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Implications of Network Structure on Public Health Collaboratives

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Abstract

Interorganizational collaboration is an essential function of public health agencies. These partnerships form social networks that involve diverse types of partners and varying levels of interaction. Such collaborations are widely accepted and encouraged, yet very little comparative research exists on how public health partnerships develop and evolve, specifically in terms of how subsequent network structures are linked to outcomes. A systems science approach, that is, one that considers the interdependencies and nested features of networks, provides the appropriate methods to examine the complex nature of these networks. Applying Mays and Scutchfields's categorization of "structural signatures" (breadth, density, and centralization), this research examines how network structure influences the outcomes of public health collaboratives. Secondary data from the Program to Analyze, Record, and Track Networks to Enhance Relationships (www.partnertool.net) data set are analyzed. This data set consists of dyadic (N = 12,355), organizational (N = 2,486), and whole network (N = 99) data from public health collaborations around the United States. Network data are used to calculate structural signatures and weighted least squares regression is used to examine how network structures can predict selected intermediary outcomes (resource contributions, overall value and trust rankings, and outcomes) in public health collaboratives. Our findings suggest that network structure may have an influence on collaborative-related outcomes. The structural signature that had the most significant relationship to outcomes was density, with higher density indicating more positive outcomes. Also significant was the finding that more breadth creates new challenges such as difficulty in reaching consensus and creating ties with other members. However, assumptions that these structural components lead to improved outcomes for public health collaboratives may be slightly premature. Implications of these findings for research and practice are discussed.

Keywords

coalitions, community health promotion, evaluation, health promotion, network analysis, quantitative methods, systems science

Developing interorganizational partnerships across sectors has become an essential function of public health agencies. Often, these partnerships are embedded in community collaboratives whose mission is to work together as a "collective" to alleviate public health issues (Dryzek, 1996; Varda, Chandra, Stern, & Lurie, 2008). These collaboratives form social networks that involve diverse types of partners, varying levels of interaction, and multiple configurations. Such collaboration has the potential to improve outcomes by leveraging resources, lowering costs, and identifying solutions that are unachievable by any one agency alone (Dryzek, 1990; Thomson, Perry, & Miller, 2009). Although it has become widely accepted that fostering interorganizational partnerships to achieve public health outcomes has advantages (Mays & Scutchfield, 2010; Singer & Kegler, 2004), and the practice of collaboration is growing within the public health system (Pinto, 2009; Werber, Derose, Domínguez, & Mata, 2012), the complex nature of these efforts has made it challenging to effectively measure and evaluate them. There are few studies that identify the organization as the unit of analysis, and even fewer research efforts focused on interorganizational collaboration (Luke & Harris, 2007). This article addresses the gap in extant literature by operationalizing interorganizational collaboration (defined as public health collaboratives [PHCs]) as social networks and analyzing how network characteristics are linked to outcomes.

Social Network Data on Public Health Collaboratives

A systems science approach, that is, one that considers the interdependencies and nested features of networks, provides the appropriate methods to examine the complex nature of

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public health networks (Mabry, Olster, Morgan, & Abrams, 2008). A key principle underlying the study of networks is identifying the structural relations among its members (Knoke & Yang, 2008). Studies of interorganizational networks at the whole network level are lacking, in large part due to the difficulty of collecting relational data (Robins, Pattison, & Woolcock, 2004), and it is not uncommon to have only a single case study, or a handful of cases, by which to compare across networks (O'Malley & Marsden, 2008; Provan, Fish, & Sydow, 2007).

Although the computational sciences have made great strides in collecting data that represent whole networks thanks to the ability to mine electronic data records (Mabry et al., 2008), the social and behavioral sciences are farther behind. However, the recent development of Program to Analyze, Record, and Track Networks to Enhance Relationships (PARTNER; www.partnertool.net) program has resulted in an unprecedented availability of whole network data on public health partnerships. PARTNER is an online social network data collection and analysis tool designed to measure and monitor collaboration among people/organizations. The tool is free (sponsored by the Robert Wood Johnson Foundation) and designed for use by collaboratives to demonstrate how members are connected, how resources are leveraged and exchanged, the levels of trust and perceived value, and to link outcomes to the process of collaboration (Varda et al., 2008). The use of this tool by the practice community has resulted in a data set of more than 200 whole networks on public health partnerships; all collected using the same methodology and core questions. The current study is preliminary and focuses on select collaboratives from this data set to investigate behaviors relevant to interorganizational collaboration. We have taken data collected from the field with the aim to translate important ideas for public health practitioners.

Conceptual Framework: Network Structure Configurations

Existing studies of public health partnerships rarely examine the "whole network" level (e.g., Chen, Roberts, Xu, Jacobson, & Palm, 2012; Merrill, Bakken, Rockoff, Gebbie, & Carley, 2007; Wholey, Gregg, & Moscovice, 2009) and the few that do often focus on descriptive characteristics including key players and level of cohesion (e.g., density and transitivity). Less research has examined the structural signatures among members of PHCs. Structural signatures are a set of measures identified within networks (much like identifying a network's DNA) used to test which network tendencies have the highest probability of occurring (Monge & Contractor, 2003). There are no findings to date to explain the probability of certain network tendencies occurring in a PHC and their relationship to outcomes. As the scale and scope of public health issues become more global and complex, it is evident that traditional quantitative models of public health intervention, implementation, and analysis will not alone suffice to effectively explain how to improve and promote public health problem solving (Dryzek, 1996; Mabry et al., 2008).

Mays and Scutchfield (2010) have addressed this gap through a systems science lens to identify three types of "network signatures" that are important for understanding and analysis of PHCs as social networks: breadth, density, and centrality. These signatures seek to capture a network's composition—the array of partners (breadth), the connectedness of these partners (density), and the influence of centrally positioned members (centrality)—to better understand network functionality.

Breadth. Differences in network composition are captured through breadth, which measures the degree of diversity inherent in a particular collaborative (Mays & Scutchfield, 2010). Diversity in network membership has been viewed as essential to innovation and sustainability (Granovetter, 1982) and allows collaboratives to address issues that no single member could resolve independently (deLeon & Varda, 2009). Mays and Scutchfield (2010) hypothesize that collaboratives with greater breadth will have more diverse resource contributions by their members, a key component for success in collaboration (Casey, 2008; Mays, Halverson, Baker, Stevens, & Vann, 2004; Mays & Scutchfield, 2010). Resource sharing is a motivating factor for members of interorganizational collaboration (Bailey, 2010; Brown, Feinberg, & Greenberg, 2011; Casey, 2008; Mays & Scutchfield, 2010); in PHCs, maximizing and leveraging resources is a vital activity (Chen et al., 2012).

Density. Although diversity enables researchers to identify the *type* of partners in a collaborative, it does not reflect the *degree* to which the members are connected. Such "connectedness" is measured by the structural index "density" (Bott, 1955, 1971). Today, there exists a number of different formulas that calculate density depending on the type of network being analyzed (e.g., egocentric vs. whole networks), but the purpose is inherently the same—to capture the proportion of ties between actors observed in a network out of all those possible (Prell, 2012). Density (the number of connections between all the members of a PHC) can indicate how well-connected members of a PHC are and to what degree the collaborative is able to diffuse resources among members.

Centrality. A high density score counts the ties present in the network, but a single or limited number of actors may have a disproportionately high number of ties, indicating that a network may not actually be as cohesive as a density measure would suggest (Prell, 2012). To account for this issue, Mays and Scutchfield (2010) include a third structural signature called centrality, a measure of an individual member's position. Centralization (used in the current study) is similar to centrality; however, whereas centrality calculates the ties linked to an individual node in the network, centralization provides a score for the network as a whole.[1] Centralization is an "overall network" index that measures the dispersion of node centralities in a network (Freeman, 1979; Sinclair, 2009). A high centralization score indicates that only a limited number of actors occupy central positions within the network. Conversely, a low centralization score indicates that centrality is dispersed across members who hold similar positions (Kang, 2007). The degree to which a PHC is centralized can indicate whether one or two members are the primary points of coordination (very centralized) versus a structure where most of the members serve as the point of coordination (very decentralized). The number of members that are responsible for coordination has implications for how the PHC is managed, the amount of resources each member is responsible for, and the degree to which members are involved in the governance of the collaborative.

According to Mays and Scutchfield (2010), these structural tendencies affect the way a network is organized, the way it operates, and possibly the outcomes the network is able to achieve, but to confirm such propositions further research is needed. In this study of interorganizational collaboration, we implement this conceptual framework to analyze the relationship among the three structural signatures of PHCs and link them to select dependent variables related to network members' behaviors and perceptions (including levels of trust, perceived value among members, reported resources, and reported outcomes). We answer the following:

Research Question 1: How do the three measures of network structure of public health collaboratives relate to one another?

Research Question 2: How does the network structure of public health collaboratives predict levels of trust, perceived value among members, reported resources, and select outcomes?

Method

Sample

This study is a secondary analysis of data from the PARTNER data set. With institutional review board approval,[2] we extracted, cleaned, and analyzed a convenience sample of 99 PHCs from around the United States selected based on a set of criteria: (a) mission focused on public health, (b) organizations as the unit of analysis, (c) use of the same or similar PARTNER survey questions and response options, and (d) state or local public health departments were members of the collaborative. Given that PHCs self-select to use the PARNTER tool, the resulting data set is a convenience sample. The data were collected between October 2009 and February 2011. There were no noted changes to public health systems policy that would indicate that these collaboratives should be substantially different based on time of data collection.

Each collaborative varies in size, level of interaction, and centralization. Missing data are not uncommon in whole network studies, but must be taken into consideration (Kossinets, 2006). Although there is little guidance or agreement on suitable response rates two studies have identified acceptable thresholds. A response rate of 75% and higher for a whole network could limit the possible negative effects of missing data in social network analysis (see Kossinets, 2006; Wasserman & Faust, 1994). Kossinets (2006) also argues that a response rate ranging from 50% to 70% is acceptable, as it is unlikely to affect the results of the analysis (Grosser, Lopez-Kidwell, & Labianca, 2010). Within the PARTNER data set, response rates vary from 43% to 100%, with a mean of 67%. In this analysis, we determined that we would include those with less than 50% because the results did not substantially change when we removed those with less than a 50% response rate.

A total of 2,486 organizations are included in the data set and collaborative size ranged from 5 to 433 organizations who received the PARTNER surveys. The surveys contain relational questions and the corresponding responses create dyadic data, that is, information reported about the relationship between each organization (N = 12,355 dyadic ties). These data are examined at the whole network level for each PHC (N = 99).

Measures

The respondents from collaboratives chosen for this study represent organizations who respond to PARTNER surveys containing both *organizational characteristic* questions and *relational* questions (Varda et al., 2008). Table 1 displays the PARTNER questions. The questions used in this analysis are highlighted. In addition, "type of organization" was coded for each organization represented in the data.

Independent variables: Structural signatures. *Breadth* was measured by the proportion of different organizations existing in the network and by low, moderate, and high diversity categories (Mays & Scutchfield, 2010). These measures are based on 15 possible organization types (e.g., public health; education; funders; hospitals, government [nonpublic health]; etc.) A collaborative was considered to have low breadth if 1 to 3 organizations (out of 15 total possible types) were represented, moderate breadth if 4 to 7 organization types were present, and high breadth if 8 or more organizations were included.

Table 1. PARTNER Questions Used to Measure Independent and Dependent Variables.

Demographic Questions (organizational description): Job title, length of time as a member of the collaborative, types of activities engaged in, outcomes of the collaborative, resources contributed to the collaborative
Perception of Success: How successful has your collaborative been at reaching its goals? (Not Successful, Somewhat Successful, Successful, Very Successful, Completely Successful)
Outcome Questions: Collaborative outcomes; Factors contributing to successful outcomes
Relational Questions: "Please list all organizations/divisions/agencies/programs with whom you have a relationship with to meet the goals of your collaborative."
Once each respondent selected their organizational partners, they were asked to answer the following questions:
1. Frequency of Interactions with Partner (none, once a year, every few months, every month, every few weeks, once a week, every day)
2. Level of quality of activity in the relationship (none, coordinated, cooperative, integrated)
3. Extent of value as follows: (a) Power/influence, (b) Level of involvement, (c) Resource contribution (none, a small amount, a fair amount, a great deal)
4. Extent of trust as follows: (a) Reliable, (b) In support of the mission, and (c) Open to discussion (none, a small amount, a fair amount, a great deal)

$$\frac{l}{n(n-1)/2}$$

Figure 1. Formula for network density.

Density is a measure of network cohesion that captures the presence or absence of relationships among collaborative members and is typically calculated mathematically as the number of ties observed in a network out of the total possible ties that could exist (Prell, 2012). Ties were indicated when organizations (represented as nodes in a network map) were asked to identify who on a list of all members of the collaborative they work with (creating dyadic ties) related to collaborative goals. Figure 1 represents network maps with nodes connected by dyadic ties. Each network image represents the density of one whole network, thus one collaborative in the data set.

In Figure 1, l is the number of lines present in the network, and this measure can vary from 0 to 1, with 1 representing a complete network. See Figure 2 for an example of density, illustrated visually.

Centralization is a measure that indicates how many organizations hold central positions (Wasserman & Faust, 1994) and represents "the variation in the degrees of vertices divided by the maximum degree variation, which is possible in a network of the same size" (De Nooy, Mrvar, & Batagelj, 2011, p. 126). Lower centralization scores reflect that a lower number of organizations are centralized in the collaborative and that the members are all very similar in their number of connections. Degree centralization is calculated by determining the maximum individual centrality scores in the network and subtracting it from all other individual scores in the network. These differences are summed and that total is divided by the maximum sum of differences theoretically possible in a network of that size. This is based on Freeman's (1979) formula for Centralization Degree (CD; Figure 3).

In Figure 3, Max(C_{Di}) is maximum centrality score in the network, C_{Di} indicates the individual centrality scores, and n is network size. See Figure 4 for an example of centralization, illustrated visually.

Dependent variables: Trust, value, resources, outcomes. The six dependent variables in our study are (a) trust within a collaborative, (b) perceptions of value that partners bring to each collaborative, (c) the number of resources reported by a collaborative, (d) the diversity of resources reported by a collaborative, (e) the number of select intermediary outcomes achieved, and (e) disagreement on which was the most important intermediary outcome achieved.

Trust and value were calculated for each collaborative, based on a three-item scale (see Table 1). Trust and value variables were calculated by aggregating mean dyadic tie scores to the whole network level (averaging the relational scores).

Resources contributed by members of each collaborative was calculated to represent that number and diversity of resources. Respondents chose from a closed form list of resources that their organization brought to the work of the collaborative. The number of resources was calculated by aggregating the number of resources members of each collaborative reported bringing to the collaborative. To normalize the variable across collaboratives, we calculated the mean of the number of resources from the total number of resources contributed by organizations and then divided by total possible for that collaborative. A higher proportion indicates that a collaborative has a higher number of types of total resources. We also calculated a score that reflected how many rare resources collaboratives had available to them through their members (organizations were scored based on whether they had none, one, or more than two). Rare

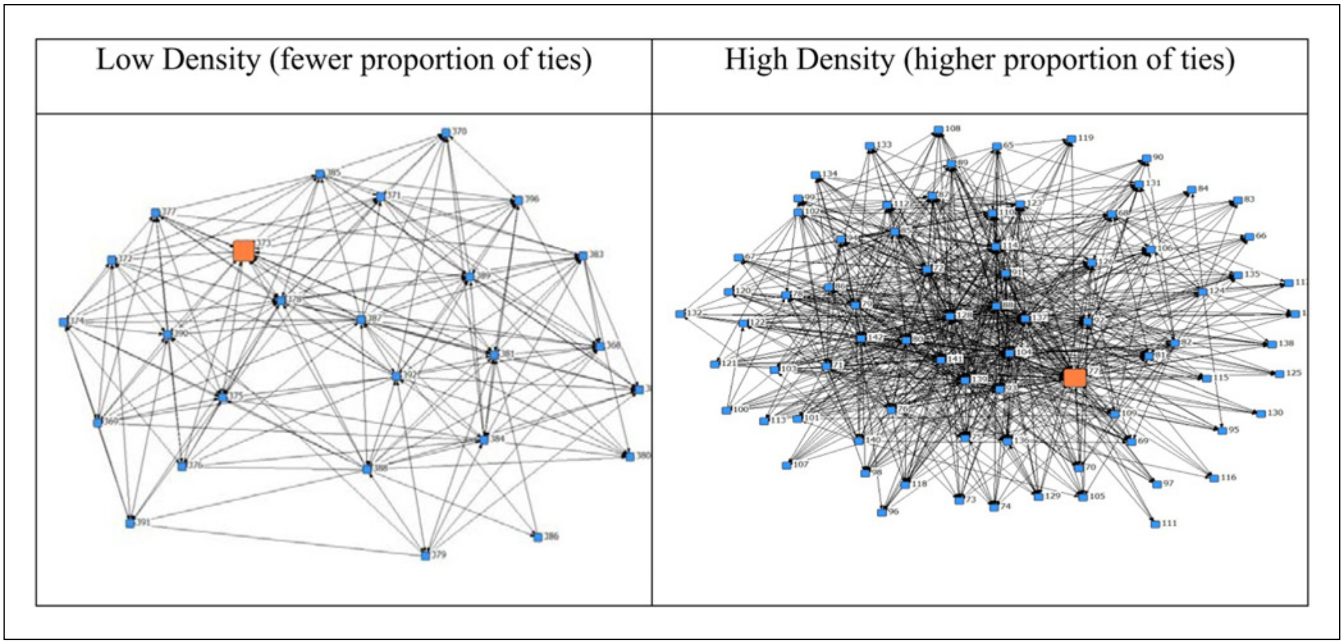

Figure 2. An example of whole networks demonstrating density.

$$CD = \frac{\sum (Max(C_{Di}) - C_{Di})}{n^2 - 3n + 2}$$

Figure 3. Formula for degree centralization.

resources were those that were not as common among all collaboratives including decision making, funding, and IT/web resources.

Outcomes were chosen by respondents from a closed-form list of potential outcomes of their collaborative work. Outcome measures were select intermediary outcomes, including process and policy outcomes (representing systems process outcomes, not population health outcomes). Examples of outcomes that were used in a closed-form list include more education, policy change, and improved services, among other outcomes that indicate systems level changes. These types of outcomes are becoming important to essential public health services,

> Evidence-based studies in public health are typically epidemiological, yielding risk factors for disease and determining optimal treatment approaches. . . . the public health literature is slowly growing to include systems research, which emphasizes complex and nested features of the organizational, economic, and policy issues that health departments must address to tackle current challenges. (Varda, Shoup, & Miller, 2011, p. 564)

These types of outcomes are highlighted in the 2011 Public Health Systems and Services Research agenda (Scutchfield, Perez, Monroe, & Howard, 2012).

We calculated the *total number* of reported select outcomes rather than the *types* of outcomes reported because the nature of these collaboratives (with varying missions) results in a variety of outcomes. To compare the outcome measure across collaboratives, we normalized the number of outcomes reported by the total number of possible outcomes for that collaborative. In addition, a variable was created to identify the amount of agreement among the members regarding what their most important outcome was. Collaboratives were scored on a scale of 1 to 3 based on the total number of outcomes that were identified as the most important, respondents could only choose one response, and therefore the number of outcomes "voted" to be most important served as a proxy score for agreement. The score given to each collaborative reflected low (more than 7 most important outcomes chosen), moderate (between 4 and 6), and high (between 1 and 3) levels of agreement.

Analysis

First, descriptive statistics are presented. Next, bivariate correlations and analysis of variance was used to examine relationships among the three structural signatures (Research Question 1). Finally, weighted least squares regression was used to test models consisting of whole network level predictor variables (structural signatures), regressed onto our dependent variables (Research Question 2). We recognize that ordinary least squares regression encounters limitations when the dependent variable is measured as a proportion (two of our DVs, quantity of resources and number of

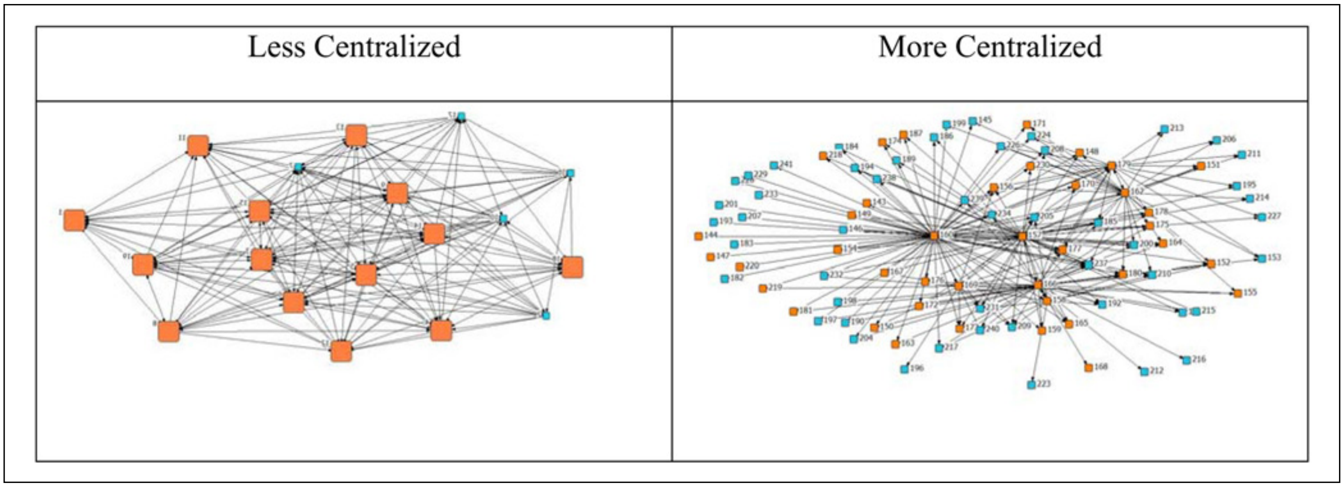

Figure 4. An example of whole networks demonstrating centralization.

Table 2. Structural Signatures.

	n	Min	Max	Mean	*SD*
Density	98	0.05	1.00	0.6147	0.28965
Centralization	98	0.00	1.00	0.3787	0.23310
Breadth (proportion)	99	0.07	0.80	0.3636	0.15599

outcome, are measured as a proportion), so to check for model specification error, we ran a fractional logit to normalize the observations in the DV (Papke, 2005; Papke & Wooldridge, 1996) and found our results are very similar to the WLS models. We report the ordinary least squares for ease of interpretation.

Results

Descriptive Results

Organization types. The most common type of organization identified in these PHCs was nonprofits (n = 646, 26%), followed by government (nonpublic health; n = 486, 19.5%), public health (n = 372, 15%), education (n = 332, 13.4%), and health care (hospitals, primary care, health clinics, hospices, dental; n = 214, 8.6%) organizations. We found no significant differences in response rates among different organization sectors; however, we did find significantly lower response rates among networks containing more than 30 organizations (F = 21.98, p < .001), compared with networks with fewer than 30 organizations.

Structural signatures. Descriptive statistics of the three structural signatures are displayed in Table 2. A total of 19.2% of collaboratives were considered to have low breadth, 58.6% moderate, and 22.2% high. The average density score was 0.61 and the average centralization score was 0.38.

Value, trust, resources, and outcomes. Among all 99 collaboratives, the mean trust score was 10.07 and the average total value score was 9.19 (both on an index of 4-12). Table 3 displays descriptive statistics for each dependent variable.

The average collaborative contributed 46% of the total possible resources. Table 4 presents the *average* percentages for all resources contributed by organizations, broken down by resource type. A total of 40.8% of collaboratives had no organizations that provided rare resources, 42.9% had only one rare resource contributed by its organizational members, and 16.3% had organizations that contributed two or more rare resources.

Respondents were asked to identify the number of select intermediary outcomes achieved by their collaborative, such as new policy development, education campaigns, and reduced health disparities. On average, respondents reported that 67% of the outcomes listed were achieved by their collaborative (range 22% to 94%). Respondents were then asked to pick which of the listed outcomes was the "most important"; they could choose only one. Collaboratives varied on how their members "agreed" that certain outcomes were the most important. About a third (35.7%) of collaboratives had low agreement, 33.3% had moderate agreement, and 31.0% had high agreement.

Inferential Results

Inferential statistics were used to answer Research Questions 1 and 2.

> *Research Question 1*: How do the three measures of network structure of public health collaboratives relate to one another?

The results suggest that there are significant associations among all the network structure variables. Findings indicate

Table 3. Descriptive Statistics for All Dependent Variables.

Dependent Variable	*n*	Min	Max	Mean	*SD*
Network Size	99	3	433	25.11	46.132
Value	99	6.56	10.87	9.1864	0.85421
Trust	99	6.40	11.66	10.0726	0.80301
Rare Resources	98	0	2	0.76	0.719
Total Resources	98	0.07	0.90	0.4638	0.12061
Number of Outcomes	99	0.22	0.94	0.6684	0.14904
Agreement on Most Important Outcome	96	1	3	2.15	0.725

Table 4. Average Percentage of Total Resources Broken Down by Resource Type.

Resource Type	Average Percentage
Community connections	76
Information/feedback	70
In-kind resources	62
Facilitation/leadership	54
Advocacy	52
Health expertise	51
Expertise (not health)	48
Data resources	42
Volunteers	40
Paid staff	31
Decision making	19
Funding	18
IT/web resources	12

that a significant inverse relationship exists between density and breadth ($r = -.652$, $p < .001$) as well as a direct relationship between breadth and degree centralization ($r = .398$, $p < .001$). Analysis of variance among the three different breadth groups reveals that collaboratives considered to have moderate breath appeared to be the most decentralized ($F = 19.45$, $p < .001$). Collaboratives with high breadth had significantly lower density than those with moderate or low breadth ($F = 75.82$, $p < .001$).

> *Research Question 2*: How does network structure of public health collaboratives predict levels of trust, perceived value among members, reported resources, and select outcomes?

Weighted least squares analysis (network size as the weight variable) was conducted between the three network structure predictor variables and six dependent variables. Table 5 presents the results of this analysis. Although interaction terms among the predictors were tested, they were not found to be significant.

The results show density is a common predictor of certain behavior and perceptions among members. Specifically, collaboratives with a higher number of connections (higher density) tend to perceive partners as more valuable and trusted, have higher agreement about most important outcomes, and more likelihood of a having rare resources. The degree to which the collaborative is centralized was related to one type of behavior and perceptions among members; more decentralized collaboratives are associated with a greater number of reported outcomes. Finally, breadth was significantly related to agreement among members about their most important outcome and total resources. Collaboratives with less breadth had greater agreement on the most important outcomes achieved by the collaborative and higher total resources contributed.

Discussion

The structural signature that had the most significant relationship to the dependent variables was density, with higher density indicating more trust and greater perceptions of value, and more rare resources. This can be interpreted to mean that in PHCs with more interaction among the members, more trust, higher perceptions of value, and greater diversity of resources are present. In this research, we did not use any kind of valence to describe these relationships but rather based this on a binary measure (partners either had a working relationship or not). Although it is not clear to what extent weighting the interactions between partners might alter the results, the data strongly support the conclusion that the more partners that establish working relationships in a collaborative, the more likely they are to achieve positive outcomes. In future analyses, we suggest analyzing whether more intense relationships (e.g., those with more occurrences of joint programming, joint funding, etc.) are significantly different than those that are simply cooperating (e.g., attending meetings together).

It is difficult to say whether having a working relationship leads to more trust and perceptions of value or whether more trust and perceptions of value lead to more instances of working relationships. Research identifies trust as a key factor in successful interorganizational collaborations (Brinkerhoff, 2002), specifically in the case of health-related organizations (Casey, 2008), and is in many ways considered foundational to network relations (Sydow, 1998; Zaheer & Harris, 2005). Antecedents of trust occurring in interorganizational networks are complex and include

Table 5. Results of Weighted Least Squares Regression Analysis.

Dependent Variable	Density (β)	t	Breadth (β)	t	Degree Centralization (β)	t	Adjusted R^2	Final Model F Statistic	Final Model Significance
Value	.530***	4.39	.137	1.14	—	—	.19	12.21	<.001
Trust	.502**	3.69	.099	.732	—	—	.17	11.03	<.001
Total Resources	−.076	−1.39	−.243***	−3.18	—	—	.18	12.22	<.001
Rare Resources	.361**	2.78	.089	.683	—	—	.08	5	.009
Number of Outcomes	—	—	.102	.741	−.409**	−3.756	.12	7.61	<.001
Agreement on Most Important Outcome	.105	1.34	−.402**	−3.715	—	—	.20	14.33	<.001

*p < .05. **p < .01. ***p < .001.

organizational attributes such as a general tendency to trust but also relationship aspects such as the variety of ways in which they interact (not necessarily regularity of interaction) with members of the network (Lee et al., 2012). The extent to which members trust and value their partners can determine levels of cooperation (Casey, 2008). This might explain how variables such as more density, greater perceptions of value, and higher trust relate to outcomes such as a greater number and diversity of resources.

We found a lack of support for the proposition put forth by Mays and Scutchfield (2010) that increased breadth in a collaborative will lead to a greater number and diversity of resources. In fact, more breadth creates new challenges such as difficulty in reaching consensus and creating ties with other members. This is not surprising, and given the finding that collaboratives with more breadth identify a greater disagreement over "most important outcomes," we hypothesize that collaboratives with less diversity will have an easier time coming to consensus about goals, a critical dynamic in collaboration success (Casey, 2008; Provan et al., 2007; Varda et al., 2011).

Although bringing together a diverse group of organizations has theoretical benefits (e.g., Granovetter's, 1982) strength of weak ties theory), in practice the reality of balancing multiple organizational missions, cultures, and governance structures can be limiting in sharing resources and achieving outcomes. More breadth may even require more centralized or hierarchical structures to reconcile the challenges of organizational differences and the desire to leverage a diversity of resources. Our findings that more decentralized collaboratives report a greater number of outcomes further support this idea. Collaboratives with less breadth appeared to have a higher number of resource contributions and higher agreement about the most important outcome in their work together. This begs the question, "Is it more effective to develop fewer, more intense relationships than attempts to increase the level of breadth in a PHC to optimally leverage resources?" This is an important finding, leading us to ask, "Is the 'cost' of including a more diverse membership compromising important network processes?"

In conclusion, we find that Mays and Scutchfield's (2010) conceptual framework identifying three structural signatures of PHCs has merit. Although their assumptions that structural components may lead to improved outcomes for PHCs may be premature in their development, they have laid the groundwork for taking a theoretically sound systems approach to understanding how members of a collaborative interact and how these complex interdependencies lead to outcomes. We tested this framework and found that there is a link between structural signatures and outcomes; however, we speculate that the evolution of these networks might be the controlling factor (and missing in our analysis) that further explains their significance. Although our results reveal only part of the story, we are left with a new hypothesis:

> Collaboratives will have more diverse resource contributions and better processes when they do not exceed a certain threshold for breadth, are highly interactive, and centralized (most likely when a lead agency such as a health department or health care organization, takes on facilitation, governance, and even fiduciary responsibilities).

Furthermore, we hypothesize that *collaboratives will become less centralized, less interactive, and more diverse over time*. Finally, we suspect that these changes are positive in that *mature collaboratives that are less centralized, less interactive, and more diverse will result in improved outcomes*. Because this study is preliminary, more research is needed to examine how various levels of network processes relate to important outcomes of interorganizational collaboration.

Limitations

Although a collection of whole network data using the same methodology provides an unprecedented opportunity for rigorous empirical research, there are several limitations. Missing data due to nonresponse from organizations within each collaborative, much like other survey studies, is a limitation that can affect some collaboratives scores. Although within SNA missing data are a concern with no common agreed upon solution, the resolutions range from basic replacement with symmetric ties (Huisman, 2009; Huisman & Steglich, 2008; Stork & Richards, 1992) to more robust Bayesian inference models (Butts, 2003). Future studies might consider such approaches to deal with missing whole network data.

Another limitation is related to the lack of population health outcomes available to include in the models. Empirically linking collaboration to population health outcomes is largely nonexistent in research today for two primary reasons. The first is that population health outcomes related to collaboration are difficult to measure (e.g., instances of teen pregnancy, decrease in cardiovascular disease, increased vaccinations) and measures vary across communities both in terms of how data are collected and response rate, making a large *N* comparative analysis such as this one difficult. Second, and even more problematic, is establishing the casual connections between collaboration (i.e., a group of organizations meeting and coordinating) and population outcomes. The relationship between these variables is viewed as beneficial primarily in theory only (so far in the existing published research). The exogenous variables that could cause a change in population health outcomes that are unrelated to the collaborative work (e.g., funding, policy change, etc.) are difficult to isolate in statistical models, thereby making claims that collaborative efforts caused population health shifts, lacking in credibility. The current state of this research makes the use of select intermediary outcome the most appropriate choice; however, we are hopeful that future research will take us to the next level of linking the complex, nested features of networks (including intermediary outcomes) to broader population health outcomes.

Some final limitations include the following. Given the high degree of correlation between density and centralization, we believed it best to not include both in the models and chose to determine which predictor contributed best to the model. We also suggest that future research should identify alternative measures of these key structural signatures to alleviate problems of multicollinearity. Finally, because of the nature of how PARTNER data are collected (self-selection and convenience sample), findings cannot be generalized, but may be of interest to collaboratives of similar characteristics, those who wish to evaluate their collaborative work, and/or those that strive to understand their work from a systems science perspective.

Conclusion

Our study addresses an important gap by investigating relationships between network structures of interorganizational collaboratives in public health using whole network data collected in the field. This research identified patterns of network structure that are related to outcomes of collaboration, specifically policy and program outcomes. Our findings suggest that network structure may have an influence on collaborative outcomes. The structural signature that had the most significant relationship to outcomes was density, leading to new questions about how the number of relationships interacts with the intensity of relationships. Assumptions that these structural components lead to improved outcomes for PHCs may be slightly premature.

The future of this field and the development of more advanced system science methodologies have great potential to bring this type of research to the next level. In our own research, we have plans to apply additional system science methods to answer outstanding questions such as the ones we outline in this article. We are working on research now that will link intermediary outcomes to population health outcomes, although it will be some time before we can do this with such a large data set (this approach is more appropriate in a case study approach because of differences in network goals and outcomes). The PARTNER data set is unprecedented, in size and scope. It currently contains more than 225 whole networks; all collected using the same survey and methodology for administration. This data set presents an opportunity to answer pressing questions for the field of system sciences. This analysis was only the first, exploratory cut at applying a systems framework to analysis. Future analyses will take multilevel and multivariate models into consideration, which will allow us to answer questions that persist in the field.

Significance to Public Health Practice

The findings in our study have several implications for public health practice. Specifically, these findings add to the body of knowledge to inform stakeholders involved in interorganizational networks including government, practitioners, and funders how to build, manage, and evaluate effective networks. A growing expectation today for public health personnel is that they engage in partnerships with other organizations as a way to achieve stated goals. Although leveraging resources by engaging in partnerships has long been a predominant activity for public health personnel (Blau & Rabrenovic, 1991), the extent to which collaboration is expected today seems to be reaching levels greater than in the past (Agranoff, 2006; Gittell & Weiss, 2004; Rethmeyer, 2005; Samaddar & Kadiyala, 2005). O'Leary, Gerard, and Bingham (2006) note that "public managers now find themselves not as unitary leaders of unitary organizations . . . instead they find themselves convening, facilitating, negotiating, mediating, and collaborating across boundaries" (p. 8). Although collaboration is embraced within the public health sector (e.g., it is common today that funders require evidence of collaboration before awarding and providing funds for program activity, as a precondition to applying for funding; Lasker, 2003), there is little guidance on how managers might consider the cost of this new expectation. In the case of collaboration, it is important to recognize that both the resources (inputs) and activities carried out (processes) must be addressed together to ensure or improve the quality of care (Quality Assurance Project, 2010). Once these dimensions are addressed, practice and policy can be affected through strategic planning, involving the workforce that makes up the bulk of leadership within public health collaboratives.

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Notes

1. For an overview of centrality indices, see Butts (2008).
2. This project was reviewed by the Colorado Multiple Institution Internal Review Board and was deemed exempt and approved for analysis as a secondary data set.

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