

# Systems Analysis of Collaboration in 5 National Tobacco Control Networks

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Networks are ubiquitous in public health. People and agencies have long organized into collaborative systems or networks to tackle specific public health challenges. Funding agencies often require collaboration because organizations working together are thought to create systems changes and community capacity to address health issues and population needs more efficiently and responsively than when working independently.<sup>1,2</sup> Interorganizational collaboration is a relational system in which 2 or more organizations share information and resources to achieve a common goal.<sup>3</sup> Collaboration is especially valued in tobacco control, where organized networks are common at local, state, national, and international levels.<sup>4</sup> For example, community coalitions address tobacco use through the passage of local smoke-free laws,<sup>5</sup> comprehensive tobacco control programs develop multiple interorganizational strategies across a state,<sup>6–8</sup> the National Harm Reduction Network<sup>9</sup> and the Global Tobacco Research Network<sup>10</sup> connect tobacco control researchers nationally and globally, and the World Health Organization's Framework Convention on Tobacco Control coordinates an international response to combating the tobacco epidemic.<sup>11</sup> However, little is known about how these networks work together as collaborative systems,<sup>4,12,13</sup> although some research has examined specific characteristics (e.g., leadership or organizational climate).<sup>14</sup> This gap has been noted in calls for public health systems research.<sup>4,12,15,16</sup>

Network analysis is a useful method for examining relationships among organizations.<sup>4,17</sup> This method has been used to describe public health network characteristics, such as level of collaboration among agencies providing chronic disease services,<sup>18</sup> role of peer influence in adolescent smoking behavior,<sup>19</sup> collaboration among tobacco harm reduction researchers,<sup>9</sup> and interorganizational relationships in state tobacco control programs.<sup>20</sup> Studies to date have largely been descriptive.

**Objectives.** We studied 5 members of the National Network Consortium on Tobacco Control in Priority Populations. These networks, which consist of governmental and nongovernmental organizations, targeted lesbian, gay, bisexual, and transgender persons; Asian Americans, Native Hawaiians, and Pacific Islanders; American Indians and Alaska Natives; African Americans; and persons with low socioeconomic status, respectively.

**Methods.** We used statistical network analysis modeling to examine collaboration among these national networks in 2007.

**Results.** Network size and composition varied, but all 5 networks had extensive interorganizational collaboration. Location and work area were significant predictors of collaboration among network members in all 5 networks. Organizations were more likely to collaborate with their network's lead agency; collaborations with other agencies were more likely if they were geographically close. Collaboration was perceived to be important for achieving the goals of the national network.

**Conclusions.** The similarity of collaboration patterns across the 5 networks suggests common underlying partnership formation processes. Statistical network modeling promises to be a useful tool for understanding how public health systems such as networks and coalitions can be used to improve the nation's health. (*Am J Public Health.* 2010;100:1290–1297. doi:10.2105/AJPH.2009.184358)

Historically, most tobacco control efforts were organized at the state level. To complement existing state-level mechanisms, better address tobacco use and industry marketing disparities, and meet Healthy People 2010 goals, the Centers for Disease Control and Prevention's Office on Smoking and Health funded 6 priority population networks in the National Network Initiative, aiming to build capacity and infrastructure and provide leadership and expertise in population-specific initiatives and best practices. The population groups were African Americans; Hispanics and Latinos; lesbian, gay, bisexual, and transgendered persons; American Indians and Alaska Natives; Asian Americans, Native Hawaiians, and Pacific Islanders; and persons with low socioeconomic status. These groups and communities face significant tobacco-related disparities. For example, recent Asian immigrants and Native Americans smoke more than do other ethnic groups, but Native American rates vary by tribe.<sup>21</sup> Gays and lesbians have a higher

smoking rate than do heterosexuals,<sup>22</sup> perhaps because of targeted advertising<sup>23</sup> and stigma.<sup>24</sup>

Network analysis has been used to examine a range of issues across organizations in a network; new network statistical modeling techniques allow examination of predictors of collaboration processes and structures.<sup>25</sup> The Center for Tobacco Policy Research was contracted by the Office on Smoking and Health in 2007 to evaluate the National Network Initiative. The center used a systems approach to examine the structural properties of each national network. A primary goal of the evaluation was to determine how the organizations worked together as collaborative networks.<sup>26</sup>

We analyzed data from this evaluation. We sought to (1) describe how common collaborations are among national networks addressing tobacco-related disparities and (2) identify specific organizational and structural predictors of network collaborative relationships. Our study moved beyond description of network characteristics and developed statistical models

to examine collaboration processes and network structures. Our results may inform the emerging discipline of public health systems research.<sup>27</sup>

## METHODS

Six networks receiving funding from the Office on Smoking and Health participated in the 2007 evaluation. An advisory group made up of representatives from the Office on Smoking and Health, each network, and the evaluation team developed network delineation criteria to guide each network lead agency in identifying core members and partners. The lead agency was the organization receiving funding from the Centers for Disease Control and Prevention to manage network activities; partners were the organizations working together to achieve the networks' goals. A core member was defined as a partner who had communicated with the lead agency in the past year and had provided network strategic planning input or had implemented tobacco control efforts. Two leaders from each network identified its core members by this definition. We invited core members to participate in a Web-based network survey in fall 2007.

We analyzed data from 5 of the 6 networks, representing a national systemic effort to address tobacco-related disparities among 5 priority populations: lesbian, gay, bisexual, and transgender persons; Asian Americans, Native Hawaiians, and Pacific Islanders; American

Indians and Alaska Natives; African Americans; and persons with low socioeconomic status (Table 1). One network was not included in this analysis because its participation in the evaluation was extremely low.

## Measures

The survey described network structure by 4 attributes: (1) awareness, (2) frequency of contact, (3) perceived importance to the network's efforts in tobacco prevention and control, and (4) collaboration. The primary relational measure was collaboration, which was measured with a tool adapted from Slonim et al.<sup>28</sup> We asked participants, "Which response best describes your organization's relationship with the following individuals/organizations?" Response options were unlinked: do not work together at all (0); communication: share information only (1); cooperation: work together as an informal work group to achieve common goals (2); collaboration: work together as a formal team to achieve common goals (3); and partnership: work together as a formal team across multiple projects to achieve common goals (4).

This scale was dichotomized so that organizations reporting working together informally or formally to achieve common goals (responses 2 through 4) were defined as collaborating. Organizations that were unlinked or only shared information (responses 0 and 1) were considered noncollaborating.

Core partners reported on 2 basic organizational characteristics: how long the

organization had been a part of the network and the organization's primary tobacco control focus. Tobacco control focus was coded as (1) prevention, cessation, and clinical services; (2) surveillance, evaluation, and research; (3) training and technical assistance; or (4) advocacy and policy. We also categorized each individual and agency respondent by type of agency (nongovernmental health organization, other nongovernmental organization, government agency, or individual). For example, a respondent representing the American Lung Association was assigned to the nongovernmental health organization category. Finally, the zip code for each organization was geocoded to provide locational information for the statistical network modeling. We have successfully used these attribute measures in previous studies.<sup>6,20</sup>

## Data Analysis

In addition to basic descriptive statistics, we used network visualization, descriptive network analysis, and statistical network modeling. Data management and descriptive statistical analyses were conducted with SPSS 15.0 (SPSS Inc, Chicago, IL) and R version 2.8.1 (R-Project; <http://www.r-project.org>). Network visualization and computation of network statistics were conducted in Pajek 1.13<sup>29</sup> and R-statnet.<sup>30</sup>

In addition to the size and age of each network, we examined network density and centralization. Density is the proportion of

**TABLE 1—Network and Collaboration Characteristics of 5 Members of the National Network Consortium on Tobacco Control in Priority Populations: 2007**

National Network	Population	Lead Agency Location	No. of Organizational Members	Year Founded	Collaboration Density <sup>a</sup>	Degree Centralization <sup>b</sup>
The National Lesbian, Gay, Bisexual, and Transgender Tobacco Control Network	Lesbian, gay, bisexual, transgender	Massachusetts	57	2006	0.15	0.26
Asian Pacific Partners for Empowerment, Advocacy, and Leadership	Asian American/Pacific Islander/Native Hawaiian	Northern California	49	1994	0.13	0.49
National Tribal Tobacco Prevention Network	American Indian/Native Alaskan	Oregon	35	2000	0.16	0.64
National African American Tobacco Education Network	African American	Central California	21	2000	0.27	0.42
National Network of Tobacco Prevention and Poverty	Low socioeconomic status	Central California	11	2000	0.58	0.39

<sup>a</sup>Density is the proportion of observed ties to the total number of possible ties.

<sup>b</sup>Degree centralization is the normalized variability of degree across all network members and reflects the tendency for network relations to be controlled or influenced by a small number of prominent network members

observed ties in a network to the total possible number of ties. For most social and organizational networks, density tends to get smaller as networks get larger.<sup>31</sup> Centralization is the tendency for network relations to be controlled or influenced by a small number of prominent network members.<sup>32</sup> Networks with low centralization typically have flat, nonhierarchical communication patterns; communication in networks with high centralization is controlled by a few prominent network members. Of the available measures of centralization, we focused on degree centralization, which is derived from the number of direct connections each network member has with other members.<sup>31</sup> Studies of public health organizational networks have shown that degree centralization is important in understanding communication and collaboration patterns among organizations.<sup>18,33</sup>

Statistical network modeling refers to predictive models of network structure and is a new and rapidly evolving area of network analysis.<sup>34</sup> New specifications for exponential random graph models (also known as  $p^*$  models)<sup>35</sup> avoid the statistical and computational limitations of earlier approaches, provide results interpreted similarly to logistic regression models, and are starting to be used in real-world applications. Exponential random graph models are generative, or bottom-up, models of network structure—they are used to describe how local properties and selection forces shape the overall structure of a network.<sup>36</sup> These local properties can be attributes of actors (e.g., type of agency or location of agency) or local network properties (e.g., tendency for similar types of agencies to work together or tendency of a lead agency to be connected to many other agencies).

Following the method of Goodreau,<sup>25</sup> we built our models from the bottom up by progressively adding predictors to a baseline null model. We used structural predictors to avoid problems of model degeneracy,<sup>37</sup> and we conducted postmodel goodness-of-fit simulations. Two other considerations guided model building. We used the same set of predictors for each network to facilitate cross-network comparison and to explore whether common factors underlay partnership formation. We also categorized predictors: structural predictors captured aspects of local network structures and processes, and attribute predictors accounted for organizational characteristics of the individual network

members. We began our 3-stage model-building process with a null model (no predictors), added the local structural predictors, and completed the model with a final block of attribute predictors. Adding the attribute predictors last enabled us to focus more clearly on the types of factors that might be manipulatable in future organizational or policy interventions.

Our 3 structural predictors captured different aspects of local clustering. The geometrically weighted dyadwise shared partnerships value indicated the tendency for any 2 network partners (linked or not) to have shared partnerships.<sup>25,38</sup> For example, a positive significant parameter for this predictor indicated that 2 network members who were both linked to the same third partner were more likely than chance to have additional shared relationships. The geometrically weighted edgewise shared partner value captured the tendency for 2 network partners who were directly linked to have multiple shared partners. Used together in our models, the geometrically weighted edgewise shared partner parameter captured shared partnership information for connected dyads, and the geometrically weighted dyadwise shared partnerships measure captured shared partnership information for unconnected dyads. The geometrically weighted degree statistic assessed the tendency for agencies with higher degrees to form partnerships with others.

Organizational attribute predictors included in the models were location distance (between 2 organizations in the network), lead agency (of the network), length of involvement (time an individual or agency had been a member of the network), tobacco control focus (capturing the effect of uniform homophily, the extent to which members with similar tobacco control foci were likely to collaborate with each other),<sup>36</sup> agency type (entered into the model as a uniform homophily effect), and perceived agency importance (ranging from 1, other agency was not important at all to the network's ability to accomplish its objectives, to 5, other agency was extremely important to the network). The final attribute allowed us to examine whether the perceived importance of agencies was related to the likelihood of collaboration between those 2 agencies. The ability to model the effects of one network relationship on another is an important strength of modern statistical network methods.

Models of overall network structure derived from both attribute and structural properties can be used to examine and test a wide variety of substantive hypotheses. To our knowledge, ours was the first study to apply these types of models to public health organizational systems.

## RESULTS

Figure 1 shows the collaborative relationships among the members of the 5 national tobacco control networks. Table 1 presents basic network characteristics. The networks varied in size (11–57 members) and density (0.13–0.58). The smallest network (low socioeconomic status) had the highest density. The 3 largest networks had approximately the same amount of interconnectedness (density=0.13–0.16). The network graphs show that even for networks with relatively low densities, most tobacco control organizations collaborated with other organizations in their networks. Across all 5 networks, more than 97% of the organizations collaborated with at least 1 other network organization (the Asian American, Native Hawaiian, and Pacific Islander network had only 3 isolates; the lesbian, gay, bisexual, and transgender network, 2; and the American Indian network, 1).

Although the 3 largest networks had similar overall density, their actual patterns of collaboration differed (Figure 1). The American Indian network had a more centralized collaboration structure, and the lesbian, gay, bisexual, and transgender network had a decentralized structure (according to degree centralization). The American Indian network had a small number of network partners who each worked with many of the other partners; conversely, the collaborative relationships among the lesbian, gay, bisexual, and transgender network partners were shared among a greater variety of organizations. This may be attributable in part to the greater number of organizations in the latter network that were primarily involved with advocacy work, which may require more collaboration.

### Attribute and Structural Predictors of Collaboration

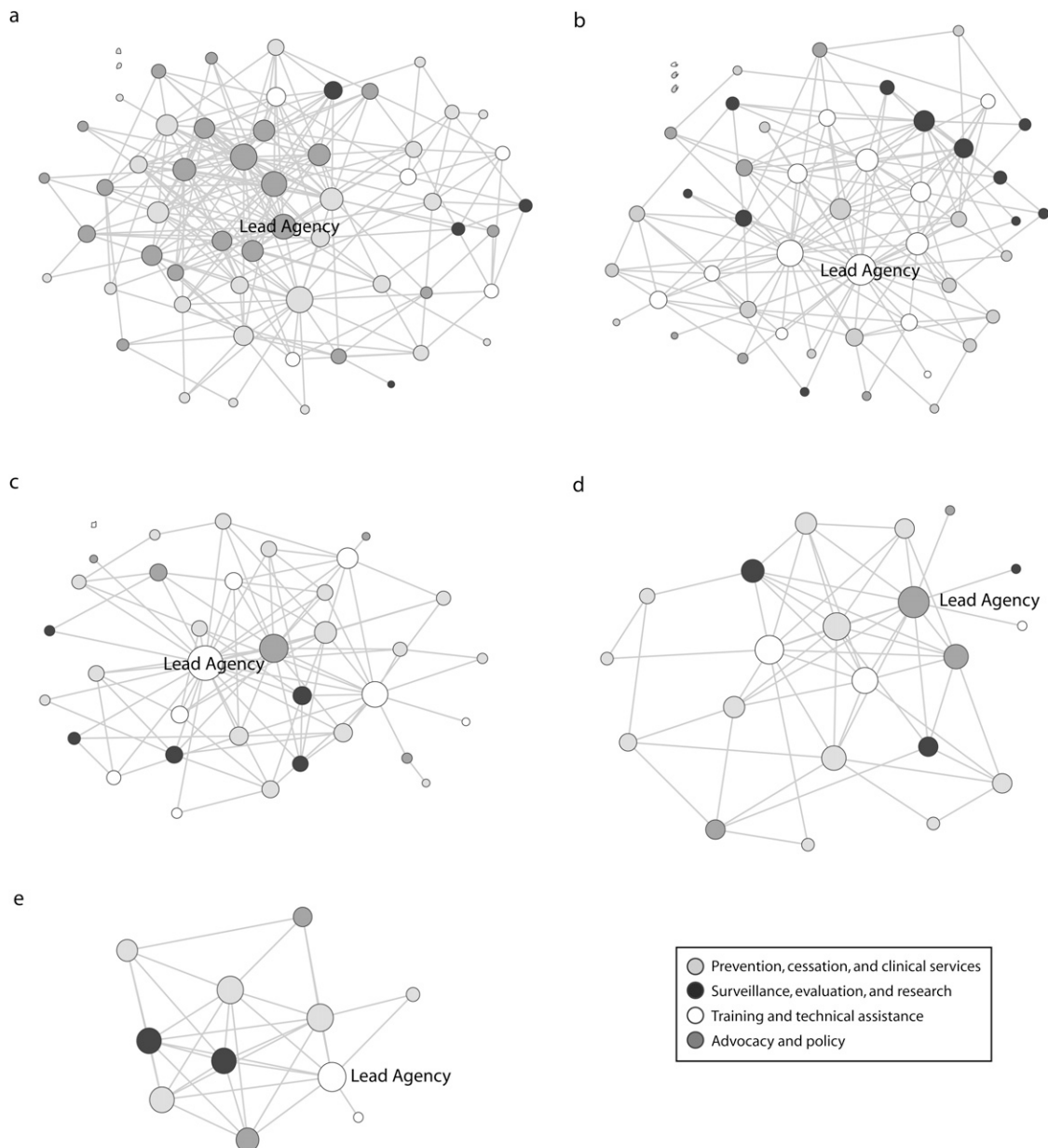
The descriptive and graphic depictions of the networks were suggestive but did not shed

much light on the specific factors associated with collaboration in national public health networks. To examine these factors more closely, we built predictive collaboration models for each of the national networks. Table 2 presents the exponential random graph model results for each network. The dependent

variable modeled was a collaboration tie between 2 tobacco control organizations. For each predictor, we calculated the log odds parameter estimate and its associated standard error. The table has 2 models for each network (results of the null models not shown): the first shows structural predictors only, and the

other has both organizational attribute and structural predictors.

The model results indicated that for all 5 networks, collaboration ties were the products of both structural and organizational characteristics of the networks. In addition, for every network except the one focusing on persons



Note. Node sizes are based on degree centrality: the more central an agency is in the network, the larger its node appears in the figure.

**FIGURE 1—National tobacco control network collaborative partnerships among the (a) lesbian, gay, bisexual, and transgender network; (b) Asian American and Pacific Islander network; (c) American Indian network; (d) African American network; (e) low socioeconomic status network: 2007.**



**TABLE 2—Structural and Organizational Predictors of Network Collaboration for 5 Members of the National Network Consortium on Tobacco Control in Priority Populations: 2007**

	LGBT		API		American Indian		African American		Low SES	
	Structural Model, b (SE)	Structural Plus Organizational Model, b (SE)	Structural Model, b (SE)	Structural Plus Organizational Model, b (SE)	Structural Model, b (SE)	Structural Plus Organizational Model, b (SE)	Structural Model, b (SE)	Structural Plus Organizational Model, b (SE)	Structural Model, b (SE)	Structural Plus Organizational Model, b (SE)
Edges	-1.57* (0.14)	-2.26* (0.23)	-3.32* (0.25)	-4.23* (0.63)	-3.72* (0.45)	-3.41* (0.45)	-0.80* (0.38)	-0.69 (1.1)	2.43 (11.0)	6.19* (1.8)
Structural predictors										
GWESP (clustering) <sup>a</sup>	0.55* (0.07)	0.47* (0.01)	0.75* (0.14)	0.60* (0.02)	0.95* (0.37)	0.92* (0.02)	0.02 (0.18)	-0.04 (0.03)	-0.38 (5.9)	0.34* (0.04)
GWDegree (degree) <sup>b</sup>	-1.75* (0.10)	-1.46* (0.12)	-2.22* (0.04)	-0.48* (0.16)	-1.06* (0.16)	-0.96* (0.11)	-2.54* (0.10)	-1.80* (0.22)	-7.8 (5.7)	2.48* (0.53)
GWDSP (structural equivalence) <sup>c</sup>	-0.18* (0.00)	-0.15* (0.00)	-0.09* (0.01)	-0.05* (0.00)	0.15* (0.06)	0.10* (0.00)	0.05* (0.01)	-0.03* (0.01)	1.8 (2.0)	-1.2* (0.04)
Organizational predictors										
Location distance		-0.36* (0.10)		-0.31* (0.02)		-0.55* (0.04)		-0.24* (0.04)		-1.03* (0.05)
Lead agency		0.95* (0.36)		1.73* (0.41)		-0.69 (0.55)		1.37* (0.61)		6.67* (1.9)
Length of involvement		0.10 (0.05)		0.15 (0.09)		0.04 (0.08)		-0.24 (0.20)		-0.84* (0.28)
Tobacco control focus		0.41* (0.13)		0.40* (0.06)		-0.48* (0.07)		-0.25* (0.11)		1.32* (0.30)
Agency type		0.33* (0.04)		-0.11 (0.07)		-0.25* (0.07)		-0.13 (0.37)		-1.16* (0.22)
Agency importance (network relation)		0.25* (0.01)		0.40* (0.01)		0.22* (0.01)		0.26* (0.07)		0.35* (0.02)
<b>Model fit</b>										
AIC (P value) <sup>d</sup>	1154.9 (.001)	1096.1 (.001)	767.4 (.001)	663.6 (.001)	382.6 (.001)	411.2 (.011)	243.1 (.001)	235.6 (.003)	45.2 (.001)	60.9 (.71)

Note. LGBT=lesbian, gay, bisexual, transgender; API=Asian American/Pacific Islander; SES=socioeconomic status; GWESP=geometrically weighted edgewise shared partner; GWDegree=geometrically weighted degree statistic; GWDSP=geometrically weighted dyadwise shared partnerships; AIC=Akaike information criterion.

<sup>a</sup>The tendency for 2 network partners who were directly linked to have multiple shared partners.

<sup>b</sup>The number of direct connections each network member had with other members.

<sup>c</sup>The tendency for any 2 network partners (linked or not) to have shared partnerships.

<sup>d</sup>Model comparison delta-*p*. The structural model is compared to a null-baseline model; the structural plus organizational model is compared to the structural model.

\**P* < .05

with low socioeconomic status, the model with organizational and structural predictors was a better fit to the data than the simpler (structural only) model.

Collaboration did not occur randomly in these national networks. For all networks, collaborative partnerships were less likely the further away the network members were from each other. Organizations were more likely to collaborate with the lead agency than with other partners in every network except the American Indian network. The type of tobacco control work an agency did and the type of agency were both significant predictors, but the results were not entirely consistent across the networks. The negative coefficients for agency type (e.g., -0.25 for American Indian networks) suggested that complementary organizations were more likely to collaborate. On the other hand, for 3 of the networks (lesbian, gay, bisexual, and transgender; Asian American, Native Hawaiian, and Pacific Islander; and low socioeconomic status networks), organizations

that worked primarily in the same area of tobacco control were more likely to collaborate (a positive homophily effect). For all 5 networks, we observed a strong positive relationship between perceived organizational importance and the likelihood of interorganizational collaboration. The only organizational characteristic that was not a consistent predictor of collaboration was the length of time the organization had been involved in the network.

With 1 exception, all the structural predictors were significant for each of the networks. The positive geometrically weighted edgewise shared partner parameter in all of the final network models indicated an increased likelihood for those who were directly linked to each other in each network to have multiple shared partners. The negative value for geometrically weighted dyadwise shared partnerships in all but 1 network (American Indian) indicated that among agencies not working directly with each other, having a partner in common lowered the likelihood

of having additional shared partners. The negative value for the geometrically weighted degree statistic in 4 of the 5 networks suggested that after adjustment for other predictors in the model, having more connections (higher degree) was not associated with higher likelihood of partner formation. Taken together, these structural predictor findings indicated that only agencies that worked together directly and had a third partner in common were likely to have additional collaborators in common.

### Model Assessment

With complex models, it is important to examine model robustness and fit. All our models were fit with no convergence problems. Model degeneracy is a common challenge with exponential random graph models,<sup>25</sup> and our lack of difficulty suggested that we had well-specified models. Another way to examine model robustness is to explore the goodness of fit of the model to the data. We employed Monte Carlo

Markov chain simulations to see how well the actual observed network matched a large series of simulated networks, according to the fitted models.

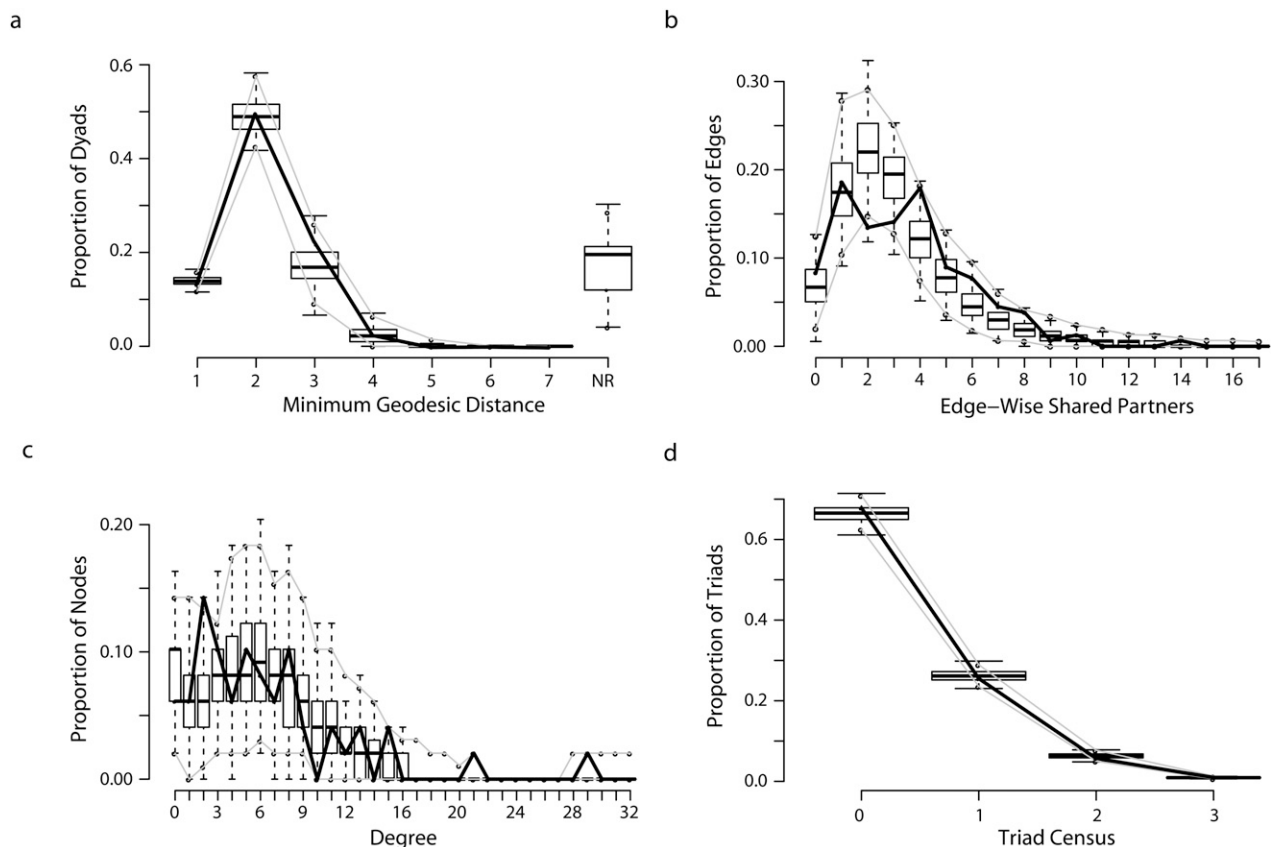
Figure 2 shows the results of these goodness-of-fit tests for the Asian American, Native Hawaiian, and Pacific Islander network structural plus organizational predictors model. After running 10 000 simulation predictions for a model, we compared 4 network characteristics of the predicted and actual networks: geodesic distances, edgewise-shared partners, nodal degree, and triad census. The figure shows how closely the observed network data matched the simulated data for both local (i.e., degree) and global (i.e., distance) network features. (If the black line lies within the gray 95% confidence interval boundaries, then it is strong

evidence for a well-fitting model.) All 5 network structural models produced good to excellent goodness-of-fit statistics. Across the 5 networks, 229 of 242 (95%) individual statistics were consistent with good fit. (The results of the individual goodness-of-fit analyses for the other networks are available from the authors.)

## DISCUSSION

We explored collaboration in 5 national tobacco control networks that focus on groups with significant disparities in tobacco use and its consequences. Despite differences in network size and age, the overall pattern of collaboration was quite similar across networks. Although collaboration density was modest (approximately 15%), almost every

agency member was working with somebody else in the network in formal or informal working groups. The rule seems to be, “You do not need to work with everybody, but everybody needs to work with somebody.” This is a useful property for a national network, because they are designed to be flexible and responsive to tobacco control needs in various states, communities, and population subgroups. When all members are involved in collaborations, the network can more quickly respond to these needs. With collaborations between partners and their lead agencies well established, these networks are taking action to increase collaboration between partners. In 2008 and 2009, these networks restructured or established coordinating councils and committees to promote increased direct collaboration among multiple network partners.



Note. Thick black lines correspond to the observed network properties. Light gray lines correspond to 95% confidence intervals for the simulated network properties. Good fit is assumed when the black line lies within the gray confidence lines.

**FIGURE 2—Structural model goodness of fit for the Asian American/Pacific Islander network attributes plus structural model showing (a) minimum geodistance, (b) edgewise shared partners, (c) degree, and (d) triad census.**

Our statistical network models revealed some important predictors of collaboration. Lead agencies were more likely to be involved in partnerships, an unsurprising finding in light of their planning, management, and funding roles in the networks. Although these networks were designed to be national in scope, partners were more likely to work together if they were physically close. This is consistent with past social and organizational science research,<sup>39</sup> but it presents a challenge for building and maintaining effective national networks. Even in the age of the Internet and virtual communities, physical proximity helps establish working partnerships.

Our analytic approach illustrated the importance of examining more sophisticated statistical models of network relationships. For example, the network graphs and degree centralization statistic suggested that the lead agency in the American Indian network played a very prominent role. However, the full statistical model for the American Indian network, which incorporated other structural and attribute predictors, indicated that the lead agency was not likely to be involved in more collaborative relationships than were other types of agencies in the network. Conversely, the lesbian, gay, bisexual, and transgender network graphic suggested that the lead agency was not notably prominent in the collaboration network, but the statistical model showed that agency partners were more likely to collaborate with the lead agency.

Our study contributes to the growing science of public health systems. Although systemic concepts in public health are not new (e.g., the spread of diseases through physical and social networks, herd immunity, and diffusion of innovations), and systems-oriented theoretical frameworks have enjoyed much support,<sup>40</sup> appropriate tools for systems analysis remain underused.<sup>41</sup> Network analysis, system dynamics, and agent-based modeling tools allow us to move beyond systems description to systems analysis. Systems approaches in tobacco control are identifying common organizational blueprints underlying state tobacco control programs,<sup>20</sup> predicting future tobacco use patterns with dynamic systems modeling,<sup>42</sup> and providing insights into transdisciplinary tobacco control science.<sup>9</sup>

Our statistical network modeling illustrates how collaboration networks form and operate. Further empirical and theoretical work is needed to better understand how collaborative partnerships form and which collaboration structures are most effective. For example, we found both positive and negative homophily relationships—that is, sometimes similar organizations were more likely to work together in the networks, and at other times they were less likely to work together. Some of the theoretical frameworks used in organizational science would enhance this understanding of public health organizational systems (e.g., alliance dynamics<sup>43</sup> or resource dependency<sup>44</sup>).

Furthermore, we know little about how health outcomes are related to various types of collaboration networks. The networks we studied were funded by the Office on Smoking and Health to help achieve ambitious and important national public health goals. Understanding more about how collaboratives collaborate and how networks network will bring us closer to designing and managing more effective public health systems. ■

### About the Authors

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### Contributors

D.A. Luke supervised all aspects of the study, conceptualized the article, and performed analyses. J.K. Harris collected data, performed analyses, wrote sections of the article, and edited the article. S. Shelton assisted in analyses and wrote sections of the article. P. Allen assisted in analyses, wrote sections of the article, and developed the figures. B.J. Carothers assisted in analyses, wrote sections of the article, and edited the article. N.B. Mueller supervised collection of the data and edited the article.

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**Note.** These findings do not necessarily represent the official position of the Centers for Disease Control and Prevention.

### Human Participant Protection

The study was approved by the Saint Louis University institutional review board.

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