Network Features and Processes as Determinants of Organizational Interaction during Extreme Events

Michael D. Siciliano[a*] and Clayton Wukich[b]

[a]Department of Public Administration, University of Illinois, Chicago
Email: sicilian@uic.edu

[b]Department of Political Science, Sam Houston State University
Email: wukich@shsu.edu

Despite the widely acknowledged importance of collaboration among participants in governance networks, a limited number of studies have attempted to statistically model the processes by which those networks form. In this article, we explore a range of network features and processes and measure their influence on network formation. We examine the case of Hurricane Katrina and employ exponential random graph models to identify the drivers of network formation in extreme events. We find that both the attributes of individual organizations and endogenous network processes affect organizational collaboration. Understanding these factors is important because the structure of the response network influences information flow, resource exchange, and performance.

Keywords: network analysis, governance networks, disaster response, exponential random graph models

1. Introduction

Disasters, whether natural or man-made, require multiple organizations to work together. Members of disaster response networks mobilize to protect life and property as well as provide citizens with necessary goods and services (Comfort, Boin, & Demchak, 2010; Kapucu, 2006). While some collaborative action among participants is planned, many of the activities in these networks develop based on rapid decisions made by participants under conditions of stress and uncertainty (Comfort, 1999; Drabek & McEntire, 2002). While necessity brings together these organizations (Weber & Khademian, 2008), coordination and collaboration are not necessarily ensured, and the lack of coordination can lead to suboptimal results (Comfort, 1999; Kapucu, 2006; Tierney, Lindell, & Perry, 2001).

Collective action problems have long been a focus of public administration research (Frederickson, 1999). Considerable attention has been given to the factors that influence

* Corresponding author.

collaboration in stable operating conditions. Research suggests that shared goals, the establishment of trust between organizations, and specific management skills facilitate interaction (Bardach, 1999; Bryson, Crosby, & Stone, 2006; Feiock, 2007). Scholars have also examined how and why agencies interact during extreme events (Comfort, 1999, 2007; Kapucu, 2006; Waugh & Streib, 2006). Given the condensed time frame for interaction during emergencies, a greater importance is placed on an organization's capacity to quickly develop and communicate strategies to coordinate action (Comfort, 2007; Kapucu, 2006).

While there is a large body of research on the importance of collaboration among participants in governance networks (Agranoff, 2007; Provan & Milward, 1995), a limited number of studies have attempted to statistically model the processes by which those networks form. According to Snijders (2011), the dependency among the ties in a network have hindered the development of suitable statistical network models. Consequently, previous work has often relied on qualitative case studies (see Agranoff, 2007), or traditional linear methods which assume that the decision maker contemplating collaboration operates in isolation (see Feiock, 2004). Even when network analysis has been used to study governance networks, the techniques employed tended to offer only descriptive measures of network properties rather than methods that capture generative processes (Kapucu, Hu, & Khosa, 2014).

In this study, we use exponential random graph models (ERGMs) to examine several network generating processes simultaneously while also appropriately handling the structural dependencies present in the data (Lusher, Koskinen, & Robins, 2013). We begin with a review of factors identified in previous research as important determinants of network structure. We then incorporate those factors into a statistical model to examine the interagency governance network that formed in Louisiana in response to Hurricane Katrina in 2005. We pay careful attention to model construction and interpretation in order to provide a clear application of ERGMs for other researchers who may be interested in applying the methodology.

2.   Interorganizational Network Formation

It is critical to understand the factors that influence collective action and network formation in public administration research (Bardach, 1998; Frederickson, 1999). Two streams of research in public administration are particularly relevant for their insights on the factors that shape and constrain interagency relationships: (i) Institutional Collect Action (ICA) (Feiock, 2004, 2013) and (ii) network management studies (Agranoff, 2007; Agranoff & McGuire, 2003), particularly those concerned with disasters (Comfort, 1999; Kapucu, 2006).

Work on ICA suggests that organizations engaged in collaborative arrangements accrue transaction costs in gathering information, negotiating agreements, coordinating joint efforts, and monitoring the performance of various partners (Feiock, 2004, 2007). The key task, therefore, is to mitigate these costs by establishing shared values and mutual

trust (Carr, LeRoux, & Shrestha, 2009; Romzek, LeRoux, & Blackmar, 2012). In stable operating environments, interorganizational networks develop over time as organizations assess the credibility and reliability of potential partners (Gulati & Gargiulo, 1999). Unlike practitioners operating under stable conditions, organizations involved in emergency response have very limited time to contemplate decisions regarding interagency collaboration (Comfort, 1999; Kapucu, 2006). Under conditions of uncertainty, individuals and organizations may be forced to rely on organizational attributes, such as sector or level of government, to make assessments of prospective partners. Attribute similarity can potentially reduce transaction costs (Feiock & Scholz, 2010) because it facilitates the establishment of trust and mutual expectations (Brass, 1995). The tendency for ties to form among actors with similar attributes or traits is known as homophily (Lazarsfeld & Merton, 1954). While recent research on governance and policy networks in stable operating environments have produced mixed results with regard to the importance of homophily (Henry, Lubell, & McCoy, 2011; Lee, Lee, & Feiock, 2012), the speed with which collaborations must form during crises suggests homophilous tendencies will be more pronounced in disaster response systems.

Hypothesis 1: Within the response network, organizations are more likely to form homophilous relationships.

Another means of reducing transaction costs is to rely on common partners to broker new relationships (Kwon, Feiock, & Bae, 2014; Thurmaier & Wood, 2002). Certain individuals and organizations play key roles in network formation by linking otherwise disparate organizations. Studies have identified key actors in response networks that both attract collaborative partners and connect others due to their roles in disaster response plans or their access to information and resources (Comfort & Haase, 2006; Kapucu, 2006; Kapucu & Demiroz, 2011).

When two organizations rely on a common partner to broker interaction, a network structure known as a transitive triad emerges where all three organizations collaborate with each other. Transitivity captures the common adage that a friend of a friend is a friend (Wasserman & Faust, 1994). Transitivity has been empirically observed in several studies on policy and governance networks (Henry et al., 2011; Lee et al., 2012). In a disaster scenario, agencies may rely on existing partners for referrals to connect with prospective partners. These referrals may help to promote trust and diminish the perceived transaction costs associated with quickly forming an ad hoc partnership.

Hypothesis 2: Within the response networks, organizations that share partners are more likely to interact with each other (i.e., form transitive relations).

While research using the ICA framework sheds light on the context and decision space confronted by public managers, studies on network management offer insight on the specific skills demonstrated by successful network participants (Agranoff, 2007). Network management scholars have identified the abilities to span jurisdictional boundaries and recruit potential members as valuable skillsets (Agranoff, 2007; Agranoff & McGuire, 2001; Goldsmith & Eggers, 2004). In many governance networks, organizations will take

lead responsibility for various administrative and operational tasks, and as a result these organizations assume central roles (Provan & Kenis, 2008). In disaster response networks, central agencies generally possess significant resources or direct access to resources and information (Comfort & Haase, 2006; Robinson, Eller, Gall, & Gerber, 2013). Research has found that the Federal Emergency Management Agency, state-level agencies charged with response duties, and local public safety departments are often at the core of disaster-response networks (Comfort & Haase, 2006; Kapucu, 2006; Kapucu & Demiroz, 2011).

With respect to social network analysis, the degree of an actor is a simple measure of activity or centrality. It is calculated by summing the number of ties that an actor has formed with other members of the network. Under a completely random process, the distribution of those ties across all actors, or the degree distribution, follows a normal curve. However, in most social and organizational networks, degree distributions follow a power law distribution (Barabási, 2002; Barabási & Albert, 1999). These networks are often centralized, as a few nodes are highly connected while the majority of nodes have only a few connections.

> Hypothesis 3: Within a disaster response network, a handful of key organizations will be disproportionately connected throughout the system (i.e., the network will tend to be centralized).

Another factor influencing organizational interaction is the concept of *propinquity*, which captures the physical distance separating two actors. There exists a strong tendency to interact with those in a shared physical space (Axelrod & Cohen, 1999). Some studies suggest that as the distance between two individuals increases, the probability of interaction drops exponentially (Allen, 1984; Krackhardt, 1994). As with individuals, organizations operating within close geographic proximity may also be more likely to collaborate due to the increased ability to share resources or services (Post, 2004) and the reductions in the transportation costs of goods (Owen-Smith & Powell, 2004).

> Hypothesis 4: Within the response network, organizations with headquarters located in close geographic proximity will be more likely to collaborate.

Taken individually, the extant literature on homophily, transitivity, degree distributions, and propinquity is fairly well established. However, much less is known about how these network properties and processes operate simultaneously. For example, how homophily and propinquity function together in generating network connections has not been adequately studied (Reagans, 2011). Also, transitivity in a network can arise via triadic closure through reliance on shared partners or it can result from homophilious tendencies to seek out partners with similar attributes (Robins, Pattison, Kalish, & Lusher, 2007; Zaccarin & Rivellini, 2010). Thus, when transitivity is observed in a network, it is not possible to disentangle the effects of triadic closure from homophily. In order to do so, one needs to use a statistical model, like an exponential random graph model, capable of modeling multiple processes simultaneously (Lusher et al., 2013; Robins, 2011; Robins et al., 2007). This approach has not been widely used to study governance networks. In their review on the state of network research, Kapucu et al. (2014) found only 7 articles across thirty-nine public administration journals over a fifteen year time span that used ERGMs.

3. Methods

Exponential random graph models allow for multiple network generating processes to be tested together (Robins, Snijders, Wang, Handcock, & Pattison, 2007; Snijders, Pattison, Robins, & Handcock, 2006). With these methods, researchers can propose and test micro-level processes that may be at work in generating the observed network (Goodreau, 2007). The observed network is simply the network for which the researcher has collected data and is interested in modeling (Robins et al., 2007).

According to Robins et al. (2007), "the network is conceptualized as a self-organizing system of relational ties. Substantively, the claim is that there are local social processes that generate dyadic relations, and that these social processes may depend on the surrounding social environment (i.e., on existing relations)" (p. 177). Even though the observed network may only be a snapshot of an evolving system, due to the stability and constancy of the micro-level processes driving actor interaction, particular patterns of tie formation will emerge from the observed data (Robins, 2011). "These patterns of network ties are indeed the structural signature of the network and provide evidence from which we may infer something of the social processes that build the network" (Robins, 2011, p. 484).

Based on the notation and terminology of Robins et al. (2007), exponential random graph models have the following general form:

$$\Pr(Y = y) = \left(\frac{1}{k}\right) \exp\left\{\sum_A \eta_A g_A(y)\right\}$$

where (i) y is a particular realization of the network; (ii) $g_A(y)$ are the network statistics corresponding to the network terms or configurations, A, included in the model (i.e., transitivity, homophily, etc.); (iii) η_A is the coefficient for a given network statistic; and (iv) k is a normalizing constant to ensure a proper probability distribution. We estimate these models using the **ergm** package of the **statnet** suite (Handcock, Hunter, Butts, Goodreau, & Morris, 2008) in the R programming environment (R Core Team, 2013). In applying ERGMs to the network that emerged in response to Hurricane Katrina, we illuminate potential factors influencing network formation in extreme events.

4. Case Selection and Data

In August 2005, Hurricane Katrina made landfall across the Gulf Coast, destroying infrastructure and overwhelming communities from Florida to Louisiana. More than 1,800 people lost their lives in one of the most deadly and, up to that point, the most costly natural disaster in United States history (Gall & Cutter, 2012). Louisiana bore the brunt of the storm as the subsequent flooding of New Orleans decimated infrastructure and created a major humanitarian crisis. Researchers in public administration and other disciplines paid considerable attention to the case (Cigler, 2007; Comfort, 2005; Comfort & Haase, 2006; Farazmand, 2007; Kapucu, Augustin, & Garayev, 2009; Kapucu & Garayev, 2011; Kiefer & Montjoy, 2006; Waugh, 2007; Waugh & Streib, 2006). Explanations for the failure of initiative that characterized the government response (U.S. House of

Representatives, 2006) tended to emphasize either individual or system wide failures. The mass media tended to focus on certain individual actors and their failings (e.g., President George W. Bush's perceived disengagement, the inefficacy of FEMA leadership, Governor Kathleen Blanco's lack of precision, and Mayor Ray Nagin's failure to organize an effective evacuation). Academic research examined what systemic factors contributed to poor outcomes (Birkland & Waterman, 2008; Cigler, 2007; Comfort, 2006; Waugh, 2007). This included work on the effectiveness of mutual aid agreements (Kapucu & Garayev, 2011; Waugh, 2007) as well as the constraints imposed on network formation related to federalism (Birkland & Waterman, 2008).

Comfort, Kapucu, and their colleagues, illustrated the features of the response system in terms of the actors involved, their interactions, and the flow of information and other resources (Comfort & Haase, 2006; Comfort, Oh, & Ertan, 2009; Kapucu et al., 2009). Findings demonstrated that while certain actors, such as FEMA, were central in the network, asymmetries existed in which many communities and organizations were not incorporated into the larger response system (Comfort & Haase, 2006).

Thus, while previous studies were able to describe the relevant characteristics and important properties of the response network as a whole, they did not allow for inferences regarding the processes that may have influenced the formation of the network. In this article, we complement prior studies by focusing on the interconnections among the organizations in the response system rather than on individual actors or whole network properties. We attempt to advance previous research by employing ERGMs to statistically model the interactions among the agencies responding to Hurricane Katrina.

Our data extends an existing dataset previously used by researchers to understand the structure and composition of the Katrina response system (Comfort & Haase, 2006; Comfort et al., 2009). The original data were derived from a content analysis of daily news reports (230 articles) published in *The New Orleans Times Picayune* and characterizes the response network that formed just prior to, during, and after hurricane Katrina (a period of 24 days). For additional information on the data, please see Comfort and Haase (2006) and Comfort et al. (2009). In total, 528 organizations[1] were identified along with 673 interactions. The network was then symmetrized to create an undirected network. Table 1 provides

Table 1

Level of Jurisdiction and Sector for the Organizations Operating in the Katrina Response System

	City/County	State	National	International	Total
Private	23	39	74	6	142
Non-Profit	30	26	23	3	82
Public	136	87	70	11	304
Total	189	152	167	20	528

[1] This number is slightly less than the number originally reported by Comfort, Oh, and Ertan (2009). The difference was due to our merging of several organizations. For example, we combined the Louisiana State University Manship School for Mass Communications with the Louisiana State University School of Journalism as these are the same entity. Likewise, we also combined West Jefferson General Hospital with West Jefferson Medical Center as these names are referring to the same organization with the same physical address.

Figure 1. Geographic Locations of Organizations Operating in the Katrina Response System.

a summary of the level of jurisdiction and sector for the organizations operating in the Katrina response. We extended the data by calculating the physical distance between each organization as a dyad level or edge attribute. Figure 1 displays a map of the locations of these organizations.

5. Variables and Measurement

We test our hypotheses by first operationalizing the following network features and processes: homophily, transitivity, degree distribution, and propinquity. Our data contain information on each organization's jurisdiction and sector. We assume that due to homophily organizations may be more likely to interact with others who operate within the same sector or on the same jurisdictional level (Lee et al., 2012; Robinson et al., 2013). To examine the role of homophily in generating ties, we constructed two different variables. The first one was *jurisdictional homophily,* which indicates whether or not two organizations operate on the same geographic scale (e.g., local, state, national, international). The second

one was, *sectoral homophily*, which indicates whether or not two organizations operate within the same sector (e.g., public, nonprofit, private). Rather than capturing an overall homophily effect for each attribute, we assumed that different homophilious tendencies were likely to exist across the categories of a given attribute. This assumption, known as differential homophily, allows the influence of organizational similarity to be estimated for each jurisdiction type and each sector independently.

Closed triads and clustering are common features in real networks. Early ERGMs often used a triangle statistic, which was simply a count of the number of closed triads, to account for transitivity. However, the use of a triangle term often led to degenerate network models where the observed network structure could not be recreated from the statistical model (Handcock, 2003; Snijders, 2002). To help avoid degenerate models, we used a geometrically weighted edgewise shared partner (GWESP) statistic, instead of a simple triangle term to account for transitivity. GWESP is one of several geometrically weighted terms developed by Snijders et al. (2006) and extended by Hunter and Handcock (2006) and Hunter (2007) to deal with problems of degeneracy that can arise in ERGMs.

Using the notation of Hunter (2007), the GWESP statistic is defined as:

$$v(y:\theta) = e^{\theta} \sum_{i=1}^{n-2} \{1 - (1 - e^{-\theta})^i\} EP_i(y)$$

where, y is the network, θ is the decay parameter, and $EP_i(y)$ is the number of edges in the network that have i shared partners.

Many observed networks, including the Katrina response, appear to follow a power law degree distribution. In order to investigate the network that emerged in response to Hurricane Katrina, a geometrically weighted degree (GWD) statistic can be used to help account for degree differentials and is preferred over k-star parameters. GWD is defined by Hunter (2007) as:

$$u(y:\theta) = e^{\theta} \sum_{i=1}^{n-1} \{1 - (1 - e^{-\theta})^i\} D_i(y)$$

and as with the GWESP statistic, y is the network, θ is the decay parameter, and $D_i(y)$ is the number of nodes in the network with degree i. For a more detailed discussion on the development and use of geometrically weighted dependency terms in ERGMs see Hunter and Handcock (2006) and Hunter (2007).

Organizational attributes may also play a role in determining which organizations are most active in the response system. For example, public organizations may be engaged in more collaborative relationships when compared to private organizations. These differences are often referred to as *main effects* and entered into the model as a set of dummy variables for the organization's jurisdiction and sector.

Propinquity is measured by calculating the geographic distance between the organizations in the response system. We assigned longitude and latitude coordinates for each organization. Using geospatial analysis, the locations for the organizations responding to Katrina

were geocoded using Esri's composite U.S. geocoder. These values were then geoprocessed to produce a table of distances between every organization. The distances were stored in a matrix and enter into the model as an edge covariate. Thus, it measures the likelihood of a tie forming between two organizations based on the physical distance between them.

6. Analyses and Results

Our analyses involve three different types of network models. We begin with a null or random graph model and then move through dyadic independent and finally to dyadic dependent models. This analytic strategy identifies how coefficients change when new terms are added to the model. For instance, homophilous effects that were significant in a dyadic independent model may no longer be present when controlling for transitivity. While we explore multiple models, it is important to note that only the final, combined model, offers an unbiased estimate of the coefficients. We used the final combined model to assess model adequacy, overall importance of network processes, and goodness of fit statistics.

The initial null or random graph model operates as a baseline. The model is built on the simple and unrealistic assumption that ties between organizations in the response system form completely at random. The model includes only an *edge term*, which functions in the same manner as the intercept in a standard linear model. It is simply the best guess

Table 2
Random and Dyadic Independent Models of the Katrina Response System

		Dyadic Independent Models		
	Null Model	Main Effects	Homophily	Propinquity
Structural Effects				
Edges	$-5.954 \, (0.053)^{***}$	$-9.899 \, (0.776)^{***}$	$-6.863 \, (0.108)^{***}$	$-5.757 \, (0.068)^{***}$
Main Effects				
Sector - Nonprofit		$-0.034 \, (0.164)$		
Sector - Public		$0.929 \, (0.108)^{***}$		
Jurisdiction - City/County		$1.252 \, (0.383)^{**}$		
Jurisdiction - National		$1.549 \, (0.384)^{***}$		
Jurisdiction - State		$1.340 \, (0.385)^{***}$		
Homophily Effects				
Both Nonprofit			$0.891 \, (0.317)^{**}$	
Both Private			$-0.141 \, (0.287)$	
Both Public			$1.299 \, (0.118)^{***}$	
Both City/County			$0.423 \, (0.143)^{**}$	
Both National			$0.976 \, (0.155)^{***}$	
Both State			$0.750 \, (0.162)^{***}$	
Propinquity				
Distance				$-0.020 \, (0.005)^{***}$
AIC	5010.141	4873.782	4838.192	4986.189
BIC	5019.984	4932.841	4907.094	5005.875
Log Likelihood	-2504.070	-2430.891	-2412.096	-2491.094

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

at the probability of a tie forming between any two organizations assuming nothing else about the organizations or network structure is known.

Building on the null model, we add dyadic independent terms one at a time. These terms are the homophily related effects, the main effects of nodal attributes, and edge covariates. These terms are considered dyadic independent because their effect on tie formation is assumed to be exogenous of the network structure. Thus, the complicated dependencies inherent in network data are ignored allowing dyadic independent models to be considered within a standard logistic regression framework (Goodreau, Kitts, & Morris, 2009; Hunter, Handcock, Butts, Goodreau, & Morris, 2008). The results for the null and dyadic independent models are presented in Table 2.

The parameter estimates for the network statistics included in the models can be interpreted as the log-odds (logit) of individual ties. The general form for ERGMs displayed previously can be rewritten to express the conditional logit of tie formation:[2]

$$logit\left(P(Y_{ij} = 1 \mid n \ actors, Y_{ij}^c)\right) = \sum_A \eta_A \vartheta g_A(y)$$

where Y_{ij}^c denotes all dyads other than Y_{ij}, and $\vartheta g_A(y)$ is the change in $g_A(y)$ when (Y_{ij}) is toggled from 0 to 1 (Goodreau et al., 2009). As Goodreau et al. (2009) note, the logit formulation clarifies the interpretation of the η vector: if forming a tie increases g_A by 1, then all else being equal the logit of that tie forming increases by η_A. Thus, relying on this interpretation, we can easily calculate the odds of a tie forming, $\exp(\Sigma_A \eta_A \vartheta g_A(y))$, as well as the probability of a tie forming,

$$\frac{exp\left(\sum_A \eta_A \vartheta g_A(y)\right)}{1 + exp\left(\sum_A \eta_A \vartheta g_A(y)\right)}.$$

In the simple random model, the probability is based solely on the edge term. The probability of tie formation is 0.0026, which we calculated using the following equation:

$$\frac{exp(-5.594)}{1 + exp(-5.594)}.$$

This probability is directly equal to the overall density of the undirected network. Again, such a model is rather uninformative and unable to capture the structural features of the observed network.

Adding dyadic independent terms to the model can help explain some of the structural features. The main effects model indicates the differences in the activity level of different organizational types compared to the base category. The base category for jurisdiction was

---

[2] While we can use a logistic regression framework to aid in the interpretation of the parameter estimates, we cannot use logistic regression to establish the parameter estimates in dyadic dependent models.

set to international and the base category for sector was set to private. The model suggests that public organizations are significantly more active compared to private organizations. For jurisdiction, the model suggests that city/county, national, and state level organizations are each significantly more active compared to international organizations.

It is instructive to calculate the probability of a tie forming between two specific organizations. Using the results of the main effect model, the probability of a tie between a public national organization and a public state organization can be calculated. The logit value is found by multiplying the statistics $g_A(y)$ by their estimated coefficients in the model. Here, we need to include the fact that the dyad of interest concerns two public organizations, one of which is a national organization, and the other which is a state organization. Using the transformation from log odds to probability gives us:

$$\frac{\exp(-9.899 \times 1 + .929 \times 2 + 1.549 \times 1 + 1.340 \times 1)}{1 + \exp(-9.899 \times 1 + .929 \times 2 + 1.549 \times 1 + 1.340 \times 1)}$$

The resulting probability of the tie, 0.006, can be compared with another dyad where the public national organization is switched to a public international organization (i.e., the base category for jurisdiction). By doing so we obtain a probability of 0.001. Holding other attributes of the dyad constant, switching one of the nodes from a national organization to an international organization makes a tie between those organizations less likely.

The homophily model examines the role of organizational similarity in tie formation. The model allows us now to investigate the question: Are agencies more likely to interact with similar agencies or might they reach out to dissimilar agencies in search of novel information, skills, or other needed resources? In terms of sector based homophily, both nonprofits and public organizations showed tendencies to form ties with organizations in their own sector. For jurisdictional homophily, an increased likelihood in tie formation among organizations of the same jurisdictional scale was found for city/county, state, and national level organizations. Homophily for international organizations was not included in the model as there were no international to international ties in the data.

The last dyadic independent model, the propinquity model, uses the edge covariate of geographic distance between organizations as a predictor of tie formation. The model suggests that organizations which are separated by greater geographic distance are less likely to work with one another in the response system. Each of these dyadic independent terms was combined together in a final model to assess their conditional effect when controlling for other organizational attributes and structural dependencies in the network.

The dyadic dependent variables used to capture the structural dependencies are GWESP and GWD. The results of the models for these two terms along with the final combined model that includes all of the dyadic independent and dyadic dependent terms are presented in Table 3.

The transitivity model indicates that there is a strong tendency for triadic closure to occur in the Katrina response system. The positive and significant effect on GWESP indicates that a collaborative tie was more likely to form between two organizations who

Table 3
Dyadic Dependent and Final Models of the Katrina Response System

	Transitivity	Degree Distribution	Final Model
Structural Effects			
Edges	$-6.244 (0.061)^{***}$	$-4.487 (0.031)^{***}$	$-5.622 (0.761)^{***}$
GWESP	$1.639 (0.081)^{***}$		$0.998 (0.089)^{***}$
GWD		$-1.837 (0.049)^{***}$	$-1.367 (0.111)^{***}$
Main Effects			
Sector – Nonprofit			$-0.371 (0.193)$
Sector - Public			$0.025 (0.374)$
Jurisdiction - City/County			$-0.024 (0.339)$
Jurisdiction - National			$0.378 (0.329)$
Jurisdiction - State			$-0.004 (0.338)$
Homophily Effects			
Both Nonprofit			$1.854 (0.485)^{***}$
Both Private			$0.101 (0.476)$
Both Public			$0.592 (0.400)$
Both City/County			$0.649 (0.241)^{**}$
Both National			$0.149 (0.263)$
Both State			$0.845 (0.251)^{***}$
Propinquity			
Distance			$-0.010 (0.005)^{*}$
AIC	4790.540	4752.930	4530.250
BIC	4810.226	4772.616	4677.897
Log Likelihood	-2393.270	-2374.465	-2250.125

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

shared a common partner. Thus, the positive coefficient for GWESP indicates a tendency toward transitivity in the network. In terms of the degree distribution, the negative and significant coefficient indicates that the degree distribution is not centralized but is rather spread more equally across the nodes in the network (Koskinen & Daraganova, 2013).

Moving to the final model, we found several significant changes in coefficient size and significance. The most noticeable one is the lack of significance for the main effects. This suggests that other factors in the model were driving the differences in organizational activity. For example, the main effect of city/county is no longer significant, and thus organizations operating at this level are not more active than the base category of international organizations controlling for the other effects. In the final model, city/county has a positive and significant homophily effect, and there is a general tendency to form ties with those nearby. These effects indicate that city/county organizations are unlikely to form ties in the response system unless those ties are with other city/county organizations and/or to other organizations operating within close geographic proximity. The homophilous tendencies of city/county organizations also help explain why coefficient on propinquity has cut in half in the final model.

Another notable difference between the single process models and the final combined model is the decrease in the size of the coefficient on GWESP. As mentioned earlier,

transitivity in networks can arise through homophily as well as through triadic closure. Given the drop in the size of the coefficient, it suggests that part of the impact of GWESP in the transitivity model was due to homophily. Once homophily was accounted for in the network, the tendency for triangles to form in the network is reduced, though still significant.

7. Model Fit

Like other statistical models, ERGMs can be assessed for overall model fit. One of the primary problems resulting from the use of ERGMs is model degeneracy. When degeneracy occurs, the model may either fail to converge or if it does converge, the simulated networks based off of the model parameters may produce structural features and patterns that are quite different from the observed data. Each of the models presented above successfully converged. Within the **ergm** package in R, a set of diagnostic tools are available to assess the overall fit and adequacy of the model. Please see the appendix for a description of these tools and a discussion of model fit with regards to the Katrina dataset.

8. Discussion

Our goal was to examine the tie formation in the Hurricane Katrina response system that emerged in Louisiana in 2005 and to test specific hypotheses regarding the network features and processes of homophily, transitivity, degree distributions, and propinquity. In doing so, we provide readers with a clear application of ERGMs. Previous studies have focused on individual actors and/or aggregate network properties, but less emphasis has been placed on the microprocesses and factors that may be at work in generating the system's structure. The use of ERGMs allowed us to describe and test several potential processes and to explore their importance for establishing collaborative ties among organizations.

The final combined model suggests that certain types of agencies sought to cluster with each other, as opposed to reaching out to more diverse organizations. Nonprofits were generally more likely to work with other nonprofits, which supports our first hypothesis. Nonprofits perhaps did not have access to state and federal resources in a timely and effective manner. Rather than a proxy for trust, nonprofit homophily might be explained based on the cooperative activities in which the organization engaged. Nonprofits make up a substantial portion of the United States' emergency support function (ESF) #6, for example, which includes mass care, housing, and human services. The American Red Cross, the Salvation Army, and many national faith-based organizations took part in this support function in Louisiana and actively coordinated efforts following Hurricane Katrina. Significant homophily effects may therefore indicate potential information asymmetries or conscious groupings of agencies around support function activities.

In addition, local agencies, those operating at the city or county level, were generally more likely to work with other local agencies. This finding along with the statistically

significant effect of propinquity provides evidence in support of our fourth hypothesis regarding the role played by geographic proximity. The interactions among local organizations may have been influenced by their physical proximities, but may also have been a product of past relationships, familiarity between personnel, and established levels of trust, all of which are considered to be initial conditions for cooperation (Bryson et al., 2006). The reliance of local organizations on other local organizations could also be due to the poor collaborative capacity demonstrated by state and federal agencies. The failure of initiative that characterized state and federal response efforts has been well documented (U.S. House of Representatives, 2006).

In support of our second hypothesis, the results suggest a strong tendency for responding organizations to form transitive structures. Because the model controls for homophily, this tendency toward transitivity exists over and above the clustering effects driven by organizational similarity. The importance of transitivity has been demonstrated in stable operating environments including regional planning networks (Henry et al., 2011), adult basic education policy networks (Park & Rethemeyer, 2014), and in networks related to economic development (Lee et al., 2012). Our study demonstrates that transitivity is also prevalent in the networks that emerge in response to extreme events. Coupled with the homophily effects, the results suggest that the organizations use bonding strategies - that is they work closely with multiple partners - to achieve desired outcomes (see Wukich & Robinson, 2013).

The coefficient on GWD, which captures the degree distribution of the network, was negative and significant. This result suggests that nodes with a high number of ties were unlikely and thus the network tended to be less centralized. This finding fails to support our third hypothesis. However, certain organizations, based on their sheer number of connections, were more central in the network than others. For these nodes that did have a high degree in the response network, their positions were likely driven by other effects in the model, such as transitivity. As discussed by de la Haye, Robins, Mohr, and Wilson (2010), this indicates that organizations which formed numerous ties generally did so in the context of clusters of organizations.

9.   Limitations and Future Research

While the Katrina dataset provided a detailed account of organizational interactions during the first three weeks of the response, some limitations of our study should be noted. Rather than viewing daily time slices of the network, the interactions are aggregated to form a picture of the overall response system that emerged immediately after the disaster. While such aggregation does not allow for dynamic network modeling it may help reduce errors in the data. Reductions in error are likely as collaboration between two organizations may only be reported by a newspaper on a particular day but the collaboration may have begun earlier and could endure longer than reported. This reality of using archival sources, suggests that aggregation at the appropriate time frame is needed to capture the response network.

While our data controlled for several attributes of the organizations engaged in the response, future research on disaster and governance networks should consider the inclusion of additional covariates. Additional variables that could be explored include organizational resources and capabilities (i.e., finances, equipment, personnel). Data on these attributes would provide researchers with the capacity to examine, among other things, the role of resource dependency in network formation. Future work can build on the network processes and models explored in this paper by adding specific managerial factors into the model that lead to collaboration (Agranoff, 2007; Agranoff & McGuire, 2001; Goldsmith & Eggers, 2004) as well as measures of trust or preexisting relationships.

Statistical models of networks, like ERGMs, provide researchers with an improved ability to test theory and hypotheses compared to more descriptive network methods or case studies (Lubell, Scholz, Berardo, & Robins, 2012; Robins, Lewis, & Wang, 2012). Consequently, one fruitful area of future research would be in the comparison of response systems within the same state or country before and after a major policy change or transition in leadership in key organizations. A comparative approach using statistical network models would allow scholars to identify if policy changes altered the importance of or type of factors affecting organizational interaction. The Post-Katrina Emergency Management Reform Act of 2006, for example, enables federal agencies to more proactively engage state and local governments during preparedness, response, and recovery periods. The extent to which a more active federal element might influence network formation and performance is a point of future research. Such dynamics could be included in an ERGM to explicitly test changes in the propensity for cross jurisdictional ties to form. Once we understand some of the underlying processes predicting tie formation, and how those processes have changed in response to policy changes, disaster managers and policymakers can more effectively develop policies to govern the response to extreme events. Future research could greatly add to statistical modeling by engaging in simultaneous and detailed qualitative interviews to better recognize the decision processes of organizational leaders as well as organizational capacity to identify where needed resources and expertise exist.

10. Conclusions

Our study builds on previous findings by exploring the network processes that influence organizational collaboration and by illuminating the generative processes at work in building the overall response network. While previous studies identified individual characteristics in isolation and described the network structure, we statistically modeled how homophily, transitivity, propinquity, and organizational attributes simultaneously shape the network.

We found that both the attributes of individual actors and endogenous network processes influence the structure of disaster response systems. Understanding these processes adds to our ability to evaluate complex systems. These processes may be prominent in emergency situations due to the level of uncertainty and speed by which organizations must make decisions and act. In these situations organizations may naturally rely on

existing partners or similar organizations to form new ties rather than seeking out other organizations that may be more suitable for solving problems. The inefficiencies that can result from this type of connection-making offer support to previous calls to improve communication and coordination during response and to engage in additional networking and preparation beforehand (Comfort, 2006; Comfort & Haase, 2006; Kapucu, 2006).

Therefore, emergency managers must understand and exercise existing plans, but also identify possible partners in the event of catastrophe beyond current planning capabilities, the so-called black swan events (Taleb, 2010). This will allow for agencies to rely less on their current network partners and span boundaries to develop relationships or at least identify available resources and contacts prior to an extreme event. We suggest that managers not just count on existing written plans or relationships with their neighbors, but actually exercise those plans, anticipate potential contingencies, and make contact with potential partners in an effort to better access necessary information and resources during an extreme event.

11. Acknowledgements

References

Agranoff, R. (2007). *Managing within networks: Adding value to public organizations*. Washington, DC: Georgetown University Press.

Agranoff, R., & McGuire, M. (2001). Big questions in public network management research. *Journal of Public Administration Research and Theory, 11*(3), 295–326.

Agranoff, R., & McGuire, M. (2003). *Collaborative public management: New strategies for local governments*. Washington, DC: Georgetown University Press.

Allen, T. J. (1984). *Managing the flow of technology: Technology transfer and the dissemination of technological information within the R&D organization*. Cambridge, MA: MIT Press Books.

Axelrod, R. M., & Cohen, M. D. (1999). *Harnessing complexity: Organizational implications of a scientific frontier*. New York, NY: Free Press.

Barabási, A.-L. (2002). *Linked: The new science of networks*. Cambridge, MA: Perseus.

Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science, 286*(5439), 509–512. doi:10.1126/science.286.5439.509

Bardach, E. (1998). *Getting agencies to work together: The practice and theory of managerial craftsmanship*. Washington, DC: Brookings Institution Press.

Bardach, E. (1999). *Getting agencies to work together*. Washington, DC: The Brookings Institute.

Birkland, T., & Waterman, S. (2008). Is federalism the reason for policy failure in Hurricane Katrina? *Publius: The Journal of Federalism, 38*(4), 692–714. doi:10.1093/publius/pjn020

Brass, D. J. (1995). A social network perspective on human resources management. *Research in Personnel and Human Resources Management, 13*(1), 39–79.

Bryson, J. M., Crosby, B. C., & Stone, M. M. (2006). The design and implementation of cross-sector collaborations: Propositions from the literature. *Public Administration Review, 66*(1), 44–55.

Carr, J. B., LeRoux, K., & Shrestha, M. (2009). Institutional ties, transaction costs, and external service production. *Urban Affairs Review, 44*(3), 403–427. doi:10.1177/1078087408323939

Cigler, B. A. (2007). The "big questions" of Katrina and the 2005 great flood of new orleans. *Public Administration Review, 67*, 64–76. doi:10.1111/j.1540-6210.2007.00814.x

Comfort, L. K. (1999). *Shared risk: Complex systems in seismic response* (1st ed.). Amsterdam, The Netherlands: Pergamon.

Comfort, L. K. (2005). Risk, security, and disaster management. *Annual Review of Political Science, 8*(1), 335–356. doi:10.1146/annurev.polisci.8.081404.075608

Comfort, L. K. (2006). Cities at risk: Hurricane Katrina and the drowning of new orleans. *Urban Affairs Review, 41*(4), 501–516. doi:10.1177/1078087405284881

Comfort, L. K. (2007). Crisis management in hindsight: Cognition, communication, coordination, and control. *Public Administration Review, 67*, 189–197. doi:10.1111/j.1540-6210.2007.00827.x

Comfort, L. K., Boin, A., & Demchak, C. C. (2010). *Designing resilience: Preparing for extreme events*. Pittsburgh, PA: University of Pittsburgh Press.

Comfort, L. K., & Haase, T. W. (2006). Communication, coherence, and collective action: The impact of Hurricane Katrina on communications infrastructure. *Public Works Management & Policy, 10*(4), 328–343. doi:10.1177/1087724x06289052

Comfort, L. K., Oh, N., & Ertan, G. (2009). The dynamics of disaster recovery: Resilience and entropy in hurricane response systems 2005–2008. *Public Organization Review, 9*(4), 309–323. doi:10.1007/s11115-009-0098-3

de la Haye, K., Robins, G., Mohr, P., & Wilson, C. (2010). Obesity-related behaviors in adolescent friendship networks. *Social Networks, 32*(3), 161–167. doi:10.1016/j.socnet.2009.09.001

Drabek, T. E., & McEntire, D. A. (2002). Emergent phenomena and multiorganizational coordination in disasters: Lessons from the research literature. *International Journal of Mass Emergencies and Disasters, 20*(2), 197–224.

Farazmand, A. (2007). Learning from the Katrina crisis: A global and international perspective with implications for future crisis management. *Public Administration Review, 67*, 149–159. doi:10.1111/j.1540-6210.2007.00824.x

Feiock, R. C. (2004). *Metropolitan governance: Conflict, competition, and cooperation*. Washington, DC: Georgetown University Press.

Feiock, R. C. (2007). Rational choice and regional governance. *Journal of Urban Affairs, 29*(1), 47–63. doi:10.1111/j.1467-9906.2007.00322.x

Feiock, R. C. (2013). The institutional collective action framework. *Policy Studies Journal, 41*(3), 397–425. doi:10.1111/psj.12023

Feiock, R. C., & Scholz, J. T. (2010). *Self-organizing federalism: Collaborative mechanisms to mitigate institutional collective action dilemmas*. New York, NY: Cambridge University Press.

Frederickson, G. H. (1999). The repositioning of American public administration. *Political Science and Politics, 32*(4), 701–711.

Gall, M., & Cutter, S. L. (2012). 2005 events and outcomes: Hurricane Katrina and beyond. In C. B. Rubin (Ed.), *Emergency management: The American experience 1900–2005* (2nd ed., pp. 191–213). Boca Raton, FL: CRC Press.

Goldsmith, S., & Eggers, W. D. (2004). *Governing by network: The new shape of the public sector*. Washington, DC: Brookings Institution Press.

Goodreau, S. M. (2007). Advances in exponential random graph (p^*) models applied to large social networks. *Social Networks, 29*(2), 231–248.

Goodreau, S. M., Kitts, J. A., & Morris, M. (2009). Birds of a feather, or friend of a friend? Using exponential random graph models to investigate adolescent social networks. *Demography, 46*(1), 103–125.

Gulati, R., & Gargiulo, M. (1999). Where do interorganizational networks come from? *American Journal of Sociology, 104*(5), 1439–1493. doi:10.1086/210179

Handcock, M. S. (2003). *Assessing degeneracy in statistical models of social networks*. (Working Paper no. 39). Manuscript in preparation. Retrieved from Center for Statistics and Social Sciences, University of Washington website: http://www.csss.washington.edu/Papers/wp39.pdf

Handcock, M. S., Hunter, D. R., Butts, C. T., Goodreau, S. M., & Morris, M. (2008). Statnet: Software tools for the representation, visualization, analysis and simulation of network data. *Journal of Statistical Software, 24*(1), 1–11.

Henry, A. D., Lubell, M., & McCoy, M. (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. doi:10.1093/jopart/muq042

Hunter, D. R. (2007). Curved exponential family models for social networks. *Social Networks, 29*(2), 216–230.

Hunter, D. R., Goodreau, S. M., & Handcock, M. S. (2008). Goodness of fit of social network models. *American Statistical Association, 103*(481), 248–258.

Hunter, D. R., & Handcock, M. S. (2006). Inference in curved exponential family models for networks. *Journal of Computational and Graphical Statistics, 15*(3), 565–583.

Hunter, D. R., Handcock, M. S., Butts, C. T., Goodreau, S. M., & Morris, M. (2008). Ergm: A package to fit, simulate and diagnose exponential-family models for networks. *Journal of Statistical Software, 24*(3), 1–29.

Kapucu, N. (2006). Interagency communication networks during emergencies: Boundary spanners in multiagency coordination. *The American Review of Public Administration, 36*(2), 207–225. doi:10.1177/0275074005280605

Kapucu, N., Augustin, M.-E., & Garayev, V. (2009). Interstate partnerships in emergency management: Emergency management assistance compact in response to catastrophic disasters. *Public Administration Review, 69*(2), 297–313. doi:10.1111/j.1540-6210.2008.01975.x

Kapucu, N., & Demiroz, F. (2011). Measuring performance for collaborative public management using network analysis methods and tools. *Public Performance & Management Review, 34*(4), 549–579. doi:10.2753/PMR1530-9576340406

Kapucu, N., & Garayev, V. (2011). Collaborative decision-making in emergency and disaster management. *International Journal of Public Administration, 34*(6), 366–375. doi:10.1080/01900692.2011.561477

Kapucu, N., Hu, Q., & Khosa, S. (2014). The state of network research in public administration. *Administration & Society*. Advance online publication. doi:10.1177/0095399714555752

Kiefer, J. J., & Montjoy, R. S. (2006). Incrementalism before the storm: Network performance for the evacuation of new orleans. *Public Administration Review, 66*, 122–130. doi:10.1111/j.1540-6210.2006.00672.x

Koskinen, J., & Daraganova, G. (2013). Exponential random graph model fundementals. In D. Lusher, J. Koskinen, & G. Robins (Eds.), *Exponential random graph models for social networks: Theory, methods, and applications* (pp. 49–76). New York, NY: Cambridge University Press.

Koskinen, J., & Snijders, T. A. B. (2013). Simulation, estimation, and goodness of fit. In D. Lusher, J. Koskinen, & G. Robins (Eds.), *Exponential random graph models for social networks: Theory, methods, and applications* (pp. 141–166). New York, NY: Cambridge University Press.

Krackhardt, D. (1994). Constraints on the interactive organization as an ideal type. In C. Heckscher & A. Donnellon (Eds.), *The post-bureaucratic organization: New perspectives on organizational change* (pp. 211–222). Thousand Oaks, CA: Sage.

Kwon, S.-W., Feiock, R. C., & Bae, J. (2014). The roles of regional organizations for interlocal resource exchange: Complement or substitute? *The American Review of Public Administration, 44*(3), 339–357. doi:10.1177/0275074012465488

Lazarsfeld, P. F., & Merton, R. K. (1954). Friendship as a social process: A substantive and methodological analysis. In M. Berger (Ed.), *Freedom and control in modern society*. New York, NY: Van Nostrand.

Lee, Y., Lee, I. W., & Feiock, R. C. (2012). Interorganizational collaboration networks in economic development policy: An exponential random graph model analysis. *Policy Studies Journal, 40*(3), 547–573. doi:10.1111/j.1541-0072.2012.00464.x

Lubell, M., Scholz, J., Berardo, R., & Robins, G. (2012). Testing policy theory with statistical models of networks. *Policy Studies Journal, 40*(3), 351–374. doi:10.1111/j.1541-0072.2012.00457.x

Lusher, D., Koskinen, J., & Robins, G. (2013). *Exponential random graph models for social networks: Theory, methods, and applications*. New York, NY: Cambridge University Press.

Owen-Smith, J., & Powell, W. W. (2004). Knowledge networks as channels and conduits: The effects of spillovers in the boston biotechnology community. *Organization Science, 15*(1), 5–21. doi:10.1287/orsc.1030.0054

Park, H. H., & Rethemeyer, R. K. (2014). The politics of connections: Assessing the determinants of social structure in policy networks. *Journal of Public Administration Research and Theory. 24*(2), 349–379. doi:10.1093/jopart/mus021

Post, S. S. (2004). Metropolitan area governance and institutional collective action. In R. C. Feiock (Ed.), *Metropolitan governance: Conflict, competition, and cooperation* (pp. 67–94). Washington, DC: Georgetown University Press.

Provan, K. G., & Milward, B. H. (1995). A preliminary theory of interorganizational network effectiveness: A comparative study of four community mental health systems. *Administrative Science Quarterly, 40*(1), 1–33.

R Core Team. (2013). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing.

Reagans, R. (2011). Close encounters: Analyzing how social similarity and propinquity contribute to strong network connections. *Organization Science, 22*(4), 835–849, doi:10.1287/orsc.1100.0587

Robins, G. (2011). Exponential random graph models for social networks. In J. Scott & P. Carrington (Eds.), *The SAGE handbook of social network analysis*. Thousand Oaks, CA: Sage.

Robins, G., Lewis, J. M., & Wang, P. (2012). Statistical network analysis for analyzing policy networks. *Policy Studies Journal, 40*(3), 375–401. doi:10.1111/j.1541-0072.2012.00458.x

Robins, G., Pattison, P., Kalish, Y., & Lusher, D. (2007). An introduction to exponential random graph (p^*) models for social networks. *Social Networks, 29*(2), 173–191.

Robins, G., Snijders, T., Wang, P., Handcock, M., & Pattison, P. (2007). Recent developments in exponential random graph (p^*) models for social networks. *Social Networks, 29*(2), 192–215.

Robinson, S. E., Eller, W. S., Gall, M., & Gerber, B. J. (2013). The core and periphery of emergency management networks. *Public Management Review, 15*(3), 344–362. doi:10.1080/14719037.2013.769849

Romzek, B. S., LeRoux, K., & Blackmar, J. M. (2012). A preliminary theory of informal accountability among network organizational actors. *Public Administration Review, 72*(3), 442–453. doi:10.1111/j.1540-6210.2011.02547.x

Snijders, T. A. B. (2002). Markov chain monte carlo estimation of exponential random graph models. *Journal of Social Structure, 3*(2), 1–40.

Snijders, T. A. B. (2011). Statistical models for social networks. *Annual Review of Sociology, 37*(1), 131–153. doi:10.1146/annurev.soc.012809.102709

Snijders, T. A. B., Pattison, P. E., Robins, G. L., & Handcock, M. S. (2006). New specifications for exponential random graph models. *Sociological Methodology, 36*(1), 99–153.

Taleb, N. N. (2010). *The black swan: The impact of the highly improbable fragility*. New York, NY: Random House LLC.

Thurmaier, K., & Wood, C. (2002). Interlocal agreements as overlapping social networks: Picket–fence regionalism in metropolitan kansas city. *Public Administration Review, 62*(5), 585–598. doi:10.1111/1540-6210.00239

Tierney, K. J., Lindell, M. K., & Perry, R. W. (2001). *Facing the unexpected: Disaster preparedness and response in the united states*. Washington, DC: Joseph Henry Press.

U.S. House of Representatives. (2006). *A failure of initiative: Final report of the Select Bipartisan Committee to investigate the preparation for and response to Hurricane Katrina*. Washington, DC: US Government Printing Office.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. New York, NY: Cambridge University Press.

Waugh, W. L. (2007). Emac, Katrina, and the governors of Louisiana and Mississippi. *Public Administration Review, 67*, 107–113. doi:10.1111/j.1540-6210.2007.00819.x

Waugh, W. L., & Streib, G. (2006). Collaboration and leadership for effective emergency management. *Public Administration Review, 66*, 131–140. doi:10.1111/j.1540-6210.2006.00673.x

Weber, E. P., & Khademian, A. M. (2008). Wicked problems, knowledge challenges, and collaborative capacity build-ers in network settings. *Public Administration Review, 68*(2), 334–349. doi:10.1111/j.1540-6210.2007.00866.x

Wukich, C., & Robinson, S. E. (2013). Leadership strategies at the meso level of emergency management in networks. *International Review of Public Administration, 18*(1), 41–59.

Zaccarin, S., & Rivellini, G. (2010). Modeling network data: An introduction to exponential random graph models. In F. Palumbo, C. N. Lauro, & M. J. Greenacre (Eds.), *Data analysis and classification* (pp. 297–305). Berlin, Germany: Springer.

Appendix: Assessing Goodness of Fit

As noted in the text, all of the models successfully converged. For the final model, we assessed the difference between the sample statistics based on simulated networks (i.e., those generated from the parameter estimates in the final model) to the actual values in the observed network. For each of the terms included in the model, no significant difference was found between the observed value and the sample statistic of that term produced from the simulated networks.

Once we were satisfied with the final model's convergence, we examined whether the model could reproduce "out-of-model statistics." These out-of-model statistics are part of the goodness of fit heuristics described by Hunter, Goodreau, and Handcock (2008). The goodness of fit measures for statistical network models assess the ability of a fitted model to reproduce certain network properties that were not specifically modeled, thus the term "out-of-model" statistics. If the out-of-model or nonfitted statistics are well captured in the simulated distribution of graphs, then there is evidence to indicate that these features may have arisen from the processes included in the model (Koskinen & Snijders, 2013). The most common out-of-model statistics used to assess goodness of fit are shared part-ners, degree, and average geodesic distance. The results are shown in Figure 2.

In each of these plots, the thick black line represents the observed value of a given statistic in the Katrina response system. The boxplots are derived from the simulated net-works. For the boxplots, 100 networks were simulated based on the parameter estimates in the final model. The relevant network statistic was then calculated for each simulated network, and the distribution of the statistic across the simulations is charted. The first goodness of fit plot reveals the proportion of edges with a given number of shared partners. The plot suggests that our model captured well the shared partner distribution observed in the Katrina dataset. While the GWESP term used in the model is assured of capturing the mean number of shared partners, it does not control for the full distribution of shared part-ners (Goodreau et al., 2009). Thus, this global property in the network is being adequately captured by the terms included in our final model.

The second plot shows the degree distribution. As with GWESP, the GWD term and the main effect terms do not model the full degree distribution. The goodness of fit plot indicates one area where our model does not adequately represent the proportion of nodes with a given degree. Specifically, the model underestimates the proportion of nodes with a degree of 1. This indicates that there are more pendants in the observed network than
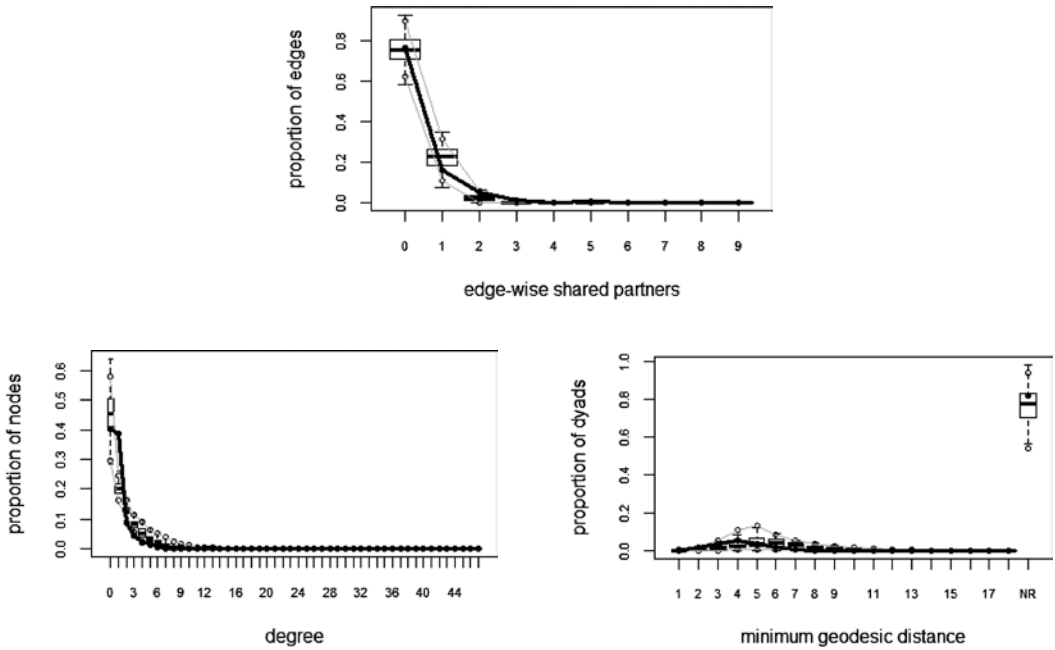
Figure 2. Goodness of Fit Plots for the Final Model.

present in the simulated networks. While the overall shape of the distribution is captured by the model, instances of under- or over-estimation represent areas for future research (Goodreau et al., 2009) and can indicate the need to explore additional model terms.

The final plot reveals the geodesic distances between organizations. These distances represent the number of links that exist between two organizations and is not directly related to any of the terms included in the final model. Due to the fragmentation of the network, the plot indicates that the largest proportion of dyads were not reachable (NR). For those that are reachable, the distribution is characterized by a small spike around geodesics of 4, 5, and 6. Overall, our final model captures the distribution of distances fairly well, as the observed line falls within each of the boxplots. Taken as a whole, we feel our model adequately captures the three out-of-model statistics, and thus provide evidence to indicate that these features could have potentially arisen from the processes included in the model (Koskinen & Snijders, 2013).