Linking Network Structure to Collaborative Governance

Nicola Ulibarri, University of California, Irvine

Tyler A. Scott, University of Georgia

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Abstract

How do social networks differ between highly collaborative and less collaborative forms of governance? Drawing on a prior study that characterized the level of collaboration for three federal hydropower relicensing processes, we develop exponential random graph models of meeting attendance and participation networks. We find that the highly collaborative relicensing process had lower overall density and propensity for relatively fewer and stronger interactions. Reciprocity is highest in the high-collaborative process, indicating that it is characterized by mutual interactions. In the low-collaboration process, patterns of connections between any three members of the network displayed a more hierarchical structure, suggesting asymmetrical interactions between active versus passive members of the network. By linking network structure to collaborative dynamics, this study helps elaborate potential mechanisms of successful collaboration.

Keywords: Collaborative governance, policy networks, GERGMs, FERC hydropower relicensing

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Introduction

Public decision-makers and managers increasingly use collaborative, networked forms of governance to address complex public problems. In a collaborative process, public agencies work jointly with non-governmental organizations to develop or implement policies and programs. The process entails building trust between participants, developing shared understanding of the problem via deliberation and negotiation, and developing the resources, capacity, and leadership to support engagement (Ansell and Gash 2008; Bryson, Crosby, and Stone 2006; Bryson, Crosby, and Stone 2015; Emerson and Nabatchi 2015a). Through collaborative governance, public agencies can overcome longstanding conflict and build stakeholder trust and acceptance of decisions (Emerson et al. 2009; C. Scott 2011). It allows participating organizations to share resources (Berardo 2014) and integrate diverse types of information into decisions (Beierle and Cayford 2002; Connick and Innes 2003; Korfmacher and Koontz 2003; Dale and Armitage 2011). While analyses of collaborative governance's long-term performance are scarce, it has been shown to positively impact the resources managed (Kelman, Hong, and Turbitt 2013; Scott 2015b).

Accompanying collaborative governance's proliferation are calls to better evaluate its performance (Koontz and Thomas 2006; Thomas and Koontz 2011; Gray 2000; Innes and Booher 1999; Thomson, Perry, and Miller 2008; O'Leary and Bingham 2003; Emerson and Nabatchi 2015b; Thomson, Perry, and Miller 2009; Newig and Fritsch 2009a; Emerson, Nabatchi, and Balogh 2012). Collaborative governance's outcomes are theorized to emerge from interpersonal and interorganizational dynamics like principled engagement amongst participants (Emerson and Nabatchi 2015a). Thus, in order to better understand what collaborative governance does, it is important to consider how process features relate to collaborative outputs and outcomes (Ulibarri 2015a).

However, assessing interorganizational collaboration poses numerous analytical challenges. Analyzing collaboration within policy networks often requires intensive data collection and analysis methods such as interviews, document analysis, and process tracing (Ulibarri 2015b; Connick and Innes 2003; Margerum 2011) or survey instruments and statistical modeling (Schneider et al. 2003; Berardo and Scholz 2010; Berardo 2014; Lubell, Henry, and McCoy 2010; Thomson, Perry, and Miller 2009; Ulibarri 2015a; Scott and Thomas 2015). The effort required to collect and analyze these data present a significant research design barrier. Perhaps more importantly, these modes of data collection do not readily facilitate cross-case comparisons, longitudinal analysis, or replication. Survey instruments or interview scripts are typically customized for the network context at hand, for instance using a specific type of "name generator" (Henry, Lubell, and McCoy 2012) to elicit responses concerning network partners. While it is technically feasible to implement longitudinal surveys, pragmatic issues related to response burden and survey fatigue loom large. It is perhaps emblematic that the best known and most extensively used longitudinal collaborative environmental governance network data are a two period sample from 1999 and 2001 (see Scholz, Berardo, and Kile 2008; Berardo and Scholz 2010).

A readily available source of network data for policy and management actions is the paper trail of meeting minutes and public comments, containing objective data concerning who participants are and how they interact. However, the extent to which readily observable actions like meeting attendance reflect underlying collaborative dynamics is unclear. This

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paper takes advantage of a unique opportunity to examine the relationship between objective participation metrics and collaborative dynamics.

Having already established the underlying level of collaboration in three planning processes using document analysis and survey data (see Ulibarri 2015b), we use statistical network analysis to assess whether observed network linkage patterns (e.g., co-attendance at group meetings) reflect the occurrence of key collaborative dynamics. Thus, we make a theoretical contribution to the public administration literature by speaking to the relationship between participatory metrics and collaboration amongst network organizations; we also aim to make an empirical contribution by demonstrating how policymakers and managers might assess the efficacy of a collaborative governance process in real-time by monitoring attendance and participation.

In what follows, we first describe the cases selected for this analysis and the process by which each case was determined to exhibit low, medium, or high collaboration. We then describe the literature concerning policy networks and collaborative governance and develop hypotheses regarding what we should observe in low-collaboration versus high-collaboration networks. Then, we specify the exponential random graph models (ERGMs) used to model networks and test our hypotheses. Finally, we assess our findings and discuss their implications.

Background

We examine this question using the case of the Federal Energy Regulatory Commission (FERC)'s process for licensing hydropower facilities. To obtain a license for continued operation of a hydropower dam, electric utilities, water districts, and other dam owners/operators (hereafter referred to as "utilities") undertake a five-year process to identify potential project impacts, develop and interpret studies to quantify those impacts, and develop a license application containing operating requirements to mitigate those impacts. FERC then assesses these proposed requirements to determine the final contents of a license. Traditionally, the application was developed unilaterally by the utility, with feedback from resource agencies and other interested stakeholders occurring after the utility submitted its license application. Since the late 1990s, however, a series of process reforms have restructured the process to integrate stakeholder feedback from the earliest scoping phases (Kosnik 2010). At minimum, FERC hydropower relicensing requires a series of public meetings to discuss scoping, study development, study results, and draft and final license applications. However, many utilities opt to exceed these requirements, working closely with federal and state agencies, local governments, tribes, non-profit organizations, and the public throughout the process.

In Ulibarri (2015b), document analysis and a participant survey were used to measure the degree to which collaboration occurred amongst stakeholders for a series of recent hydropower relicensing processes. Collaboration was conceptualized following Emerson et al.'s (2012) "Integrative Framework for Collaborative Governance," which focuses on three dynamics. The first, principled engagement, reflects the use of face to face deliberation and negotiation to develop shared problem definitions and decisions. The second, shared motivation, captures the extent to which participants trust one another and believe the process is legitimate. The third, capacity for joint action, measures the leadership, structure, and resources necessary to support collaboration. We developed measures to operationalize these three dynamics, drawing on a survey of relicensing participants (to measure perceived levels of trust, efficiency, and co-creation) and analysis of meeting minutes, public comments, technical reports, and other documents developed during the relicensing (to qualitatively and quantitatively assess who participated, how they interacted, and whether the broader structure supported collaboration). These were then used to measure collaboration in eight recently-completed relicensing processes across the country. For more information, see Ulibarri (2015b).

In this analysis, we consider three distinct relicensings, shown in Table 1. All three processes took place after FERC's shift to a more collaborative relicensing approach. These three cases were selected because they represent three distinct levels of collaboration. In Washington (high collaboration), stakeholders were engaged via deliberation and negotiation throughout the relicensing process, such that both large and small decisions incorporated the full set of interests in the relicensing. In Missouri (medium collaboration), the process was designed to be collaborative and inclusive, with regular meetings, neutral facilitation, and interest-based negotiation. However, stakeholders did not trust one another, so once discussions entailed developing the actual management regime, stakeholders no longer engaged jointly and most large decisions were made by subsets of stakeholders. In Georgia (low collaboration), stakeholders were engaged only to the degree required by FERC regulation and most decisions were made unilaterally by the utility.

Table 1: Level of collaboration by case

	Washington	**Missouri**	**Georgia**
Principled engagement	High	Medium	Low
Shared motivation	High	Medium-low	Low
Capacity for joint action	High	Medium	Medium-low
Overall collaboration	High	Medium	Low

Note: Overall collaboration is aggregated from principled engagement, shared motivation, and capacity for joint action. See Ulibarri (2015b) for more information.

Hypotheses

The levels of collaboration shown in Table 1 stem from survey instruments and document analysis applied to each case. What we ask here is to what extent statistical network analysis of process participation tracks with the more detailed findings summarized in Table 1. Statistical network analysis is a common methodological toolkit applied to institutional collective action and collaborative governance research (Henry, Lubell, and McCoy 2011; Berardo and Scholz 2010; Berardo 2014; Berardo, Heikkila, and Gerlak 2014; Lee, Lee, and Feiock 2012; Leifeld and Schneider 2012; Jasny 2012; Jasny and Lubell 2015; Lubell et al. 2012; Henry 2011; Scott and Thomas 2015; Scott 2015a). Using network analysis allows us to characterize interorganizational network structure and to test hypotheses concerning individual network behaviors.

Because this paper seeks to compare network structures and observed collaboration level, we are particularly interested in what might be expected in each case. In other words, what should a network around hydropower facility relicensing to look like when collaboration is high versus when collaboration is low? The policy network literature informs our expectations regarding what structural characteristics should--or should not--be prominent in processes with a given level of collaboration, as different network configurations distinctly affect the ability of a collaborative network to solve the problem it was created to solve (Berardo 2014; Bodin and Crona 2009).

Network density

Network density refers to the average value of a randomly chosen network tie. Simply put, denser networks have more ties and/or higher value ties, so the average value of a tie is greater. Bodin and Crona (2009) hypothesize that in general, a greater number of ties presents greater opportunities for joint actions by increasing communication and fostering the development of norms of reciprocity and trust. This hypothesis reflects the broader notion that trust and social capital amongst actors facilitate collective action (Putnam 2000; Ostrom 2000; Axelrod 1997; Pretty and Ward 2001); further, several analyses of natural resource governance networks demonstrate a positive relationship between network density and joint action (Hahn et al. 2006; Sandström and Carlsson 2008).

H1: High collaboration processes will exhibit greater network density than low collaboration processes.

Our network data (described below) consist of discrete count data reflecting the total number of interactions between two actors within observed relicensing meetings. Coded network ties are thus counts, rather than a binary metric, allowing us to explore the extent to which interactions are concentrated within a relatively small subset of network actors, or whether interactions are more evenly distributed across the network. Specifically, network density can be increased in two ways: either by increasing the number of total ties in the network, or by increasing the value of ties that are already greater than zero.

Recall that in essence, network density is expected to increase collaboration because each network tie presents an opportunity for communication and joint action (Bodin and Crona 2009). However, two networks can exhibit similar density statistics and yet be structured very differently. Networks in which interactions are highly concentrated amongst a limited subset of actors, with more isolated actors and fewer paths of communication, can have high overall density due to these dominant relationships even if there is a lack of overall connectivity. Accordingly, one might anticipate that networks characterized by a stronger bimodal distribution of high-value ties and empty ties might not facilitate joint action.

Specifically, overall density (tie presence and magnitude) and non-zero density (tie presence) will differ to the extent that a few actors tend to dominate dialogue and deliberation (which will increase overall density but not non-zero tie density) versus more broadly participative processes (which will increase overall density and non-zero tie density). Thus, we hypothesize that relicensing processes shown to be more collaborative will differ from less collaborative relicensing processes in terms having more observed connections between actors (i.e., more ties with a value of at least one [“non-zero” ties]), but not necessarily in terms of the average tie value (which is driven by both the number of non-zero ties and the magnitude of each tie value).

H2: High collaboration processes will exhibit a lesser tendency to have empty ties than low collaboration processes.

Network reciprocity: Mutual ties

Low-level structural characteristics within a network, such as the patterns of ties between network actors, greatly influence network-level outcomes (Provan and Kenis 2008). For instance, reciprocated ties (i.e., a tie from A → B and from B → A) can serve to make cooperation more feasible by increasing credibility amongst actors (Berardo and Scholz 2010). Governance processes that involve complex systems--in the case of hydropower relicensing the system includes energy production, aquatic ecosystems, and water resources--require a high degree of information exchange amongst relatively specialized actors (Crona and Bodin 2006). Patterns of mutual exchange can strengthen relationships between these actors (Berardo and Scholz 2010; Putnam, Leonardi, and Nanetti 1993).

The collaborative governance literature strongly emphasizes the need for trust and commitment amongst stakeholders for collaborative efforts to be successful (Wondolleck and Yaffee 2000; Margerum 2011; Margerum 2002). Particularly in situations where actors do not largely agree on goals, trust and information credibility are critical for sustaining collective action and reducing defection (Berardo 2014; Leach and Sabatier 2005). Thus, while reciprocated ties might be redundant--and thus inefficient--in terms of information sharing, network structures that are minimally redundant can impede performance when credibility is at a premium (Lazer and Friedman 2007). Reciprocity can enhance the credibility of actors' commitment to one-another and thus support collaboration (Berardo and Scholz 2010).

H3: Higher collaboration processes will exhibit a stronger tendency for reciprocal ties than low collaboration processes.

Network cohesion: efficiency, credibility, and inclusiveness

While reciprocated ties might be important for fostering joint action, the presence of dense, close knit subgroups within a network can drive or inhibit joint action, depending upon the problem context (Bodin and Crona 2009). One one hand, dense subsystems of ties in which actors are all closely connected are duplicative, and thus potentially inefficient in terms of gathering and sharing information. Accordingly, low network cohesion--in terms of the presence of clearly definable, densely connected subgroups--can have negative effects on the capacity for joint action across the broader network (Bodin and Crona 2009). Linkages that span subgroups and increase network cohesion facilitate access to external knowledge and resources, thereby supporting collective action (Newman and Dale 2007; Sandström and Carlsson 2008). For instance, greater cross-subgroup linkage has been shown to increase collective action beliefs and trust in governance processes (Schneider et al. 2003), whereas low network cohesion (i.e., more isolated subgroups) can also inhibit broader collaboration and foster dueling coalitions (Borgatti and Foster 2003).

On the other hand, more isolated subgroups and lower network cohesion do not always deter effectiveness. Groups can act as a buffer against the "constant influx of less relevant information from numerous other actors" (Bodin and Crona 2009, 368) and foster informational diversity by allowing different knowledge to develop in different subgroups (Bodin and Crona 2009). Further, smaller groups of close-knit actors can be more efficient at decision-making (Provan and Kenis 2008).

This tension reveals an efficiency-inclusivity tradeoff (Provan and Kenis 2008) between the strategic benefits of changing the scale or level of government actions to involve non-state actors on one hand (Newig and Fritsch 2009b), and the time, effort, and costs of coordination and cooperation on the other (Margerum 2011). Thus, collaborative governance institutions must navigate tradeoffs between involvement (providing access to resources [(Schneider et al. 2003)], increased perceived legitimacy [(Dietz and Stern 2008; Bryson, Crosby, and Stone 2006; Margerum 2011)], diverse knowledge that can improve policy [(Beierle and Cayford 2002; Sirianni 2009)], and scale advantages [(Gerlak, Lubell, and Heikkila 2012; Karkkainen 2002; Feiock and Scholz 2009; Feiock 2013)]) and exclusion (facilitating quick action [(Wondolleck and Yaffee 2000; Imperial 2005; Margerum 2011)], reducing external decision costs [(Feiock 2013)], and excluding actors who lack sufficient expertise [(Lasker and Weiss 2003; Day and Gunton 2003)] or resources [(Wondolleck and Yaffee 2003)] to contribute meaningfully). These dueling forces place a premium on collaborating with the right people and advantage cases where there are fewer "wrong" people involved.

One way that networks exhibit tendency towards either broader cohesion or more insular subgroups is through transitivity. Transitivity reflects the “a friend of a friend is my friend” axiom, in that networks with high transitivity are those where if actor A is connected to actors B and C, then actors B and C are more likely to be connected to one-another as well (Kilduff and Tsai 2003; Lubell et al. 2012). This tendency for transitive structures to arise is known as triad closure bias, because it means that network two-paths (e.g., k→i→j on left side of Figure 1) tend to close into triangles (right side of Figure 1). Thus, high transitivity is reflected in dense, interconnected networks (Berardo and Scholz 2010) that reinforce direct ties between participants (Desmarais and Cranmer 2012a). In contrast, a network of

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similar density but with lower triad closure bias is characterized by fewer isolated subgroups and greater overall cohesion (for instance, if triad closure bias is lower, actor *k* in Figure 1 is relatively more likely to choose actor *m*).

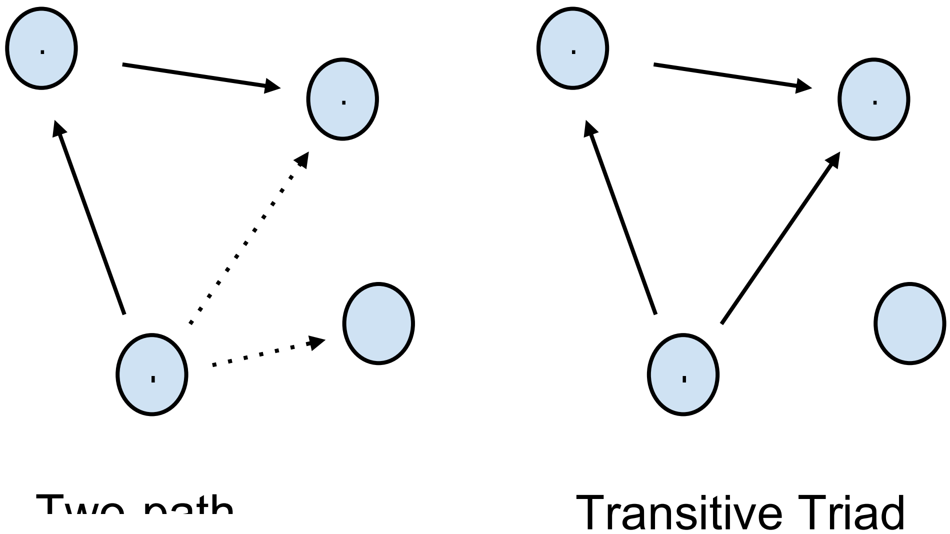

Figure 1: Two-paths and transitive triad network structures

Berardo and Scholz (2010) discuss how the collective action dilemma itself can shift the optimal balance between dense, more redundant subgroup structures and more dispersed, cohesive tie patterns.[1] The case at hand, hydropower relicensing, exhibits a great deal of fragmented authority because it involves local, state, and federal actors in different policy subfields of energy, fish and wildlife, water resources, and land use. Scholz et al. (2008) show that search costs are a more significant transaction cost barrier than credibility issues in networks constituted by fragmented authority; thus, network effectiveness (in

[1] Berardo and Scholz (2010) specifically demonstrate that actors are more likely to choose "bonding" structures that maximize credibility and minimize defection in higher-risk cooperation dilemmas and more likely to choose "bridging" structures that maximize information transmission and network cohesion in lower-risk coordination dilemmas. While our analysis does not specifically use the bridging and bonding capital framework, the Berardo and Scholz "Risk Hypothesis" nonetheless demonstrates the importance of problem context.

terms of whether the relicensing network is able to successfully collaborate and produce quality outputs) in light of fragmented authority is anticipated to require connectivity and network-wide cohesion over credibility and commitment.

H4: High collaboration processes will exhibit lower triad closure bias than low collaboration processes.

Table 2: Hypothesized differences between high- and low-collaboration processes

H1: High collaboration relicensing processes will exhibit greater network density than low collaboration processes
H2: High collaboration relicensing processes will exhibit a lesser tendency to have empty ties than low collaboration processes
H3: Higher collaboration relicensing processes will exhibit a stronger tendency for reciprocal ties than low collaboration processes.
H4: High collaboration relicensing processes will exhibit lower triad closure bias than low collaboration processes

Data

As described above, instead of measuring collaborative networks using respondent-generated data, this paper tests the linkages between observed participation and collaborative dynamics. We code the relevant network in each case to be the full set of individuals who are recorded as having attending at least one meeting at some point in the relicensing process. Ties between individuals are then coded based upon recorded comments recovered from meeting minutes.

Records of meeting attendance and meeting minutes for the three cases were obtained from http://elibrary.ferc.gov. All meetings were catalogued by purpose, location, and date.

Because two of the cases held many meetings, a subsample of meetings was selected for further analysis. For Washington, every tenth meeting chronologically was selected (resulting in 34 of 336 total meetings). For Missouri, approximately half of the meetings had minutes available, and every other meeting of those with minutes was selected (for 32 of 138 meetings). For Georgia, which held a comparatively small number of meetings, every meeting with minutes was included in the sample (for 9 of 11 meetings).

For sampled meetings, all attendees were catalogued, along with their organization and organization type (utility, federal agency, state agency, local government, NGO, business, tribe, consultant/lawyer, facilitator, or individual). To identify how attendees participated, meeting minutes were analyzed using *QSR NVivo 10* qualitative analysis software, cataloguing every instance where an individual (1) made a presentation or (2) participated in a discussion.

Emerson and Nabatchi (2015a) characterize "principled engagement" within collaborative governance as an interactive process of discovery and deliberation. The extent to which principled engagement occurs is a key collaborative dynamic that drives beneficial outcomes (Ulibarri 2015a, 2015b). The meeting minutes we code provide direct evidence of dialogue and deliberation amongst stakeholders, demonstrating which participants present or discuss key issues. If a given participant gives a presentation or substantively engages in discussion at a given meeting, we code a tie value of 1 from the discussant to all other meeting attendees.[2] If a meeting attendee does not participate in discussion, ties from

[2] We do not assume that a positive tie value implies collaboration between the two parties, as participants might be voicing disagreement with one another. Rather, a positive tie value simply represents an act of engagement.

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said attendee to other meeting attendees are given a value of 0. Because of the one-way nature of this interaction (one individual is talking to--not necessarily with--another individual) these are directed ties that originate at the discussant and terminate with audience members. Thus, in each network a tie from one individual to another is not necessarily reciprocated (i.e., A-->B does not equal B-->A).[3]

Since deliberation amongst participants can occur at more than one meeting, tie values between individuals are not limited to 0 and 1. After coding meeting-specific ties, we then sum the meeting-specific tie values across all meetings. For instance, the tie value between individuals A and B (A-->B) is equal to the number of times that individual A has engaged in substantive discussion at a meeting in which individual B was in attendance. These tie values summarize the extent to which each organization had the opportunity to learn about the perspectives and goals of other network organizations within the collaborative relicensing process. Table 3 summarizes descriptive network statistics for each relicensing.

[3] An alternative for examining co-participation would be to just use meeting attendance, as presumably there are verbal (and nonverbal) interactions that occur at meetings (e..g, hallway conversations) that contribute to network function. However, this poses a modeling challenge in that if attendance is used as a basis for coding interactor ties, then every attendee at a given meeting would be coded as having a tie to every other attendee. This makes estimation problematic, since the network then consists of complete subgroups (in which all possible ties exist) and empty subgroups in which no ties exist. Going forward, we hope to generate data that can be used to examine participation in more detail, but using meeting minutes to code deliberation is an important step in this direction.

Table 3: Network summary statistics

	# Actors	**Total Edges**
Washington	146	1241
Missouri	157	5119
Georgia	84	1297

While we sampled the meetings to make the research endeavor feasible (as coding hundreds of meeting would take a substantial amount of time), it does potentially affect our analysis. ERGMs rest on the assumption that all ties are observed; by sampling, we knowingly omit some ties. However, these omitted ties are missing randomly (given our sampling protocol), and therefore should represent the full network were we to code all ties. Moreover, the unsampled meetings are not substantively different from those included in the sample--whether by topic, location, or timing over the course of the relicensing--so we have no reason to assume that a substantially different pattern of attendance or dialogue took place at those meetings. Finally, unsampled meetings--and resultant missing edges--are less problematic in this cross-sectional analysis since we are simply summing observed interactions across observed meetings. In doing so, we are not making an assumption about what did or did not happen at other meetings (as we would be in a longitudinal framework where ties might be assumed to form or dissolve over time), but rather simply assessing overall patterns of dialogue across observed meetings.

Two additional notes are merited about potential limitations underlying our data. First, given the wildly different number of meetings in each case, we might expect to see differences in network structure that stem purely from differing opportunities to engage.

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With fewer meetings, we would expect to have larger attendance; with more meetings, people might be more selective about when they attend, potentially increasing the prevalence of zero-valued ties. However, these differences should not affect our other network measures. A tie represents a unidirectional flow of engagement, not simply co-attendance, so the overall statistics should capture differences in the internal dynamics of each meeting regardless of who shows up. Second, the extent to which the meeting minutes captured every participant action varied across the three cases. The Georgia minutes provided word-for-word transcriptions, and Missouri provided thorough summaries with a name attached to every idea. Washington had some similarly detailed minutes, but other minutes (particularly during settlement negotiations) instead tracked only the organization or mentioned a topic that was discussed without attribution. Because not every participant action was captured in the Washington minutes, they likely undercount tie values relative to actual levels of engagement.

Modeling Networks

Since this research concerns collaboration amongst network actors, we use a statistical network analysis to analyze links between individual actors as the dependent variable. In a network, the presence of one network tie influences the presence of others, thus violating the standard independence assumptions of most regression models (Robins, Lewis, and Wang 2012). We use exponential random graph models (ERGMs), which explicitly model interdependence amongst network ties (Lubell et al. 2012) by modeling every tie conditionally based upon all other observed ties (Lusher, Koskinen, and Robins 2013). Appendix A discusses the mechanics of ERGMs in detail.

While ERGMs are commonly applied to binary networks where a tie is simply present or absent, recent methodological advances enable the use of generalized ERGMs (GERGMs) that model valued network ties (Desmarais and Cranmer 2012b; Krivitsky 2012a). As described previously, we represent each tie as the sum of all unidirectional engagement across meetings from one participant to another. As these summary values are count data, a Poisson-reference GERGM is used to model the overall network (see Krivitsky (2012b) and Krivitsky and Butts (2013a) for a detailed explanation of the Poisson GERGM specification).

GERGMs facilitate inference on a network of interest by comparing the observed network to a distribution of simulated networks that have similar characteristics. Appendix A provides a fuller discussion of this process (and presents model goodness-of-fit analysis). Essentially, we model the observed network as a function of endogenous structural characteristics and exogenous attributes of participating organizations, and then compare the estimated parameters to a distribution of parameters estimated from a set of simulated networks weighted according to similarity to the observed network. Empirical parameters that fall in the extreme of either tail of the simulated parameters distribution are considered "significant," since it is unlikely that a given network structure occurred simply due to random variation.

An example of a structural term that can be fit in a GERGM is a two-path, wherein two actors (Organization A and Organization C) are linked via a path of ties, first from Organization A to Organization B (A-->B) and second from Organization B to Organization C (B-->C). Of course, a primary challenge is linking these types of structural terms to the theoretical hypotheses outlined above. We draw upon several recent analyses linking theoretical network concepts with network measures (Burt 2005; Bodin and Crona 2009; Scholz, Berardo, and Kile 2008; Borgatti 2005; Henry and Vollan 2014) and recent ERGM scholarship (Lusher, Koskinen, and Robins 2013; Desmarais and Cranmer 2012b; Desmarais and Cranmer 2012a; Krivitsky 2012a) to link the four hypotheses developed above with expected model results.

To represent network density (H1), we use the *Sum* parameter in the R *ergm* package (Handcock et al. 2014). This parameter reflects the expected value of a tie between *i* and *j* based upon the value of all ties observed in the network. Network density is computed as:

$$g(y) \quad = \textstyle\sum_{(ij)\in Y} \quad y_{ij} \qquad \text{(Eq. 1)}$$

where y_{ij} is the value of an observed tie from individual *i* to individual *j*, and *Y* is the set of all network members. The *sum* term acts as an intercept, in that it reflects the expected value of a randomly selected tie across all actors. Given that we code tie values based upon observed deliberation at meetings, it is important to consider that average tie value is potentially subject not only to what happens at meetings but the number of meetings that are observed. Network density increases as ties take on higher values (which can only happen as more meetings are observed) and decreases as more participants are observed (because density is a ratio of total tie values to number potential actor pairs, or dyads). Thus, in order to test Hypothesis 1 using a consistent basis of comparison across the three cases, we control for the number of meetings each actor attends in estimating the *Sum* parameter. This serves to produce density estimates that differ from the raw ratio of the sum of all observed ties over total dyads (because the *Sum* parameter estimate is the predicted value of a tie from actor *i* to actor *j* controlling for the number of meetings that actor *i* attended), and accounts for sampling differences so as to enable more accurate comparison of network density. We thus test Hypothesis 1 by comparing the sign and magnitude of the *Sum* parameters in GERGM models that also include number of meetings attended as a covariate.

Hypothesis 2 asserts that high and low collaboration networks will be of similar overall density, but that high collaboration networks will have fewer non-existent ties. To test Hypothesis 2, we add a *Non-zero* term that reflects the total number of ties greater than zero observed in the network (i.e., total number of edges):

$$g(y) = \sum_{(ij)\in Y} I(y_{ij} \neq 0) \qquad \text{(Eq. 2)}$$

to the baseline models used to test Hypothesis 1. Having controlled for overall network density, the sign and magnitude of the *Non-zero* term thus reflects the tendency for a network to have more ties between actors (independent of magnitude). The estimated non-zero coefficient represents the additive log change in the expected value of a tie between nodes *i* and *j* given that the number of non-zero ties held by node *i* increases by one.

To compare reciprocity and transitivity across the three relicensing networks, we fit a third series of models that include terms for mutual ties and transitive triads. The *Mutual* term (Handcock et al. 2014) models the prevalence of reciprocated ties between nodes for non-binary network ties:

$$g(y) = \sum_{(ij)\in Y} min(y_{ij}, y_{ji}) \qquad \text{(Eq. 3)}$$

by recording the minimum observed tie value between each pair of actors. This reflects how the observed tie value from node *i* to node j influences the expected value of a tie from node *j* to node *i*. If network reciprocity is high, then this statistic will be higher because $y_{ij}$and y_{ji}show a tendency to increase in concert and thus raise $min(y_{ij}, y_{ji})$.

Transitivity is modeled using the *transitiveweights* parameter in the *ergm* packages (Handcock et al. 2014), which models triad closure bias for non-binary network ties. The formula:

$$g(y) \quad = \sum_{(ij)\in Y} \quad min(y_{ij}, max_{k\in N}(min(y_{ik}, y_{kj}))) \qquad \text{(Eq. 4)}$$

is based upon the generalization of transitivity terms used in binary ERGMs for valued tie data provided by Krivitsky (2012a). Essentially, this term first identifies the minimum value along each two-path by which nodes *i* and *j* are connected; that is, if A-->B = 2 and B-->C = 3, then $min(AB, BC) \ = \ 2$. Next, it identifies the maximum value out of all observed two-paths between nodes *i* and *j* (e.g., A-->B-->C). Finally, it identifies the minimum value between the former result and the actual tie value from node *i* to node j. The basic intuition here is that in networks with high transitivity, the final value for this term should be higher on average since more triangles tend to be "closed."

Table 4 summarizes how each term is computed.

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Table 4: Relating hypotheses to terms in ergm package

	Network Concept	**Term in ERGM packages**	**Term Structure**
H1	Network density	*sum*	$g(y) = \sum_{(ij)\in Y} y_{ij}$
H2	Non-zero tie density	*non-zero*	$g(y) = \sum_{(ij)\in Y} I(y_{ij} \neq 0)$
H3	Reciprocity	*mutual*	$g(y) = \sum_{(ij)\in Y} min(y_{ij}, y_{ji})$
H4	Transitivity	*transitiveweights*	$g(y) = \sum_{(ij)\in Y} min(y_{ij}, max_{k\in N}(min(y_{ik}, y_{kj})))$

Results and Analysis

While basic network density can be computed algebraically simply by dividing the number of total possible ties by the total summed value of all ties to compute average tie value, as noted above it is important to account for the number of meetings that a given actor attends. We thus estimate the *Sum* parameter (described above) for each case within a GERGM model that includes a term for the number of observed meetings that a given actor has attended. These results are shown in Table 5:

Table 5: Baseline models with density parameter and control for attendance

Case (collaboration level)	***Washington (high)***	***Missouri (medium)***	***Georgia (low)***
Sum	-3.62*** (0.04)	-3.18*** (0.03)	-3.03*** (0.05)
Meetings Attended	0.12*** (0.002)	0.19*** (0.001)	0.28*** (0.01)

***p < 0.01, **p < 0.05, *p < 0.1

In each model, the *Sum* parameter functions in a similar fashion to the intercept in a regression model by providing a baseline tie value estimate before factoring in other parameters. Parameter estimated for the Poisson-reference GERGM models shown in Table 5 (and below in Tables 6 and 7) can be interpreted as having an additive effect on the natural log of the expected value of a tie between any two network organizations. That is, we can exponentiate a parameter ($exp\ (\beta)$) to identify its multiplicative relationship to expected tie value. While we provide more detailed interpretations in the remainder of this section, two general heuristics hold: negative coefficients serve to reduce the expected value of a tie (affected by the network structure represented by the coefficient) while positive coefficients increase the expected tie value, and coefficients that are larger in magnitude (either positive or negative) evidence a larger marginal effect.

For instance, by exponentiating the *Sum* parameter ($exp(-3.62)\ = 0.03$) we find that the expected tie value between any two randomly selected individuals in the Washington relicensing network is 0.03. For the Georgia case, the baseline expected tie value between any two individuals is only slightly greater, 0.04 ($exp(-3.18)\ = 0.04$). Missouri exhibits a slightly higher baseline density, with an expected tie value prior to factoring in other parameters approximately 0.05 ($exp(-3.03)\ = 0.05$).

Turning to Hypothesis 2, concerning the extent to which network interactions are concentrated amongst a few individuals or more widely dispersed, we can first visualize the relative proportions of zero-valued and non-zero ties across each network. Figure 2 shows how the each network compares in terms of the proportion of all possible ties ($N * [N-1]$) for each network that are of a given value. As shown in Figure 2, the Georgia network appears to have a reduced prevalence for non-zero ties relative to the other networks, followed by the Missouri network and then the Washington network.

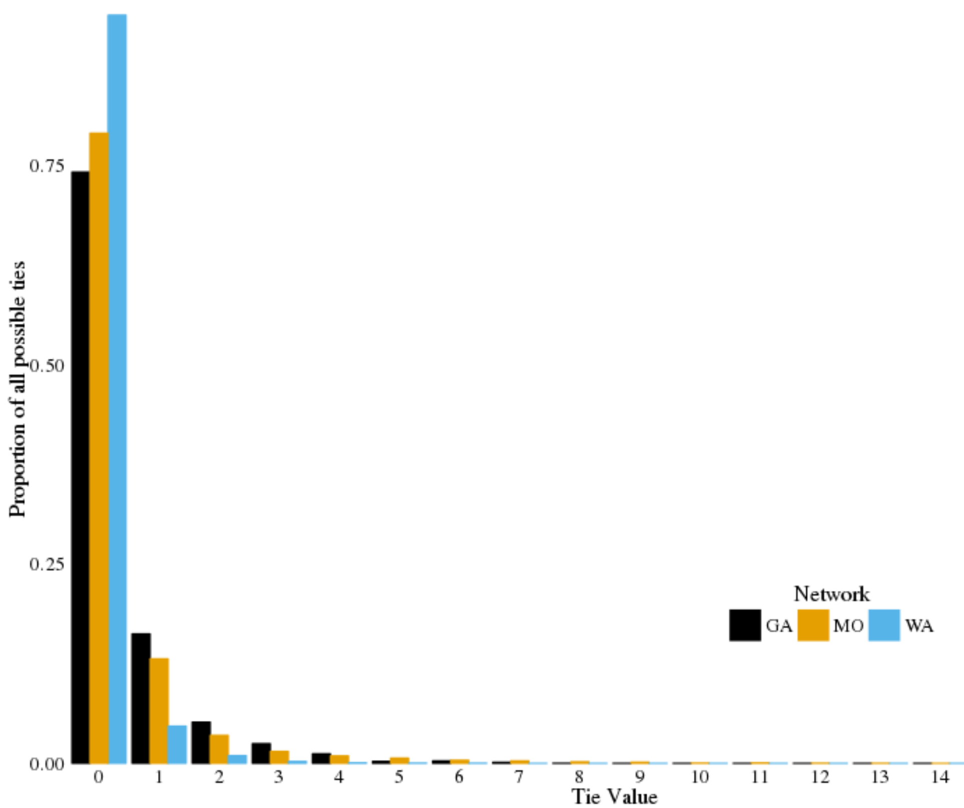

Figure 2: Proportion of all possible ties observed at a given value for each network

To quantify this prevalence, Table 6 presents a model for each case that incorporates the *Non-zero* statistic, which accounts for the extent to which each network has an excess of dyads with a value of zero (i.e., no tie) relative to the Poisson reference distribution, net of the other model terms. The intuition for this term is that a network can exhibit bimodality such that many pairs of nodes have no tie (i.e., tie value equals zero) while other node pairs have higher value ties; in this case, simply fitting a *Sum* parameter (which averages tie value across all potential ties) does not accurately represent what we observe in the network.

A negative, large-magnitude coefficient indicates that there are more dyads with no observed tie than would typically be expected by the Poisson reference distribution. In other words, a negative coefficient for the *Non-zero* parameter pulls down the baseline tie value expectation to account for a higher prevalence of ties with a value of zero. For the three models in Table 6, we observe that all three networks have a negative value for the *Non-zero* coefficient, indicating that all three cases have a relatively strong prevalence for zero-valued ties.

Table 6: Density and non-zero ties with control for attendance

Case (collaboration level)	***Washington (high)***	***Missouri (medium)***	***Georgia (low)***
Sum	-1.92*** (0.08)	-2.05*** (0.13)	-2.09*** (0.22)
Non-zero	-1.67*** (0.09)	-1.09*** (0.04)	-0.85*** (0.06)
Meetings Attended	0.083*** (0.003)	0.15*** (0.002)	0.22*** (0.007)

***p < 0.01, **p < 0.05, *p < 0.1

However, the Washington case has the largest negative value, showing that of the three relicensing processes it has the lowest non-zero tie density (i.e., more zero value ties). The parameter value of -1.67 is interpreted as reducing the expected value of a tie between two randomly selected individuals in the network by 81% ($exp(-1.67) = 0.19$). The Georgia and Missouri relicensing networks are again are very similar for this parameter: for the Georgia the *Non-Zero* parameter reduces the expected value of a tie by 66% ($exp(-1.09) = 0.34$), while for Missouri the *Non-Zero* parameter reduces the expected value of a tie by 57% ($exp(-0.85) = 0.43$).

Lastly, we turn to Table 6, which presents the results for each network model that includes all terms of interest. The high collaboration case (Washington) exhibits of by far the highest degree of mutuality between network participants. As described above, the *Mutuality* parameter models the extent to which the tie value observed between nodes *A* and *B* (y_{AB}) corresponds to the tie value from B to A (y_{BA}). In other words, it models the reciprocal tendency of a network. In the Washington network, for each 1-unit increase in y_{ij} the predicted value of y_{ji} increases by 458% ($exp(1.72) = 5.58$).

Table 6: ERGM parameter estimates for three relicensing networks

Case (collaboration level)	***Washington (high)***	***Missouri (medium)***	***Georgia (low)***
Sum	-2.99*** (0.08)	-3.72*** (0.13)	-3.92*** (0.21)
Non-zero	-2.44*** (0.09)	-1.23*** (0.04)	-1.27*** (0.06)
Mutuality	1.72*** (0.09)	0.11*** (0.04)	0.76*** (0.07)
Transitive Triads	1.91* (0.03)	1.84*** (0.12)	2.41*** (0.21)
Meetings Attended	0.02*** (0.003)	0.14*** (0.002)	0.15*** (0.007)

***p < 0.01, **p < 0.05, *p < 0.1

This might at first seem like an outlandish increase, but bear in mind that the baseline expected tie value between *any* two randomly selected nodes is very, very low; that is, an 458% increase from 0.1, for instance, is still only 0.46. More importantly, the large magnitude of this predicted increase reflects the informational gain for predicting y_{ji} that is provided by knowing the value of y_{ij}. If we know that $y_{ij} > 0$, then it makes sense that our expectation for y_{ji} is markedly different than the baseline value because nodes *i* and *j* are decidedly not just any two randomly selected nodes but rather nodes who already have some form of relationship. In any case, this tendency for reciprocated ties is lessened in the Georgia case, as a one unit increase in y_{ij} predicts a 114% increase ($exp(0.76) = 2.14$) in the value of y_{ji}. The *Mutuality* term is even weaker in the Missouri case, as a one unit increase in y_{ij} predicts just a 12% increase in tie value ($exp(0.11) = 1.12$).

The *Transitive Triads* parameter (the *transitiveweights* statistic in the *ergm* package (Handcock et al. 2014)) can be interpreted as predicting how a one-unit increase in the strongest two-path through which node *i* already reaches node *j* (e.g., A → B → C) increases the expected value of a direct tie between nodes *i* and *j* (y_{ij}, *e.g., A→ C*). This statistic is smallest for the medium-collaboration Missouri case and largest for the low-collaboration Georgia case. For the Georgia relicensing network, a one-unit increase in the strongest two path between two nodes (measured as $max_{k \in N}(min(y_{ik}, y_{kj}))$) increases expected value of a tie between nodes *i* and *j* (y_{ij}) by 1013% ($exp(2.41) = 11.13$). While we return to this finding in the context of our hypotheses below, clearly the Georgia relicensing case exhibits a very strong triadic closure tendency. In the Missouri relicensing, triad closure strength is smaller than Georgia, but still highly significant, with a one-unit increase in the strongest two path between two nodes increasing the expected value of a tie between nodes *i* and *j* (y_{ij}) by 530% ($exp(1.84) = 6.30$). Finally, in the high-collaboration Washington case, a one-unit increase in the strongest two path between two nodes predicts a 575% increase in the value of a direct tie between said nodes ($exp(1.91) = 6.75$).

Each model also includes a control for the number of meetings each individual attended. Since tie values are based upon meeting attendance and participation, one would expect that meeting attendance is positively associated with tie values independent of any underlying network drivers. As expected, each meeting an actor attends significantly increases the expected tie value between that actor and every other network participant, although the magnitude of this increase is small: 5% ($exp(0.02) = 1.05$) for Washington, 16% ($exp(0.15) = 1.16$) for Georgia, and 15% ($exp(0.14) = 1.15$) for Missouri. The magnitude this parameter is small in each model partly because it models the general increase in expected tie value to *any* network member; thus, while meeting attendance should increase the expected value of a network tie, it does necessarily provide fine-tuned guidance about specific ties.

Discussion

Our first hypothesis (Table 2) was that high collaboration processes will exhibit greater participation network density than low collaboration processes. However, in the restricted ERGM model containing only terms for density and meetings attended (Table 5), the highest collaboration case (Washington) is shown to have the lowest density. At first glance, this runs counter to the expectation of Hypothesis 1 that high collaboration processes will be evidenced by stronger network density relative to low collaboration processes.

However, Table 6 (as well as Figure 2) indicates that there is more to this story, as the Washington network also exhibits the strongest proportion of zero-valued ties, which serves to pull down the overall density estimate. Hypothesis 2 holds that high collaboration processes will exhibit greater non-zero tie density than low collaboration process but not differ in terms of average tie value. This expectation is also not borne out in our results, as the high collaboration process (Washington) has the lowest non-zero tie density (i.e., a higher proportion of dyads with no tie), followed by medium collaboration Missouri, with the low-collaboration Georgia having the lowest density of non-zero ties. In summary, the case with highest collaboration exhibits the lowest overall participation density and has many more isolated actors.

What might account for the unexpected result that the most collaborative network is also the most exclusive of the three nominally collaborative relicensing processes? Bodin and Crona (2009) hypothesize that because network interactions represent potential opportunities for developing common ground and initiating joint action (i.e., dialogue and discourse create more opportunities for collaboration to occur), networks with more ties should be the most collaborative. However, others suggest that the most successful collaborative ventures (in terms of reaching agreement and producing high quality collective outputs) are instances where a small (relative to the overall network) group of actors collaborate with one another to leverage resources and influence policymaking (Lubell 2004a; Ansell and Gash 2008). As discussed above, inclusion of a greater number of

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network actors increases the time and effort required to reach decisions and take action (Wondolleck and Yaffee 2003; Margerum 2011; Imperial 2005) and raises external decision costs (Feiock 2013). Thus, high-functioning collaborative decision-making forums might not be the most inclusive in terms of incorporating all network actors into decision-making, but rather institutions where a subset of key network actors are heavily involved (i.e., stakeholders who offer particularly relevant information, hold key resources, or are otherwise critical for achieving successful outcomes).

Put in terms of our empirical findings, it is possible that networks having slightly lesser overall density, and a greater proportion of dyads having no tie (as observed in the Washington case), evidence this phenomenon at work, revealing relicensing networks that are sufficiently collaborative to leverage resources and get things done but not so much that they invite disagreement or delay.[4] This does not mean that density necessarily hinders collaboration, but rather indicates that network density is insufficient to distinguish amongst processes or decision forums that are all nominally "collaborative."

This interpretation is further supported by the results of the *Mutuality* parameter used to test Hypothesis 3 (that high-collaboration processes will exhibit a stronger tendency for reciprocal ties). Indeed, across the three cases the Washington network has the greatest degree of mutuality by far (although mutuality is also higher in low-collaboration Georgia than in medium-collaboration Missouri). Even though relicensing process participants

[4] A less theoretically interesting possibility is that the unexpected lack of ties between many of the participants in high-collaboration Washington reflects the differences in how closely the meeting minutes identified each speaker across the three cases. Washington had the least detailed minutes of the three cases, so the observed data likely undercount tie values relative to the other cases.

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come from many different organizations, the strength of reciprocal ties in the Washington case evidences that many participants engaged in repeated, two-way dialogue with one-another. Such interactions can help create strong within-group connections that foster shared understanding and enable joint action (Emerson and Nabatchi 2015a).

The final structural attribute, transitivity, is shown to be strongest in the network with the lowest observed collaboration (Georgia). This supports the expectation of Hypothesis 4, that high-collaboration processes will exhibit lower triad closure bias. As to why this occurred, recall that we measure a tie as a unidirectional link between a meeting attendee who gave a presentation or participated in a discussion to all other attendees. Thus, triadic structures such as that shown in Figure 1 reveal a hierarchical structure in which some participants dominate dialogue and others are passive listeners. The prevalence of transitive triads indicates that meetings were structured more hierarchically in Georgia than the other two cases. This stands in contrast to the high degree of mutual deliberation in the Washington case, which perhaps evidences a more equal field of participants as attendees who are speaking are also receiving information from others.

A final observation is of the similarity in network structure between the low collaboration case and the medium collaboration case, despite seemingly different levels of interaction arising from the initial document analysis. In low-collaboration Georgia, there was very little interaction between participants relative to the other two cases. The utility held only eleven public meetings. While the meetings were attended by a diverse network of organizations, the meetings were dominated by formal presentations by the utility and a few other stakeholders. Thus, there was very little authentic deliberation (Innes and

Booher 2010) between participants. In contrast, the medium-collaboration Missouri process looked a lot more like collaborative engagement. The utility hired a well-known facilitator to design the process, and participants used deliberation and interest-based negotiation to jointly define problems and develop technical studies. However, when the participants began to develop actual management recommendations, participants reverted to positional negotiation and the final recommendations reflected only a subset of stakeholder interests. (See Ulibarri 2015b for more details on each process.) Thus, the paper trail for these two processes look very different, with one case having minimal consultation and the other with more extensive engagement. These differences were not picked up by the network analysis; the network results instead more closely reflect the overall level of collaboration (which includes very low levels of trust from the Missouri survey, drawing the final ranking downward). This suggests that the network analysis was effective in capturing the overall level of collaboration, but may not mirror individual dynamics as effectively.

Conclusion

In this study, we asked whether network structure metrics reflect the quality and extent of collaborative decision-making. Using meeting attendance and participation records from three FERC hydropower relicensing processes, we tested metrics for network density and network cohesion, then related them to the underlying level of collaboration in each case. Our findings serve to demonstrate how patterns of individual-level interaction relate to the level of collaboration on a more general basis. Specifically, we observe more concentrated interactions, more reciprocated ties, and lesser hierarchical tendency in the high

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collaboration case, and higher overall involvement but with fewer two-way patterns of communication in the low collaboration case. These results speak to the complexity of collaborative governance in policy networks, in that inclusion and widespread involvement (often touted as theoretical advantages of collaborative governance) must be balanced against time and capacity constraints and the need to reach agreements.

One intent of this analysis was to provide network-based metrics of collaborative dynamics that can be scaled up or used to compare across cases more readily than the more qualitative or case-specific measures in the literature. In our previous analysis, principled engagement was found to be the dynamic that most strongly influenced the content and quality of hydropower licenses (Ulibarri 2015a; Ulibarri 2015b); connecting these findings to network metrics reveals that triadic closure bias and mutuality potentially represent useful network-based measures of principled engagement for analyzing collaboration and its outcomes.

This study was subject to methodological limitations that provide fruitful avenues for future research. First, as an exploratory study, we assessed only three cases by identifying trends among our data. While measuring collaboration and collecting network ties for a large number of cases would require substantial manpower, using a larger sample size would allow for trends to be ascertained with more statistical certainty. Second, examining the evolution of collaborative governance networks over time is a critical way to build upon current work. Neither collaboration nor network structures are static phenomena, but vary over the course of a decision-making process. With frequent meetings occurring over multiple years, participants have the opportunity to get to know one another very well, learn to cooperate, and possibly even adopt one another's beliefs (Leach et al. 2013; Lubell 2004b). The network and associated collaborative actions might start by building connections across relatively disparate actors but evolve toward close-knit in-group bonding.

Additionally, recent scholarship speaks to how the plethora of decision-forums within modern policy subsystems requires network actors to allocate their time towards forums where they are best able to exert their influence and garner benefits (Lubell 2013; Lubell, Robins, and Wang 2014; Lubell, Henry, and McCoy 2010). The complexity incentivizes affiliation with forums that contain like-minded actors (Henry, Lubell, and McCoy 2011; Gerber, Henry, and Lubell 2013). Given this, it is possible that peripheral actors will drop out of collaborative decision forums by virtue of their peripheral status, increasing network concentration not through increased interaction but by reducing the number of participants.

Thus, adding a temporal component, both in assessing how collaboration changes over time (e.g., via process tracing) and how the networks change over time (e.g., via temporal ERGMs), offers to deepen understanding of how networks and collaboration interrelate. In particular, if they evolve at different rates, it may suggest that one is driving changes in the other, an important finding for process designers seeking to encourage effective collaboration. Recent theoretical (Emerson and Nabatchi 2015a) and methodological (Ingold and Leifeld 2016; Leifeld et al. 2015) contributions provide a roadmap for longitudinal analysis of collaborative governance and networks going forward.

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APPENDIX A: Model Specification and Goodness-of-Fit

Model Specification

A GERGM assumes that the observed network (i.e., pattern of ties) represents a sample from a hypothetical distribution of possible network realizations. To draw inferences about the underlying network phenomena, a GERGM compares the observed network to the distribution of possible network graph configurations, with each hypothetical graph weighted based upon similarity to the observed configuration. Comparing the observed network to the distribution of possible networks provides a probabilistic assessment of whether a particular driver is more or less prevalent in the observed network (by showing whether a given structure occurs more or less in the observed network than if ties are distributed at random) (Lusher, Koskinen, and Robins 2013, Kolaczyk 2009).

For non-trivial networks, a vast number of possible network configurations exist and it is infeasible to analyze all possible graphs. Thus, GERGMs use a Markov chain Monte Carlo (MCMC) maximum likelihood estimation technique that samples from the distribution of possible network configurations. Sampling is weighted based upon similarity to the observed network in terms of descriptive characteristics such as density and structural attributes such as the number of triangular-patterned ties in order to generate a distribution of network graphs that are a suitable basis for comparison.

Basically, the MCMC procedure iteratively proposes a single tie change to the network and then compares the likelihood of the pre-change and post-change network graphs. Every time the proposed change increases the likelihood of the simulated network graph, the MCMC process makes the proposed change and then repeats the same steps. When the proposed change decreases the likelihood (shown below) of the network graph, the MCMC process only elects to make the proposed change a fixed percentage of the time (e.g., 50%) (Lusher, Koskinen, and Robins 2013). This iterative procedure searches the parameter space to (hopefully) converge on a stationary distribution of network graphs that resemble the observed network.

Social networks are often sparse, in that actors who interact often interact multiple times and many other actors have zero ties. This means that the dyad-wise tie distribution is zero-inflated relative to a standard Poisson distribution (Krivitsky and Butts 2013b). Krivitsky (2012a) specifies the likelihood function for a zero-modified Poisson-reference GERGM as:

$$Pr_{\theta;h,\eta,g}(Y=y) \propto \prod_{(i,j)\in Y} \quad exp(\theta_1 y_{ij} + \theta_2 1_{y_{ij}>0})/y_{ij}! \qquad \text{(Equation A1)}$$

with the reference distribution represented by h(y):

$$h(y) = 1/\prod_{(i,j)\in Y} y_{ij}! \qquad \text{(Equation A2)}$$

Equation A1 specifies the model sans any additional model terms as the observed baseline distribution of network ties. Additional terms are then added to the model to account for endogenous structural characteristics and exogenous attributes of participating organizations.

Model Goodness-of-Fit

When fitting a GERGM, it is important to ensure that the MCMC estimation process does not exhibit degeneracy; a degenerate MCMC cascades to a completely full or completely empty model (i.e., all high value ties or all no-value ties) and weights these unrealistic network graphs too highly (Lusher, Koskinen, and Robins 2013; Kolaczyk 2009; Handcock et al. 2003).

Figures A1, A2, and A3 show traceplots for each parameter across iterations of each MCMC chain to demonstrate that the the model is mixing sufficiently and not straying outside of the parameter space (Krivitsky and Butts 2013b).[5] Each model in this paper is fit via a four parallel sampling chains. Every chain discards the first 10,000 networks to ensure that samples used for estimation purposes are drawn from a stable distribution (Lusher, Koskinen, and Robins 2013). After this "burn in" period, each chain takes 160,000 samples

[5] Note that the goodness-of-fit plots shown in this appendix refer to the unrestricted models presented in Table 7; we also performed goodness-of-fit analysis for the restricted models shown in Table 5 and 6. Each model mixes adequately, exhibits consistent, unimodal estimation within and across MCMC chains, and faithfully replicated the structural characteristics of the observed networks. Because the unrestricted models in Table 7 are more difficult to fit, we focus on their goodness-of-fit in this appendix.

(with each sample being a different possible network graph). So that all draws are not taken from the same small area, each chain is thinned by discarding 1000 individual perturbations between each sample. Figures A1, A2, and A3 respectively thus trace the maximum likelihood parameter estimates for each MCMC chain and parameter in the corresponding model. The seemingly random, back-and-forth movement of each chain demonstrates that the model is searching throughout the parameter space, and the lack of an upward or downward trend shows that each model does not become degenerate and trend towards a completely empty or completely full network.

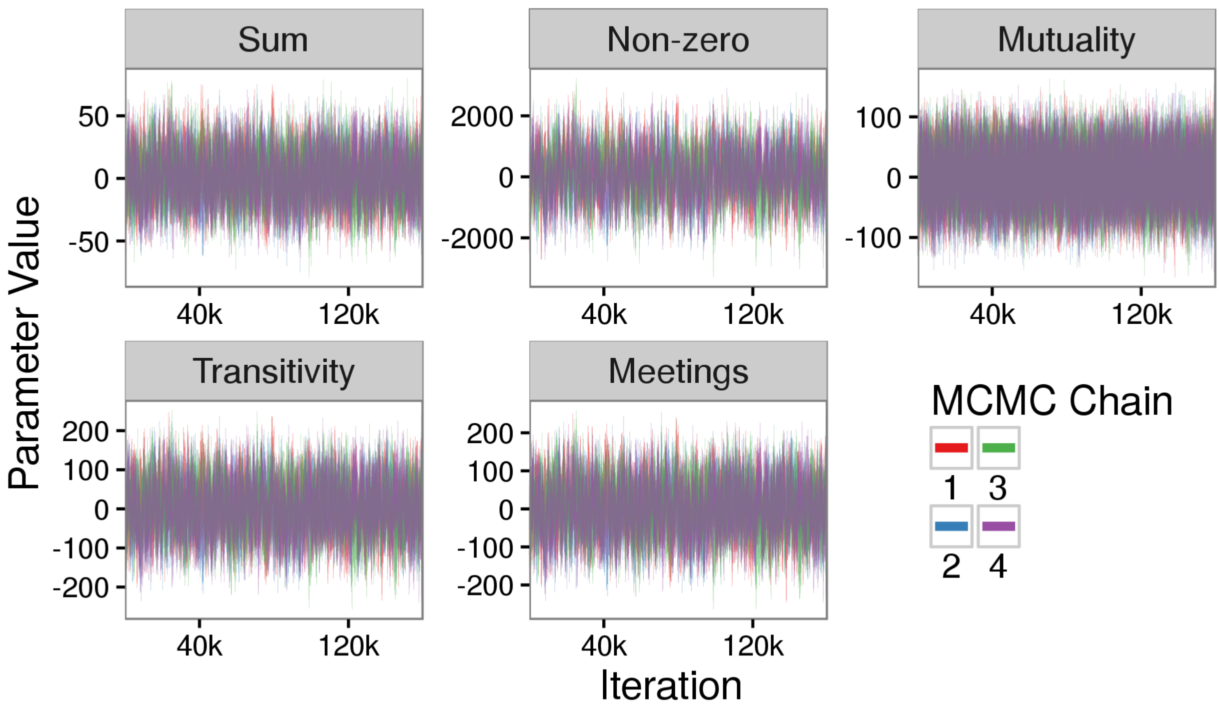

Figure A1: Tracing MCMC parameter estimates for Washington network model

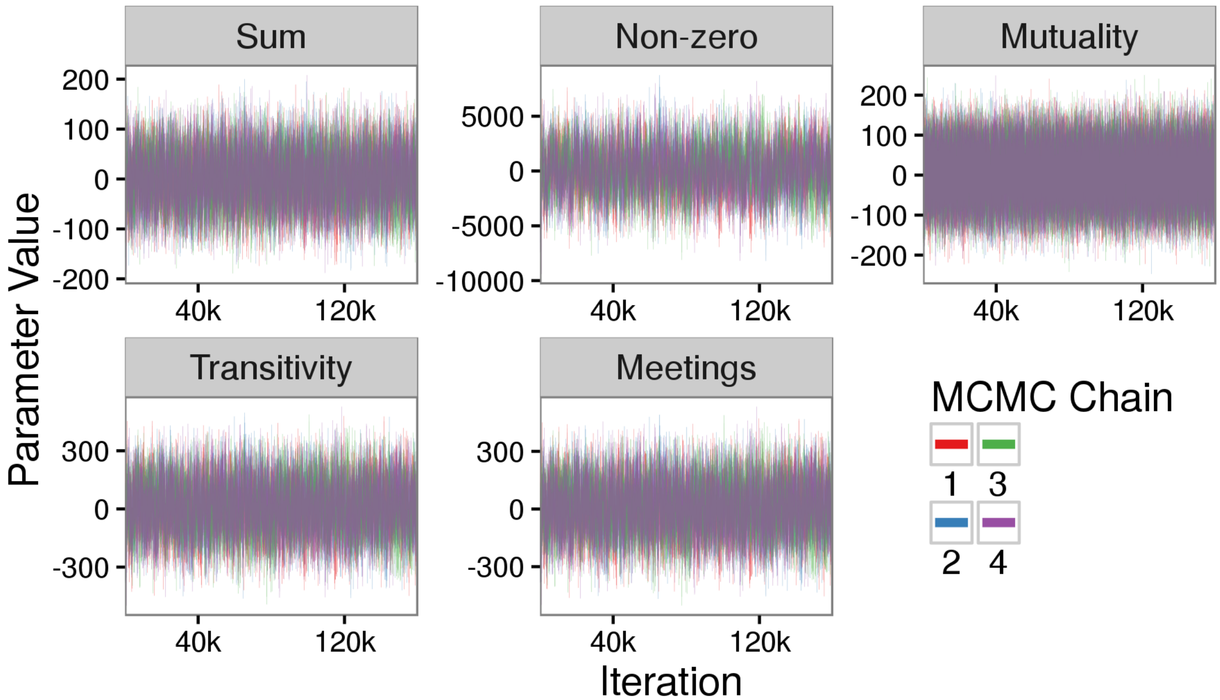

Figure A2: Tracing MCMC parameter estimates for Missouri network model

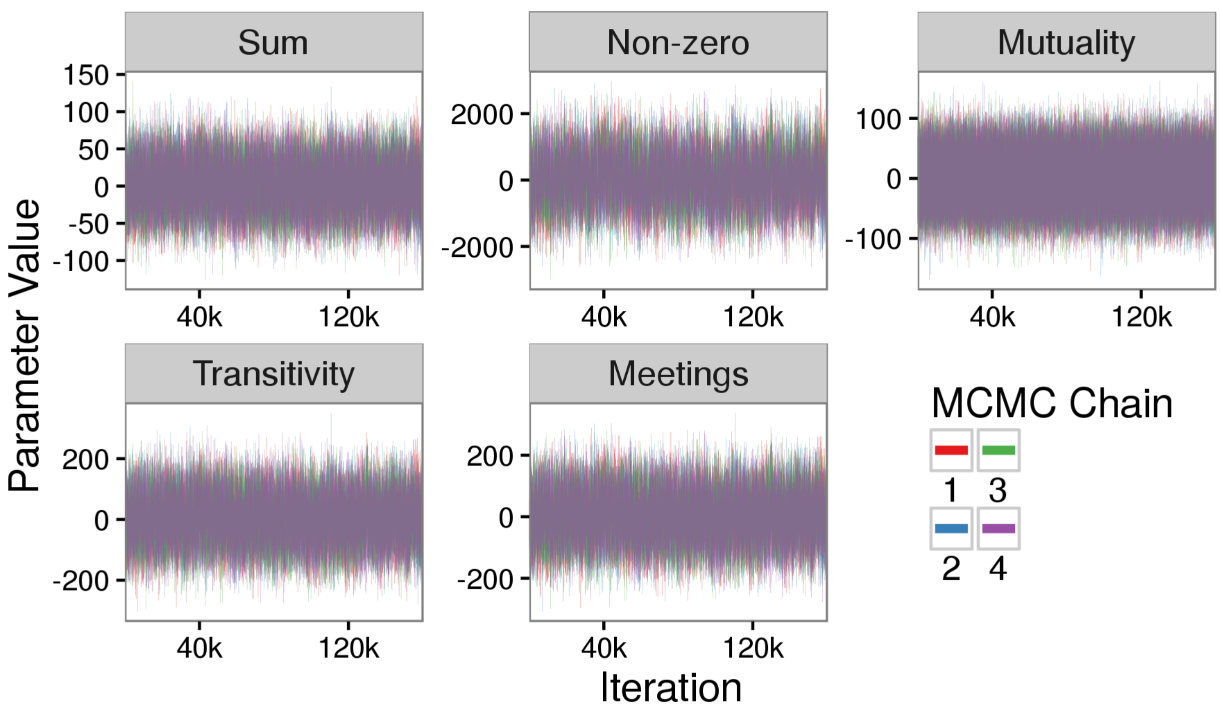

Figure A3: Tracing MCMC parameter estimates for Georgia network model

Along with mixing adequately and sufficiently searching the parameter space, it is also important that the parameter estimates for each MCMC chain converge and that the distribution of estimates generated by each chain are unimodal and approximately normally distributed. Figures A4-6 show density plots for each model parameter for Washington, Georgia, and Missouri, respectively.

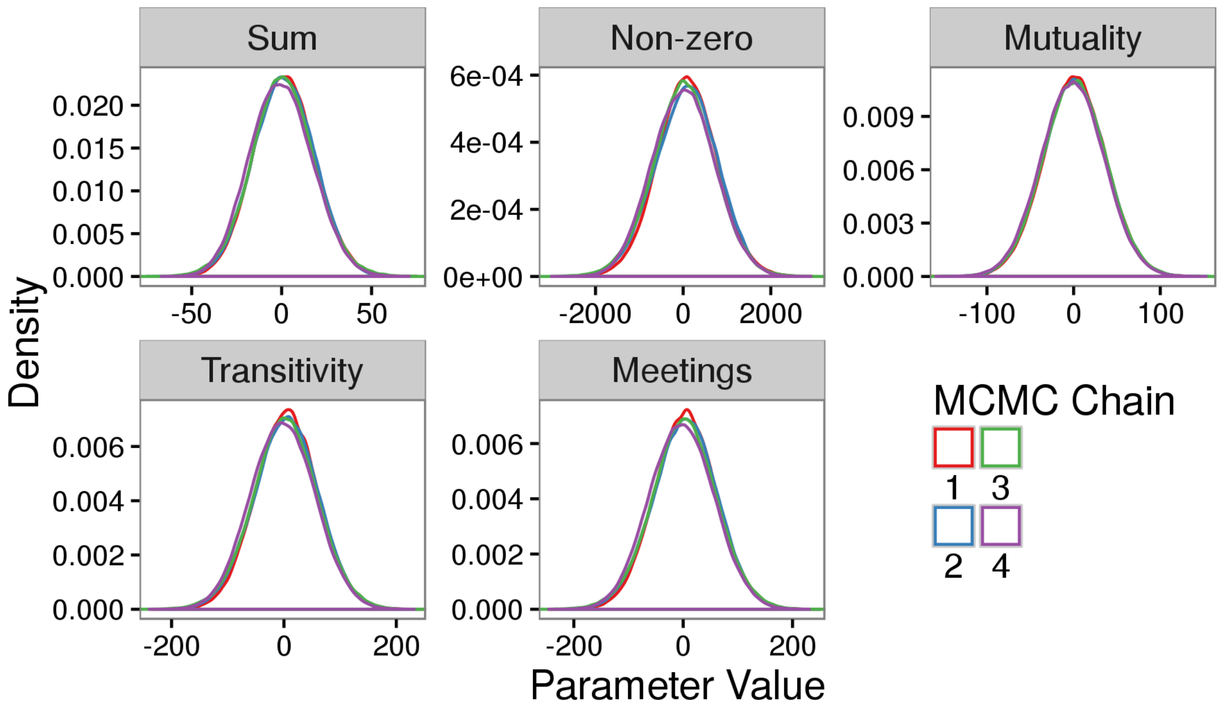

Figure A4: Density of MCMC parameter estimates for Washington network model

One advantage of the parallel modeling approach we use, in which each model uses four separate MCMC chains, is that comparing chain-specific distributions demonstrates model robustness. Figures A4, A5, and A6 demonstrate that the four parallel chains converge around consistent estimates for each model parameter. This is an important improvement upon many published ERGMs that do not use parallel processing. While serial processing still allows the analyst to establish whether the single MCMC chain produces a unimodal distribution, comparing the results of several chains fit in parallel shows the extent to which model results are consistent and replicable.

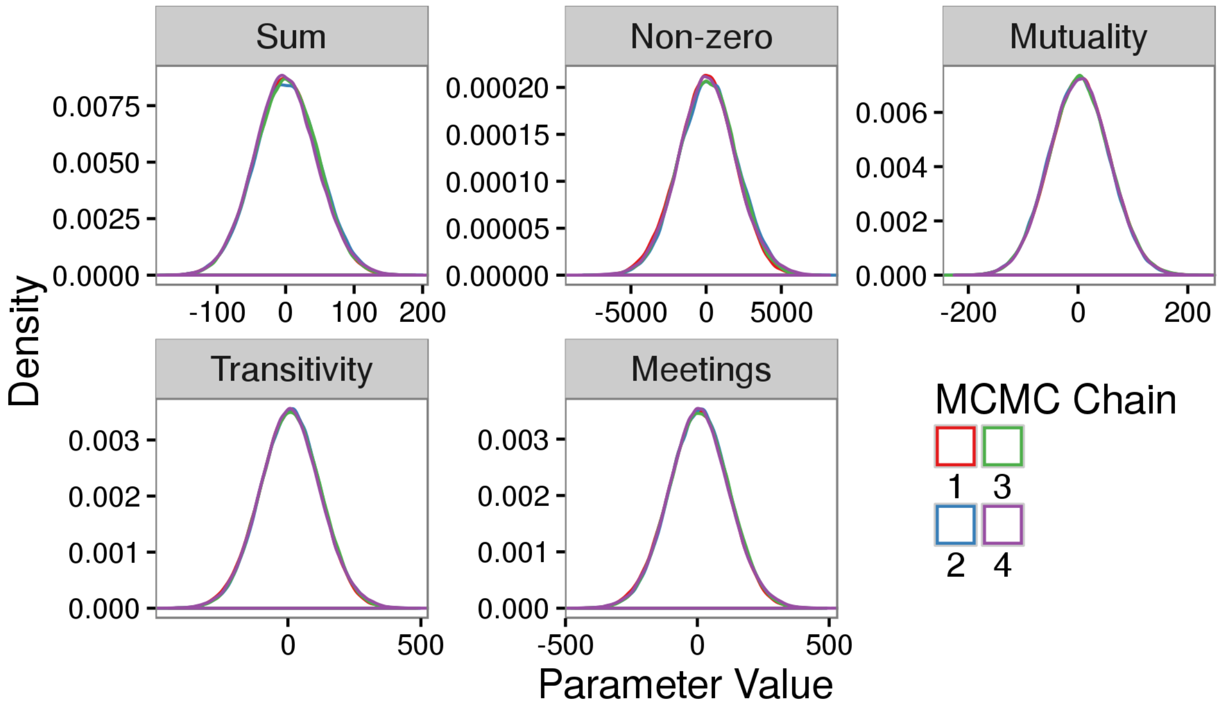

Figure A5: Density of MCMC parameter estimates for Missouri network model

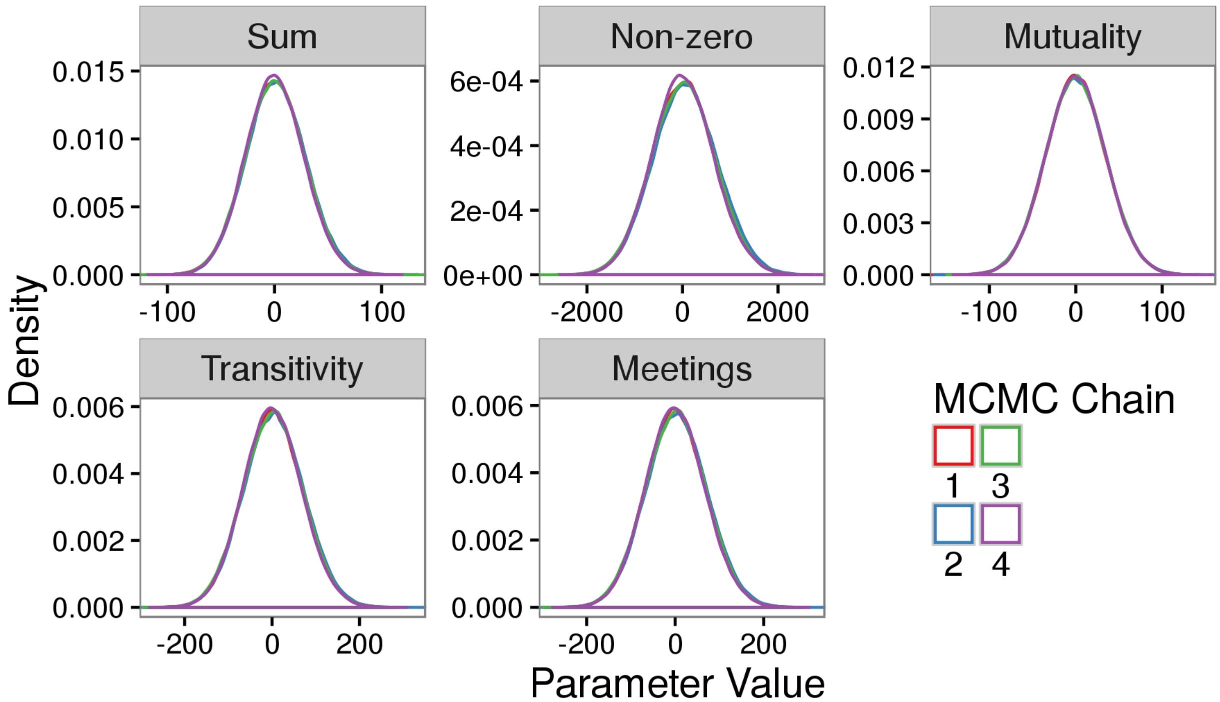

Figure A6: Density of MCMC parameter estimates for Georgia network model

Finally, in the discussion of model goodness-of-fit above in the main body of the manuscript, we noted that GERGM inference is based upon comparing the observed network to the distribution of simulated networks generated by the model. That is, if we simulate a large number of networks based upon estimated model parameters, we should expect that the simulated networks generally resemble the observed network. To test this, we simulate 100,000 hypothetical networks based upon each best-fit model presented above, and compare the distribution of network statistics found in the simulated networks to the observed values in Washington, Georgia, and Missouri.

Figures A7, A8, and A9 plot the density of simulated values and show where the observed statistics fall within these distributions using a dashed line. In each case the observed statistic is near the middle of the simulated values and the simulated values appear to be

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approximately normally distributed around the observed statistics. The unrestricted Washington model (Figure A7) is the poorest fit in this regard, as the model struggles to simulate networks that closely resemble the observed network. This is not the case for the restricted models with only *Sum*, *Non-zero*, and *Meetings Attended* parameters (shown in Tables 5 and 6).

The conundrum here is that dropping model terms to increase the goodness-of-fit with regards to simulation makes comparison to other network models more problematic, since adding or subtracting parameters changes each estimate (see Tables 5, 6, and 7). Since our analysis focuses on comparison across the three cases, this issue is paramount. Moreover, given that: (1) the goodness-of-fit metrics presented above (Figures A1 and A4) speak to adequate MCMC mixing and consistency in parameter estimation within and across MCMC chains; and (2) the worst-fitting parameter in Figure A7 is the Meetings Attending parameter, which is not of substantive importance to the results in any case, we believe that it is still appropriate to make comparisons using the three models.

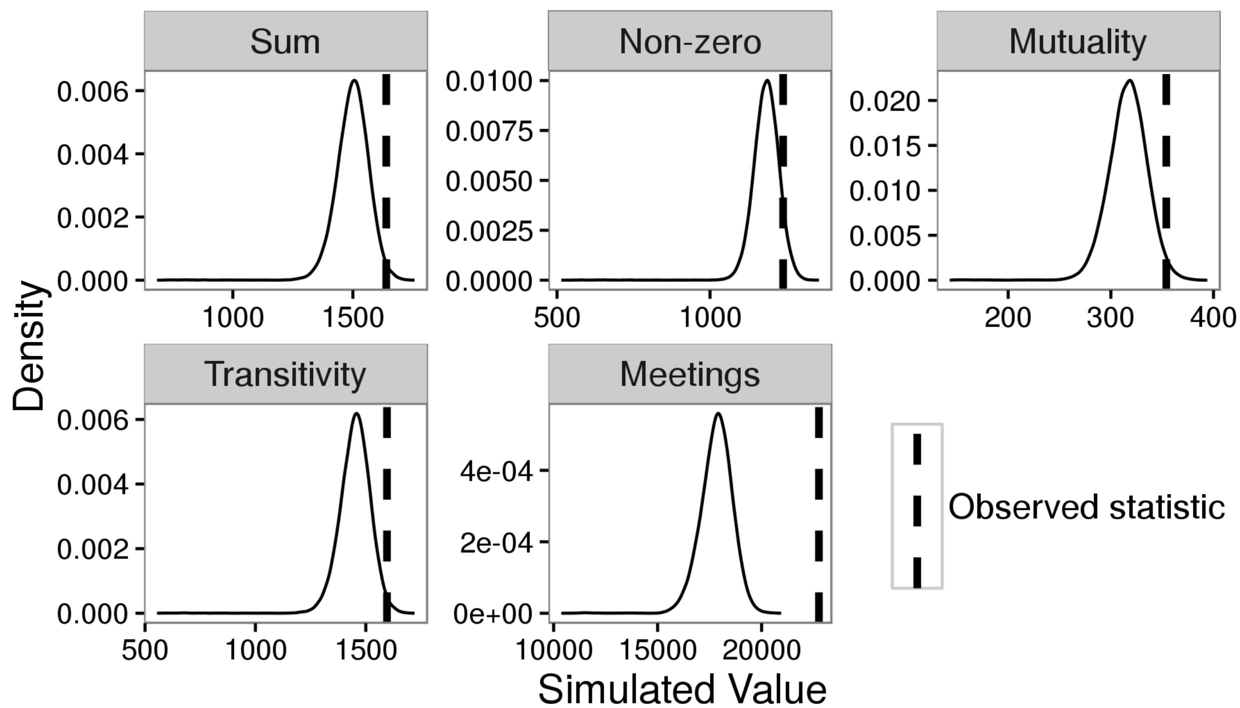

Figure A7: Distribution of simulated network statistics based upon Washington model

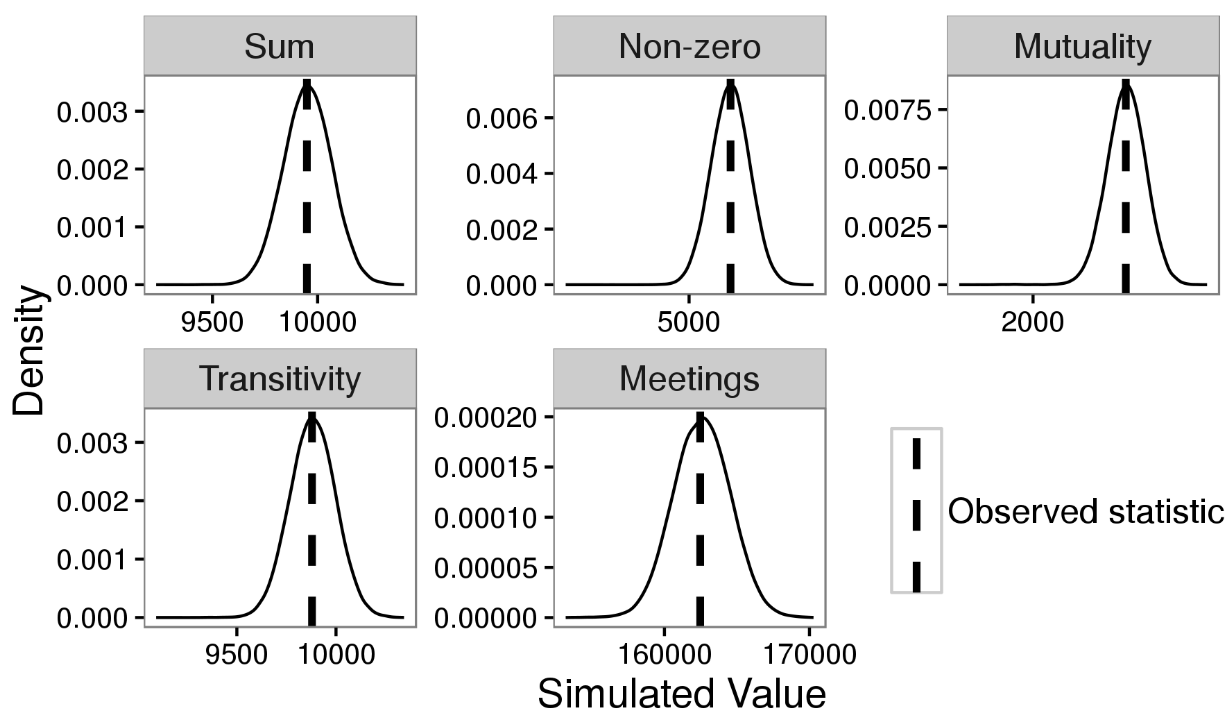

Figure A8: Distribution of simulated network statistics based upon Missouri model

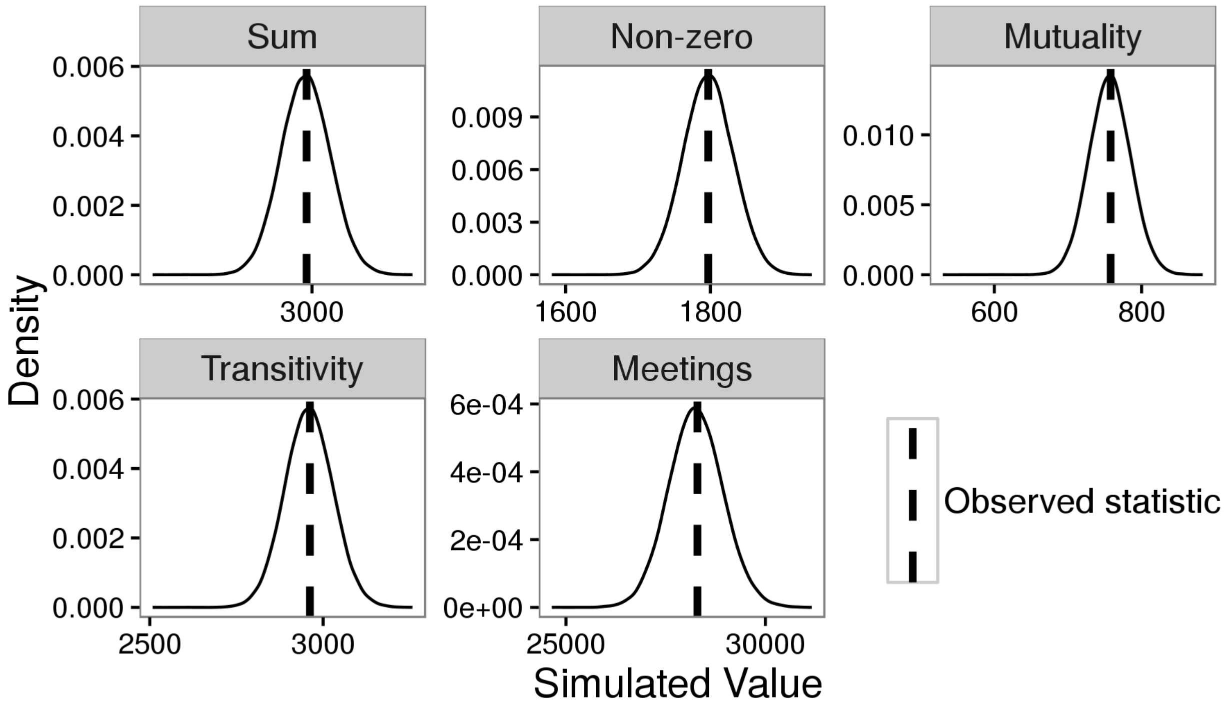

Figure A9: Distribution of simulated network statistics based upon Georgia model