanisms (exogenous)*. Behavioural approaches are based on the extent of participation behaviour at an organizational level. This contributes to our understanding of how the behaviours of individual organizations affect their chances of engaging in the collaborative network. It is proposed that organizations are more likely to engage in projects with established or experienced partners to maximize collective value.

Theories of network selection propose that the choice of network ties depends on the attributes and network embeddedness of actors as well as their possible alters. Social influence means that the behaviour (which also represents characteristics, attitudes, performance, etcetera) of actors depends on their own attributes and network position, but also on the attributes and behaviour of the actors with whom they are directly or indirectly tied in the network. In our paper, we presume that the relationship between participation and network formation may be explained by selection (ego seeks highly participating alters) or by influence (alters' participation influences the participation of ego). Each process has different implications. Determining the direction of causality is important for understanding the potential contribution of network dynamics [20].

Models have also been developed for the evolution of non-directed networks, such as collaboration networks, alliance networks, and knowledge sharing networks. For example, [21] studied the effect of job mobility of managers on inter-firm networks; [22] explained the development of interorganizational networks; [23] investigated the industrial alliance networks and found that reputation based on past performance was a strong predictor of alliance formation; and [24] examined how to facilitate innovation spreading in knowledge sharing networks.

3 DATA AND METHODS

The KvK research program is an ongoing collaborative program that was started in 2008. The program can be regarded as a constantly evolving social network of temporary collaborations [25,26]: collaboration is organized on the basis of projects that dissolve once the project, for which organizations are specifically set up, is completed. It includes 108 distinct but interrelated projects, and involves 102 organizations. The entire project and membership database of the KvK research program has been made available by the programme office. The master database has been cleaned and coded, and currently contains extensive information linking 1,131 individual members to projects, recording the starting and ending dates of their involvement in projects, showing the roles the individuals played in projects and the organization the individuals represent, and indicating the theme to which the project belongs.

The data include details about the individual and institutional program members, the nature and timing of their involvement in different projects, as well as data describing the various projects. This allows us to examine how organizations and individuals collaborate and to study the mechanisms that facilitate or inhibit network formation and evolution.

Using this information, we constructed non-directed one-mode networks at an organizational level based on a binary association matrix indicating how individuals are indirectly linked with each other through the same project. This resulted in a symmetric association matrix of organizations with 102 rows and columns, where '1' represented a non-directed tie in which the row organization participated in the same project as the column organization, and '0' represented the absence of a tie.

The networks were divided into four waves according to the project periods: 2008, 2009, 2010, and 2011. The relationship between the organizations in each wave was visualized using Gephi [27]. The input information included (1) the association matrix, (2) the type of organizations, and (3) the geographic longitude and latitude coordinates of the organizations.

The similarity between consecutive waves was measured using the Jaccard index. The index is calculated as the number of ties present at both consecutive waves divided by the combined total number of ties. Since it is generally assumed that the change process is gradual, the Jaccard value should preferably be higher than 0.3 [12].

We use RSIENA to conduct stochastic actor-based simulation as described in [9], [10], [11], and [12] to estimate and evaluate a set of parameter values of interdependencies specified in an objective function that describes the development of KvK networks.[4] One advantage of RSIENA is that it allows us to infer the direction of causation between network selection and social influence [11,20]. Stochastic actor-based simulation has proved highly suitable for analysing longitudinal social network data and was specifically designed for estimating actor-driven network dynamics.

The set of parameters, or independent variables, include items that capture the structural, componential, functional and behavioural mechanisms, as described in Table 1. These parameters were first tested by score-type tests for statistical evidence about their effects without controlling for the effect on each other. The significant parameters were selected as the best specification for simulations.

Algorithmically, the simulation procedure begins with a set of preliminary estimates of the parameters, iteratively producing a sequence of parameter estimates based on a continuous-time Markov process, then comparing the resulting network and attribute matrices with the observed network data, and updating parameter values to reduce discrepancies. These iterative processes are repeated until the deviation between the parameter values and predetermined target values (t-ratio) are smaller than 0.1. The final parameter estimates are then used to simulate a new set of networks. In the simulations, we derived the standard errors of estimation for each parameter based on the set of simulated networks [9]. We constructed rate parameter models to assess the amount of change between consecutive waves, i.e. the speed with which the dependent variable changed. Three set of simulations were done, based on different models. The baseline model (model 1) included the set of significant parameters verified by score-type tests. The baseline model was then extended to incorporate both selection and influence processes. The organizational participation behaviour for the network and behaviour dynamics was tested in model 2. In model 3, we added control variables to balance the effects across groups.

Finally we used a function in RSIENA to assess the fit of model with respect to auxiliary functions of networks. The auxiliary functions concern the attributes of the network, such as degree distributions, which are not included among the target statistics for the effects in fitted models. Goodness-of-fit was visualized using "violin plots". A p-value for the goodness-of-fit was derived from a Monte Carlo Mahalanobis Distance Test [28]. The null hypothesis for this p-value is that the auxiliary statistics for the observed data are distributed according to the distribution simulated in phases of the estimations.

Parameter	Description or definition
Structural dimensions (endogenous)	
Degree (density)	(Intercept) Representation of the tendency to connect with arbitrary ties. Normally it is a negative value indicating the unlikelihood of forming ties randomly.
Transitive triads	Defined by the number of transitive alters in one ego's relations.
Degree popularity	Defined by the the sum of square root of the degree of the alters.
Indirect relations at distance 2	Defined by the number of alters at geodesic distance two.
Componential dimensions (exogenous)	
Identity	Defined by the type of organizations (program center, university, other knowledge institutes, government, firms, and NGOs and knowledge platforms).
Geodistance	Calculated by the logarithm of the geographical distance from each organization to the program center.
Geoproximity	Calculated by the logarithm of the geographical distance between each two of organizations.
Functional dimensions (exogenous)	
Role_max	Calculated by the highest role among individuals of each organization.
Role_average	Calculated by the average role among individuals of each organization.
Behavioral dimensions (exogenous)	
Role_sum	Calculated by the sum of roles of individuals belonging to each organization.
Individual_sum	Calculated by the number of individuals belonging to each organization.

Table 1. The description of dependent variables.

4 RESULTS

Figure 1 and Table 2 present the basic properties of the KvK network over time. They show how the network experienced a boost at the beginning and moderate changes in the following years. Over time, the network became more dense (graph density) and the number of collaborative partners of organisations increased (average degree). The changes of ties in consecutive networks, shown in Figure 1, were treated as the dependent variable in RSIENA modelling.

RSIENA program needs a certain amount of variation in ties between the network waves to be able to estimate the parameters. Jaccard coefficients for the similarity of consecutive

[4] The R software package RSIENA is freely available at http://www.stats.ox.ac.uk/~snijders/siena/siena.html.

networks were 0.140, 0.582, and 0.791, indicating an increasing similarity between the four waves. The Jaccard coefficients suggest that waves 2, 3 and 4 are best suited for modelling, because the change processes became gradual after wave 1.

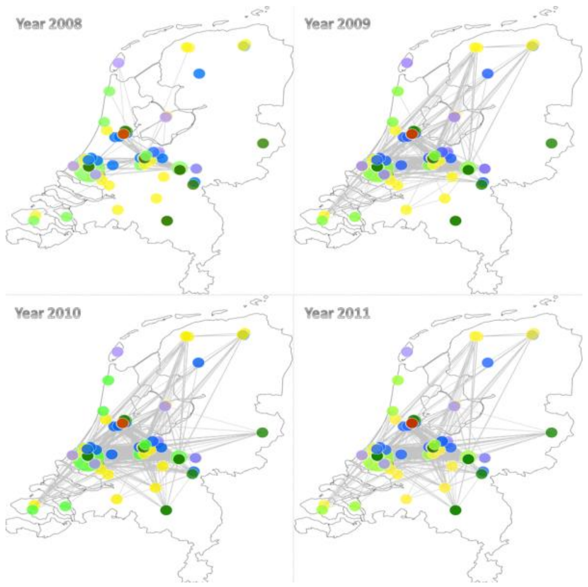

Figure 1. The graphical representations of four consecutive snapshots of KvK collaboration networks from 2008 to 2011. The nodes represent the organizations located geographically on a map of the Netherlands. The colour of nodes indicates the identity of the participating organizations, namely 3 program centres (red), 29 universities (dark green), 17 other knowledge institutes (light green), 28 government (yellow), 17 industrial firms (blue), and 8 NGOs or other knowledge platforms (purple). The existence of a collaboration tie between a pair of organizations is indicated using a solid grey line linking two nodes.

Observation time	Wave 1 (2008)	Wave 2 (2009)	Wave 3 (2010)	Wave 4 (2011)
Graph density	0.023	0.121	0.202	0.160
Average degree	2.294	12.196	20.431	16.157
Number of ties	117	622	1042	824

Table 2. Network density indicators

The modelling results are presented in Table 3. We began the analysis by simulating the endogenous and exogenous mechanisms. Model 1 in Table 3 shows all 12 identified parameters postulated for KvK network change and stability, including considerations of structural, componential, functional and behavioural dimensions. They were statistically verified with an acceptable fit to the data.

Structural parameters have a pronounced effect on network evolution. First, the negative effect of density (beta = -3.16, P < 0.001) is consistent with established knowledge obtained for most sparse networks [12]. This negative effect can be interpreted as an intercept, indicating that the costs of forming an arbitrary tie outweigh the benefits. In our case this suggests that it is unlikely that organizations form ties randomly. Second, KvK networks tend to be closed or transitive, as seen in the significant effects of transitive triads (beta = 0.48, P < 0.001). This finding is consistent with previous literature stating that collaborative partners of collaborative partners tend to become collaborative partners. Degree popularity (the square root of the degree of alters) measures the extent to which organizations tend to seek or be sought in the collaborative network. The positive effect size (beta = 0.47, P < 0.001) suggests that central organizations in the KvK network become even more central over time. The benefit of forming a tie must compensate for the cost per tie. Our results suggest that organizations should collaborate with a very central organisation with at least 45 relations in order to compensate for the -3.16 cost of creating a new collaboration (0.47*√45 = 3.16).

Componential mechanisms involve the identity of collaborating organisations. There is a significant segregation according to identity (beta = -0.37, P < 0.001), meaning collaboration in the KvK program is influenced by the organization type. Moreover, organizations tend to collaborate with the same type of organizations (beta = 0.65, P < 0.001).

To measure the *functional* mechanisms, we weighted actor roles according to the substantive nature of their involvement in projects. The negative parameter estimates (beta = -0.44, P < 0.001; beta = -0.68, P < 0.001) imply that the more concrete the role actors played, the less likely it was that they sought for more network ties. For example, project leaders or principal investigators (weighted higher) appear less likely to connect to others, compared with regular project members (weighted lower). In addition, actors were less likely to participate in relations with actors having the same roles (beta = -3.03, P < 0.001). This effect may reflect a task division within collaborative projects, in which organizations jointly participated with a diversity of roles.

We found no significant effects among the *behavioural* mechanisms. Model 2 also incorporates the dynamics of behaviour, which models the organizational behavioural changes as a function of itself and the network evolution. The results showed that past participation behaviour had a significant effect in the long run (-0.06*(the extent of participation) + 0.00*(the extent of participation)^2). The average of alters' behaviour also had a significant influence on the ego's participation behaviour (beta = 0.00, P = 0.046), which means that organizations tend to adapt their participation behaviour to the average behaviour of their collaboration partners. However, all these effects are very small. Therefore, the evidence for participation-based social influence is weak.

The KvK research programme consists of eight geographical hotspots (Schiphol Mainport, Haaglanden Region, Rotterdam Region, Major rivers, South-West Netherlands Delta, Shallow waters and peat meadow areas, Dry rural areas, Wadden Sea) and eight research themes (climate proof flood risk management, climate proof fresh water supply, climate adaptation for rural areas, climate proof cities, infrastructure and networks, high-quality climate projections, governance of adaptation, decision support tools). Hotspot projects are the essence of the program. They were developed around specific locations in the Netherlands which are particularly vulnerable to the consequences of climate change. These locations function as real-life laboratories where knowledge is put in practice. Given the special functional and geographical importance of hotspot projects, we have tested the effects of project type (hotspots or not) separately in Model 3.

Table 3. Parameter estimates of KvK evolution model, with standard errors and two-sided p-values.

Effect	Model 1 (Baseline Model)			Model 2 (Bahaviour Dynamics)			Model 3 (Control Variable)		
	Estimates	SE	p-value	Estimates	SE	p-value	Estimates	SE	p-value
Network Dynamics:									
Rate function:									
0.1 Network rate period 1	4.65	0.23		4.61	0.27		4.92	0.26	
0.2 Network rate period 2	5.16	0.41		5.65	1.17		5.02	0.38	
Objective function:									
Structural dimensions (endogenous)									
1. Degree (density)	-3.16	0.40	0.000 ***	-2.44	0.09	0.000 ***	-3.20	0.35	0.000 ***
2. Transitive triads	0.38	0.06	0.000 ***	0.41	0.06	0.000 ***	0.36	0.04	0.000 ***
3. Degree popularity	0.47	0.11	0.000 ***	0.27	0.07	0.000 ***	0.44	0.11	0.000 ***
4. Indirect relations at distance 2	-0.05	0.04	0.206	-0.03	0.03	0.333	-0.06	0.04	0.069 +
Componential dimensions (exogenous)									
5. Identity	-0.37	0.09	0.000 ***	-0.38	0.11	0.000 ***	-0.37	0.08	0.000 ***
6. Same identity	0.65	0.16	0.000 ***	0.63	0.17	0.000 ***	0.61	0.14	0.000 ***
7. Geodistance	0.02	0.05	0.716	0.02	0.06	0.766	0.02	0.05	0.708
8. Geoproximity	-0.03	0.05	0.503	-0.04	0.06	0.574	-0.04	0.05	0.472
Functional dimensions (exogenous)									
9. Role_max	-0.44	0.11	0.000 ***	-0.49	0.23	0.031 *	-0.42	0.10	0.000 ***
10. Same role_max	0.02	0.18	0.923	0.00	0.18	0.989	-0.02	0.16	0.878
11. Role_average	-0.68	0.20	0.001 ***	-0.59	0.27	0.028 *	-0.67	0.20	0.001 ***
12. Role_average similarity	-3.03	0.58	0.000 ***	-3.00	0.67	0.000 ***	-2.86	0.56	0.000 ***
Behavioral dimensions (exogenous)									
13. Role_sum	-0.01	0.03	0.716	0.00	0.07	0.984	-0.01	0.02	0.648
14. Role_sum similarity	0.01	9.06	0.999	-0.39	3.98	0.921	-0.34	8.68	0.969
15. Individual_sum	0.00	0.05	0.923	0.02	0.04	0.536	0.01	0.04	0.900
16. Individual_sum similarity	-4.35	9.62	0.651	-3.73	8.52	0.661	-4.42	9.32	0.635
Control variables									
17. Hotspots							0.78	0.32	0.017 *
Behavior Dynamics:									
0.3 Behavior (role_sum) rate period 1				704.36	94.60				
0.4 Behavior (role_sum) rate period 2				188.03	30.19				
18. Behavior (role_sum) linear shape				-0.06	0.02	0.004 **			
19. Behavior (role_sum) quadratic shape				0.00	0.00	0.003 **			
20. Behavior (role_sum) co_degree				0.00	0.00	1.000			
21. Behavior (role_sum) co_average alter				0.00	0.00	0.046 *			

The two-sided P-values were derived based on the normal distribution of the resultant test statistics (estimate devided by standard error). +p<.1, *p<.05, **p<.01, ***p<.001.

In Model 3, we have added a control variable to test if the effects identified in Models 1 are changed when we take into consideration the difference between hotspot projects and regular projects. The results show a statistically significant positive difference (beta = 0.78, P = 0.017), suggesting that organizations active in hotspots projects are more likely to form new collaborations over time than organizations that work in regular projects. The other effects remain similar.

All parameter estimates in the three models converged well below 0.1, indicating a good fit between the simulated ties and the observed ties. We also did sensitivity tests for the weighting of roles, but changing the weights did not influence the results. Overall goodness-of-fit (Figure 2) is with a p-value of 0.014, which is improved from 0.003 when only structural dimensions are included in the model. Most observations are nicely within the 95% regions of the simulated distributions, that indicates an acceptable fit of the models to the data.

5 CONCLUSIONS AND DISCUSSIONS

Stimulating and facilitating multi-actor collaborations for joint problem solving is considered to be one of the key challenges for modern organization studies. In practice, the emergence of new collaborative networks invariably entails a decision regarding who will participate and which partners to select. How organizations are connected can have lasting consequences for their performance. Yet, the mechanisms that may connect one actor to another remain insufficiently understood, owing to a restrictive focus on mechanisms of network endogeneity to the exclusion of exogenous mechanisms. In order to understand the mechanisms that influence the formation and evolution of collaborative networks, we have used a stochastic actor-based simulation model to study the evolution of a collaborative multi-actor program, combining endogenous and exogenous mechanisms of network formation.

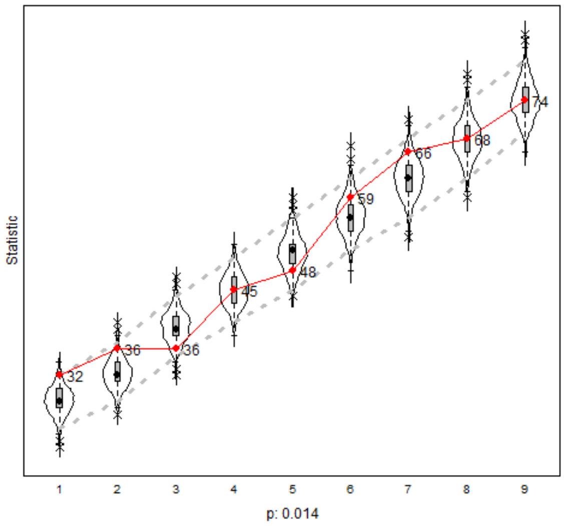

Figure 2. The goodness of fit of degree distribution.
The "violin plots" show, for each number of nodes with degree < x, the simulated values of these statistics as both a box plot and a kernel density estimate. The solid red line denotes the observed values. The dashed grey line represents a 95% probability band for the simulations.

The results of our analysis match the findings in previous literature with respect to endogenous network structural dimensions: transitivity and centrality play a key role in the evolution of the KvK network. The results also reveal the influence of exogenous mechanisms: actors tend to collaborate with other actors from the same type of organizations (componential) and patterns of collaboration are affected by the nature and differences in roles (functional), which may reflect task division within collaborative projects.

Our analysis reveals a gap between actors from different sectors and a gap between actors working on global problems and those working on local problems. The KvK research program was designed as platform to encourage and support the collaboration between actors from different sectors. The program aims to form a bridge between communities without necessarily closing the gap.

Our results also suggest that organizations active in hotspots projects are significantly more likely to form new ties than those active in theme projects. Hotspots projects focus on developing practical solutions for local and regional problems, while theme projects comprise teams of geographically dispersed scientists working to solve global challenges. The balance between global and local is reflected in the structure of the network.

Finally, our study has both theoretical and practical relevance. By addressing the mechanisms that inhibit or facilitate the development of collaborative networks, we provide theoretical insights in the position of organizations as strategic actors, attempting to effectively participate in organizational collaboration for knowledge creation. The practical value of our findings is that they may help identify and bridge gaps between actors from different societal organizations in a meaningful and purposeful way.

Our study is not without limitations, which also points the way for further research. First, we could only construct the presence or absence of ties (non-directed networks) from the available data. More information about who took the initiative to start a collaboration and other direction-related effects such as reciprocity would permit a more in-depth understanding and might also result in a better model fit. Second, the models were restricted to binary network data. Third, the project-based collaborations were affected by top-down (programme) interference for which we could not model. Finally, it would be interesting to investigate the emergent network at the individual level, which calls for a model with extended computational power.

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