The Effect of Collaborative Partnerships on Inter-organizational Networks

Tyler Scott
Doctoral Candidate
Daniel J. Evans School of Public Affairs
University of Washington

Craig Thomas
Associate Professor
Daniel J. Evans School of Public Affairs
University of Washington

Abstract

The terms collaborative governance and organizational networks are not always clearly distinguished in the literature. Therefore it has been difficult to understand how one affects the other. We define collaborative governance as the creation and support of collaborative partnerships by public agencies. Networks, by contrast, are organically developed by organizations independently of or within collaborative partnerships. These definitions allow us to analyze the extent to which state-sponsored collaborative partnerships enhance organizational networks. Our data come from a member survey of 57 collaborative partnerships for restoring marine areas and fresh water ecosystems in the US. We find that network ties increase when organizations participate in collaborative group activities, but the effect diminishes as organizations belong to an increasing number of groups. This effect is strongest for organizations that report that their participation in a collaborative group has increased their access to information and resources and increased their awareness of other organizations. Given that state agencies often use collaborative partnerships as a tool to implement policies, it is important to know whether these partnerships enhance the inter-organizational network ties that facilitate delivery of those services.

Introduction

Collaborative governance and organizational networks are popular and well-documented topics, but the relationship between them is not always clear. In particular, scholars often fail to distinguish between specific, purposefully created entities, such as collaborative groups or partnerships, and the overall policy networks in which these structures are embedded. Recent work by Ansell and Gash (2008) and Emerson et al. (2012) has served to better distinguish between collaborative governance and networks. However, to date little empirical analysis has been conducted to examine the link between collaborative institutions and underlying networks (with Margerum [2011] being a considerable exception). Instead, the literature tends to examine network-level variables (e.g., Berardo and Scholz 2010; Henry et al. 2010; Prell et al. 2009; Schneider et al. 2003) or within-group variables (e.g., Benson et al. 2013; Imperial 2005; Sabatier et al. 2005; Sabatier and Shaw 2009) without examining how the latter influences the former.

To address this knowledge gap, we use a transactions cost-based approach to examine the extent to which state-sponsored collaborative partnerships enhance organizational networks. Our overall research question is *to what extent does participation in a collaborative partnership foster inter-organizational network ties?* In the following section, we describe the theoretical rationale for our research, outlining hypotheses drawn from a transactions cost perspective that links participation in collaborative group outputs (e.g., meetings or conferences) to network outcomes (e.g., coordinated planning or joint policy implementation). We then describe our data and methods, present the results, and discuss our findings.

Theoretical Rationale

To understand the effect of collaborative governance on organizational networks it is necessary to begin with a framework that distinguishes one from the other. In this regard, Margerum (2011) identifies collaborative governance as “an approach to solving complex problems in which a diverse group of autonomous stakeholders deliberates to build consensus and develop networks for translating consensus into results” (6) and networks as “sets of individuals bound by communication, relationships, positions, or interest area” (33). Emerson et al. (2012) similarly define collaborative governance as “the processes and structures of public policy decision making and management that engage people constructively across the boundaries of public agencies, levels of government, and/or the public, private and civic spheres” (2). In both frameworks, collaborative governance occurs within networks. Networks may precede collaborative groups, and collaborative groups may enhance networks.

We view collaborative governance as a policy tool used by government officials to achieve specific ends, including enhancing organizational networks. In this regard, Ansell and Gash (2008) offer six criteria that characterize a collaborative governance intervention by state actors:

> *(1) The forum is initiated by public agencies or institutions, (2) participants in the forum include nonstate actors, (3) participants engage directly in decision making and are not merely ‘consulted’ by public agencies, (4) the forum is formally organized and meets collectively, (5) the forum aims to make decisions by consensus (even if consensus is not achieved in practice), and (6) the focus of collaboration is on public policy or public management (Ansell and Gash 2008, 544).*

The rationale for government support of collaborative groups is often a perceived lack of coordination amongst actors in networks. Network coordination is not costless. Government sponsorship of collaborative groups is one way to reduce these costs.

Organizations are presumed to pursue network relationships when the benefits of doing so outweigh the transaction costs (Hill and Lynn 2003; Sabatier et al. 2005). Thus, these "transaction costs" (Coase 1960) largely dictate the existing network landscape. The literature concerning the benefits of forming and maintaining network ties characterizes them broadly, including information access, issue understanding, conflict reduction, and implementation support (Moreland et al. 1993; Gigone and Hastie 1993; Cragan and Wright 1990; Hill and Lynn 2003; Susskind et al. 1999; Sabatier et al. 2005). There are also time and resource costs associated with collaboration that constrain networking. For instance, Thomas (2003) finds that travel time is a key predictor of involvement in coordination activities, and Margerum (2011) describes interviews with high-level managers who are forced to selectively participate in specific meetings of various coordinative groups due to the overall volume of groups and group activities. There are also more intrinsic factors such norms of reciprocity (Putnam 2000) or shared beliefs and preferences (Schneider et al. 2003; Sabatier and Jenkins-Smith 1993) that can constrain (when they do not exist) or motivate (when they do exist) inter-organizational collaboration.

The rationale for government support of collaborative groups is often that such groups will alleviate a perceived current lack of coordination amongst network actors (by reducing or subsidizing transaction costs of networking). While collaborative groups are widely employed throughout the US and internationally (Niles and Lubell 2012), there is little evidence regarding the effect of collaborative groups on organizational networks. Lubell et al. (2010) and Thomas (2003) find that collaborative groups reduce such relational transaction costs. However, other studies concerning the overall effectiveness of collaborative groups in this regard present mixed results depending on history, participation incentives, power and resource imbalances, leadership, and institutional design (Ansell and Gash 2008; Heikkila and Gerlak 2005; Koontz and Thomas 2006; McCloskey 1999; 2001; Newig and Fritsch 2009; Weible 2011). Most importantly, none of these works are able to link collaborative groups to network structure and thus examine *how initiating and supporting a collaborative group alters an underlying organizational network.* In this analysis, we attempt to get inside the "black box" of "collaboration" that remains unexplained in the previously discussed works and examine how state sponsorship of collaborative groups affects organizational networks.

Policy makers can use collaborative partnerships to subsidize the transaction costs of networking by doing such things as funding a venue, sponsoring a coordinator and staff, and providing administrative support. Since other network organizations do not have to bear these costs, this shifts the benefit-cost equation of group membership, since organizational costs are now limited largely to time and travel. For members of the group then, the basic premise is that participation in group activities will increase familiarity and trust (i.e., social capital, see Burt [2000] and Putnam [2000]) with other group members and thereby further reduce transaction costs. In the context of collaborative groups, Emerson et al. (2012) refer to these transaction cost reducing mechanisms as "principled engagement" and "increased capacity for joint action." The question we seek to address in this paper is whether increased network ties are attributable to participation in collaborative group activities. If collaborative groups do foster principled engagement amongst network organizations and increase the capacity for joint action, we would expect that this effect stems from participation in group activities such as attending a monthly meeting or participating in a group project. Since building inter-organizational rapport requires that both organizations be present, we also expect that this effect is conditional on the extent to which two organizations participate in collaborative group activities; we hereafter refer to this pairwise group co-participation level as "shared group activity level." Accordingly, we hypothesize that it is not only shared group membership, but shared group activity level, that is positively related to the likelihood of reporting a tie with another group member:

H1: Shared group activity level with a given organization is positively related to the likelihood of reporting a network tie with that organization.

Again, while we certainly expect shared group activity level to be positively related to network ties, if only because it denotes organizations that are in close proximity to one another, we are most interested in how strong this effect is, as it speaks to the effectiveness of state support for collaborative groups as a policy tool for enhancing organizational networks.

Further, it is important to acknowledge that collaborative groups exist within a broader pattern of inter-organizational ties and institutional structures. This speaks to an issue raised by Lubell et al. (2010), who describe collaborative opportunities as representing a tradeoff (e.g., which meeting to attend or which organization to work with). Given this, a collaborative group might create principled engagement and increase the capacity for joint action, but still not increase inter-organizational collaboration because member organizations already possess ample network partners, already collaborate with group members, or simply switch partners resulting in a zero-sum change. Broadly, this overabundance of collaborative opportunities is known as "collaborative fatigue" (Huxham and Vangen 2005).

Whereas many analyses of collaborative governance emphasize the group dynamics associated with one collaborative group (or particular groups in disparate regions), a primary contribution of our analysis is that we take stock of the thick layer of collaborative groups that exist above, below, and in concert with our state sponsored "treatment" groups. In essence, what we aim to test is the extent to which the potential for network change is mitigated by participation in other collaborative groups, a key implication for policy makers considering initiating and supporting a collaborative group.

H2: Participation in external collaborative groups (i.e., those that are not initiated or supported as part of a state-sponsored network intervention) decreases the effect of co-membership in a state-sponsored group on the likelihood of reporting a network tie with another member of a state-sponsored group.

While shared group activity level speaks to the degree to which collaborative groups foster interaction between network organizations, participation in group activities does not fully speak to the causal mechanisms by which collaborative groups are theorized to alter network structure and function. The literature concerning collaborative groups places great importance on face-to-face interaction and relatively simple variables such as awareness of the capabilities and capacities of other network organizations. Emerson et al. (2012) refer to these types of mechanisms respectively as "principled engagement" and "increased capacity for joint action." Principled engagement (e.g., face-to-face interaction) and increased capacity for joint action (e.g., increased access to technical information) are key drivers of network outcomes because they are internal mechanisms that reduce inter-organizational transaction costs (Emerson et al. 2012).

For instance, increased awareness of the activities and capabilities of other network organizations makes it easier to take advantage of resources offered by other organizations, such as data or administrative support. Similarly, even if two organizations do not share the same preferences or agree on policy decisions (a focus of much of the collaborative governance research done by Schneider et al. [2003], Leach et al. [2005], and Scholz et al. [2008]), shared concepts, terminology, and definitions (i.e, knowing what each other are talking about) makes it much easier to productively dialogue with other organizations. While most of the literature on collaborative governance emphasizes the role of credibility and trust amongst network actors (elements more closely related to the concept of principled engagement), increasing the capacity for joint action has been also shown to be greatly important. For instance, Scholz et al. (2008) find that "information about potential partners appears to pose the greatest constraint to the expansion of joint programs" (404) (in comparison to attitudes related to trust and credibility).

Our final hypothesis thus represents an empirical test of the collaborative governance framework outlined by Emerson et al. (2012), who hypothesize that principled engagement and increased capacity for joint action are what motivate collaborative group outcomes.

H3: Organizations that report an increase in principled engagement and capacity for joint action stemming from their participation in a collaborative group are more likely to report a network tie with other group members.

Methodology

Case Selection

Our research focuses on a set of 57 collaborative partnerships in Washington State that are working on environmental issues related to the Puget Sound, which is the second largest estuary in the U.S. The Puget Sound case is interesting because in 2007 the Washington State Senate passed a bill authorizing the creation of the Puget Sound Partnership (PSP) as a coordinating body. Despite its confusing name, the PSP is in fact a state agency, not a collaborative partnership. The PSP is tasked with administrative oversight and coordination amongst local, state, and Federal organizations engaged in environmental policy efforts in the Puget Sound region.

A primary charge of the PSP has been to initiate and support local and regional collaborative groups throughout the Puget Sound region. This includes local education and outreach collaborative groups referred to as "ECO Nets," local coordinating groups comprised of local stakeholders and policy makers known as "Local Integrating Organizations", and regional groups such as the "Ecosystem Coordination Board." In all, 34 different groups were either created or began receiving significant funding (e.g., to hire a full time coordinator) as part of the PSP's efforts to subsidize collaborative group formation and maintenance. Thus we are able to examine the extent to which state-sponsored collaborative groups enhance organizational networks.

Also in our sample are a set of 23 collaborative groups that preceded the PSP. These include inter-organizational deliberative bodies (e.g., the Puget Sound Federal Caucus) and local collaborative groups such as County Marine Resource Committees and Watershed Inventory Resource Areas. These groups predate the groups formed by the PSP and continue to exist in concert. This provides an extensive comparison group and allows us to model group membership inside and outside of the PSP sponsorship umbrella, thus providing a more comprehensive picture of the overall network than would be facilitated by simply looking within PSP-sponsored groups. In sum, our sample of 57 collaborative groups includes 34 groups that were part of the state-sponsored intervention and 23groups that preceded the intervention.

Survey Sampling

We asked all members of the 57 collaborative groups in our sample to fill out a survey on their network activities. We worked with the PSP to identify the universe of collaborative groups working on Puget Sound environmental issues, including both the groups the PSP initiated and those it did not. We then contacted group members through the group coordinators. That is, we asked the group coordinators to send out the survey request as a direct email from themselves to group members on the official group email list. Respondents were instructed not to forward the survey link to anyone else. Thus, those included in our target sample are precisely those individuals who are considered to be formal group members. Moreover, receiving the request from a familiar contact presumably lends credibility to our request and improves our participation rate. We further discuss sampling, particularly our participation and completion rates, in the data and analysis section that follows.

Survey Instrument

Our survey technique uses a variation on the “hybrid name generator” technique developed by Henry et al. (2012). Our online survey instrument asked respondents to list up to five organizations with which they regularly engage in: (1) joint projects or program implementation (given that many organizations are consulting, funding, or administrative support bodies, this includes activities such as permitting assistance); (2) coordinated planning or strategy development; and (3) informal consultation (e.g., information sharing). Thus, each respondent could potentially list up to 15 organizations. While many respondents likely could have listed more organizations as collaborators, we limited responses in order to make survey completion tractable and to emphasize regular, substantive organizational ties. Along with asking respondents to identify network partners and the collaborative groups in which they participate, the survey instrument also produced data on their level of participation in collaborative group outputs (e.g., attendance at meetings), as well as each respondents' assessment of the benefits and effects of their participation in each collaborative group in which they are a member (e.g., increased awareness of the goals or the capabilities of other participating organizations).

Data and Analysis

Survey Response

We are unable to provide an exact response rate because we did not have access to all of the group lists. Recall that we contacted respondents through group coordinators, all of whom forwarded our request to their group members, but some of whom did not want to share their lists. Thus we estimated our response rate by using published membership rosters, from which we estimate that the 57 collaborative groups in our sample included approximately 1600 "group-seats". The estimate is not exact because membership is constantly in flux and not every group maintains a roster. These 1600 group seats, however, are filled by a smaller number of individuals, because some people are members of more than one group. Thus, we were able to identify 902 unique organizational representatives from available rosters. Based upon the size of groups for whom we were able to access rosters, we assume that the groups for whom no roster was available represent an additional 100 individuals, giving us a sample population of approximately 1000 organizational representatives.

While 498 individuals accessed the survey instrument, our workable sample was smaller. In particular, 63 respondents did not provide an organization that they represent, which means that they cannot be included in our organizational network analysis. An additional 35 did not complete the portion of the survey in which they were asked to identify network ties. Since it would be incorrect to model these individuals as having zero network ties, they are also excluded from the statistical analysis. Given our working sample size of 400 individuals, this equates to a response rate of around 40%.

Modeling Network Data

We use exponential-family random graph (ERG) models to analyze the network data as a way to account for the lack of independence amongst observations (Kolaczyk 2009). ERG models, or ERGMs, treat the observed network as the dependent variable and fit structural parameters and covariates to “explain” network structure (Prell 2012). Standard regression approaches are not viable for network data, since observations are non-independent of one another; thus, ERGMs are frequently used to analyze dependent relational data in the policy literature (e.g., Desmarais and Cranmer 2012; Lee et al. 2012; Jasny 2012).

Our analysis uses a recently developed modification of the standard ERGM MCMC fitting procedure: an approximate maximum likelihood estimation technique developed by Hummel et al. (2012) that uses a partial stepwise approach to iteratively update parameter estimates. Though a full discussion of this approach is beyond the scope of this paper, briefly, the ERGM fitting algorithm alternates between adjusting parameter estimates based upon either (1) the observed network statistics or (2) the mean network statistics from the series of simulations, ultimately converging on the maximum likelihood parameter estimates. We can then build on this model by adding organizational and pairwise attributes (such as shared group activity level from H1) to the model and testing our hypotheses.

Model Specifications

As with other model fitting applications, parameter selection requires making tradeoffs between thoroughness, goodness-of-fit, and statistical significance. Since every network is unique, fitting an ERG model is a "trial-and-error process" (Lusher et al. 2013, 184); thus, the baseline model that we present in Table 1 and describe below is the best-fit model stemming from a series of stepwise model fittings. A common problem in ERGM analysis is that the distribution of graphs to which the observed network is compared can place far too much weight on a small subset of simulated outcomes (Kolaczyk 2009). This issue, known as model degeneracy, makes model estimation unfeasible since it places too much weight on a small set of outcomes (Handcock 2003) and thus renders the underlying simulated distribution an extremely poor fit for the observed network (Goodreau et al. 2009). In particular, this issue arises in the context of comparing the observed number of higher order network structures (e.g., triangles) to those simulated.

Because of the potential for degeneracy, it is important to establish that our base model is a good fit for our observed data before proceeding to fit covariates and test our hypotheses (or else we cannot adequately test our parameters of interest). To do this, we use the fitted ERGM to simulate a large number of networks and then compare the resultant distribution for each network statistic to the statistics in the fitted model (i.e., statistics derived from observed data) (Goodreau et al. 2009).

Figure 1 provides a gauge of model fit for the model used in our analysis below, showing the distribution of network statistics from networks simulated using parameters from the fitted model. The unimodal distribution for each structure, nearly centered upon the observed statistics (646 edges and 1088 triangles) indicates that our model is not degenerate, since the simulated distribution does not trend towards a fully saturated network or empty network (i.e., complete density or zero density):

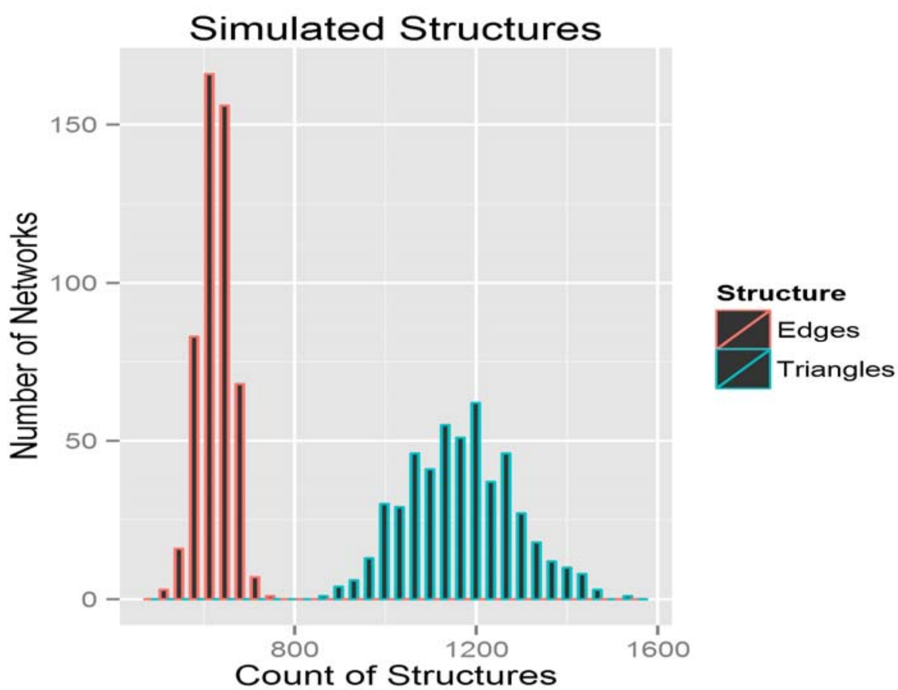

Figure 1: Edge Count and Triangle Count for Simulated Networks

Figure 2 (below) presents similar information, but this time focusing on the characteristics of each simulated network. The solid black line in each panel represents the observed network. For instance, the upper right panel shows how the distribution of "out-degrees," or ties *from* an organization, compares to the out-degree distribution for the series of simulated networks. The lower right panel represents the distribution of edgewise shared partner counts (triangles where A→C, B→C, and either A→B or B→A), and the lower left panel represents the distribution of minimum geodesic distances from each simulated network (geodesic distance is the number of ties it takes to connect one organization to another). The y-axis in each panel represents the proportion of nodes (organizations) which have a given number of each structure type. These plots demonstrate that our model is a good fit in this regard as well, as our simulated networks closely match the sparseness of the observed network.[1]

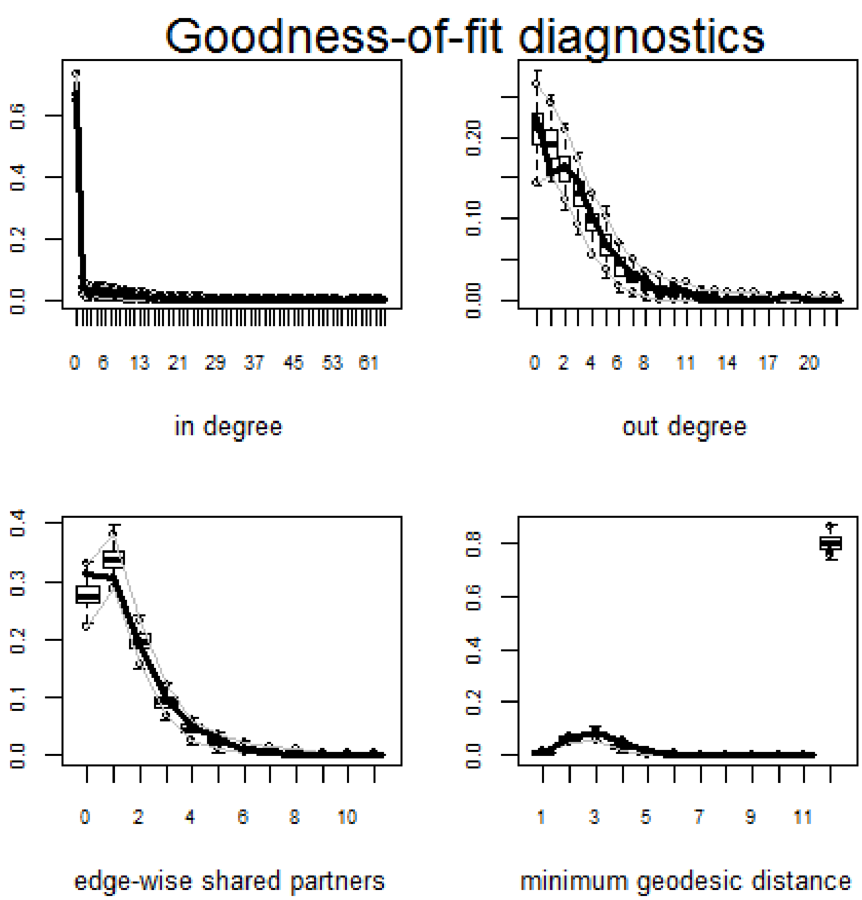

Figure 2: Goodness-of-Fit Diagnostics

[1] Note that the floating box in the lower right panel represents organizations who are an "infinite" length apart in then network; in other words, there is no path of edges linking one organization to the other.

Hypothesis Testing

Having established that our simulated distribution provides appropriate grounds for comparison to our fitted model, we can then proceed to fit further organizational and dyadic (pairs of organizations) covariates in order to test our hypotheses. We take advantage of the two-mode nature (organizations and collaborative groups) of our dataset to test whether co-participation in one or more collaborative groups increases the likelihood of two organizations actually reporting network ties. Specifically:

H1: Shared group activity level with a given organization is positively related to the likelihood of reporting a network tie with that organization.

To examine this relationship, we develop a "shared group activity level" metric that reflects the intersection between two organizations that participate in collaborative groups. While it would be relatively simple to use a summation technique and assign each organizational pair a score that reflects the total number of group memberships held in common, obviously all "participation" is not created equal. Thus, we use data on participation in group activities to assign a value to each pairwise combination of organizations that accounts for degree of participation. The possible group activities in the survey are: (1) send or respond to group emails; (2) attend group meetings; (3) attend other group events; (4) participate in group projects or programs; (5) read or review group reports and documents; (6) produce group reports or documents; and (7) other types of participation.

Since there is no obvious hierarchy amongst the different types of group participation, we treat the seven categories as nominal. Each reported group membership is assigned one point for each type of participatory activity the respondent reports engaging in. Thus, the maximum score for participating in any one group is seven, and the minimum score is zero. We then use a minimums method (Hanneman and Riddle 2005) to assign a shared group activity level score for each pair of organizations. For instance, if a participant in one group participates in two of seven group outputs, and another participates in five of seven, then the two organizations would be assigned a value of 2 to reflect the degree to which they participate collectively in collaborative group outputs.[2]

This score does not depend on these organizations reporting participation in the same two activities, just that they each report participation in at least any 2 of the 7 possible activities.[3] This is because we intend for this variable to holistically capture the relative level of involvement an organization has in a collaborative group. For instance, to continue the current example, if one organization attends group meetings and participates in "other" group activities, and the second organization responds to group emails, writes group documents, reviews group reports, attends other group events, and participates in group projects, matching on specific activities would still produce a shared activity level of 0. This would not reflect the degree to which both organizations are involved in the group, which is the primary variable we are

[2] For organizations that each participate in two or more of the same collaborative groups, we sum the minimum value from each joint group. Continuing the example above, if those same two organizations also participated in five and two outputs of a local watershed group and a regional group focused on education/outreach, then their overall score would be four (the minimum shared activity level from the watershed group [2] plus the minimum shared activity level from the education/outreach group [2]). This ensures two organizations that are primarily active in different groups do not receive a high overlap score as would two organizations that are very active in the same group. Note also that after generating and "overlap" score for each pairwise combination of respondents, the overlap scores are then aggregated for respondents from the same organization.
[3] Note that some organizations are represented more than once in our sample; typically, these are large state or county organizations that have multiple representatives on several collaborative groups. For these cases, we aggregate overlap within an organization.[3]

interested in. We believe that matching by activity type would represent an overly specific assumption, since: (1) the activity categories are interrelated to an extent; and (2) even if two organizations both respond that they work on group projects and review group reports, it is very possible –if not probable– that they have worked on entirely different projects and reviewed different reports. Thus, we cannot firmly posit direct interaction in any case, and run the risk of overly discounting the impact of group participation if we strictly match on activity type.

Conceptually, this shared group activity level metric is important, because H1 is built on the theory that participation in collaborative group activities reduces the transaction costs associated with engaging in joint activities with other organizations (because it provides a subsidized opportunity to engage with other organizations and build rapport and trust). For the hypothesized mechanism to actually work, however, both organizations must engage in group activities. These data can then be fitted as an independent variable in an ERGM model to asses the extent to which shared group activity level is predictive of an inter-organizational collaborative tie. Further, while we are able to generate a unique numeric shared group activity score for every combination of organizations, we believe that the construct we are attempting to measure (interaction within collaborative groups) is in fact best treated categorically. For instance, one might posit that zero interaction, limited interaction, and extensive interaction are in fact highly distinct states, but that small changes in interaction scores within these broader categories are less impactful. Thus, we fit shared group activity as an ordinal categorical variable with four levels: no overlap, limited overlap (less than or equal to 7), moderate overlap (less than or equal to 14), and significant overlap (more than 14). These break-points were chosen because the maximum overlap score possible from joint membership in one group is 7.

Table 1 presents the results from our first model testing H1 (compared to the baseline model discussed above), including several structural parameters recommended by Snijders et al. (2006) and Lusher et al. (2013) for fitting ERGMs. Interpreting an ERGM is somewhat similar to interpreting a logistic regression model, in that both model the probability of observing a binary outcome. In this case, we observe whether or not there is a network tie between two organizations (0 for not present, 1 for present). Thus, effect estimates are given in additive log-odds, which we can then exponentiate to find a multiplicative effect on the odds of there being a tie. For instance, the "edges" parameter reflects the overall density of ties in the observed network (density equals the number of observed ties over the number of possible ties). The baseline odds of two randomly selected organizations possessing a network tie is 0.008 to 1 (which we calculate by exponentiating the parameter (-4.78) to get a multiplicative effect on the odds ratio), which speaks to the fact that the observed network is large and sparse.[4]

[4] The "mutual" parameter reflects the change in likelihood that A→B given that B→A. One organization reporting a tie to another organization increases the odds of the second organization reporting a reciprocal tie by more than 800% (since we multiply the baseline odds by 9.11 = exp(1.16)); this large magnitude is unsurprising given the sparseness of the overall network, as in this context we would expect a mutual tie to be much more likely than a tie to a randomly chosen organization. The "ctriple" term is a cyclic closure parameter which reflects a tendency for generalized reciprocity amongst organizations, e.g., triangle of A→B, B→C, and C→A. The "twopath" term reflects the number of organizations linked to a given organization by two "edges" (e.g., A→B→C) (Lusher et al. 2013, 175). The GWIDegree parameter stands for geometrically weighted in-degree; this reflects the distribution of tie frequency reported to organizations in the network. Most organizations in our network are named as a partner by just one or two other organizations. This is reflected by the GWIDegree parameter estimate, in which each reported tie to an organization decreases the probability of another reported tie by 98% (0.015 = exp(-4.19)). The geometrically weighted out-degree parameter ("GWOdegree") is similar, in that it reflects the distribution of outgoing ties reported by respondents. Finally, the GWESP parameter, or "geometrically weighted edgewise shared partners," accounts for network transitivity. Essentially transitivity refers to the realization of the "friend of my friend is my friend" axiom. In keeping with what we might expect, if two organizations share a common network partner (e.g., A→C and B→C), then they are 169% more likely to report a tie themselves (A→B or B→A) (2.69 = exp(0.99)). We also add a control parameter for the number of organizational respondents included in our sample, since these organizations thus had an increased opportunity to identify network ties. A one person increase in respondent number increases the probability of a reported tie by 18% (1.18 = exp(0.17)).

Table 1: Testing H1

	Model 0[5]	Model 1
(Structural Parameters)		
edges	-4.87***	-4.78***
mutual	2.50	2.21
Twopath	-0.07*	-0.07*
Ctriple	-0.02	-0.39
GWIDegree (α=ln(2))	-3.89***	-3.58***
GWODegree (α=ln(2))	-0.34	-0.01
GWESP (λ=2)	1.14**	0.99***
(Covariates)		
Number of Responses	0.21*	0.17*
Number of Groups	0.02	-0.03
Shared Group Activity Level (0 to 3)		1.03***
Bayesian Information Criterion (BIC) :	4201.5	3994.1

* < 0.10, ** < 0.05, *** <0.01

Proceeding to the parameter of interest, Model 1 in Table 1 has the same specifications as the baseline model (Model 0) but with an additional parameter showing the estimated effect of shared group activity level. The lower BIC score evidences that Model 1 is a better fit. Model 1 estimates that a one category increase in shared group activity level increases the likelihood of a network tie between two organizations by 180% (2.80 = exp(1.03)). In other words, organizations that have a limited shared group activity level are more than twice as likely to report a network tie with one another than with no shared activity level; likewise, an increase from limited shared group activity to moderate shared group activity more than doubles the odds of a network tie again.

It is important to remember that part of the magnitude of this parameter stems from the fact that the baseline probability for a tie existing is very low, since our network is large and

[5] Note that we remove some of the other parameters included in the original baseline model used to establish goodness-of-fit using structural parameters only because they lack statistical significance and decrease the goodness-of-fit of the model once the actor covariates are added in. Whereas in standard regression applications, insignificant covariates do not hurt the model even if they do not improve model fit, additional insignificant parameters can cause ERG models to become unstable and/or degenerate, thus it is appropriate to remove them (see Lusher et al. 2013).

sparse; that is to say, even a 100% increase of a very low probability is still a low probability. Nonetheless, this result still speaks to a substantive increase in actual collaborative activity engendered by participation in collaborative group outputs. While this result does indicate that there is a relationship between shared group activity level and network ties, this result alone cannot speak to a causal relationship, since we cannot rule out the possibility that network ties foster participation in collaborative group outputs, rather than the other way around. For instance, an employee of one organization might invite a project partner from another organization to join a collaborative group, or inform them about an upcoming meeting or event. In the next section, we specifically examine participation in groups recently created by the PSP to address this possibility.

H2: Participation in external collaborative groups (i.e., those that are not initiated or supported as part of a state-sponsored network intervention) decreases the effect of co-membership in a state-sponsored group on the likelihood of reporting a network tie with another member of a state-sponsored group.

While the PSP itself was formed in 2007 and subsequently initiated its own collaborative groups, other groups predate the PSP and the groups it supports. Figure 3 speaks to the sheer volume of collaborative groups active in the region. The frequency distribution of the number of groups that each organization surveyed participates in shows the density and breadth of collaborative opportunities available to network actors. It is not likely, then, that many participants in the more recently created PSP groups were encountering other organizations for the first time.

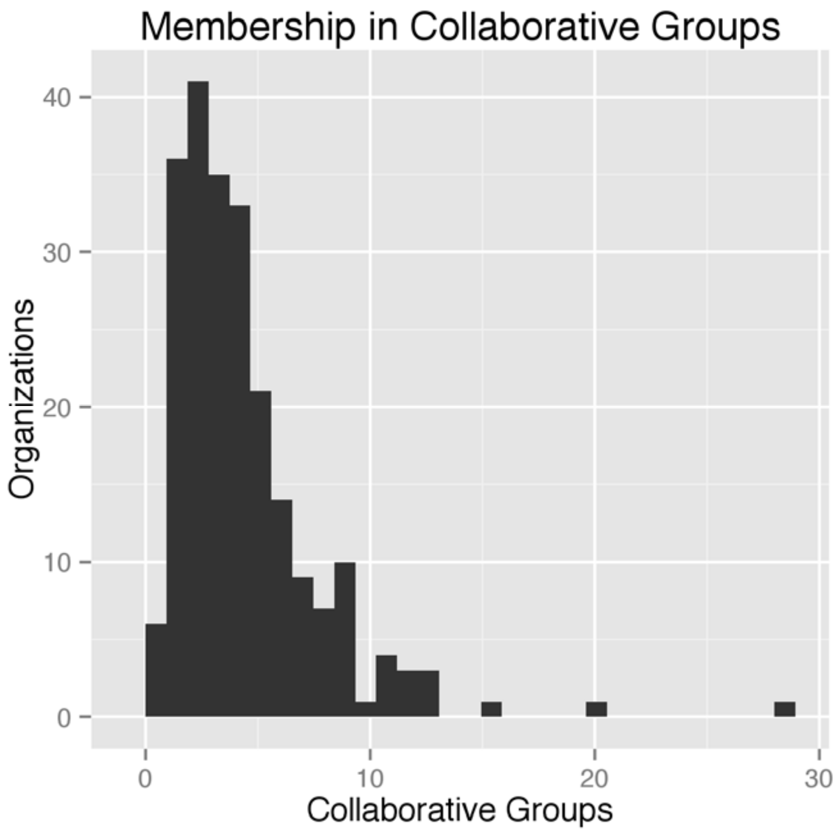

Figure 3: Distribution of Number of Collaborative Group Memberships by Organization

Simply put, our hypothesis is based on the assumption that there are decreasing returns to membership in collaborative groups, and that organizations have limited bandwidth for collaboration. Thus, we expect that the marginal impact of participation in a PSP-initiated collaborative group would be lessened for organizations that already participate in other collaborative groups. In order to test this, we partition the shared group activity levels for PSP-sponsored groups and non-sponsored groups. The shared group activity level of PSP-sponsored groups thus represents the increase in shared group activity wrought specifically by these interventions. We then test H2 using a series of interaction terms, shown in Table 2.

Table 2: Testing H2

	Model 2	Model 3	Model 4	Model 5
(Structural Parameters)				
edges	-5.02***	-5.16***	-5.21***	-5.23***
mutual	2.28*	2.04	1.70	1.36
twopath	-0.05	-0.06	-0.04	-0.04
ctriple	-0.33	-0.03	-0.28	-0.28
GWIDegree (α=ln(2))	-3.77***	-3.64***	-3.70**	-3.96**
GWODegree (α=ln(2))	-0.02	-0.02	0.07	0.09
GWESP (λ=2)	1.06***	1.01***	0.97*	1.01***
(Covariates)				
Number of Responses	0.18*	0.18**	0.15	0.14
Number of Non-PSP Groups	-0.01	-0.01	0.01	-0.01
Non-PSP Shared Group Activity Level	0.87***	0.67**	0.73*	0.97*
PSP Shared Group Activity Level		0.96***	1.25**	1.44**
# Non-PSP Groups * PSP Shared Group Activity Level			-0.03	
Non-PSP Shared Activity Level * PSP Shared Activity Level				-0.55
BIC:	4067.0	3977.8	3958.1	3929.7

* < 0.10, ** < 0.05, *** <0.01

First, we fit a baseline model (Model 2) that controls for only shared group activity in non-PSP sponsored groups (i.e., those that are not part of the state sponsored network intervention). Model 2 does show a strong effect (a 139% increase in probability for a one category increase in shared group activity level, calculated by exponentiating the parameter estimate (2.39 = exp(0.87)) and multiplying this by the odds ratio) for shared group activity level amongst organizations for these groups as well. In Model 3, we then add in shared group activity level for PSP-sponsored groups. Again, as we would expect this is a positive effect: shared group activity makes organizations 160% more likely (2.61 = exp(0.96)) to engage in collaborative activity with one another relative to organizations with which they have little shared group activity. We then use Models 4 and 5 to test H2.

Model 4 incorporates a term that interacts the number of non-PSP groups that an organization participates in with the group activity level this organization shares with each other organization in a PSP-sponsored group. Our hypothesis (H2) is that the more additional groups that an organization participates in, the less impactful participation in a state-sponsored network intervention will be. This is because we assume that organizations that are already part of many other collaborative groups simply have less to gain from additional networking. While the interaction parameter (*Non-PSP Groups * PSP Shared Group Activity Level*) is insignificant and small, something very interesting happens when it is included in the model. The direct effect of shared group activity level in PSP groups becomes much stronger than in Model 3. This linear term now represents the estimated effect of shared group activity level for an organization that participates in no unsponsored groups (since the interaction term cancels out): for an organization that participates in no outside groups, a one category increase in shared group activity level increases the odds of a network tie by 250% (3.49 = exp(1.25)). While the statistical insignificance of the interaction term prevents us from accepting H2 and rejecting the null hypothesis, the model results do indicate that the effect of shared group activity in a collaborative group is much stronger for organizations that are not already active in other collaborative groups.

Model 5 conducts a similar test, this time interacting the shared group activity levels for PSP and non-PSP groups. This parameter is also insignificant, thus we again technically fail to reject the null hypothesis. Nonetheless, it is interesting to consider: (1) the large negative effect estimate for this term; and (2) how both the predicted independent effect of shared group activity level in both types of collaborative groups become much larger. What this indicates is that the effect of shared group activity is generally strongest for organizations that are not members of many other groups (since the negative interaction term is canceled out when there is no shared group activity in one of the two categories). To summarize, while we do not have sufficient statistical power to reject the null hypothesis and accept H2, the ERGM results do appear to evidence the theoretical contention that there are diminishing returns to shared activity in collaborative groups. We discuss the implications of this in greater detail in the discussion section below. Next, we proceed to test our final hypothesis regarding the effect of collaborative group membership and participation on organizational networks.

H3: Organizations that report an increase in principled engagement and capacity for joint action stemming from their participation in a collaborative group are more likely to report a network tie with other group members.

Principled engagement is a process in which organizations get to know each other by meeting and engaging with one another. In other words, they learn about the perspectives and viewpoints of their counterparts, as well as the goals and actions of each organization (Emerson et al. 2012). Thus, our survey instrument asks respondents whether participation in a collaborative group has: (1) increased their awareness of the interests and values of other organizations; (2) increased the amount of face-to-face communication they engage in with other organizations; and (3) increased their understanding of commonly used language in the field (i.e., fostered a more common frame of reference). Each question is scored on a 1 to 5 Likert scale from “strongly disagree” to “strongly agree.” For instance, a respondent who reported that they “Agree” with the statement: “My participation in [group name] has increased the amount of face-to-face communication I engage in with other organizations” receives a score of 4 for this variable. The variable is then coded so that the "Principled Engagement: Increased Face-to-Face Communication" score between that organization (A) and every other organization (e.g., B) that reports membership in the same group is 1 ($PE_{(face)AB} = 1$) (Organizations that share no common group memberships are given a 0).

However, if organization B is also surveyed and provides a "Strongly Disagree" response to the same question, then $PE_{(face)BA} = -2$. Thus, coding for each response results in a series of asymmetric matrixes representing each component of principled engagement both from and to each organization. For all organizations with which an organization does not share a group, the score is zero, since presumably the amount of principled engagement between these organizations did not change. For two organizations that are both a member of multiple groups, we use the mean reported score across all shared groups. Table 3 presents the results of models containing each variable.

Table 3: Principled Engagement

	Model 6	**Model 7**	**Model 8**
(Structural Parameters)			
edges	-5.70^{***}	-5.87^{***}	-5.55^{***}
mutual	-2.36	-3.15^{*}	-2.14^{*}
twopath	-0.07^{***}	-0.07	-0.07^{***}
ctriple	-0.19	-0.18	-0.22
GWIDegree (α=ln(2))	-4.12^{***}	-3.66^{***}	-4.40^{***}
GWODegree (α=ln(2))	0.01	0.19	0.01
GWESP (λ=2)	0.74^{***}	0.81^{***}	0.79^{*}
(Covariates)			
Number of Responses	0.22^{*}	0.23^{***}	0.23^{***}
Number of Groups	0.01	-0.01	-0.02
Shared Group Activity Level	-0.01	-0.03	0.05
Face-to-Face Communication	1.72^{***}		
Awareness of Interests and Values		1.81^{***}	
Understanding of Common Language			1.82^{***}
BIC:	2046.0	2030.9	2124.8

* < 0.10, ** < 0.05, *** <0.01

As Table 3 shows, higher levels of all three subcomponents of principled engagement are associated with a strong increase in the probability of reporting a network tie with another organization. For instance, we can exponentiate the Face-to-Face Communication term and observe that a 1 scale-unit increase in perceived amount of face-to-face communication in a collaborative group increases the odds an organization reporting a tie to another group member by more than 450% (exp(1.72) = 5.58). While this might at first glance seem outlandish, it is important to remember that the magnitude of our parameters is somewhat misleading due to the fact the baseline odds of a network tie between two organizations are so low, owing to the size and sparseness of the observed network. For instance, without considering other covariates, the baseline odds of a tie between any two organizations in Model 6 is 0.003 to 1; thus, even a 450% increase only increase the odds to about 0.02 to 1. Nonetheless, these results indicate a strong predicted effect of principled engagement, as organizations that report an increase in face-to-face communication, understanding of the interests and values of other organizations, and understanding of common language stemming from membership in a collaborative group are much more likely to report a tie to other group members, even after controlling for shared group activity level.

A final key observation is that each principled engagement variable appears to account for most of the effect that was previously attributable to shared group activity level. In all three models, the shared group activity level parameter is close to zero and insignificant now. None of the other covariates or structural parameters demonstrate any noteworthy changes, with the exception of the “mutual” estimate, which became strongly negative in all three models, and slightly significant in Models 7 and 8. It is unclear why this would occur, and we hope to explore this further in future analyses.

Note that we do not fit an unrestricted model with all three subcomponents together since the three variables are highly correlated (thus the model would be subject to multicollinearity). Due to this correlation (about 98% for each pairwise combination), we also do not highlight distinctions between the subcomponents, instead focusing on the broader estimated effect of principled engagement in general. The intercorrelation between sub-components is not unexpected, since they are largely interdependent (e.g., face-to-face communication facilitates increased awareness of other's beliefs and preferences, and increasing awareness of other's beliefs and preferences requires at least some form of communication). In this regard, it is important to note that the shared group activity level and each subcomponent of principled engagement are not highly correlated (no more than 40% in any case), evidencing a distinct effect of principled engagement net of shared group activity level.

We next estimate the effect of "increased capacity for joint action" in a similar manner. Increased capacity for joint action refers to processes wherein organizations (often via principled engagement) become more aware of the organizational capacity of those in their collaborative group and gain increased knowledge of available resources and opportunities (Emerson et al. 2012). Accordingly, our survey instrument gauges whether collaborative group participation has increased the capacity for joint action by asking respondents whether participation in a collaborative group has: (1) increased awareness of and/or access to scientific, technical, or policy-specific information; (2) increased access to human resources such as administrative support or IT services; and (3) increased access to financial resources such as grant opportunities. Table 4 presents our model results.

Table 4: Increased Capacity for Joint Action

	Model 9	Model 10	Model 11
(Structural Parameters)			
edges	-5.55***	-5.38***	-5.48***
mutual	-2.82*	-0.82	-1.98*
twopath	-0.07***	-0.06***	-0.03***
ctriple	-0.23	-0.10	-0.10
GWIDegree (α=ln(2))	-3.85***	-4.77***	-4.90***
GWODegree (α=ln(2))	0.18	0.34	0.36
GWESP (λ=2)	0.81***	0.87***	0.75****
(Covariates)			
Number of Responses	0.19***	0.16***	0.15*
Number of Groups	-0.01	-0.01	-0.01
Shared Group Activity Level	-0.09	0.34***	0.16
Access to Information	1.82***		
Access to Human Resources		1.95***	
Access to Financial Resources			1.79***
BIC:	2022.6	2475.4	2276.9

* < 0.10, ** < 0.05, *** <0.01

Again, we observe a strong effect associated with each covariate, indicating that increased capacity for joint action (as perceived by respondents) increases the likelihood of engaging in inter-organizational collaboration with other collaborative group members.[6] Unsurprisingly, these subcomponents are also highly correlated (though less so than for principled engagement, at approximately 90% for each pairwise combination), indicating considerable ambiguity across these concepts. We believe that this is likely a reflection of what organizations actually experience, however, as we would expect that in most cases these three effects occur in concert or not at all. For instance, a group that increases an organization's access to administrative support (such as the ability to communicate with group members via email list-serv) likely also then inherently provides increased ability to share information and learn about

[6] Again as well, the "mutual" term remains negative, but is of lesser magnitude and significance than for the principled engagement models. Otherwise, the structural parameters remain similar to that of previous models. One covariate change is with regards to Model 10: the shared group activity level parameter remains fairly strong and statistically significant. This indicates that administrative support and group participation do not go hand in hand to the extent that access to information and group participation apparently do.

grant opportunities and other funding sources. Thus, the main implication we draw relates to the more general concept, as all three variables are all largely uncorrelated with shared group activity level (about 30% in all three cases), indicating that the degree to which a group increases an organization's ability to engage with other organizations does have a strong relationship to actual inter-organizational collaboration.

Discussion/Conclusion

Our results provide concrete evidence of how collaborative groups affect an organizational network in which they are embedded. Prevailing wisdom holds that collaborative groups can increase policy effectiveness by reducing inter-organizational transaction costs without requiring formal structural changes or reorganization (Bardach 1998; Heclo 1978; Provan and Milward 1995; Schneider et al. 2003), but there has been little systematic analysis to date as to what specific effects result from the use of collaborative groups. Most importantly, while collaborative groups have been studied and written of extensively, the policy literature has largely failed to consider the use of collaborative groups as a policy tool. In particular, the current body of research regarding collaborative groups does not adequately address the fact that most collective action situations involve multiple institutions, not just the collaborative group itself (Lubell et al. 2010). Because of this, there is little theoretical guidance as to when such interventions might be warranted (Schrank and Whitford 2011) or what effects policy makers might anticipate from such efforts (Carlsson and Berkes 2005; Crona and Hubacek 2010). In this paper, we have sought to contribute to this discussion by taking a network perspective to analyze how state sponsorship and support of collaborative groups affects an organizational network. In other words, we seek to leave the normative discussion of collaborative governance aside and focus on what collaborative groups accomplish and how these affects vary given institutional context.

Specifically, we find that organizations that participate in the same collaborative group are much more likely to also engage in collaborative activities such as informal consultation, coordinated planning, and joint policy implementation with one another. This indicates that by sponsoring collaborative groups, policy makers can influence inter-organizational collaboration amongst organizations that are invited to participate. This effect is directly influenced by level of participation, indicating that group activities do serve to mitigate or reduce inter-organizational transaction costs.

Further, we find that this effect diminishes as the number of collaborative groups an organization participates in increases. This presents a very important consideration for policy makers, particularly in highly institutionalized contexts where other collaborative groups working on related issues may already exist. Organizations have limited time, resources, and bandwidth for collaboration. Thus, creating additional groups might not increase their overall network ties with other organizations. Conversely, the strong effect we found for organizations with previously limited group membership speaks to the potential for significant network changes that can be achieved by sponsoring groups that involve organizations that do not currently participate in other groups.

Finally, we find support for the theoretical framework for collaborative governance posed by Emerson et al. (2012) regarding the importance of principled engagement and increased capacity for joint action. Collaborative group activities are effective at fostering inter-organizational collaboration because they create opportunities for principled engagement. Policy makers seeking to initiate or utilize a collaborative group would do well to consider this in designing and structuring the group, taking care to provide opportunities for organizations to engage in direct communication, develop a common operating language, and learn about the goals and capabilities of other organizations. Collaborative groups are also effective at fostering inter-organizational collaboration when they make it easier for organizations to engage in joint activity together. Group activities and outputs that ease communication, illuminate which organizations possess particular resources and abilities, and make it easier for organizations to access data and technical information are all strongly predictive of network tie formation between group members. If organizations do not have to search for grant opportunities or email contacts, or know exactly who to contact for an informational request, search costs are reduced and they are much more able to engage in such activities.

Going forward, there are at least two important questions that remain to be addressed. First, from a practical perspective, it is important to examine whether these network effects produced by collaborative groups ultimately result in improved policy implementation. We have shown the conditions under which collaborative groups change network structure and function, but not whether these changes improved social or environmental conditions. Second, from a methodological perspective, our cross-sectional analysis represents a snapshot of a network at one point in time, and does not allow us to trace the effects of collaborative group participation over time. We hope to continue to build our current data into a longitudinal dataset that will provide a temporal perspective on organizational network dynamics, which will provide better insight into the causal effects of collaborative group formation and support by state actors. Nonetheless, we believe that our current analysis contributes to an evidence base that will enable more strategic use of public resources by helping policy makers to wield collaborative groups as a context-appropriate policy tool rather than a one-size-fits-all panacea for addressing policy problems.

References

Ansell, C., and A. Gash. 2008. “Collaborative Governance in Theory and Practice.” *Journal of Public Administration Research and Theory* 18 (4): 543–571.

Bardach, E. 1998. *Getting Agencies to Work Together: The Practice and Theory of Managerial Craftsmanship*. Washington, D.C.: Brookings Inst Press.

Benson, David, Andrew Jordan, Hadrian Cook, and Laurence Smith. 2013. “Collaborative Environmental Governance: Are Watershed Partnerships Swimming or Are They Sinking?” *Land Use Policy* 30 (1): 748–757.

Berardo, Ramiro, and John T. Scholz. 2010. “Self-Organizing Policy Networks: Risk, Partner Selection, and Cooperation in Estuaries.” *American Journal of Political Science* 54 (3): 632–649. /z-wcorg/.

Burt, R. S. 2000. “The Network Structure of Social Capital.” *Research in Organizational Behavior* 22: 345–423.

Carlsson, L., and F. Berkes. 2005. “Co-management: Concepts and Methodological Implications.” *Journal of Environmental Management* 75 (1): 65–76.

Coase, Ronald Harry. 1960. “Problem of Social Cost, The.” *Journal of Law and Economics* 3: 1–69.

Crona, B., and K. Hubacek. 2010. “The Right Connections: How Do Social Networks Lubricate the Machinery of Natural Resource Governance?” *Ecology and Society* 15 (4): 18–22.

Desmarais, Bruce A., and Skyler J. Cranmer. 2012. “Micro□Level Interpretation of Exponential Random Graph Models with Application to Estuary Networks.” *Policy Studies Journal* 40 (3): 402–434.

Emerson, K., T. Nabatchi, and S. Balogh. 2012. “An Integrative Framework for Collaborative Governance.” *Journal of Public Administration Research and Theory* 22 (1): 1–29.

Gigone, D., and R. Hastie. 1993. “The Common Knowledge Effect: Information Sharing and Group Judgment.” *Journal of Personality and Social Psychology* 65 (5): 959–974.

Goodreau, Steven M., Mark S. Handcock, David R. Hunter, Carter T. Butts, and Martina Morris. 2008. “A Statnet Tutorial.” *Journal of Statistical Software* 24 (9): 1–27.

Handcock, Mark. 2003. “Assessing Degeneracy in Statistical Models of Social Networks”. Working Paper no. 39. http://www.csss.washington.edu/Papers/wp39.pdf.

Hanneman, Robert, and Mark Riddle. 2005. *Introduction to Social Network Methods*. Riverside, CA: University of California.

Heclo, H. 1978. “Issue Networks and the Executive Establishment.” In *The New American Political System*, edited by A. King, 94:87–124. American Enterprise Institute.

Heikkila, T., and A. K Gerlak. 2005. “The Formation of Large□scale Collaborative Resource Management Institutions: Clarifying the Roles of Stakeholders, Science, and Institutions.” *Policy Studies Journal* 33 (4): 583–612.

Henry, A. D, M. Lubell, and M. McCoy. 2011. "Belief Systems and Social Capital as Drivers of Policy Network Structure: The Case of California Regional Planning." *Journal of Public Administration Research and Theory* 21 (3): 419–444.
———. 2012. "Survey□Based Measurement of Public Management and Policy Networks." *Journal of Policy Analysis and Management* 31 (2): 432–452.
Hill, C., and L. Lynn. 2003. "Producing Human Services: Why Do Agencies Collaborate?" *Public Management Review* 5 (1): 63–81.
Hummel, Ruth M., David R. Hunter, and Mark S. Handcock. 2012. "Improving Simulation-based Algorithms for Fitting ERGMs." *Journal of Computational and Graphical Statistics* 21 (4): 920–939.
Huxham, Chris., and Siv Vangen. 2005. *Managing to Collaborate : the Theory and Practice of Collaborative Advantage*. New York: Routledge.
Imperial, M. T. 2005. "Using Collaboration as a Governance Strategy Lessons from Six Watershed Management Programs." *Administration & Society* 37 (3): 281–320.
Jasny, Lorien. 2012. "Baseline Models for Two□Mode Social Network Data." *Policy Studies Journal* 40 (3): 458–491.
Kolaczyk, Eric D. 2009. *Statistical Analysis of Network Data: Methods and Models*. Springer.
Koontz, T. M, and C. W Thomas. 2006. "What Do We Know and Need to Know About the Environmental Outcomes of Collaborative Management?" *Public Administration Review* 66: 111–121.
Leach, William D., and Paul A. Sabatier. 2005. "Are Trust and Social Capital the Keys to Success? Watershed Partnerships in California and Washington." *Swimming Upstream: Collaborative Approaches to Watershed Management*: 233–258.
Lee, Youngmi, In Won Lee, and Richard C. Feiock. 2012. "Interorganizational Collaboration Networks in Economic Development Policy: An Exponential Random Graph Model Analysis*." *Policy Studies Journal* 40 (3): 547–573.
Lubell, M., A. D Henry, and M. McCoy. 2010. "Collaborative Institutions in an Ecology of Games." *American Journal of Political Science* 54 (2): 287–300.
Lusher, Dean, Johan Koskinen, and Garry Robins. 2012. *Exponential Random Graph Models for Social Networks: Theory, Methods, and Applications*. Cambridge University Press.
Margerum, R. D. 2011. *Beyond Consensus: Improving Collaborative Planning and Management*. Cambridge, MA: MIT Press.
McCloskey, M. 1999. "Problems with Using Collaboration to Shape Environmental Public Policy." *Valparaiso University Law Review* 34: 423.
Moreland, R. L, J. M Levine, and M. A Cini. 1993. "Group Socialization: The Role of Commitment." In *Group Motivation: Social Psychological Perspectives*, edited by M. A. Hogg and D. Abrams, 105–129. London: Harvester Wheatsheaf.
Niles, M. T, and M. Lubell. 2012. "Integrative Frontiers in Environmental Policy Theory and Research." *Policy Studies Journal* 40: 41–64.
Prell, C. 2012. *Social Network Analysis: History, Theory and Methodology*. Sage.
Prell, C., K. Hubacek, and M. Reed. 2009. "Stakeholder Analysis and Social Network Analysis in Natural Resource Management." *Society and Natural Resources* 22 (6): 501–518.
Provan, K. G, and H. B Milward. 1995. "A Preliminary Theory of Interorganizational Network Effectiveness: A Comparative Study of Four Community Mental Health Systems." *Administrative Science Quarterly* 40 (1): 1–33.
Putnam, R. D. 2000. *Bowling Alone*. Simon & Schuster.

Sabatier, P. A, W. Focht, M. Lubell, Z. Trachtenberg, A. Vedlitz, and M. Matlock. 2005. *Swimming Upstream: Collaborative Approaches to Watershed Management*. MIT Press.
Sabatier, P. A, and H. C Jenkins-Smith. 1993. “Policy Change and Learning: An Advocacy Coalition Framework.” *Boulder: Westview*.
Sabatier, Paul A., and Lauren K. Shaw. 2009. “Are Collaborative Watershed Management Groups Democratic? An Analysis of California and Washington Partnerships.” *Journal of Soil and Water Conservation* 64 (2): 61A–64A.
Schneider, M., J. Scholz, M. Lubell, D. Mindruta, and M. Edwardsen. 2003. “Building Consensual Institutions: Networks and the National Estuary Program.” *American Journal of Political Science* 47 (1): 143–158.
Scholz, J. T, R. Berardo, and B. Kile. 2008. “Do Networks Solve Collective Action Problems? Credibility, Search, and Collaboration.” *Journal of Politics* 70 (2): 393–406.
Schrank, A., and J. Whitford. 2011. “The Anatomy of Network Failure*.” *Sociological Theory* 29 (3): 151–177.
Snijders, Tom AB, Philippa E. Pattison, Garry L. Robins, and Mark S. Handcock. 2006. “New Specifications for Exponential Random Graph Models.” *Sociological Methodology* 36 (1): 99–153.
Susskind, L. E, J. Thomas-Lamar, and S. McKearnen. 1999. *The Consensus Building Handbook: A Comprehensive Guide to Reaching Agreement*. Sage Publications, Incorporated.
Thomas, Craig W. 2003. *Bureaucratic Landscapes : Interagency Cooperation and the Preservation of Biodiversity*. Cambridge, Mass.: MIT Press.
Weible, C. M. 2011. “Political-Administrative Relations in Collaborative Environmental Management.” *International Journal of Public Administration* 34 (7): 424–435.