To connect or not to connect? Examining the evolutionary dynamics of shared membership in network domains

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Abstract

In practice, solutions to complex social problems are often delivered through networks that are favored by government and philanthropic investment (Kania & Kramer, 2011). Despite broad application of this collective approach, theory development for understanding this phenomenon has fallen behind in explaining system-wide dynamics (Milward, 2016). Using an insular view of networks, studies have overlooked the broader network domain, defined as collections of networks sharing an environmental niche in a single geographic and problem-area (Nowell, Hano, & Yang, 2018). Moreover, network evolution studies have not yet addressed the tensions between a network's formation impetus and its internal capacity (Bryson, Crosby, & Stone, 2015). In this study, shared membership is considered an important mechanism establishing ties between networks in their network domain. Traditional board interlocks studies view these connections as valuable and strategic (Zona et al., 2016), while resource dependency suggests that sharing members creates scarcity in human capital assets (Pfeffer & Salancik, 1978). Further, collaborative engagement theories suggest that the more embeddedness, the better (Agranoff & McGuire, 2001; Nowell & Foster-Fishman, 2011). This research seeks to clarify these tensions by examining: 1) What effects do shared membership have on a network's evolution? and 2) What effects do internal capacity have on a network's evolution? This study utilizes a bipartite longitudinal network data set that includes 74 networks with a 97+% population response rate. The two-mode dataset includes more than 2600 individuals' connections to networks in their network domain. Hypothesis testing regarding the effects of network domain dynamics and network capacity is accomplished using a Stochastic Actor-Oriented Model (SAOM). The SAOM examines the contribution of both network and network domain attributes in evolution (Burk, Steglich, & Snijders, 2007). Results address dynamics of shared membership, suggesting that network domain density may negatively affect survival, yet centrality of a single network in the domain supports survival. Findings also indicate that capacities like the presence of a convening organization, funding, and paid staff have unique dynamics when the network domain effects are included. This study advances current network theories by addressing the tension between differing views of the utility or liability of shared membership. Additionally, this research contributes to conversations in practice that are examining the challenges of evaluating network success in network domains with multiple, embedded networks. This study, by describing and clarifying the dynamics of shared membership in network domains, can also help inform future impact investing and network leaders' strategic decisions.

This article focuses on the application of a stochastic actor-oriented model (SAOM) to longitudinal network and network domain data. The specific research question is: To what extent do network domain dynamics and network capacity have an effect on the expansion or contraction of networks over time? Not only does this analysis point to possible network attributes that lead to stability over time, it also reveals network domain dynamics that can lead to strain on a community's ability to house new networks without causing others to disband.

To address this research question is to also examine the relative effects of exogenous versus endogenous factors on the trajectory of a network over time. Endogenous factors that have been empirically examined include attributes of a network like size, organizational composition, funding, staffing, governance structure (Milward, Provan, Fish, Isett, & Huang, 2010; Provan & Milward, 1995), and presence of influential leaders (Gray, 1985). Exogenous factors have been considered in past network studies, resulting in some theoretical frameworks that link contextual factors to success. Some external factors include financial or community control over a network (Heikkila & Isett, 2007; Provan & Milward, 1995; Turrini, Cristofoli, Frosini, & Nasi, 2009), community-wide resource munificence (Provan & Milward, 1995; Raab, Lemaire, & Provan, 2013; Turrini et al., 2009), and the broader context of changes in the network domain's overall resources and complexities (Andrews & Entwistle, 2010; Raab et al., 2013). While these scholars consider factors that exist outside of the network, these past studies do not consider membership interlocks, referred to in this study as shared membership, as a key exogenous factor in fully defining a network domain and its dynamics.

This article begins with an introduction of the external view of networks within a network domain. This frame is necessary to support the application of the SAOM analysis. Following the external view, variables of interest are discussed in the context of past theories that have yet to be applied to the whole-network level of analysis prior to this research. Hypotheses are offered that

leverage micro-level theories from organization and network literature and apply them to the meso-level of the network as a node within the network domain. Next, the method and results of the SAOM are discussed.

The external view of networks: Coupling endogenous and exogenous effects

The goal of this research is to examine a variety of both network domain and covariate effects that are present as networks expand or contract in membership over time. In current scholarship, this level of analysis has yet to be established and described, much less related to potential mechanisms that may support changes. Below, the context for this research is established within an external view of networks, highlighting the potential theoretical space to deductively examine both network and network domain mechanisms involved. For the purposes of this research, networks are defined as three or more organizations that meet regularly to accomplish shared goals (Provan & Kenis, 2007). Networks are multi-organizational groups that come together to solve problems that cannot be achieved, or achieved easily, by single organizations (Agranoff & McGuire, 2001; Nowell & Foster-Fishman, 2011). These networks are also specifically community-based and made of actors who represent nonprofits, for-profit companies, public agencies, and community groups that all share a common interest in a specific issue area (Nowell & Foster-Fishman, 2011). These groups are unique from contracted service delivery networks in that they emerge organically to both identify and implement strategies for improving community outcomes in their shared issue area (Foster-Fishman, Berkowitz, Lounsbury, Jacobson, & Allen, 2001; Nowell & Foster-Fishman, 2011). This definition of a network aligns with a more limited view of networks as advanced by Provan et al. (2007), situating this work in the tradition of examining networks as formal entities of collective action and as governance mechanisms in and of themselves (Emerson, Nabatchi, & Balogh, 2012; Koliba, Meek, & Zia, 2010). The network domain refers to a

population of networks who occupy the same environmental niche, as related to Hannan and Freeman's (1977) theory of Population Ecology. The network domain established in this study is defined as a group of networks that address the same problem space of community health and wellness in the same geographic area (Nowell, Hano, & Yang, in press)

While network research in Public Administration has expanded in the last two decades, many studies regarding network governance as a tool to solve complex problems are approached from an ego-centric, or organization-based, internal perspective that uses the components within a network as the unit of analysis (Hu, Khosa, & Kapucu, 2015). Other studies explore the strategic choices of organizations to engage in networks (for example: Ahuja et al., 2012; Borgatti, 2003; Powell et al., 1996) but do not consider the more complex dynamics that are occurring within a community that houses many networks operating in the same domain. As noted by more recent research, prior network literature has largely overlooked the influence of the external environment, in particular the existence of shared members across networks, instead studying them as if they are in isolation (Nowell et al., in press).

Indeed, a broader perspective is necessary to frame the context of this study and examine the phenomenon of network evolution within a network domain. In past research, an internal emphasis has driven a focus on describing and defining the components of networks through description of attributes like governance structures, processes, and activities. Scholars have also advanced research agendas that focus on components of networks being improved for the highest outcomes (Raab, Mannak, & Cambre, 2015; Turrini et al., 2009). Alongside these inward-facing research agendas has been a contingency approach that defines the network's context based only on the characteristics of members (Provan & Kenis, 2007) without also considering the broader network domain in which it must function. Additionally, overarching rational-actor assumptions (Feiock, 2007) have driven definitions of

networks and internal behaviors as a function of individuals' strategic choices without recognition of external forces, such as competing initiatives, in the same network domain.

As noted above, some exogenous factors have been considered in past network studies, including financial or community control over a network (Heikkila & Isett, 2007; Provan & Milward, 1995; Turrini et al., 2009), community-wide resource munificence (Cristofoli & Markovic, 2016; Provan & Milward, 1995; Raab et al., 2013; Turrini et al., 2009), and the broader context of changes in the network domain's overall resources and complexities (Andrews & Entwistle, 2010; Raab et al., 2013). These past approaches, based on their narrow focus, have overlooked more complex dynamics that occur within a community which houses many networks drawing from a common resource pool for members, funding, information, and so forth.

This research also answers a decades-old call by Raab and Kenis (2009) to further develop a holistic theory of networks by considering the network itself as the unit of analysis. Additionally, theory development may be able to gain more traction by moving away from dyadic analysis of organizational or personal ties only (Raab & Kenis, 2009). Studying networks as governance forms to address complex problems, or a "network for itself" (Raab & Kenis, 2009, p. 206), inherently must include a description and examination of the system in which the network is situated. In addition to recognition of the network domain itself, the mechanisms within that domain that translate to exogenous effects on networks have received less attention in the literature. As argued by Raab and Kenis (2009), one possible way to establish empirically testable mechanisms would be to consider the actions and choices of individual actors who engage in multiple networks within a network domain.

In this research, a key mechanism within a network domain is shared membership, defined as the phenomenon of an organizational member in one network also being a member of another network in the same network domain. Nowell, Hano, and Yang's (in press) study confirms the existence of

members engaged in more than one network that focuses on the same issue area in a community, while also highlighting the importance of how shared membership allows for networks to be connected to one another in meaningful ways in the larger network domain. By broadening the focus and moving up a level of analysis in their study, Nowell, Hano, and Yang (in press) offer the foundational stages of conceptualizing an important phenomenon at the network level of analysis within the network domain, as demonstrated in Figure 7.

One view, from the tradition of board interlocks research, suggests that the connections established by shared membership are both valuable and strategic for the firms involved (Zona, Gomez-Mejia, & Withers, 2018). Network engagement studies reify this perspective by suggesting that the more embedded and connected the organization or initiative, the better (Agranoff & McGuire, 2001; Nowell & Foster-Fishman, 2011). An opposing view can be drawn from resource dependency theory (Pfeffer & Salancik, 1978). Shared membership could pose a threat to highly connected networks in a network domain if issues of scarcity of human capital arise.
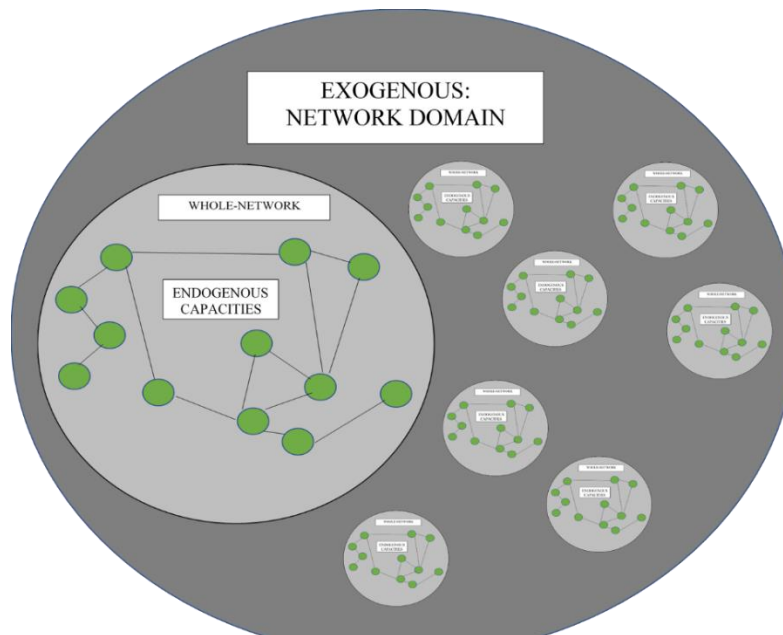
**Figure 1: The exogenous network domain and whole-network
endogenous capacities.**

This research examines the network domain and meaningful ties based on the existence of shared members. Recognizing shared-membership as a meaningful tie between networks and a mechanism for justifying the network itself as the level of analysis suggests the integration of the view that a network is a social structure and a governance form. The network itself is a governance form, while the ties that create the network domain are socially driven. This view aligns with a community-systems perspective in which a collection of autonomous actors shares common involvement in a problem domain, which creates interdependencies (Nowell, 2009). Shared membership across networks then constitutes the network domain of formal and informal relationships that can evolve over time. This external view and recognition of meaningful connections between networks in a network domain supports the necessity of examining the research question here: To what extent do network domain dynamics and network capacity have an effect on the expansion or contraction of networks over time?

Examining network-level evolution in network domains

This second section focuses on the concepts and dynamics of interest in this research, with a specific emphasis on situating them within the context of current network theories and aspects of applicable organizational theory. These are grouped in two categories, including 1) exogenous formation and impetus dynamics and 2) endogenous capacities of a network. The variables discussed below are applied using an external view of networks that explores changes in shared-member ties across a network domain over time. As such, current theories of network evolution alone have little utility in examining how the network as the unit of analysis is evolving; thus, the mechanisms of change presented below are drawn from multiple sources in both organizational and network theory.

Exogenous factors and network domain dynamics

Path dependency based on formation motivation or impetus has been considered an important aspect of the nature of changes within a network. Before its application to network theories, path dependency was prominent in organizational literature. Pierson's (2004) book examined the nature of an organization or agency's history, institutional inertia, and place in society, recognizing that the starting conditions can encourage subsequent or emergent strategies. These starting conditions can also affect the nature of processes and structures that are a product of initial path dependencies (Pierson, 2004). Indeed, the mechanism underlying path dependency theories are closely related to concepts in Population Ecology, supporting the connection between a network's starting niche and its trajectory over time (Hannan & Freeman, 1984).

Recent applications of path dependency theories in organizations examine and emphasize processes. For organizations, becoming path dependent involves a narrowing of the scope of actions over time, which occurs from self-reinforcing actions (Schreyögg & Sydow, 2011). In this study of network evolution, path dependency is related to creation, maintenance, and deletion of ties based on the assumption that members of a network have the agency to both create and break links to a group (Axelrod & Cohen, 2000; O'Toole, 1997), meaning that the members in a network have the ability to make their own decisions about making or breaking ties when the group faces challenges.

The networks included in this research are diverse in their starting conditions, spanning from more prescribed forms like policy mandates to more emergent forms like grassroots initiatives. As noted by several scholars, policy mandated networks that are established and determined by an outsider can lack important pre-existing relational embeddedness of members. These networks may have to work harder to build relationships and trust as compared to their grassroots counterparts (Hall et al., 2003; Ring & van de Ven, 1994; Stephens, Fulk, & Monge, 2009). Additionally, mandated networks created by policy can create different conditions for strategic management. Mandated networks also often lack

an initial normative system to encourage member commitment and capacity building beyond the mandated requirements (Provan & Kenis, 2007). This past research suggests:

> *H1: Grassroots-organized networks are less likely to contract over time than philanthropically-funded, government-funded, or policy-mandated networks.*

To date, the concept of centrality in network research has considered the organization as the unit of analysis. Powell et al.'s (1996) work specifically examined the network position of organizations, finding that a firm or organization's central location can positively influence its reputation and subsequent access to resources. In this study, the unit of analysis is the network itself and its network domain position is created through the presence of shared ties with other networks.

If the level of analysis from Powell et al.'s (1996) theories is applied to networks themselves, there is one possible argument for the positive nature of shared membership or centrality. In organizational literature, being central in a network can have positive outcomes supported by access to a wider variety of information, resources, and status (Ahuja et al., 2012). Embedded organizations also may have the opportunity to shape their own environments for their advantage (Borgatti, 2003, 2005). The mechanism considered in this study, borrowed from organizational literature, is that central networks will not only be more attractive to new members due to access to resources, but these networks also will have more access to other networks that enable them to influence their network domain to support their survival.

A counter argument can be synthesized from Resource Dependency Theory (Malatesta & Smith, 2014; Pfeffer & Salancik, 1978), which views organizations as engaged in a constant struggle to acquire and maintain resources to survive. Resource Dependency Theory also recognizes that organizations are not self-contained, but rather must strategically engage with the larger environment where other organizations are competing for the same resources (Pfeffer & Salancik, 1978). When considering the

challenges of networks to survive within network domains, members are not always a dependable resource, given the nature of time needed to engage in networks (Provan & Huang, 2012), and shared members could be especially more likely to change network affiliations as the network domain changes. In this way, shared membership or centrality in the network domain may be more of a liability than an asset. While these two views are opposing, the traditional dynamics from ego-centric organizational theory are used to suggest:

> *H2: Networks with a higher centrality are less likely to contract than networks that are on the periphery of the network domain.*

Endogenous network capacities

A discussion of each of the variables within the capacity area continues below. Convening organizations are considered an integral part of the necessary relationships for forging network and interorganizational spaces (Gray, 1985). In many theories of how networks form, there is a problem-setting phase in which stakeholders to be engaged in the process are identified, while also giving an identity to the problem that the group sets out to solve (Gray, 1985; McCann, 1983). During this problem-setting phase, stakeholders also go through the process of recognizing their interdependence and address their perceptions of legitimacy of other network members (Gray, 1985). This action takes the work of a skilled convener, and, indeed, network success or failure can be attributed to convener activity both at the beginning of a network and throughout its life cycle (Gray, 1985).

Conveners themselves hold power and legitimacy, and they can embody the power and legitimacy of the organization that they represent. As noted by Friend, Power, and Yewlett, (1974) and Sarason and Lorentz (1979), networks that succeed often have conveners who enhance the potential for mutual exchange and envision a mission that can be fulfilled through joint participation. Conveners also serve in an important role throughout the life of the network by offering their ability to scan the

environment to build and sustain the group (Sarason & Lorentz, 1979). The long-term presence of convening organizations suggests:

> *H3: Networks that retain convening organizations are less likely to contract over time.*

Resource availability is also considered an important characteristic of networks in this research. Some mechanisms for the importance of funding are tied to the discussions of path dependencies above, as well as being related to network context (Provan & Milward, 1995). As first established by Provan and Milward's (1995) work, and explored across future network case studies (Provan & Huang, 2012), resource stability allows for more capacity to meet goals. Indeed, resource scarcity constrains a network's capacity, even if there are other characteristics that are positively related to survival or achieving goals (Milward et al., 2010; Provan & Milward, 1995), and plentiful resources can support network stability even when other resources like information and reputation do not flow easily (Provan & Huang, 2012). This past research suggests:

> *H4: Networks that maintain funding over time are less likely to contract than those that lose funding.*

> *H5: Networks that increase funding over time are less likely to contract than those that lose funding.*

Related to issues of funding is also the presence of paid staff who officially coordinate the work of a network. Paid support staff can facilitate improved coordination and communication among members (Provan & Kenis, 2007; Provan & Milward, 1995). Additionally, a paid staff member enables the centralized integration of other important capacities of the network, including information sharing, group activities, and achievement of goals (Provan & Kenis, 2007; Provan & Milward, 2001). On the other hand, lack of staff members, especially in emergent networks that depend on participatory governance, can pose a coordination burden on network members, which can be a strain on the

sustainability of the network and deter the interest of new members (McGuire & Agranoff, 2011; Provan & Kenis, 2007). These dynamics suggest:

> *H6: Networks with more paid staff members are less likely to contract over time than those with fewer staff or no staff at all.*

Building from the foundations of Population Ecology (Hannan & Freeman, 1984), network membership size and age are considered important measures of capacity in this study. Larger networks with more members, normed for comparison purposes, may have more access to resources through their membership (Powell et al., 1996), but they also may build up too much inertia and become unable to adapt for survival over time (Hannan & Freeman, 1984). Additionally, the age of the network can be associated with Population Ecology's "liability of newness" concept. In this context, new networks may struggle to establish their legitimacy and claim a niche within a network domain (Human & Provan, 2000). If stable enough over time, new networks may be able to establish legitimacy that supports their survival (Hannan & Freeman, 1984). These mechanisms suggest:

> *H7: Proportionally larger networks are less likely to contract than smaller networks.*

> *H8: Older networks are less likely to contract than newer networks.*

Methods

Stochastic agent-oriented models (SAOM) have been developed to account for the interdependencies that are intrinsic in longitudinal network data (Burk, Steglich, & Snijders, 2007). SAOMs utilize an objective function rationale that allows for actors to periodically reconsider their whole set of ties (Block, Stadtfeld, & Snijders, 2016; Snijders, van de Bunt, & Steglich, 2010). These changes in ties are modeled as micro-steps (Burk et al., 2007), and due to the nature of this study's

bipartite data (actor to network ties), these changes aggregate to expansion or contraction of ties between networks in a network domain (Snijders, Lomi, & Torló, 2013). Thus, the dependent variable is conceptualized as the expansion or contraction of actor ties between networks.

These models treat the overall connections between networks as a dichotomous relational variable, while allowing for the modeling of actor dependencies. SAOMs are a main-effects approach that provides parameter estimates, standard errors, and t-ratios for each of the predictor variables included in the model (Snijders et al., 2010). The resultant rate and network parameters are interpreted by direction of effect, but the effect sizes are not comparable as in traditional OLS models (Snijders, 2018). Actor covariate (behavior function) parameters are shown as log-odds, with a one unit change in the covariate resulting in an increased probability for tie creation (Snijders, 2018; Steglich, 2018).

In this research, the SAOM is implemented using RSIENA, which estimates the model based on a maximum likelihood estimator utilizing a three-phase stochastic approximation algorithm (Burk et al., 2007; Snijders et al., 2010). The first phase calculates likely starting values for the parameters of all variables by holding each constant at its initial value. The second phase simulates the choice process of each actor based on the starting values of all network and covariate variables and compares the simulated network with the observed network data. In this second phase, parameter values are adjusted to reduce differences between the simulated and observed networks. The final phase uses a number of iterations, often set to 500, to determine the frequency distribution of errors in predicting the observed from the simulated network. This distribution is then used to calculate the standard errors for the final parameters in the output.

By combining random utility models, Markov processes, and simulation (van de Bunt & Groenewegen, 2007), SAOMs can explain observed changes in the global network structure by modeling choices of actors at a micro level. This statistical model simulates network evolution between

observations and estimates parameters for the underlying mechanisms of network dynamics by combining discrete choice models, Markov processes, and simulation (Snijders et al., 2010). In SAOMs, endogeneity of network structure, or the propensity for networks to reproduce themselves through mechanisms like homophily, triadic closure, and so forth, is seen as an essential source of data for modeling network evolution (Block et al., 2016).

SAOMs can be interpreted under the assumption that an actor decides between two networks that only differ by one unit on the variable in question (e.g., centrality) (Snijders, 2018). The estimate is the logarithm of the probabilities for an actor to choose the outcome network that scores one unit higher (being more central in the network domain) versus the one that scores one unit lower (being less central in the network domain). For behavior-effects in a SAOM, the artificial comparison of two outcomes refers to the decision between moving up by one unit on the behavior scale versus not moving up, assuming that these situations again differ by one unit on the explanatory variable like percentage of convening organizations or paid staff retained.

The dependent variable in SAOM is not a list of dyads but the structure resulting from relationships between a set of actors or the particular way relationships between actors are organized (Snijders et al., 2010). In this research, network expansion or contraction, in the form of more or less shared members, serves as the resulting relationship to be modeled. The dynamic nature of SAOM lies in the fact that the model explains how the observed structure of relations evolves from time t to time $t+1$. Therefore, the dependent variable is a set of consecutive observations of links between actors, which are organized as time series:

$$x(t), t \in \{t_1, \ldots t_m\}$$

for a constant set of individuals $N = \{1, \ldots, n\}$. These network structures are then modeled as a continuous-time Markov chain $X(t)$ described above (Snijders, 2018; Snijders et al., 2010).

The main assumptions of SAOMs address the propensity of members being connected to networks, network attributes, and the nature of network dynamics. Each actor is assumed to optimize his or her position. In the case of this data, where the targets are the networks themselves, members adhere to short-term preferences and constraints that are modeled in the algorithm (Block et al., 2016). Additionally, changes in a network domain are modeled separately from individual behaviors by using transition probabilities between possible states (Burk et al., 2007). These states are defined as all possible configurations of the combinations of network and individual behaviors.

SAOMs also differ in meaningful ways from their longitudinal network analysis counterparts, (T)ERGMs. In a SAOM, the modeling is actor oriented, meaning that the resulting parameters assume that the actor considered the costs and benefits of all possible ties between each observation (Block et al., 2016). This assumption is critical and appropriate for this research because the focus is on network domains comprised of a distinct set of individuals who have limited time and resources to join local networks (McCartha, 2019). It is also assumed that members of networks in a community will indeed weigh options for membership against each other. (T)ERGMs are tie-oriented and based on the assumption that actors consider ties independently and without comparison (Block et al., 2016). In this research context, (T)ERGMs would be inappropriately overlooking meso-level dynamics of members' decision-making by assuming they are only concerned with micro-level, tunnel vision of the potential networks to join.

Research context

This research leverages a unique, longitudinal population-level dataset that includes all health-oriented networks in three counties in a southeastern state. The data used for this analysis are a population-level dataset of 74 networks and their members taken over two timepoints. Time 2 data collection achieved a 97% response rate, and Time 1 data collection achieved a 100% response rate from

all identified health-oriented networks in the counties included in the study. The list of networks was cross-validated by county informants as well as an exhaustive web search to ensure comprehensiveness. The resulting sample is a population of networks, not a random sample. The population-level dataset, while not generalizable to all network domain types, does allow for a deeper understanding of community-level dynamics when the unit of analysis is the network itself.

Networks in this unique dataset are defined as three or more organizations that meet on a regular basis and have a health or wellness focus to their work. This definition of a network served as the inclusion criteria for data collection for the duration of the project. Each participating network was asked to provide a current list of their members and associated organizational affiliations. Network coordinators were then asked to participate in a structured phone interview to validate the activity level of all members and provide descriptive information about the network's funding, convening organizations, and staff.

Sampling procedures

Networks active in 2012 were identified using a two-stage chain referral sample development design. In the first phase, an online survey was sent to members of large health-oriented networks in each county. This survey included a question that asked respondents to identify other health/wellness related networks in their county. Responses to that question were used to create the initial sample used in the second phase of the 2012 study. In the second phase, a chain referral or snowball methodology was implemented to develop an exhaustive list of health and wellness networks in the county.

Each network that participated in the 2012 second phase reviewed the evolving sample for errors and omissions. Prior to adding a recommended network to the sample, research assistants determined eligibility based on three inclusion criteria: 1) the network comprises three or more organizations; 2) the network has a health or wellness focus to its work; and 3) the network convenes meetings on a regular

basis. Once a network was included in the sample, the coordinator or organizer was contacted and invited to participate in the study. In 2017, key leaders of large health-oriented networks in each county were first contacted by phone to discuss the status of all networks in the 2012 study and to add any new networks that had emerged since the first study. Again, each network that participated in the 2017 interviews reviewed the evolving sample for errors and omissions.

Data collection procedures

Each participating network coordinator was asked to first clarify if the network was still meeting as a group in 2017. If the network remained active, the coordinator 1) participated in a semi-structured interview (see Appendix A for interview questions), and 2) provided the research team with a current list of their members and associated organizational affiliations. Network coordinators were then asked during the semi-structured phone interview to validate the activity level of all members and provide descriptive information about the network. Coordinators of inactive partnerships also participated in a semi-structured interview (see Appendix B for interview questions) but did not provide a membership list because the group was no longer functioning as a network based on the study's inclusion criteria.

From the interviews with coordinators of active networks, three kinds of data were collected. The qualitative data was used to establish the origin or impetus of the network. The quantitative dataset includes measures of convening organizations, the amount of funding, number of paid staff, network age, and network size. The network data are created from membership lists containing the names of individuals, the organization they represent, and the network(s) to which they belong by aggregating them together into a relational database that can be cross-referenced across three levels of analysis: individual, organization, and network. Only individuals who actively participated in meetings over the past year were included for analysis.

Measures and measure development

In a SAOM, a researcher can investigate the relative contribution of both nodal and network attributes in explaining network change over time (Burk et al., 2007). In this study, the nodal attributes are impetus and capacities measures for each network, and network attributes are structural aspects of the network domain. RSIENA's effects estimation function offers a list of possible effects that can be included in the model based on the nature of the network data provided. As discussed in more detail below, the density of the network domain, as well as the possibility for 4-cycle closure is included in the model. Four-cycle is applied to two-mode networks to examine the propensity for members to connect to two different networks, as illustrated below (Snijders, 2018).

Like triadic closure in a one-mode network, 4-cycle accounts for when two members who belong to another network in the network domain are members of second network as well (Koskinen & Edling, 2012). Mechanisms for creating these interlocks can be considered on the individual or organizational level and are aggregated to the network. Some forces like homophily and peer referral are possible drivers of 4-cycle network connections (Koskinen & Edling, 2012).

While outside of the scope of this paper, see Yang (2016) for a more in-depth examination of individual and organizational-level dynamics. A noted limitation of this research is that actor-level characteristics are not available for analysis. Thus, the results focus on modeling the nature of which
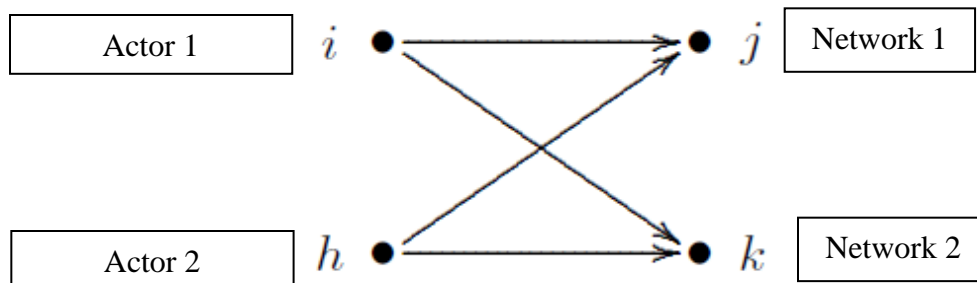
networks are connected through actor choice, rather than the attributes of those members who choose to be members in multiple networks.

Table 5 below describes the operationalization of the constant covariates included in the SAOM. These measures are attributes of each network within the network domain.

Table 1: Variables of interest and operationalizations.

SAOM Variable	SAOM operationalization
DV: Propensity for an actor to create, maintain, withdraw, or not create a tie to a network	T1 and T2 bipartite network data
IV: EXO: Impetus/path dependency of network	Categorical indicator of grassroots, philanthropically-funded, government-funded, or policy-mandated network
IV: EXO: Shared members in the network domain	Normed centrality of the network
IV: EXO: 4-cycle connections between networks	Closure of connections between networks based on transitivity
IV: ENDO: Funded or unfunded network	Binary of funded or not funded network
IV: ENDO: Presence of paid staff to support network	Binary indicator of whether the network has paid staff
IV: ENDO: Funding increase in network	Binary indicator of increase in funding from T1 to T2
IV: ENDO: Paid staff changes in a network	Normed (based on highest number of paid staff possible) measure of paid staff present at T2
IV: ENDO: Membership size of a network	Normed average number of members at T1 and T2
IV: ENDO: Age of network	Numeric value representing age at T1 and T2

Data preparation

Network domain data used in this analysis is a two-mode network that considered a bipartite structure representing members' association with networks at T1 and T2. The original data was in the form of an edgelist and was converted to adjacency matrices using UCINet (Borgatti, Everett, & Freeman, 2002). Once the matrices for each domain were prepared, re-coding of member numbers and network numbers was necessary to differentiate the domains within the data. Additionally, structural

zeros were utilized as a feature of the RSIENA software. This feature offers the possibility of analyzing several network structures simultaneously under the assumption that the parameters are identical (Snijders, 2018). In other words, all three domains can be modeled together because the data is structured such that no member from Domain A can possibly be connected to networks in Domain B or C. This approach is appropriate due to the geographic distance between the three domains and the improbability of an actor being engaged in more than one domain.

Network and network domain descriptive statistics

The tables below present overall descriptive statistics for the full sample of 74 networks and the domains they belong to. As shown in the Table 6 below, each of the domains included in the SAOM analysis not only experienced the influx of new networks—and the discontinuation of others—the percentage of members from T1 networks engaged by new networks at T2 ranges from 16 to 31 percent. This not only demonstrates that shared members represent an important aspect of the network domain but also that new networks recognize and activate existing members in the domain to begin engaging with the broader system.

Table 7 presents the formation or impetus distribution of the networks in the sample. As the data shows, almost half of all of the networks in the sample were convened from grassroots engagement, suggesting that the populations of networks in the health-oriented network domains in this study are more bottom-up than top-down. Table 8 represents all descriptive statistics for other network capacity measures included in the SAOM.

Before running a SAOM, RSIENA can estimate a Jaccard index, or measure of stability, from multiple observations of network data. If Jaccard indices are very low (approaching 0), while the average degree is not strongly increasing, this indicates that the turnover in the network may be too high to consider the data as an evolving network that RSIENA can analyze (Snijders, 2018; Snijders et al.,

2010). For networks with average degrees that do not vary widely between observations, Jaccard values of .3 and higher are good. Very sparse networks, with most degrees less than 2, also may have lower Jaccard values without negative consequences for estimation. The Jaccard index for the model presented below is 0.43.

Table 2: Network domain variation.

	2012 networks	2017 new networks	2012 dead networks	2017 networks	% members from existing networks
Domain A	12	6	3	18	16%
Domain B	14	4	2	16	31%
Domain C	34	7	11	30	23%

Table 3: Exogenous impetus.

Impetus/path dependency (n=74)	Number (percentage)
Grassroots	33 (45%)
Philanthropic funding	14 (19%)
Government funding	13 (17%)
Funded policy mandate	7 (9%)
Unfunded policy mandate	3 (4%)

Table 4: Network capacities.

N=74	Mean	Median	Mode	St. Dev	Variance
Impetus			5-Grassroots		
% convening orgs present at T2	28.7	25	33	2.15	4.66
Funding increase (0/1) at T2			1		
Funding (0/1) at T1 and T2			0		
% staff change at T2	25	50	20	3.8	14.4
Size (normed) at T2	27.1	20	17	22.1	485
Age at T2	13.2	11	7	9.89	7.8

Table 5: Average network domain descriptives.

	Time 1	Time 2
Density	.028	.031
Average degree	2.587	2.643
Number of ties	2604	2610

Model estimation

Because the bipartite data used in this study is undirected, meaning there is no differentiation of senders versus receivers, Model 2 is chosen for this analysis. Model 2, otherwise called "Unilateral Initiative and Reciprocal Confirmation" assumes that an actor takes the initiative and proposes a new tie or dissolves an existing tie (Snijders, 2018*)*. This model captures actors' decisions in a two-steps process: 1) whether to form a tie or not depends on whether the actor wants to increase or decrease her number of ties (degree), and then 2) the actor decides whether to form a tie or not (Snijders, 2018; Snijders et al., 2010).

Findings

The findings discussed below are the result of two runs of the model, each with a lower convergence ratio. After the initial run, the parameters from the previous model estimation were used as the initial starting conditions for the second estimation of the model. The final convergence ratio was 0.08. Convergence ratios nearing zero are ideal (Snijders, 2018).

Table 10 below represents the parameters from the final run of the model. Both network domain and covariates were significant and are discussed here. Based on the possible effects that could be modeled with the data, rate, density, and four-cycle were included. The rate estimate represents creation of ties and indicates expansion of ties in general from T1 to T2. Rate is always included in SAOM estimation as a constant. Four-cycle connections were not statistically significant in this model. This finding shows no support for networks that are connected to two or more other networks being more likely see tie expansion. While not established as a hypothesis before running the model, network domain density is found to have a statistically significant effect. Denser network domains may see tie constriction over time.

Network capacities also had significant effects in the model. H2 is supported and suggests that networks that are more central are less likely to see tie constriction than those networks that are on the periphery of their network domain. In other words, networks with many members who share ties to many other networks are more likely to maintain or strengthen their ties over time. H3 is also tentatively supported with retention of convening organizations supporting ties over time. The percentage of paid staff retained over time also has a significant effect, but this result refutes H6 and suggests that networks with paid staff are more likely to experience tie constriction over time. Given that this result is counter to the hypothesis, more research is needed to clarify what the potential mechanism may be at the

network level of analysis when the nature of the network domain is considered as an important

exogenous factor.

Table 6: SOAM results.

Network domain effects	Parameter
Rate (T1-T2)	3.89
Network domain: Density	-0.18 **
Network domain: 4cycle	-0.33
Covariate effects	Parameter
EXO: Grassroots impetus	0.02
EXO: Network: Centrality	0.21**
ENDO: % convening organizations present at T2	0.83 *
ENDO: Funding (1/0)	0.84**
ENDO: Funding increase (1/0)	-0.09*
ENDO: % staff present at T2	-0.30*
Normed size	-0.25**
Age	0.45

$** p < 0.05 \quad * p < 0.10$

Funding and increases in funding were also significant covariates in the model. Both measures

are binary and are interpreted as either having funding or no funding, and either having an increase in

funding or no increase in funding. H4 is supported and suggests that networks that have funding will not experience tie constriction. H5 is not supported because the significant effect is negative. Thus, increases in funding also increase a network's odds of tie constriction over time. Grassroots networks did not have a significant effect in the model, suggesting that H1 is not supported. In this data, grassroots networks were no more likely to see significant changes in ties as counterparts that are philanthropically funded, government funded, or mandated by policy.

H7 suggested that larger networks are more likely to survive than smaller networks. Although size does have a statistically significant effect, the parameter shows a negative relationship. Proportionally larger networks are more likely to see tie constriction over time. Age did not have a significant effect in the model. Thus, H8 is not supported and this model does not suggest any relationship between network age and ties across a network domain.

Discussion and conclusion

This research seeks to answer: What effects do the network domain and the network's capacity have on network ties over time? By demonstrating the existence of network domain effects on network expansion or contraction, this research pushes beyond prior network literature that has overlooked the influence of the external environment, including the existence of shared members across networks, by studying networks as if they are in isolation (Nowell et al., in press). As demonstrated by the findings regarding network domain density and network centrality, complex dynamics do exist when the external view of networks is considered. Results also reinforce that a key mechanism within a network domain is shared membership, defined as the phenomenon of an organizational member in one network also being a member of another network in the same network domain (Nowell et al., in press).

Prior network literature as discussed above has largely focused on understanding changes in networks by examining endogenous characteristics, while also assuming that a network's behavior is not influenced by exogenous factors. The results here demonstrate that one set of factors alone does not have an effect on tie expansion or contraction over time, and the coupling of both endogenous and exogenous forces are key to understanding changes in networks that are nested within a network domain over time.

For the 74 networks analyzed, both density of their domain and their proportional membership size matter over time. Highly dense network domains—those with a large portion of all ties shared among partnerships—behave differently than current network theories and organizational literature would suggest. In this data, dense domains lead to tie constriction over time, suggesting that there may be a "carrying capacity" for collaboration in a community. Defining and clarifying this phenomenon is an important future research direction as it applies to both theory and practice. Very large networks also have unique dynamics when considered as one node of a larger network domain. Members can be sources of information and resources, but they also can become a coordination challenge. In this data, very large networks are more likely to constrict, losing members overall.

In addition to the coupling of the exogenous effect of density and the endogenous capacity of membership size, centrality also plays a key role. Centrality, which represents the proportional number of shared members in a network, has a positive effect. These dynamics suggest that it's not just connections that matter overall but the "right" connections that support each network individually. Results show that networks are less likely to contract when they are connected to other networks through key members in other central networks in their domain. Additionally, too many connections in an already crowded network domain may have diminishing returns.

Endogenous capacity also has a key role to play, but findings point to different dynamics than those currently present in network theories and organizational literature. The formation impetus and path dependencies of a network alone do not drive tie expansion or contraction. While this effect was not statistically significant in the SAOM, causal pathways identified in the QCA suggest that a future interaction of this exogenous network attribute with endogenous variables could yield more informative results. Maintaining capacity in the form of staffing and funding may actually become a burden over time, which may drive members to break connections.

While powerful and highly useful for analyzing longitudinal network data, SAOMs do have limitations. First, the model is not able to account for unspecified systematic influences, and if a researcher leaves out a variable, the model may be biased (Burk et al., 2007; Snijders et al., 2010), just as omitted variable bias can be present in methods like OLS. Also, because the actor covariate output of a SAOM is expressed in terms of log odds, but network parameters are not interpreted as log odds, the effect sizes of network versus covariate variables cannot be compared (Snijders, 2018). A researcher can look at the significance of a parameter estimate, but these numbers are not comparable to results from other methods. Also, SAOMs only handle the presence or absence of a dyadic tie. Ties in SAOMs cannot be given values as they can be in other multivariate methods that can integrate social network analysis results (Burk et al., 2007). Finally, as noted above, data was not available for the actor level of analysis, only the network level. In this bipartite, two-mode analysis, results can only shed light on the attributes of what networks members chose to belong to, not the members themselves.

Overall, this study contributes to network theories in Public Administration and pushes their boundaries in important ways. First, this analysis leverages a nearly population-level longitudinal dataset. To date, very few datasets of this kind are being used by Public Administration scholars. Next, this analysis specifically addresses the tension between endogenous and exogenous explanations of

network change, finding that using an external view of networks can highlight the unique coupling of these forces. While this data operationalizes the ties between networks within a network domain as shared members, networks can be meaningfully connected through many factors like funding sources, information channels, and so forth. These connections are common among networks in which public agencies participate (Bryson, Crosby, & Stone, 2015) and should be considered more carefully during the design phases of collaborations. Additionally, funders who focus on collective impact models to address complex community issues (Kania, Hanleybrown, & Splansky Juster, 2014; Kania & Kramer, 2011) will benefit from first understanding and defining the domain that already exists before suggesting new interventions.

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