The promise of evidence-based public health rests on our ability to translate, disseminate, and implement effective programs and policies (Brownson, Dreisinger, Colditz, & Proctor, 2012). In many areas of public health, such as tobacco control, we already have a solid scientific evidence base on which to build effective community policies and practices. However, we still have major challenges in putting that evidence into practice—that is, we still do not know how to best translate, disseminate, implement, and sustain the programs that are built on the scientific evidence (Green, Ottoson, Garcia, & Hiatt, 2009; Scheirer & Dearing, 2011). Disseminating and implementing new evidence-based practices is complex, requiring organizational and individual behavior change over time. Systems science concerns itself with the study of such complex systems (Forrester, 1961) and may be very useful for making progress in understanding effective dissemination and implementation of evidence-based public health programs (Holmes, Finegood, Riley, & Best, 2012). The purpose of this article is to demonstrate the utility of network analysis, one type of systems science tool, in the study of dissemination of evidence-based guidelines in tobacco control.

In 1999, the Centers for Disease Control and Prevention (CDC) released Best Practices for Comprehensive Tobacco Control Programs (Best Practices; CDC, 1999), a set of evidence-based guidelines encompassing strategies for effective state tobacco control programs. Best Practices provides program-level guidance, as well as upper and lower funding estimates for each state tobacco control program. At that time, it became the most widely used CDC document in the nation, and the use of the strategies it promoted was

**Network Influences on Dissemination of Evidence-Based Guidelines in State Tobacco Control Programs**

**Douglas A. Luke, PhD**, **Lana M. Wald, MA**, **Bobbi J. Carothers, PhD**, **Laura E. Bach, BA**, and **Jenine K. Harris, PhD**

**Abstract**

Little is known regarding the social network relationships that influence dissemination of evidence-based public health practices and policies. In public health, it is critical that evidence-based guidelines, such as the Centers for Disease Control and Prevention’s Best Practices for Comprehensive Tobacco Control Programs, are effectively and efficiently disseminated to intended stakeholders. To determine the organizational and network predictors of dissemination among state tobacco control programs, interviews with members of tobacco control networks across eight states were conducted between August 2009 and September 2010. Measures included partner attributes (e.g., agency type) and relationships among network members (frequency of contact, extent of collaboration, and dissemination of Best Practices). Exponential random graph modeling was used to examine attribute and structural predictors of collaboration and dissemination among partners in each network. Although density and centralization of dissemination ties varied across states, network analyses revealed a consistent prediction pattern across all eight states. State tobacco control dissemination networks were less dense but more centralized compared with organizational contact and collaboration networks. Tobacco control partners in each state were more likely to disseminate the Best Practices guidelines if they also had existing contact and collaboration relationships with one another. Evidence-based guidelines in public health need to be efficiently and broadly disseminated if we hope to translate science into practice. This study suggests that funders, advocacy groups, and public health agencies can take advantage of existing public health organizational relationships to support the communication and dissemination of evidence-based practices and policies.

**Keywords**
dissemination, evidence-based public health, network analysis, systems science, tobacco control

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associated with a decline in tobacco use in all 50 states (Green et al., 2009). From 1985 to 2003 smoking prevalence rates for adults decreased from 29.5% to 18.6% (Farrelly, Pechacek, Thomas, & Nelson, 2008). In 2007, CDC released an update to the Best Practices guidelines to incorporate new practices and changes in state funding recommendations (CDC, 2007). Because of the importance of evidence-based guidelines such as Best Practices, it is critical that they are effectively and efficiently disseminated in order to facilitate adoption and implementation of practices by intended stakeholders. However, evaluation of CDC’s Best Practices has shown that these evidence-based guidelines are not well disseminated outside state public health departments (Mueller, Burke, Luke, & Harris, 2008).

Although there are numerous conceptual frameworks that help explain public health program implementation (Beck, Bergman, Rahm, Dearing, & Glasgow, 2009; Feldstein & Glasgow, 2008; Proctor et al., 2009; Wandersman et al., 2008), less is known about the structures and processes that support effective dissemination of evidence-based practices. One must understand the process by which information is sent in order to deliver it to the community through cost-effective, high-impact channels. Examining paths of information dissemination can inform future efforts to facilitate information transfer across public health networks.

Diffusion of innovations theory has been influential in studying the dissemination of evidence-based practices in public health (Dearing, 2008). Early on, diffusion of innovations theory focused on the roles of individuals, such as “innovators” and “early adopters” (Rogers, 2003), enabling public health officials to better understand the influence of the individual and the communication channels created by those individuals within an organizational system. Knowing a partner’s role within a system helps to understand a particular network structure (Rogers, 2003; Ryan & Gross, 1943; Valente, 2002), which can lead to the development of effective dissemination approaches to knowledge diffusion by knowing who to target. However, diffusion of innovation theory underplayed the more complex role of social structure—how does the complex communication system among communities and organizations influence the dissemination of new science?

Wandersman et al. (2008) developed a framework to decrease the gap between science and practice and emphasize the importance of communication and collaboration among members of our public health system. Without interaction among stakeholders, the translation of research into practice is less likely to occur (Wandersman et al., 2008). Although this framework emphasizes the need for increased communication, an understanding of how these systems interact is still not known. Ineffective information transfer may occur without knowledge of the structure and capacity of a network. Green et al. (2009) found that the gap between science and practice is due to highly centralized information and funding centers organized at the institutional level both federally and nationally; however, the science is applied at the state and local level, representing a decentralized approach to information delivery. Thus, a disconnect occurs between the scientists who develop the information and the needs of the intended stakeholders (Green et al., 2009). Taking a systems view of dissemination may allow us to understand how to match the structural characteristics of public health organizational networks to the information needs of its organizational and community members.

Social network analysis is a powerful tool for measuring relationships among groups or individuals (Wasserman & Faust, 1994). Social network analysis is increasingly being used in public health, and is especially helpful for mapping organizational structures, as well as describing how information flows across community, organizational, and public health networks (Luke & Harris, 2007; Provan, Veazie, Staten, & Teufel-Shone, 2005). This approach represents a method for understanding the interactions among individuals or organizations by exploring the relationships among partners within a network. Interesting examples include inter-agency relationships among tobacco control networks (Harris, Luke, Burke, & Mueller, 2008), collaboration among chronic disease service provision agencies (Provan, Veazie, Teufel-Shone, & Huddleston, 2004), needle sharing and high-risk sexual behaviors among intravenous drug users (Curtis et al., 1995; Friedman et al., 1997; Latkin et al., 1995; Neaigus et al., 1994; Rothenberg et al., 1998; Valente & Vlahov, 2001), and social support networks among cancer patients (Lugton, 1997). The utilization of network analysis increases the understanding of relationship ties across organizations and the central roles individuals or agencies play within a larger network through both visual and quantitative methods.

Network analysis can be similarly useful for exploring dissemination networks. In addition to visualization of these networks (sometimes called network mapping), network analysis can be used to identify prominent network members (those who are in a position to aid or direct dissemination communication), describe overall dissemination network structures, and identify predictors of dissemination ties. Taken together, these types of analyses can then shed light on how effective dissemination programs can be designed to take advantage of existing communication channels in public health organizational systems (Luke, 2012).

The general purpose of this study is to apply a systems science perspective on evidence-based dissemination in public health programs. More specifically, we apply network analysis to examine three types of relationships among state tobacco control programs: contact, collaboration, and dissemination. After describing each of these three network types, we test the hypothesis that dissemination ties are related to contact and collaboration network ties. Results of these network models may help public health officials recognize the routes of efficient dissemination of evidence-based guidelines, which is a necessary prerequisite to adoption and
implementation of evidence-based practices, and ultimately to improvements in health outcomes.

**Method**

**Sample**

Data were gathered from an evaluation conducted by the Center for Public Health Systems Science at Washington University in St. Louis. The primary goal of this evaluation was to understand how evidence-based guidelines were disseminated, adopted, and used within state tobacco control programs. In consultation with the CDC Office on Smoking and Health, states were selected to participate in the evaluation using criteria designed to produce a diverse set of state tobacco control programs, including geographic location, funding level, organizational structure, and evaluation history. The resulting evaluation assessed tobacco control networks in eight states: Oregon, Texas, Florida, Indiana, Colorado, Arkansas, Wyoming, and Washington, D.C. In addition to providing regional diversity, these states varied in funding (Wyoming was funded at 53% of the CDC-recommended level while Texas was funded at 4%), organizational structure (Indiana’s lead agency was separate from the state health department, whereas the lead agencies for the other states were housed within their health departments), and evaluation history (Indiana and Wyoming had participated in a prior evaluation of Best Practices [Mueller, Luke, Herbers, & Montgomery, 2006], whereas the other states had not).

A modified reputational snowball sampling method (Doreian & Woodard, 1992; Farquharson, 2005) was used to identify tobacco control program network members. The evaluation team contacted the program manager at the lead agency of the tobacco control program in each state who generated a list of key tobacco control partners within their state program. Out of the approximately 187 individuals who were invited, a total of 176 partners participated in the evaluation representing an average of 19 agencies in each state. The agencies fell into six categories: lead agency (of the state tobacco control program), contractors and grantees, voluntary and advocacy groups, coalitions, other state agencies, and advisory and consulting agencies (Harris et al., 2008).

**Data Collection**

A semistructured interview was completed by all participants. This interview included both qualitative and quantitative questions, and was conducted either in-person or via telephone. Interview questions covered awareness, dissemination, and implementation of evidence-based guidelines as well as questions regarding communication and collaboration with other agencies within their state tobacco control program.

**Measures**

Agencies were identified as local, state, or national. Distance between organizations was calculated by finding the square root of the number of miles between organizations (Draft Logic, 2011; Hipp & Perrin, 2009). Tobacco control experience was measured by the self-reported number of years an individual had been involved in tobacco control for their respective state.

Three questions were asked to assess network relations within each state to measure contact, collaboration, and dissemination of Best Practices. Respondents were asked how often their agency had contact with each of the other agencies. Response choices were daily, weekly, monthly, quarterly, yearly, or no contact. Respondents were then asked to indicate the degree of collaboration with each agency on a 5-point scale: “don’t work together at all,” “share information only,” “work together informally to achieve common goals,” “work together as a formal team to achieve common goals,” or “work together as a formal team on multiple projects to achieve common goals.” Finally, dissemination was assessed by asking respondents to indicate which other agencies they had formally talked to about the Best Practices guidelines. Although this is a somewhat simplistic measure of dissemination, it captures the communication about a specific set of evidence-based guidelines. The contact and collaboration items were based on past studies of public health organizational networks (Luke et al., 2010). If more than one person from an agency participated, the highest value was taken for all measures.

**Data Analysis**

Data management was conducted with Pajek 2.03, (De Nooy, Mrvar, & Batagelj, 2005) and R 2.12.2 (The R Foundation, 2012). Computation of network statistics was conducted with R-statnet Version 2.6 (Goodreau, Handcock, Hunter, Butts, & Morris, 2008; Handcock, Hunter, Butts, Goodreau, & Morris, 2003).

Density and betweenness centralization were calculated for the contact, collaboration, and dissemination networks for each state. Density is the percentage of existing ties out of all possible ties in the network. Betweenness centralization is a network-level measure of the variability of the individual node-level betweenness centrality scores. An individual node (a particular tobacco control partner) has high betweenness centrality when it sits “between” other nodes in the network. High measures of network centralization indicate a more hierarchical communication structure where a few nodes have the potential to control the flow of information for the entire network (Wasserman & Faust, 1994). Betweenness was chosen as the measure of centralization because centrality scores for each node are based on the structure of the entire network (and therefore a node’s importance for moving information through it), while degree centrality scores are based only on
how many local connections each node has and ignores their relative importance compared with other nodes in the network.

Consistent with prior research (Harris et al., 2008; Leischow et al., 2010; Luke et al., 2010), the contact and collaboration network scales were dichotomized for the density and betweenness analyses. For the contact measure, tobacco control agencies were considered to be linked if they had formal contact with each other on a quarterly or more frequent basis. For the collaboration measure, agencies working together informally or formally were considered collaborating, and partners who did not work together at all or only shared information were considered noncollaborating. For the purposes of these analyses, communication on a yearly basis or less was too infrequent, and collaboration at sharing information or less was not strong enough to consider these relationships meaningful.

Exponential random graph modeling (ERGM) is a relatively new analytic method used to build and test statistical models of network structure (Harris, in press). ERGM models are powerful tools because they can be used to predict the probability of network ties. ERGM parameters can be interpreted similarly to logistic regression models and the method is designed to handle the complex dependencies inherent in network data that otherwise violate the assumption of independence underlying linear modeling techniques (Goodreau, 2007). Network ties can be predicted based on attributes of network partners, attributes of the relationships among network partners, and structural patterns of the network. We use it here to predict dissemination between partners, and our approach is based on previous successful applications of ERGM methods to public health organizational networks (Harris, Carothers, Wald, Shelton, & Leischow, 2012; Luke et al., 2010).

For each state, the ERG models were developed in three steps using parameter terms from Morris, Handcock, and Hunter (2008). First, a model based on network structural patterns, network partner attributes, and partner relationships was estimated. Network structural patterns were estimated with the geometrically weighted degree (GWDegree) term, which accounts for the likelihood of agencies with higher degrees to be linked to others (Hunter & Handcock, 2006). Network partner attributes were years of tobacco control experience and geographic reach (local, state, or national). The model tested whether dissemination links increased with years of experience and whether dissemination links were more common between agencies of the same geographic reach. Physical distance between agencies was a relationship attribute. This first model serves as a baseline prediction of dissemination. Second, the relationship term for contact between partners was added to test how well it predicted dissemination over and above the baseline variables. Third, the relationship term for collaboration between partners was added to test how well it predicted dissemination over and above contact and the baseline variables. Model fit and diagnostics were examined at each step. By comparing Models 2 and 3 with the first model, we would be able to tell whether dissemination ties between tobacco control partners were predicted by existing contact and collaboration relationships.

Results

Figure 1 shows the density and betweenness centralization results. The size of the networks varied (15-26 agencies; average = 18.88) as well as the density for contact (0.41-0.63; average = 0.56), collaboration (0.38-0.61; average = 0.51), and dissemination (0.29-0.56; average = 0.43). Similarly, betweenness centralization among networks varied for contact (0.08-0.38; average = 0.15), collaboration (0.06-0.43; average = 0.19), and dissemination (0.15-0.53; average = 0.32). A general pattern emerged across all eight states (with the possible exception of Texas), the dissemination relationship was less dense but more centralized than contact or collaboration. Some agencies, particularly lead agencies, emerged as “brokers” connecting agencies that would not otherwise be connected, especially for dissemination.

Figure 2 shows the contact, collaboration, and dissemination relationships among Indiana agencies as a representative example (network graphics for all states are available online as supplemental material at http://heb.sagepub.com/supplemental). In the figure, each node represents one of the key tobacco control agency partners for the Indiana program, and the size of the node corresponds to the agency’s betweenness centrality score. The larger the node, the more central the agency. Note how the lead agency (darker node) for the Indiana program is most central for the dissemination network. The Indiana network graphics demonstrate the pattern described above, of how density decreases (fewer lines connecting the nodes) and betweenness centralization increases (greater variation in sizes of nodes) as we move from contact, through collaboration, to dissemination.

The network graphics and descriptive statistics suggest that there may be important consistencies in network structures across the state programs, and that there might be an association among the three types of network relationships. To test this, ERG models were built to predict tobacco control partner dissemination relationships based on a variety of network structural characteristics, tobacco program agency characteristics, and existing contact and collaboration relationships. Table 1 shows the ERGM results for each state, including model estimates and fit comparisons. The dependent variable was whether dissemination of Best Practices had occurred between two agencies. Parameter estimates are log-odds of a tie. The table has three models for each state: the first with network partner attributes (years of experience and whether the agency operated at the local, state, or national level), partner relationships (distance between
**Figure 1.** Density and betweenness centralization for contact, collaboration, and dissemination ties for each state.

**Figure 2.** Contact, collaboration, and dissemination networks in Indiana.

*Note.* Nodes sized by betweenness centrality. Betweenness centrality for the lead agency (darker node) was 0.127 for contact, 0.207 for collaboration, and 0.423 for dissemination.
### Table 1. Exponential Random Graph Modeling (ERGM) Results Using Experience, Geographic Reach, Distance, Degree, Contact, and Collaboration to Predict Dissemination.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Indiana ((g = 26))</th>
<th>Texas ((g = 21))*</th>
<th>Wyoming ((g = 20))</th>
<th>D.C. ((g = 19))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M1 b (SE)</td>
<td>M2 b (SE)</td>
<td>M3 b (SE)</td>
<td>M1 b (SE)</td>
</tr>
<tr>
<td></td>
<td>(-3.04)</td>
<td>(-4.63)</td>
<td>(-4.64)</td>
<td>(-2.39)</td>
</tr>
<tr>
<td>Degree</td>
<td>(-0.23 (0.51))*</td>
<td>(-3.41 (0.28))*</td>
<td>(-2.81 (0.29))*</td>
<td>(-4.22)</td>
</tr>
<tr>
<td>TC experience</td>
<td>0.12 (0.02)*</td>
<td>0.09 (0.02)*</td>
<td>0.08 (0.02)*</td>
<td>0.10 (0.05)*</td>
</tr>
<tr>
<td>Geographic reach</td>
<td>1.21 (0.10)*</td>
<td>0.82 (0.08)*</td>
<td>0.54 (0.09)*</td>
<td>0.74 (0.16)</td>
</tr>
<tr>
<td>Agency distance</td>
<td>0.008 (0.002)</td>
<td>0.009 (0.010)</td>
<td>0.003 (0.010)</td>
<td>0.050 (0.014)*</td>
</tr>
<tr>
<td>Network contact</td>
<td>1.26 (0.02)*</td>
<td>0.87 (0.02)*</td>
<td>0.58 (0.02)*</td>
<td>0.72 (0.04)*</td>
</tr>
<tr>
<td>Network collaboration</td>
<td>1.26 (0.02)*</td>
<td>0.87 (0.02)*</td>
<td>0.58 (0.02)*</td>
<td>0.72 (0.04)*</td>
</tr>
</tbody>
</table>

|                     | M2 b (SE)             | M3 b (SE)            | M1 b (SE)             | M2 b (SE)         |
|                     | \(-3.04\)             | \(-4.63\)            | \(-4.64\)            | \(-2.39\)         |
| Degree              | \(-0.23 (0.51)\)*    | \(-3.41 (0.28)\)*   | \(-2.81 (0.29)\)*   | \(-4.22\)         |
| TC experience       | 0.12 (0.02)*          | 0.09 (0.02)*         | 0.08 (0.02)*         | 0.10 (0.05)*      |
| Geographic reach    | 1.21 (0.10)*          | 0.82 (0.08)*         | 0.54 (0.09)*         | 0.74 (0.16)       |
| Agency distance     | 0.008 (0.002)         | 0.009 (0.010)        | 0.003 (0.010)        | 0.050 (0.014)*    |
| Network contact     | 1.26 (0.02)*          | 0.87 (0.02)*         | 0.58 (0.02)*         | 0.72 (0.04)*      |
| Network collaboration| 1.26 (0.02)*          | 0.87 (0.02)*         | 0.58 (0.02)*         | 0.72 (0.04)*      |

|                     | M3 b (SE)            | M1 b (SE)             | M2 b (SE)             | M3 b (SE)         |
|                     | \(-3.04\)             | \(-4.63\)            | \(-4.64\)            | \(-2.39\)         |
| Degree              | \(-0.23 (0.51)\)*    | \(-3.41 (0.28)\)*   | \(-2.81 (0.29)\)*   | \(-4.22\)         |
| TC experience       | 0.12 (0.02)*          | 0.09 (0.02)*         | 0.08 (0.02)*         | 0.10 (0.05)*      |
| Geographic reach    | 1.21 (0.10)*          | 0.82 (0.08)*         | 0.54 (0.09)*         | 0.74 (0.16)       |
| Agency distance     | 0.008 (0.002)         | 0.009 (0.010)        | 0.003 (0.010)        | 0.050 (0.014)*    |
| Network contact     | 1.26 (0.02)*          | 0.87 (0.02)*         | 0.58 (0.02)*         | 0.72 (0.04)*      |
| Network collaboration| 1.26 (0.02)*          | 0.87 (0.02)*         | 0.58 (0.02)*         | 0.72 (0.04)*      |

|                     | M1 b (SE)             | M2 b (SE)             | M3 b (SE)             | M1 b (SE)         |
|                     | 335.4                 | 250.8                 | 242.4                 | 178.2             |
| Model fit           |                       |                       |                       |                   |
| AIC                 | .73                   | .88                   | .92                   | .91               |
| GOF%                | .78                   | .89                   | .92                   | .83               |

|                     | M2 b (SE)             | M3 b (SE)             | M1 b (SE)             | M2 b (SE)         |
|                     |                       |                       |                       |                   |
| AIC                 | .73                   | .88                   | .92                   | .91               |
| GOF%                | .78                   | .89                   | .92                   | .83               |

|                     | M3 b (SE)            | M1 b (SE)             | M2 b (SE)             | M3 b (SE)         |
|                     | 335.4                 | 250.8                 | 242.4                 | 178.2             |
| Model fit           |                       |                       |                       |                   |
| AIC                 | .73                   | .88                   | .92                   | .91               |
| GOF%                | .78                   | .89                   | .92                   | .83               |

|                     | M1 b (SE)             | M2 b (SE)             | M3 b (SE)             | M1 b (SE)         |
|                     | 154.9                 | 109.6                 | 86.3                  | 104.8             |
| Model fit           |                       |                       |                       |                   |
| AIC                 | .78                   | .89                   | .92                   | .97               |
| GOF%                | .78                   | .89                   | .92                   | .88               |

Note. GWDegree = geometrically weighted degree; TC = tobacco control; AIC = Akaike information criterion; GOF% = goodness-of-fit percentage.

* Model produced interpretable estimates, but failed to converge without degeneracy issues.  
* Model comparison delta-p. M1 is compared with a null-baseline model, M2 compared with M1, M3 compared with M2.  
* Goodness-of-fit percentage (GOF%) quantifies the proportion of the observed network measures that fit within the 95% confidence intervals around the model simulations.

\(p < .05\)
agencies), and network structural patterns (GWDegree). The second model added level of contact between agencies and the third added level of collaboration between agencies. Model 3 had the best AIC (Akaike information criterion) fit for all states except Florida, and the best goodness-of-fit percentage (GOF%) for all states except Wyoming, Washington DC, and Florida (Goodreau, 2007). (Goodness-of-fit graphics are available online as supplemental material at http://heb.sagepub.com/supplemental.) When controlling for all other variables, the likelihood of Best Practices dissemination increased with higher levels of contact and collaboration for all states with the exception of Florida, where collaboration did not predict dissemination over and above contact. This is the primary result of this study—dissemination connections among public health organizations are more likely when there is also an existing contact and collaboration relationship between the two agencies. Table 2 shows the odds ratios of the final models for each state as a measure of effect size for all parameters.

Generally speaking, years of experience was positively associated with dissemination. The coefficient for geographic reach was usually positive, indicating that dissemination was more likely between agencies of the same reach (local, state, or national) with the exception of Wyoming and Arkansas ($b = -0.22$ and $b = -2.0$, respectively), where dissemination was more likely between agencies of different reach. Results for distance between agencies were mixed, with dissemination more likely between agencies with greater distance between them in the states of Oregon ($b = 0.065; SE = 0.006$), Florida ($b = 0.017; SE = 0.007$), and Colorado ($b = 0.054; SE = 0.019$), but more likely between agencies with less distance between them in the states of Texas ($b = -0.088SE = 0.005$), Wyoming ($b = -0.011; SE = 0.003$), and Arkansas ($b = -0.014; SE = 0.006$). No significant relationship for distance between agencies and dissemination was identified in the Indiana and Washington, D.C. networks.

### Discussion

The purpose of this study was to apply a systems science approach to studying dissemination of evidence-based guidelines among public health organizations. By studying real-world public health networks, we can start identifying the mechanisms that facilitate the dissemination and utilization of evidence-based practices. The main result of this study was that dissemination of the Best Practices guidelines between two tobacco control partners was more likely if those partners also had an existing contact or collaborative relationship. This relationship was also generally quite strong. For example, in Indiana dissemination of Best Practices between two agencies was $78\%$ more likely if those two agencies also had a collaboration tie, holding all else constant. This is not an altogether surprising finding; it makes sense that information about a specific set of evidence-based guidelines would flow along existing organizational partnership ties.

Another discovery in this study was that as the organizational relationship became more formal (moving from contact to collaboration and on to dissemination), the lead agency in
each state played a more central role. That is, particular agencies become “brokers” within the network. This emphasizes the need to include lead agencies in formal dissemination efforts; in highly centralized networks, it is important that brokers act to facilitate the movement of information lest they become bottlenecks and hinder the dissemination process. However, as past studies have suggested (Mueller et al., 2008), it would be a mistake to focus only on lead agencies and not on their extended community partners.

This is one of the first studies to examine how interorganizational relationships in a public health network influence the dissemination of evidence-based guidelines, and to our knowledge the first to do this using ERGM. Also, the ability to examine multiple network ties across eight separate state networks adds to the strength of the study. The use of ERGM allows us to go beyond the examination of descriptive network structures to see how characteristics of network partners and the relationships between them influence the likelihood of a dissemination tie between two network members.

The results of this study have specific policy and practice implications. As we have discovered, higher levels of contact and collaboration between tobacco control agencies independently predict a higher probability of information dissemination. The main implication of this is that funders, advocates, and other public health institutions (such as the CDC) can assume that their dissemination efforts will proceed through preexisting channels established via organizational collaborations. Network analysis can continue to play an important role here. Network maps can be produced of public health organizational systems. These maps can be used to identify important dissemination brokers who can be used to support the dissemination or, maybe even more important, the maps can be used to identify critical gaps in the network that would need to be addressed before effective dissemination would be possible.

One limitation of our study was that we asked whether or not partners talked about Best Practices with one another but not how that information was disseminated (e.g., a specific person, e-mail correspondence, conferences). Also, the dissemination connection in our study was nondirectional. Typically, we think of dissemination having a source and multiple targets—that is, dissemination is more accurately conceived as a directional process. Subsequent studies of dissemination of evidence-based guidelines should use a more nuanced method of assessing information flow that takes into account its mode and directionality. A second limitation was the cross-sectional method of data collection, which prevented a truly longitudinal examination of whether contact and collaboration must precede dissemination.

Public health deals with complex systems of all types, and that is certainly true when we consider the complicated interplay of organizations and information flow when new scientific discoveries are translated and disseminated to influence practice and policy (Luke & Stamatakis, 2012). In early 2000, Stephen Hawking proclaimed that “I think the next century will be the century of complexity” (Chiu, 2000, p. 29A). However, skepticism of the benefits of systems science is also common, and this will remain true until we demonstrate the utility of systems science theories and methods in public health. This study, by using network analysis to identify the structures and processes underlying dissemination, is a small step toward that end.

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Authors’ Note
Lana M. Wald is now at the Department of Psychology, American University, Washington, DC. Laura E. Bach is now at the Gillings School of Global Public Health, The University of North Carolina at Chapel Hill. The contents of the article are solely the responsibility of the authors and do not necessarily reflect the views of the Centers for Disease Control and Prevention (CDC) or National Association of Chronic Disease Directors (NACDD).

The online graphics are available at http://heb.sagepub.com/supplemental.

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References


