New Perspectives on the "Silo Effect": Initial Comparisons of Network Structures Across Public Health Collaboratives

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Objectives. We explored to what extent "silos" (preferential partnering) persist in interorganizational boundaries despite advances in working across boundaries. We focused on organizational homophily and resulting silo effects within networks that might both facilitate and impede success in public health collaboratives (PHCs).

Methods. We analyzed data from 162 PHCs with a series of exponential random graph models to determine the influence of uniform and differential homophily among organizations and to identify the propensity for partnerships with similar organizations.

Results. The results demonstrated a low presence (8%) of uniform homophily among networks, whereas a greater number (30%) of PHCs contained varying levels of differential homophily by 1 or more types of organization. We noted that the higher frequency among law enforcement, nonprofits, and public health organizations demonstrated a partner preference with similar organizations.

Conclusions. Although we identified only a modest occurrence of partner preference in PHCs, overall success in efforts to work across boundaries might be problematic when public health members (often leaders of PHCs) exhibit the tendency to form silos. (*Am J Public Health.* Published online ahead of print February 17, 2015: e1–e6. doi:10.2105/AJPH.2014.302256)

In a response to scarce public resources and the nature of complex intractable public health problems, there have been increased multiorganizational and multisector collaborations to address population needs. Building organizational capacity to better serve community public health and other public service needs is an important mandate for improving the integrity and performance of public health systems.[1] Fostering interorganizational partnerships to achieve public health outcomes is believed to have distinct advantages,[1,2] and the practice of collaboration is growing within the public health system.[3,4] Although this trend toward collaborating continues to increase, it is not clear to what extent the disciplinary and organizational silos that traditionally characterize public health still exist. Organizations are more inclined to work across boundaries, but that does not mean that they have aborted the tendency to work with those most "like" them, perpetuating the accompanying "silo effect." We explored to what extent silos persist in this new era of interorganizational collaboration in the public health sector.

INTERORGANIZATIONAL NETWORKS IN PUBLIC HEALTH

Development of interorganizational networks is 1 of the most promising ways to attain resources, share knowledge, and, in turn, improve population health outcomes.[5] Listed as one of the *Ten Essential Public Health Services*, interorganizational networks represent an essential function of public health agencies, which are defined as mobilizing "community partnerships and action to identify and solve health problems."[6,7] The push toward collaboration has also led to recent shifts in the expected core competencies of public health professionals. As a result, a new set of public health approaches are being developed to appropriately assess how an array of diverse partners are collectively and systematically addressing complex public health problems and population health goals.[8]

With the practice of collaboration growing within the public health system[3,4] these partnerships, also referred to as coalitions, alliances, and consortia,[9] are often embedded in communities with the intent to encourage organizations to work together as a collective to tackle public health issues.[1,10,11] In a collective, participation is built, in part, through partnerships that are "created by an understanding that the antecedents of poor health are multi-factorial and thus require a multisystemic approach."[11(pE1)] As a result, public health collaboratives (PHCs) are essentially social networks that involve diverse types of partners, varying levels of interaction, and multiple configurations.

The most unique characteristic among these networks is the emphasis on working collaboratively and across boundaries to increase knowledge and resource sharing. Networks have the potential to improve outcomes by leveraging resources, lowering costs, and identifying solutions that are not achievable by any 1 agency.[12,13] However, there is little guidance for public health professionals on how to create interorganizational networks, and, as a result, the tendency to continue working with disciplinary or sector-based silos may persist.[14–16] Working within a familiar silo is easier to manage and may be less resource intensive, whereas working across boundaries increases opportunity costs and increases risk of failure.[14] In turn, the challenges of managing organizations working across varying boundaries remain significant.

The existing literature on interorganizational networks strongly suggests a tendency among network members to perpetually favor a homophilic pattern in which partner "similarity breeds connection."[17–20,21(p415)] The concept of homophily is important to advancing an understanding of public health collaboration, because it has been argued that activities are influenced by disciplinary silos.[18–22] Homophily refers to the principle that contact between similar organizations occurs at a higher rate than among dissimilar organizations.[21,23,24] In interorganizational networks, researchers have found that partnerships are more likely to form between those with similar status and power.[25,26] In addition, as organizations form new ties, there may be a greater likelihood to form homophilous relationships.[27–31]

Although membership within these alliances and consortia may reflect a diverse composition, internal dynamics within these collaborations may remain siloed, wherein organizations connect, or interact, preferentially with others that are most like themselves.[18–22] A key way to understand how preferential tendencies, or silos, may persist within a collaborative environment is to identify the structural relations among its members.[32] It is especially important to differentiate whether homophilous tendencies are more generalized (uniform) across the network or, alternatively, more localized among specific (differential) types of organizations.

We focused on the extent to which homophily and the resulting "silo effect" within networks can potentially serve as a mediating characteristic that can both facilitate and impede success in public health collaboratives. The questions explored in our study are the following: (1) To what extent does this silo or homophilous tendency persist within collectives designed to promote collaboration? (2) To what extent do organizations exhibit partner preferences? (3) Do silo effects persist across organization types or is there more simply a preference among specific organization types?

METHODS

To address these questions, we used social network analysis to examine the relationships and patterns of interaction among the actors and their partners that were related to collaborative activities. The relations among the organizations were analyzed in 2 ways: overall network characteristics and tendencies in interaction patterns. Using data from the Program to Analyze, Record, and Track Networks to Enhance Relationships (PARTNER) Tool (http://www.partnertool.net) collected between spring 2010 and fall 2012, we sought to understand organizational actions within the context of structured relationships, and subsequently, the structures themselves. PARTNER is an online social network data collection and analysis tool designed to measure and monitor collaboration among members of varying networks, which has resulted in an unprecedented network dataset of public health interorganizational networks.[11] As a result, we were able to more effectively explore potential partner preference across public health collaboratives (PHCs).[11,15,33,34]

Using PARTNER Data

With consistent methodology and core questions, the PARTNER survey collects data on individual organizational characteristics, including type of organization, length of time participating in the partnership, what resource contributions the organization provides to the collaborative, what outcomes the collaborative focuses on, the perceived level of success for accomplishing collaborative goals, and reasons for successful collaborations. The survey also contains relational questions that ask organizations to identify other organizations in the network that they work with. Using a roster-based checklist, organizations subsequently answer questions about how frequently they interact with each organization, the quality of those interactions, and perceptions of trust and organizational value for each partner organization (using 3 measures of trust and 3 measures of value). We focused on the presence (or absence) of a reported interaction among the organizations in the collective. The dataset for our study contained a subset of 162 whole networks that consisted of approximately 4500 organizations and 18 000 interactions, which we defined as the presence of a directed tie (arc) between 2 organizations (dyad).[35] These PHCs varied in terms of size and focus, but all of them were made up of a bounded group of organizations within a community that worked collaboratively to address a public health topic. Because of the survey-based nature of the network data collection, the data we selected for this study included those whose response rates were greater than 70% (n = 162), from a range of 2% to 100% (n = 177). We reviewed the selected collaboratives to determine the nature of the missing data, which we attributed to random nonresponse.[36] Although missing data are not uncommon in whole network studies, we chose to maintain a high response rate threshold to improve the reliability of the data.[36–38]

In addition to the summary descriptive statistics of the networks, including size and diversity, we calculated several graph-level descriptive statistics, including network density, centralization, connectedness, and reciprocity, to provide a description of the PARTNER networks. These measured the number of ties as a proportion of all possible ties (density), the degree to which connections in a network were centralized around 1 or more nodes (centralization), the extent to which organizations were connected to each other in the network (connectedness), and the proportion of relations among organizations that reported mutual ties (reciprocity).[35] In addition, we also completed node-level measures to determine the frequency of interactions among organizations, including in-degree (ties "received") and out-degree (ties "sent") centrality, as well as total degree centrality.[39]

Exponential Random Graph Models

To test for preferential tendencies in each network, we applied a series of exponentially parameterized random graph models—often called exponential random graph (ERG) models—to estimate effects across the network.[40–43] The ERG model framework provides a general way of representing probabilistic models that specify the potential sources of dependence and heterogeneity that contribute to network structure. We explored the extent to which organizations' attributes might influence tie formation, and thereby estimated the tendencies toward interaction with similar organizations based on the classification of the organizations.

Through a set of 2 ERG models, we modeled the probability of collaborative interaction between 2 organizations based on the specific type of organization to determine the potential influence of uniform (model 1, M_1) versus differential homophily (model 2, M_2) between organizations. We also identified the propensity for partnerships with similar organizations.[44,45] These types of analyses allowed us to answer our research question by identifying whether organizations within each PHC demonstrated an overall, more uniform propensity to interact more so with similar or "like" organizations versus only a select subset of organizations that might exhibit a differential preferential bias. The results of the model reflected the maximum likelihood estimates, the SEEs for each parameter, and the corresponding probability measures (probability = $\exp^{\text{parameter estimate}}/[1+\exp^{\text{parameter estimate}}]$, with a probability range from 0 to 1[38]). Positively or negatively significant parameter estimates indicated a greater likelihood for the attribute to influence the structure of the observed network rather than by random chance. Because the effects of a particular attribute might differ within and among organizations, we examined each PHC network independently to determine which effects might be significant. Descriptive and ERG model analyses were conducted using the *statnet* suite of packages within the computing environment of *R*.[46,47]

RESULTS

Of the 162 PHCs, we found membership counts ranged from 7 to 99, with an average of 18 members for each PHC. In terms of diversity of organization membership, 15 possible organization types were identified, but, on average, each collaborative contained only 4 types of organizations. Within each PHC, diversity varied from 1 organization type up to a maximum combination of 10 organization types. In addition, the diversity of PHC membership was positively correlated with the size of the collaborative (Pearson's $r = 0.608$; Figure 1). Among the individual PHCs, public health organization membership counts ranged from 1 to 74, with an average count of 5 in each collaborative (n = 599 total). Among all of the organizations (n = 3544), we found members reported a wide range of relationships with other organizations,[3–20] with an average of 9 to 10 partners.

As the size of the collaborative increased, the level of reciprocity (67%) increased and the level of connectedness decreased, reflecting a high level of strong (mutual) ties among the organizations. Connectedness ranged from 0 to 1, reflecting the ability of network actors to reach all other organizations. These types of measures (graph-level indices) were known to inherently vary with size.[48] To determine the density in these directed networks, we divided the number of ties in each network by the number of all possible ties, $n(n - 1)$. When all possible ties were present, the density was found to vary from 0.24 to 1.0, with an average of 0.43. As the size of a network increased, the number of possible ties also increased exponentially. The networks tended to be largely de-centralized, with an average of 0.328.

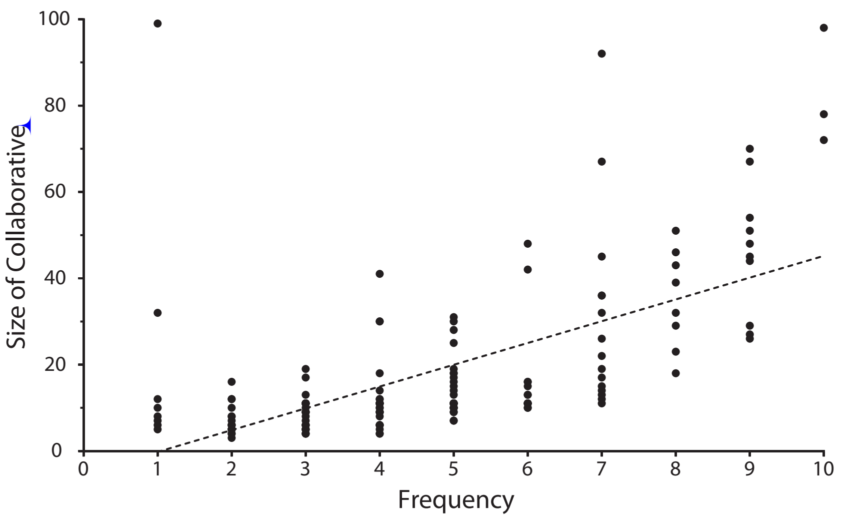

FIGURE 1—Frequency of organization types (n = 162), by size of collaborative: Spring 2010–Fall 2012.

Homophily in Public Health Collaboratives

We observed that organizations made decisions about whom they maintained connections with, and therefore, were able to maintain ties with this subset of organizations within a collaborative. In this analysis, we were most interested in whether potential silos or bias persisted within PHCs designed to promote collaboration. The first ERG model (M_1) tested whether there was an overall tendency toward uniform homophily based on type of organization. We identified uniform homophily in only 13 (8%) of the 162 PHCs. In these networks, there was a general tendency among organizations to interact preferably with similar organizations versus those of varying organizational types, which was in contrast to the expectation in networks that members would form diverse connections.

Although we did not observe an overall (uniform) tendency toward organizational homophily in a majority (87%) of the networks, this did not exempt these networks from potentially demonstrating differential homophily (M_2) or preferential partnerships existing within the networks among specific types of organizations. This addressed our second research question to determine the extent to which specific organization types exhibited partner preference within PHCs. We found 48 (30%) of the 162 PHCs contained some level of differential homophily by 1 or more types of organization. The percentage reflected the frequency of differential homophily among all possible PHCs for the specified organization type. Note, to identify the presence of homophily, a PHC had to have at least 2 organizations of the same type.

Homophily Among Organizational Types

Reviewing each PHC in more detail, we focused on the persistence of these preferential ties among specific organizations types. We identified 7 organization types that demonstrated a preferential tendency to partner with similar organizations, in 1 or more networks, including nonprofit (n = 12), public health (n = 11), medical care (n = 5), government (n = 4), law enforcement (n = 4), education (n = 3), and professional (n = 1)

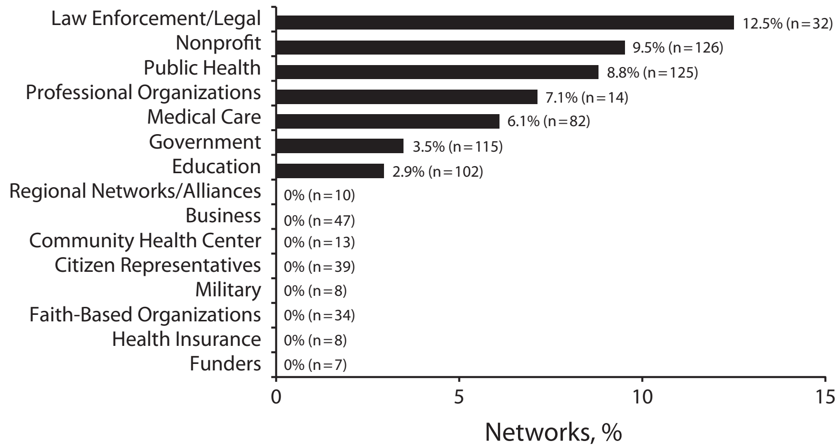

FIGURE 2—Percentage of networks with homophilous partner preferences, by organization type: Spring 2010–Fall 2012.

organizations. Eight types of organizations did not exhibit similar partner preferences, including funders, health insurance companies, businesses, faith-based organizations, military, citizen or patient advocates, regional representatives, and community health centers. Figure 2 offers a summary of these results by presenting the frequency of homophilous tendencies relative to the total number of PHCs in which the organization types were present (the full table of estimates indicating the types of organization that demonstrated a significant bias is available as a supplement to the online version of this article at http://www.ajph.org).

The results summarized the presence and frequency of preferential bias within and among the collaboratives and organizations, noting the higher frequency among law enforcement (12.5%), nonprofits (9.5%), and public health organizations (8.8%) for homophily. In posthoc analysis, we also found a moderate correlation ($R = 0.5$) between network size and the frequency of differential homophily among the 162 networks. In other words, as network size increased, we were more likely to observe a potential bias among specific organization types to interact with similar organizations or demonstrate a potential silo effect.

DISCUSSION

Although it has become widely accepted that fostering interorganizational networks to achieve public health outcomes has advantages,[1,2] the complex nature of these efforts has made it challenging to effectively translate these benefits into practice. As networks continue to be a critical function of successful health departments,[49–52] it is helpful to understand the real benefits and potential pitfalls of homophily. The unique approach of our study, which had access to a large dataset containing PHCs, illuminated some important aspects of practice with public health collaborations for network managers. Furthermore, our findings contributed to the literature in a distinctive and useful way by identifying and examining patterns that advanced network management research and presented a set of future hypotheses. The evidence offered by our study suggested that coordination of a collaborative requires increased levels of effort as the size of the collaborative increases. More specifically, in this analysis, we observed a connectedness decrease relative to the increasing size of the PHC, whereby the collaborative became more disconnected, which could potentially lead to diminished capacities to fulfill intended goals (effectiveness). In addition, with increased network size, costs associated with maintaining connections and relationships with others had a greater likelihood to become increasingly more expensive, relative to time and effort. As an example, although time and effort applied to e-mails, phone calls, and meetings for 17 contacts might be accomplished with some ease, maintenance of ties with 49 or more organizations might quickly become exceedingly costly.

Without some form of strategic management at the collaborative and organizational levels, the efficiency of a collaborative and all the assumed collaborative advantages associated with contributed time and effort could quickly disappear. However, an important aspect of assuring collaborative efficiency relates to how organizations might interact with other organizations based on their attributes. We primarily focused on how an attribute, specifically, a type of organization, could influence how they might tend to interact (or not) with similar partners, which we identified as a silo effect or preferential partnering. Our results of this analysis illuminated some of the underlying homophilic tendencies, or biases, that might persist in influencing collaborative partnerships.

By focusing on specific organization types, our investigation of homophilous tendencies found half of all organization types (7 of 15), which included public health organizations, demonstrated a preference to partner with similar organizations in 1 or more networks. Primarily, although it was evident that collective efforts to form networks were widely adopted, there still might be a tendency among select organization types to form silos within these networks. This could, in turn, result in less efficient and effective collaborations.

Limitations

In practice, a network leader's ability to bridge gaps, break down silos, and create a collective synergy is often credited to a successful collaborative process. Because of public health agencies were often the leadership of a PHC, this could be problematic in the long-term. In 1 out of 4 (28%) PHCs, public health agencies were found to engage in higher levels of homophilic interactions; therefore, these networks could experience detrimental effects to collaboration efforts because of prolonged silo patterns.[53–55] Future research could look at this possibility more closely and determine "how does a public health department's tendency to either engage in siloed behaviors (or not) affect the ability of the larger network to reach its collective goals?" This represents a critical challenge to the translation of policy into practice, because of the limited research that has examined the processes of how collaborative networks form and evolve, based on the dyadic interactions among its members. The evidence of a greater tendency for public health partners to engage in siloed behaviors than other types of organizations might warrant additional review of the leadership roles by public health agencies in these networks and continue to assess the degree of homophily before consideration of alternative leadership arrangements.

Although these results were positive overall for the field of interorganizational networks, we learned that silos might still persist in some cases, which could be challenging for overall network cohesiveness. More importantly, our research emphasized that better understanding of how members of a network interact could provide much needed evidence to inform network leadership. There continues to be a lack of information and skills to help network leaders build and manage their networks. The skills and cultural shifts necessary to put this into practice are extremely limited. For these collaborative efforts to be most effective, cultural shifts within organizations may need to occur.

Conclusions

At present, the core competencies for public health practitioners are stated; however, specific tools, evaluations, and research to determine how to implement systems thinking and leadership are largely limited. Additional research could address the necessary competency-based trainings and education needed to manage and promote successful interorganizational collaborations to achieve the goals and missions for which they are created. Rather than sending the message that network leadership means attending more meetings with more people, we could use studies, similar to ours, to provide an evidence-based approach to network leadership, both with a deeper understanding of how members' form relationships, but also to use data to inform action steps to improve network performance overall. ■

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Contributors

J. H. Retrum and D. M. Varda led the design and data collection of the original study. C. A. Bevc led the data analysis and interpretation for this article, in collaboration with J. H. Retrum and D. M. Varda. C. A. Bevc and J. H. Retrum drafted the article, with D. M. Varda revising it for important intellectual content. C. A. Bevc revised the article based on reviewer comments and suggestions. All authors approved the final version of this article.

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Human Participant Protection

This study was approved by the Colorado multiple institutional review board, CB F490, under COMIRB Protocol 11-0098 (initial application).

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