University of Pittsburgh

CDM WORKING PAPER SERIES

The Use of Exponential Random Graph Models to Investigate the Micro-Level Processes of Inter-Organizational Network Formation

Michael Siciliano

Working Paper: 1106

http://www.cdm.pitt.edu/Portals/2/PDF/WorkingPaperSeries/CDM_Working_Paper_1106.pdf

CENTER FOR DISASTER MANAGEMENT
Graduate School of Public and International Affairs
University of Pittsburgh
3913 Wesley W. Posvar Hall
230 S. Bouquet St
Pittsburgh, PA 15260
November 3, 2011

The Use of Exponential Random Graph Models to Investigate the Micro-Level Processes of Inter-Organizational Network Formation

Michael Siciliano
CDM Working Paper No. 1106
November 2011

Abstract: The response systems that emerge after large-scale disasters like the Haitian Earthquake on January 12th, 2010, or the recent series of events unfolding in Japan, are defined by the complex interactions of organizations. These response systems are often analyzed by investigating the structure of the network and the consequences of its structural properties. While there is a growing body of work on the consequences of response networks, there is limited research on the antecedents of these networks. This paper provides statistical inferences on the selection processes that exist among organizations entering the response system and highlights the micro-level processes that give rise to the global structure. Part of the reason for the lack of research on the antecedents of disaster response networks has been due to limitations in the statistical modeling of networks that required the researcher to investigate potential generative processes in isolation. Recent advances in exponential random graph models (also referred to as p* models) provide a flexible statistical framework to examine multiple interdependent processes simultaneously. This paper proposes and tests theoretically driven micro-level processes believed to be responsible for generating the global structure of the observed response networks that emerged after recent earthquakes in Indonesia, Haiti, and Japan. These findings offer fresh insight into the mechanisms driving tie formation between organizations in emergencies and provide guidance on future research into the antecedents of networks

Michael Siciliano
Center for Disaster Management
Graduate School of Public and International Affairs
University of Pittsburgh
mds55@pitt.edu

1. Introduction – Networks In Disaster Management

The response systems that emerge after large-scale disasters like the Haitian Earthquake on January 12th, 2010, or the series of events that unfolded in Japan in the spring of 2011, are defined by the complex interactions of organizations. These response systems can be viewed and analyzed as an inter-organizational network where various actors are linked together in a web of informal and formal relationships. Utilizing a network perspective, successful outcomes for response systems are viewed not only as a product of the distribution of resources and capacity within the system, but also as a product of the distribution of relationships (Brass 1995; Cross et al. 2003).

The relationships that link actors together in a broader social structure facilitate communication, collaboration, knowledge transfer, and innovation (Kilduff and Tsai 2003; Kilduff and Krackhardt 2008) and therefore can have substantial implications on the performance of the network. Experimental work dating back to the 1950s has demonstrated the importance of communication patterns of people operating in groups by altering the configuration of relations in the group and documenting the subsequent changes in outcomes (Bavelas 1950; Guetzkow and Simon 1955; Leavitt 1951; Shaw 1964). Results of these studies indicate that performance at the group level is directly related to network structure.

In the field of disaster management, response networks have been analyzed by describing the empirical structure of the network and by discussing the effect of structural properties on system performance. As with other fields, the bulk of research on networks in disaster management has been concerned with the consequences of network structure. As Borgatti and Foster (2003) note, a primary reason why research has been predominantly engaged with the consequences of networks is the need to establish, initially, the importance of network variables. Once network variables have been legitimized, a logical next step is to investigate the processes leading networks to cohere in certain ways by allowing for statistical inferences about network determinants.

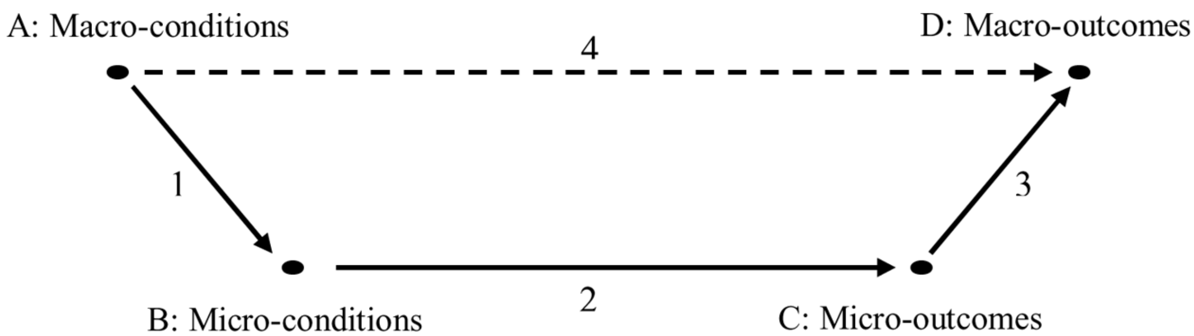
This paper specifically investigates the antecedents of response systems by building appropriate selection models for organizational interaction. Utilizing three datasets on the response systems that emerged after the recent crises in Indonesia, Haiti, and Japan, this paper employs exponential random graph models (ERGMs also known as p* models) to provide statistical inference about the proposed micro-level generative processes in a comparative framework. Ultimately, this work is interested in explaining the macro-level structure of a response network through a parsimonious model of micro-level interactions.

The next section discusses the sociological foundation of micro-macro linkages. Section 3 details a brief background on ERG models and the functionality of the method. Section 4 gives an overview of the three datasets under study. Section 5 highlights the modeling of the disaster response networks and the results. Section 6 investigates the goodness of fit of the ERG models for each response system. Section 7 concludes by discussing limitations in our modeling efforts and by offering advice for future work on the antecedents of response network formation.

2. Modeling Micro-Macro Linkages

One of the classic views in the social sciences on the relationship between micro and macro conditions was developed by James Coleman (1990). In his 'bathtub model', shown in Figure 1, there are two conditions, two outcomes, and four processes that link conditions and outcomes (Raub et al. 2011).

Figure 1: Coleman's Scheme (Image from Raub et al. 2011).



The first process depicted in the scheme details how micro-conditions of individual actor attributes and behavior are affected by the macro-conditions of the actor's environment. The second process links micro-conditions to micro-outcomes. The third process concerns emergent phenomena, meaning how individual actions ultimately generate macro-outcomes. Finally, the fourth process is the relationship between macro-conditions and macro-outcomes or "propositions about an empirical regularity at the macro-level" (Raub et al. 2011, p. 3).

The vast majority of current and historical network research views social structure as an independent variable. Networks are used to explain other phenomena of interest – a consequence perspective. Within Coleman's framework, the literature on disaster response networks has tended to investigate the fourth process, accepting the network structure as a factor providing explanation of variance in response and recovery outcomes. Very little research has occurred from the perspective of networks as the phenomena to be explained – the antecedent perspective. Given the relative dearth of work on the micro-macro linkages of response networks, this paper's analysis of response systems focuses on the micro-macro influence[1] as we seek to explain the emergence of the overall network. Thus, this paper is primarily interested in modeling and understanding processes 2 and 3.

The difficulty of modeling social networks as the explanandum arises from the fact that the relations formed within a network are not independent of one another, causing problems for estimating statistical models for network inference. Therefore, it is crucial to utilize statistical distributions that take into account the inherent dependency among the dyads in the network under study (Monge and Contractor 2003).

[1] Klein and Kozlowski (2000) state that while multi-level models that bridge micro-macro and macro-micro perspectives are the ideal end state for any organizational theory, in little explored research areas it may be most appropriate to begin with a single directional analysis.

As discussed by Goodreau et al. (2009), historically, researchers have examined the potential generative processes in isolation. This limited approach was due to the lack of a framework for statistical estimation that allowed multiple interdependent processes to be considered jointly. The problem with examining processes individually is that the appearance of global properties can occur through different means. For example, there is a clear relationship between the density of a network and the number of closed triangles (sets of three actors all connected to one another). As the density in a network increases, the number of triangles will also increase. For a more nuanced example, clustering in networks can occur through triadic closure as supported by balance theory (Heider 1958) or through a homophily effect based on attributes. As Zaccarin and Rivellini (2010, p. 298) note, only a model that includes both of these effects simultaneously is capable of assessing whether triadic closure or homophily or both are important processes in forming the network. Exponential Random Graph Models provide an opportunity to model multiple processes simultaneously and hence, determine the size of the effect of various micro-parameters on network formation.

3. Use Of ERGMS for Questions of Network Formation

A flexible method for generative network formation known as exponential random graph models (see Wasserman and Pattison 1996; Robbins et al. 2007a) has been developed that allows for multiple parameters to be tested together thanks to recent advances in estimation techniques (Handcock 2003; Snijders et al. 2006). These models are designed to allow the researcher to propose and then test theoretically driven micro-level processes that may be at work in generating the global properties in 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. 2007a).

Robins (2007a, p. 177) states, "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)." When a researcher measures an empirical network, he/she can then make conjectures about the organizing principals that would give rise to the observed structure. Even though the network under study may be a single representation 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. (2007a p. 178-179), exponential random graph models have the following form:

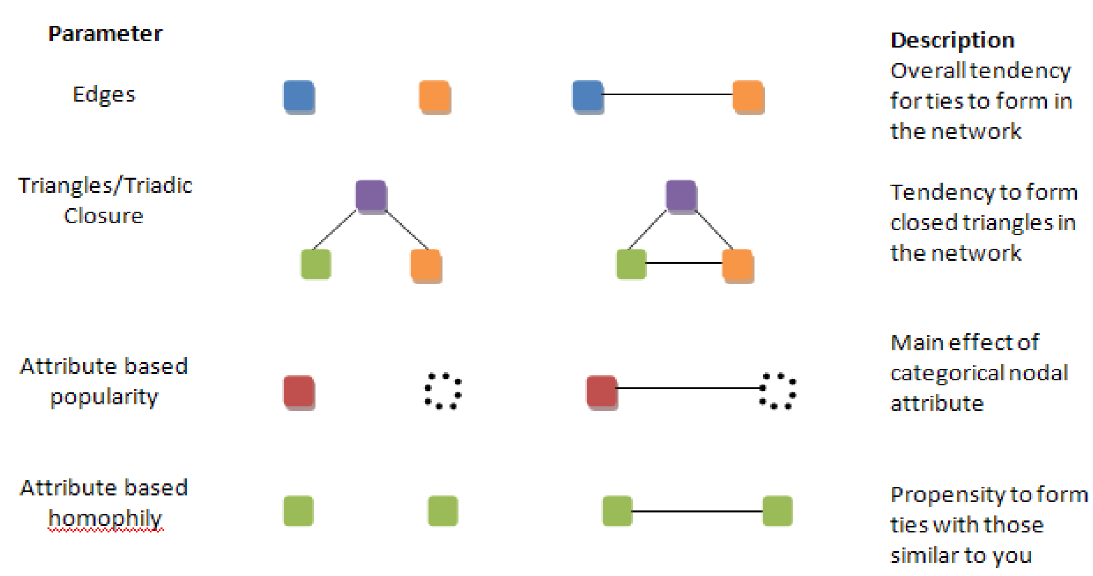
$$\Pr(Y = y) = \left(\frac{1}{k}\right) exp\{\textstyle\sum_A \eta_A \mathrm{g}_A\,(y)\} \qquad (1)$$

Where (i) the summation is over all configuration types A; (ii) η_A is the parameter corresponding to configuration A; (iii) $\mathrm{g}_A(y)$ is the network statistic corresponding to the configuration A, such that $\mathrm{g}_A(y)$ =1 if the configuration is in the observed network (y) and $g_A(y)$ =0 otherwise; and (iv) k is a normalizing constant to ensure a proper probability distribution. [2]

ERGMs can be modeled with dyadic independence or dyadic dependence. Assuming that there is no dependence in the network and that dyads simply form at random via a Bernoulli process or form based only on the properties of the actors, then the likelihood function needed to calculate an ERGM simplifies to a standard logistic regression (Handcock et al. 2008; Goodreaux et al. 2009). These models are referred to as dyadic independent models because the probability of a tie between any two actors is independent of the existence of any other tie in the network. "By contrast, models for processes with dyadic dependence require computationally intensive estimation and imply complex forms of feedback and global dependence that confound both intuition and estimation" (Handcock et al. 2008, p. 5). To deal with the dependency and feedback processes the **ergm** package of the **statnet** suite (Handcock et al. 2003) in the R programming environment is used along with Markov chain Monte Carlo (MCMC) maximum likelihood estimation.

Figure 1 below details some of the popular network statistics that can be included in an ERGM model for undirected networks. For directed networks, common parameters would also include reciprocity, sender effects, receiver effects, and balance effects. A full list of potential parameters for directed, undirected, and bipartite networks are provided in the **ergm** package in **statnet**.

Figure 2: Examples of Possible Network Statistics



[2] Note that the constant k is impossible to calculate on all but the smallest of networks given the number of potential graphs equals $2^{n(n-1)/2}$ where n is the number of nodes (Hunter et al. 2008). Therefore, the likelihood is approximated using Markov chain Monte Carlo simulation methods (Snijders 2002; Hunter et al. 2008a).

4. Data

The three datasets used in the analysis are from: i) the September 30th, 2009 earthquake in Padang; ii) the January 12th, 2010 earthquake in Haiti; and iii) the March 11th, 2011 earthquake and tsunami in Japan. All of the datasets were constructed in a systematic fashion relying on standardized coding techniques. The Center for Disaster Management at the University of Pittsburgh has conducted a series of analyses of actual disaster response systems. The datasets, which indicate the set of organizations involved in the response and their interactions, are derived from i) content analysis of daily news reports regarding organizational actions taken in response operations; ii) documentary reports of organizational actions from governmental and professional sources; and iii) on-site semi-structured interviews with responsible managers, including direct field observations of the disaster context. For each event, content analysis of appropriate sources was performed for the first three weeks after the initial event.

The coding results in an adjacency matrix of size $n \times n$ where n is the number of organizations operating in the response system. The dyadic interaction, Y_{ij} ,is a random variable for the tie between organization i and organization j ($Y_{ij} = 1$, if i and j are collaborating in some form during the response, and $Y_{ij} = 0$ if i and j were not collaborating during the response). Given the nature of the interaction among organizations in a response system, the links between actors i and j are coded as symmetric or undirected, and thus $Y_{ij} = Y_{ji}$ for all i,j. In addition to these structural features, the dataset contains nodal covariates that are exogenous attributes of the organizations. The attributes are the funding type (private, public, nonprofit) and the jurisdiction (international, national, and set of regional and local categories) of the responding organization. These attributes are exogenous because they are not determined by the structure of the observed network.

The interaction data over the first three weeks of each crisis is aggregated to form a picture of the overall response system that emerged immediately after the disaster. Such aggregation both introduces error and reduces error in the model. It introduces error by merging together connections between organizations that took place at different points in time and analyzing the network as a single static system. Aggregation also reduces error as collaboration between two organizations may only be reported by a newspaper or situation report on a particular day but the collaboration may have begun earlier and could endure longer than reported. The aggregated response systems analyzed in this paper are the collective set of interactions that occurred between organizations entering and interacting in the response system at any point during the initial three weeks after the triggering event.

Indonesia Dataset[3]

Nearly five years after the devastating tsunami hit Indonesia, a 7.6 magnitude earthquake struck off of the southern coast of Sumatra on September 30th, 2009. The earthquake resulted in the loss of over 1,000 lives, but due to the depth of the epicenter, did not result in a tsunami. Data on the Padang earthquake was derived from

[3] Thanks to Leonard J. Huggins and Jian Cui for their help in coding this dataset.

Antara, the Indonesian news agency. Every article posted by the news agency concerning the earthquake during the first three weeks was coded for organizational interaction.

The content analysis of the Anatara news articles resulted in 286 organizations being mentioned as participants in the response and reconstruction after the earthquake. The data, as originally coded, had 5 levels of jurisdiction: local, district, provincial, national, and international. However, there were only 4 organizations within the category district, so district and local were combined for purposes of analysis. A cross-tab of the 286 organizations' funding and level of jurisdiction is provided in Table 1 below.

Table 1: Attributes of the Organizational Actors in Indonesia

	Local/District	Provincial	National	International
Private	1	6	10	7
Non-Profit	12	1	16	17
Public	19	21	80	96

Haiti Dataset[4]

On January 12th, 2010, a 7.0 magnitude earthquake struck Haiti less than 20 miles from the capital, Port-au-Prince. The quake devastated much of the city and outlying areas, leaving 1.5 million people homeless and claiming the lives of several hundred thousand individuals. The data for the organizational response to the Haitian earthquake was derived from situation reports from actors operating on the ground. These reports were obtained and downloaded from the ReliefWeb and OneResponse websites that operated as clearinghouses for information on the response and recovery efforts. In all, 139 situation reports from 12 different agencies were analyzed and coded.

Based on the situation reports, 532 actors were identified as participating in the response.[5] The data as originally coded had 5 levels of jurisdiction: local, sub-departmental, national, regional (Caribbean community), and international. Local and sub-departmental were combined into one category as only two organizations in the response were coded as sub-departmental. Attributes of the organizational actors are shown in Table 2.

Table 2: Attributes of the Organizational Actors in Haiti

	Local/Sub-Dept	National	Regional	International
Private	1	2	12	22
Non-Profit	1	10	2	116
Public	19	31	65	251

[4] Thanks to Steven Scheinert and Ralitsa Konstantinova for providing this dataset.

[5] The datasets for all response systems, given the use of news articles and situation reports, are geared toward highlighting major events and interactions among large organizations. This is clearly evident in the attribute tables indicating small numbers of local and district level organizations in the response systems of Haiti and Indonesia. For instance, in Haiti, which has been dubbed an NGO Republic, there were some 5,000 NGOs working on the ground before the quake, many of which were small, locally based organizations. However, the interactions of these actors are not well represented by the data, primarily because such organizations play smaller roles in the response and thus do not receive the media or reporting coverage that an international NGO or a national government would.

Japan Dataset[6]

A series of crises began in Japan with a 9.0 magnitude earthquake that hit 230 miles northeast of Tokyo on March 11, 2011. The earthquake, the most powerful ever to hit the country, triggered a tsunami and also damaged nuclear power plants. Three reactors at the Fukushima Daiichi Nuclear Power Station experienced partial meltdowns releasing radioactive material into the atmosphere, ground, and sea water. The data of the response system that emerged to deal with these three interdependent events was based on the news and reporting of the Japanese newspaper Yomiuri. In total, 1,101 organizations were identified as participating in the response. Attributes of the organizational actors are shown in Table 3 below.

Table 3: Attributes of the Organizational Actors in Japan

	Local	Municipal	Prefectural	Regional	National	International
Private	48	18	33	27	234	36
Non-Profit	14	7	16	1	69	8
Public	107	51	91	4	215	122

5. Results of Modeling Network Formation

For each of the response systems four different models will be analyzed and discussed separately. The best fitting model for each system will then be compared. All models will include a term for edges in order to control for the actual density of the network. Model 1 will include the main effect of the nodal attributes, namely funding and jurisdiction. These main effects can be interpreted as the propensity for a particular node class to form ties. For instance, with the attribute of jurisdiction, the base category is local, and for the other categories of jurisdiction a mean effect for the likelihood of tie formation for actors of each category will be calculated. The same process occurs for funding, where the base category is private, and a mean effect for the likelihood of tie formation is calculated for the non-profit and public categories. The main effects of each category represent an increase or decrease in the likelihood of a tie conditioned on the likelihood of edge formation in the base categories. Model 2 will investigate the effect of homophily or selective mixing in the network with regard to nodal attributes. The parameter will estimate the effect on the likelihood of tie formation between two actors of the same category. One may expect to find that two private organizations are less likely to interact with one another when compared with the likelihood of two non-profits. Model 3 will include a dyadic dependent term to measure triadic closure in the networks. The term used to capture triadic closure is a geometrically weighted edgewise shared partner distribution (GWESP). This statistic is an alternative to counting triangles that often lead to poor fit in ERGMs. For more information on GWESP and its properties see Hunter (2007) and Hunter and Handcock (2006). Model 4 will include all terms from the preceding three models.

The parameter estimates for the network statistics included in the 4 different models can be interpreted as the log-odds (logit) of individual ties. Equation 1 can be rewritten to express the conditional logit of tie formation:[7]

[6] Thanks to Aya Okada for providing this dataset.

$$logit\left(P\left(Y_{ij}=1 \mid n\ actors, Y_{ij}^{c}\right)\right) = \sum_{A} \eta_{A} \vartheta g_{A}(y), \tag{2}$$

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 increase by η_{A}. Thus, relying on this interpretation, we can easily calculate the odds of a tie forming, $\exp(\eta_{\mathrm{A}})$, as well as the probability of a tie forming, $\frac{\exp(\eta_{\mathrm{A}})}{1+\exp(\eta_{\mathrm{A}})}$.

Indonesia

The results of the four models for Indonesia are displayed in Table 4. Findings show a negative estimate for the edge statistic. The negative coefficient indicates that in general, ties are unlikely to form between organizations in the response system. In model 4, with a coefficient of -7.68779, the overall probability of a tie forming for an organization in the base categories of private and local is 0.000458, indicating an extremely low probability of a tie forming. Such a low probability is not unexpected given that the overall density of the observed network is 0.00680. Based on the AIC[8] measures, model 4 provides the best fit, and thus the discussion below will rely on the estimates in model 4, unless otherwise specified.

In model 4 we find a large a significant main effect for the public funding attribute, indicating that ties between public organizations are over 2.5 times more likely than private organizations, conditional on the other parameters. The effect of tie formation for non-profits is not statistically different from that of private organizations. The main effect for jurisdiction indicates that national organizations are more likely to form ties, while international organizations are less likely to form ties compared to local organizations. In terms of the homophily effect, the –Inf value (negative infinity) means that there were no observed ties between two private organizations, and thus the probability of a tie forming based on the model is zero. This finding is due, in part, to the fact that there were only 24 private organizations in the network. For the jurisdictional attribute, local organizations had a negative coefficient value, though insignificant, indicating that the likelihood of a homophilous tie between local organizations is just as likely as a tie forming between a local and non-local organization.

The QWESP term can be interpreted as the increase in the log-odds of a tie for each triangle formed by a tie. Again, if a tie does not form any triangles, conditioned on the other parameters, its log-odds is -7.68779. If the addition of a tie adds one triangle to the network , its log-odds is, -7.68779 + 1.06109, indicating a tie that forms single triangle is 1.9 times more likely to form than a tie that does not.[9]

---

[7] 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 estimates in dyadic dependent models.

[8] AIC is the Akaike Information Criterion. It used to assess the fit of a statistical model relative to other models.

[9] It is possible for an edge to form multiple triangles in the network, the log-odds of a tie for each additional triangle, however, is not a factor of 1.06109, but rather a fraction of that value given the parameter used to weight the GWESP term. See Goodreau et al. (2009, p. 114) for an intuitive discussion.

Table 4: Model Results for Indonesian Disaster Response System

Terms	Model 1	Model 2	Model 3	Model 4
Edges	-7.92183***	-6.19854***	-6.0574***	-7.68779***
Main Effects				
Non-Profit	0.39372			0.30670
Public	1.37383***			1.29776***
Provincial	-0.01118			-0.16428
National	0.72068***			0.51958**
International	-0.17963			-0.56592***
Homophily				
Private		-Inf		-Inf
Non-Profit		0.01462		0.59996
Public		1.20578***		-0.15297*
Local/District		0.050644		-0.24592
Provincial		0.84834*		0.90136***
National		1.40053***		-0.17658***
International		0.10788		1.44074***
Triadic Closure				
GWESP			2.2205***	1.06109***
AIC	3153.3	3152.7	3044.8	2890.3

Significance Codes: p-value < .01=***; p-value <.05=**, p-value <.10 = *

More nuanced findings can also be discussed. For instance, the homophily effect for public organizations changes from a positive significant value in model 2, to a negative significant value in model 3, indicating once the main effect of funding is controlled for along with triadic closure, public organizations are less likely to form homophilous ties. Also, we see the size of the GWESP coefficient cut in half when comparing model 3 to model 4, revealing that a good portion of the clustering found in the Indonesian response network was due to homophily.

Haiti

The edge term in the Haitian response as shown in Table 5, for all models, is also negative. The log-odds of a tie forming in the network is again quite low. Model 4 for Haiti, based on the AIC measure, had the best fit, and the parameter estimates from this full model will be discussed. Private organizations had the smallest main effect, though indistinguishable from non-profits (given the non-significant effect of non-profit over and above the base effect of private organizations). As with the Indonesian system, public organizations had the largest main effect. In terms of the homophily network statistics, public organizations were most likely to form ties with other public organizations, while both non-profit and private organizations had negative homophily values. The negative values on homophily signify that a tie spanning two non-profits or two private organizations would be less likely to form than a tie between heterogeneous organizations.

For three of the four categories of jurisdiction, the homophily effect was positive and significant. Regional organizations had the largest main effect. Regional organizations in the Caribbean played a significant role in the Haitian response, managed by the regional response organization CDEMA (Caribbean Disaster Emergency Management Agency). This is an interesting finding, and one that we cannot compare to the other datasets given the current categorical coding, as regional organizations were labeled as international actors in the Indonesia and Japan datasets. The finding does reveal that CDEMA was effective in engaging regional countries in the response system.

The homophily effect on local/sub-department was –Inf and, as with private organizations in the Indonesia response, reveals that no ties were found in the observed network between local/sub-departmental organizations. The finding supports the conclusion of Comfort et al. (2011) that local organizations played a reduced role in the response effort due to language barriers (many of the United Nations Office for the Coordination of Humanitarian Affairs' (OCHA) meetings were in English) and travel barriers to the log-base located an hour or more drive from the capital.

The triadic closure term, as expected, was also positive, and slightly smaller than the coefficient in the Indonesian response.

Table 5: Model Results for Haitian Disaster Response System

Terms	Model 1	Model 2	Model 3	Model 4
Edges	-9.0624***	-6.07174***	-5.55967***	-9.311546***
Main Effects				
Non-Profit	0.2244			0.181858
Public	1.0569***			0.759827***
National	1.2804***			1.471013***
Regional	1.1985***			0.607271***
International	1.2678***			1.266714***
Homophily				
Private		-1.18164		-0.600401
Non-Profit		-0.40445**		-.559135***
Public		0.97227***		0.289312***
Local/SubDept		-Inf		-Inf
National		1.39049***		0.396918***
Regional		2.06014***		2.698969***
International		0.82467***		0.339224***
Triadic Closure				
GWESP			0.98128***	1.022487***
AIC	11979	11745	11094	10487

Significance Codes: p-value < .01=***; p-value <.05=**, p-value <.10 = *

Looking across the models, the direction and significance of the estimates remain consistent in the Haiti dataset. While the incorporation of new terms in the models altered the overall size of the effect, its general characteristics were unaltered. Unlike the Indonesian model, the effect of triadic closure was practically unchanged (an increase of .04) when adding the homophily network statistics.

Japan

Similar to Indonesia and Haiti, model 4 in Japan provided the best fit. For the funding main effect, a non-homophilous, non-triangle-forming tie had the greatest likelihood of occurrence for non-profits. The main effect of jurisdiction was the largest at the regional level and the smallest at the municipal level.

Homophily for funding in the full model was nearly three times as large for public organizations than for non-profit organizations, indicating that while the main effect of public was smaller than non-profit, public organizations form homophilous ties at a much greater rate. Private organizations had no significant change in the likelihood of tie formation due to homophily. We find a large and significant effect on municipal homophily. Combined with the large negative main effect, we can conclude that in the Japanese response system, municipal organizations are quite unlikely to form ties that do not involve another municipal level organization. The homophily effect at the prefectural level was not significantly different from zero.

Table 6: Model Results for the Japanese Response System

Terms	Model 1	Model 2	Model 3	Model 4
Edges	-10.9991***	-8.78587***	-7.0859***	-9.30235***
Main Effects				
Non-Profit	0.88676***			0.62624***
Public	2.21759***			0.45045***
Municipal	-0.90938***			-1.58752***
Prefectural	-0.69143***			-0.72733***
Regional	1.5899***			1.25441***
National	0.83618***			0.52865***
International	-0.12632			-0.28475***
Homophily				
Private		-0.57871**		-0.02525
Non-Profit		1.41714***		0.77641***
Public		2.43158***		2.05743***
Local		0.42556*		0.33654***
Municipal		1.18523***		4.25864***
Prefectural		-0.69307		0.39878
Regional		4.19462***		1.46009***
National		1.60048***		0.2274***
International		0.63841***		0.46224***
Triadic Closure				
GWESP			2.8903***	1.28184***
AIC	8648.9	8652.6	8527.8	7699.0

Significance Codes: p-value < .01=***; p-value <.05=**, p-value <.10 = *

Comparing across the models for Japan, only the main effect of the jurisdictional category international changed in significance, and only the homophily effect of Prefectural changed in direction (though its value was insignificant in both models). Similar to the results of Indonesia, we find the GWESP coefficient reduced by half when the homophily terms are included.

We also find a ranking difference for the funding effects when comparing across models. In model 1, we find that public organizations had the highest main effect. However, in the full model, conditioned on all of the other terms, the effect of non-profit exceeds the effect of public organizations. This change in ranking is due to the large homophily effect for public organizations.

Comparative Analysis

Across all three datasets, model 4 was shown to have the best model fit. In order to facilitate comparison, the results of the fourth model for each disaster are printed next to each other in Table 7 below. Because each country had different types and numbers of categories for jurisdiction, the categories have been relabeled with a number to indicate an increasing distance from the local level. For instance, in all three models the local

(local/district or local/sub-departmental) level is labeled as level 1, and each category moving away from the local level to the international level is noted by increasing sequential numbers. Hence, for Indonesia and Haiti, there will be level 1 through level 4, while Japan will also include level 5 and level 6.

Table 7: Comparing Factors Across Response Systems

Terms	Indonesia	Haiti	Japan
Edges	-7.68779***	-9.311546***	-9.30235***
Main Effects			
Non-Profit	0.30670	0.181858	0.62624***
Public	1.29776***	0.759827***	0.45045***
Level 2	-0.16428	1.471013***	-1.58752***
Level 3	0.51958**	0.607271***	-0.72733***
Level 4	-0.56592***	1.266714***	1.25441***
Level 5			0.52865***
Level 6			-0.28475***
Homophily			
Private	-Inf	-0.600401	-0.02525
Non-Profit	0.59996	-.559135***	0.77641***
Public	-0.15297*	0.289312***	2.05743***
Level 1	-0.24592	-Inf	0.33654***
Level 2	0.90136***	0.396918***	4.25864***
Level 3	-0.17658***	2.698969***	0.39878
Level 4	1.44074***	0.339224***	1.46009***
Level 5			0.2274***
Level 6			0.46224***
Triadic Closure			
GWESP	1.06109***	1.022487***	1.28184***

Significance Codes: p-value < .01=***; p-value <.05=**, p-value <.10 = *

Note: National Level for Haiti is Level 2; Regional (i.e. Caribbean Community is Level 3)

The main effect of funding was quite similar across the three datasets. We find that the likelihood of ties forming for non-profits and public organizations was larger than the likelihood of the base group private. However, though the effect was positive, the coefficient on the non-profit category for Indonesia and Haiti was not significant. The main effect of jurisdiction is less straightforward to compare given the lack of consistent categories of jurisdiction across the datasets. We can compare the main of effects of national and international. The main effect of organizations in the national category was positive and significant for all response systems (recall, that national is category 2 for Haiti). In terms of the international category, the main effect was negative and significant in Indonesia and Japan, but positive and significant in Haiti. Given the lower level of economic development and disaster preparedness in Haiti, the international community played a much larger role in the response system and thus we can see international organizations were more likely to form ties in the network.

Furthermore, in Indonesia and Japan, the response was managed by the respective country's disaster management agency. In Haiti, the response was lead by UNOCHA, an international organization.

In terms of homophily, private organizations were found to have a negative effect, though not significant in all the three datasets. For the category of non-profit, the results are quite varied, with an insignificant effect for Indonesia, a significantly negative effect for Haiti, and a significantly positive effect for Japan. With regard to the public category, we find significant effects for all response systems, but a negative one in Indonesia and positive ones in Haiti and Japan. The conflicting coefficients in these models are likely the result of the unique functioning of the disaster response systems due to the variation in the significance of the crisis. Weighted against the size of the disaster in Haiti and Japan, the Indonesian earthquake was a relatively small scale crisis. Normal activity resumed fairly quickly in Indonesia, and thus for many of the Indonesian governmental actors the level of collaboration necessary to deal with response was not sufficiently high.

As with the main effects of jurisdiction, jurisdictional homophily is also more difficult to compare given the lack of consistent categorical coding. Because homophily effects do not require a base category, we can look at the effect of local, national and international as these categories all existed in our three datasets. International organizations in Haiti, Indonesia, and Japan, all had a positive and significant likelihood of homophilous tie formation. National organizations had a positive and significant effect in Haiti and Japan, and negative and significant effect in Indonesia. At the local level, homophily was insignificant in Indonesia, did not occur in Haiti, and was positive and significant in Japan.

Comparing the structural terms of edges and GWESP, the results in direction and significance were equivalent across the three response systems. We find that, in general, ties are unlikely to form in a disaster response system, but ties that involve triadic closure are significantly more likely to emerge.

6. Goodness of Fit

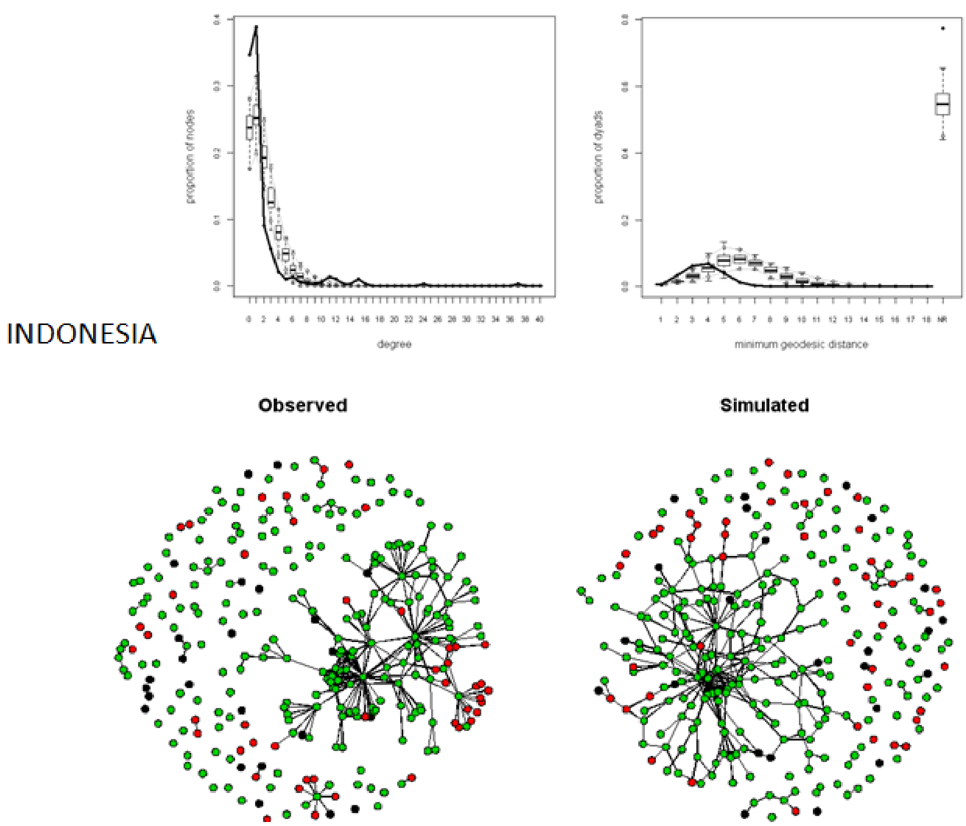
Beyond looking at the estimates of AIC as a means to assess model improvement , one can simulate networks based on the model parameter estimates to determine if the parsimonious model of micro-processes can generate similarly structured networks as the one we observed. As Hunter et al. (2008b) explain, it is possible to compare the structural statistics of the observed network with those of the simulated networks generated by the parameter estimates in the model as a measure of goodness of fit. Using the parameter estimates of the full model for each disaster response system, 100 networks were simulated, and the graph level properties of degree and geodesic distance were calculated. Below, in Figure 3-5, graphs of these network level properties reveal the correspondence between the values in the observed network (dark line) with the average values in the simulated networks (box plots). These network level properties represent macro-structural features of the graph that were not explicitly modeled in our ERGMs and thus are properties that arise through micro-level processes.

Below the graphs, a network diagram of the observed response system is displayed along with one of the simulated networks to allow for a visual comparison. The nodes in the graph are colored based on level of funding where, Private-Black, Non-Profit -Red, and Public-Green. One would expect the simulation of the network to approximate the structural features of the observed network. If the two network maps are similar, then the model may be successful at determining macro-structure from the micro-level processes of the model.

Indonesia

In Figure 3, there are several areas of error worth mentioning in the goodness of fit graphics. First, in the degree distribution graph, we underestimate the number of nodes with 1 and 2 connections, and overestimate the number of nodes with 3, 4, 5, and 6. Also, there are two peaks in the degree distribution around 11 ties and 15 ties that are underestimated in the data. Second, in terms of geodesic distance, we find that we overestimate the number proportion of nodes with average distances between 4 and 8 steps. The results of the over and underestimation of various macro-structures can be seen by comparing the observed network with the simulated network. As seen in the observed network, there are several instances of nodes having 5 to 12 ties with little to no ties among their alters. This interesting structural feature of the Indonesian response system could not be recreated with the parameters used in the exponential random graph models. One solution, would be to add a term to condition on the degree distribution.

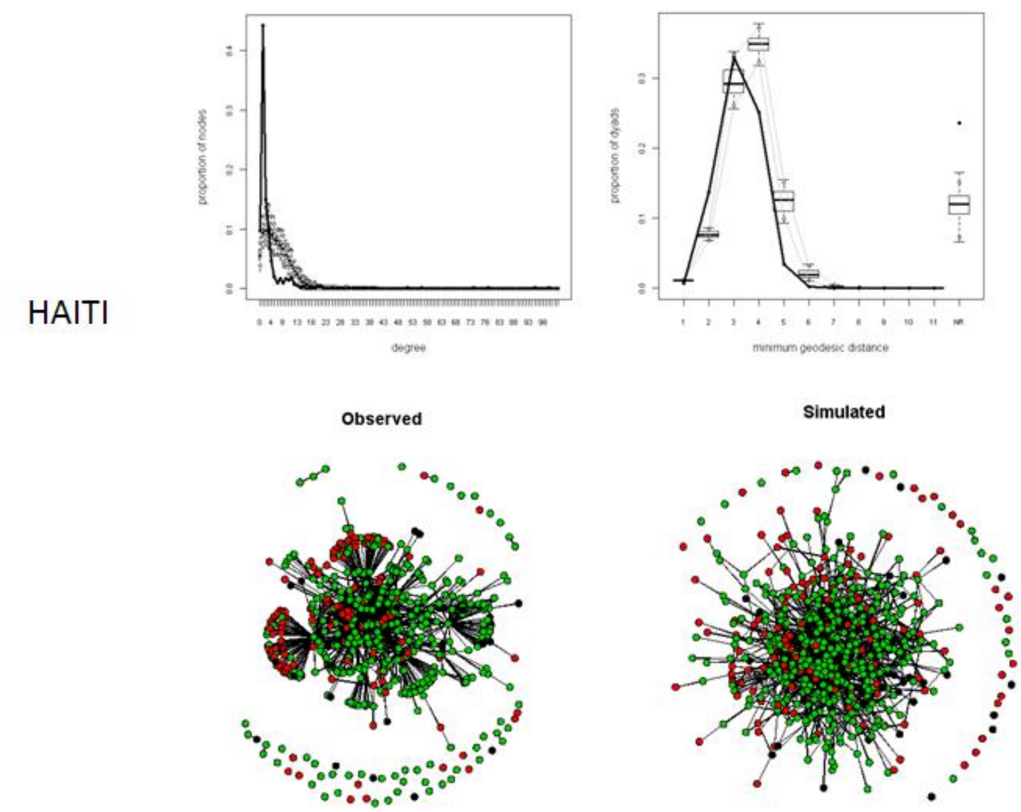
Figure 3: Goodness of Fit , Indonesia



Haiti

The models developed for the Haitian response system appear to do a poor job of capturing the degree distribution. Most notable is the severe underestimation of the nodes with one tie and the overestimation for nodes with approximately 5 to 15 ties. In the observed network there are 235 nodes with only 1 tie; in the simulated network the average number of nodes with one tie is 38. Despite a lack of fit for the degree distribution, the geodesic distance provides a fairly good fit. There is a slight underestimation in the proportion of nodes reachable at distances of 3 and 4. Visually, the simulated network is clearly missing the large number of 1 degree nodes. The fan-like structures that characterize the observed response are missing.   Additional parameters may be necessary to capture these unique structures such as the addition of a term to control for propensity of 1 degree nodes to form.

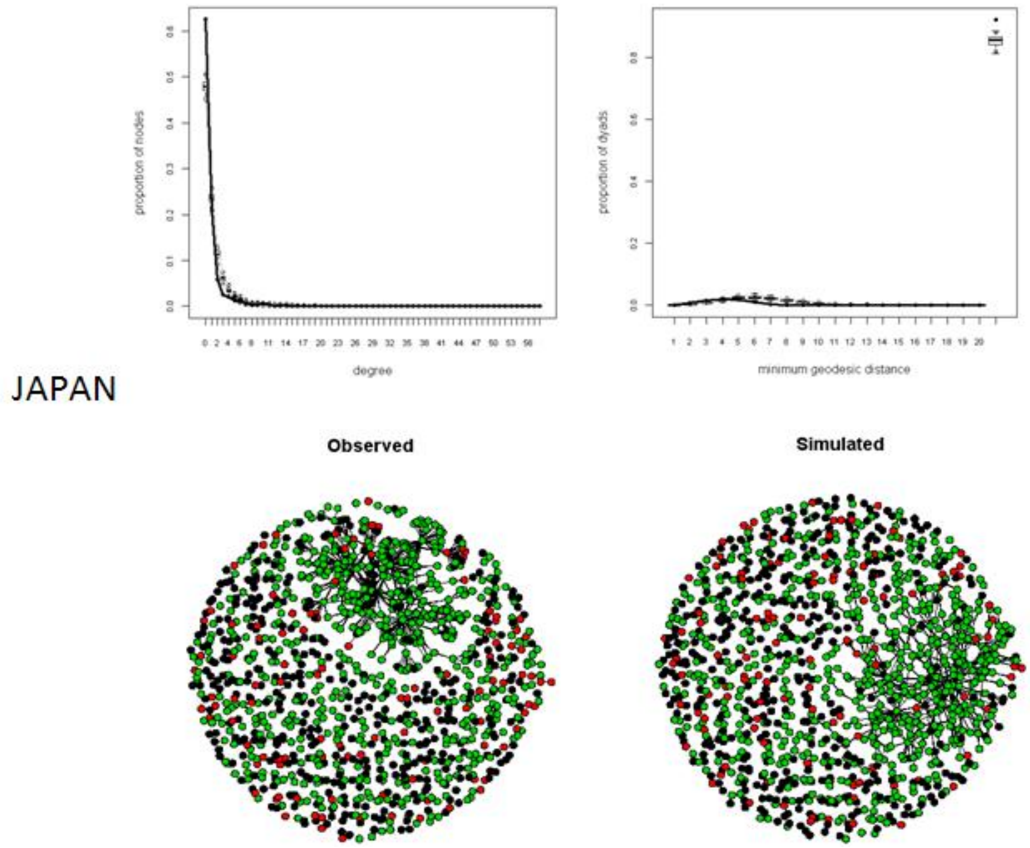
Figure 4: Goodness of Fit, Haiti



Japan

The goodness of fit of the degree distribution for the Japanese response is much improved from the fit for either the Haiti or Indonesia response. The geodesic distance is also reveals a good fit, with the true line falling within the box plots. Given the capability to reproduce the macro features of the response we would expect, and find, that the network diagrams are quite similar. In Japan, more so than the other networks, the few micro-level processes modeled were adequate to produce the macro-level structure of the response system.

Figure 5: Goodness of Fit, Japan



7. Discussion and Conclusions

The ERGMs have proven to be useful tools for analyzing response networks. However, there are several opportunities for improvement. For all three datasets, there is a consistent underestimation of one degree nodes and an overestimation, to varying amounts, of the geodesic distance in the middle range of the distribution. The lack of fit for these structural parameters indicates the need for additional model building and the inclusion of additional parameters.

The datasets used in this analysis were originally developed for purposes other than modeling selection processes. As such, there are potentially important nodal attributes that may be missing. Of primary importance is an attribute indicating the organization's primary response activity. What are the changes in probability of interaction between two organizations both working on sanitation issues as opposed to one who works on sanitation and one who works on economic development? One may also want to gather data on the number of resources or the size of the organization as these variables are likely to influence interaction.

Additionally, the nature of the interaction between the organizations would be an important covariate. Is the interaction primarily due to a hierarchical relationship, resource sharing, general communication needs, or other forms of interaction? One could then create a matrix indicating a 1 if organizations *i* and *j* engage in a specific type of interaction. This would allow a researcher to explore how types of interactions are influenced by the attributes of the organizations. Perhaps more resource sharing occurs between NGOs and little to no resource sharing between governments. Such models would provide a clearer understanding of the selection processes and be most applicable to the needs of disaster managers.

Beyond potential missing variables, the datasets themselves may be prone to errors of reporting or lack of coverage of specific interactions. Clearly, if additional news sources, situation reports, or interviews were included the network would take on a different shape and increase in size. The question is if the overall micro-processes of the network would be altered through the addition of new data. So, for instance, if in addition to the reports provided in Yomiuri newspaper we added reports from the New York Times, would the types of interactions reported in the Japan response be structurally different? In other words, is there a reason to suspect that we would find more or less triangulation or larger homophily effects from interactions reporting in one source compared to another source? It would seem that Yomiuri and the New York Times would not bias their reporting in any way that would influence the formation of triangles or the prevalence of homophily in the networks and thus the effects that we find should prove robust in the face of additional sources of data on the event. This assumption can and should be tested empirically through future work.

Despite these limitations, the ERGM framework has a lot to offer for disaster managers. This paper clearly shows the utility of ERG models in understanding the micro-determinants of network structure. The next step is to collect data on attributes that is guided by testable theories. For example, we may want to test whether or not the theory of resource dependency drives tie formation. This theory can be tested in an ERG model if one has data on the resources different organizations bring to the response system. By modeling how variation in resources at the dyadic level impacts tie formation, one determine if theories of resource dependency are sufficient for understanding the dynamics of response systems. Advancing the use of statistical models of network formation in disaster contexts is an important next step in the field. Ultimately, if researchers hope to understand the dynamics of response systems, and eventually develop ways to improve the management and coordination of response systems, it is necessary to investigate both the consequences of network structure and the micro-level processes that give rise to that structure.

Once the determinants of network formation are known, disaster managers can improve the efficiency and effectiveness of response systems in three ways. First, managers can begin to design and shape a set of policies and incentives to facilitate communication and coordination during disasters. Second, by building a knowledge base of how and why organizations interact during extreme events, disaster managers can more effectively utilize technological tools and communication systems to improve collaboration among specific actors. Third, disaster managers can more selectively collect and share relevant information regarding response operations and capacity to all organizational actors. By improving the accuracy and timeliness of information flowing in the response network the overall performance of the system can be increased (Comfort, 1999).

Works Cited

Bavelas, A., 1950. Communication Patterns in Task-Oriented Groups. The Journal of Acoustical Society of America 22, 271-282.

Borgatti, S.P., Foster, P.C., 2003. The Network Paradigm in Organizational Research: A Review and Typology. Journal of Management 29, 991-1013.

Brass, D.J., 1995. A Social Network Perspective on Human Resources Management, Research in Personnel and Human Resources Management. JAI Press, Greenwich, CT, pp. 39-79.

Coleman, J.S., 1990. Foundations of Social Theory. Belknap Press, Cambridge, MA.

Comfort, L.K., 1999. Shared Risk: Complex Systems in Seismic Research. Pergamon, Amsterdam.

Cross, R.L., Parker, A., Sasson, L., 2003. Networks in the Knowledge Economy. Oxford University Press, Oxford.

Goodreau, S.M., 2007. Advances in Exponential Random Graph (p*) Models Applied to Large Social Networks. Social Networks 29, 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, 103-125.

Guetzkow, H., Simon, H.A., 1955. The Impact of Certain Communication Nets Upon Organization and Performance in Task-Oriented Groups. Management Science 1, 233-250.

Handcock, M., 2003. Assessing Degeneracy in Statistical Models of Social Networks, Working Paper. Center for Statistics and Social Sciences, University of Washington.

Handcock, M.S., Hunter, D.R., Butts, C.T., Goodreau, S.M., Morris, M., 2003. Software Tools for the Statistical Modeling of Network Data., URL http://statnetproject.org.

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, 1-11.

Heider, F., 1958. The Psychology of Interpersonal Relations. Wiley, New York,.

Hunter, D.R., 2007. Curved exponential family models for social networks. Social Networks 29, 216-230.

Hunter, D.R., Handcock, M.S., 2006. Inference in Curved Exponential Family Models for Networks. Journal of Computational and Graphical Statistics 15, 565-583.

Kilduff, M., Krackhardt, D., 2008. Interpersonal Networks in Organizations: Cognition, Personality, Dynamics, and Culture. Cambridge University Press.

Kilduff, M., Tsai, W., 2003. Social Networks and Organizations. Sage, London.

Kozlowski, S.W.J., Klein, K.J., 2000. A Multilevel Approach to Theory and Research in Organizations: Contextual, Temporal, and Emergent Processes, in: Klein, K.J., Kozlowski, S.W.J. (Eds.), Multilevel Theory, Research, and Methods in Organizations: Foundations, Extensions, and New Directions. Jossey-Bass, San Francisco: CA, pp. 3-90.

Leavitt, H.J., 1951. Some effects of certain communication patterns on group performance. Journal of Abnormal and Social Psychology 46, 38-50.

Monge, P.R., Contractor, N.S., 2003. Theories of Communication Networks. Oxford University Press, New York.

Raub, W., Buskens, V., Van Assen, M.A.L.M., 2011. Micro-Macro Links and Microfoundations in Sociology. The Journal of Mathematical Sociology 35, 1-25.

Robins, G., 2011. Exponential Random Graph Models for Social Networks, in: Scott, J., Carrington, P. (Eds.), The SAGE Handbook of Social Network Analysis. SAGE Publications Ltd, Thousand Oaks, CA.

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

Shaw, M.E., Leonard, B., 1964. Communication Networks, Advances in Experimental Social Psychology. Academic Press, pp. 111-147.

Snijders, T.A.B., 2002. Markov Chain Monte Carlo Estimation of Exponential Random Graph Models. Journal of Social Structure 3.

Snijders, T.A.B., Pattison, P.E., Robins, G.L., Handcock, M.S., 2006. New Specifications for Exponential Random Graph Models. Sociological Methodology 36, 99-153.

Wasserman, S., Pattison, P., 1996. Logit Models and Logistic Regressions for Social Networks: I. An Introduction to Markov Graphs and p*. Psychometrika 61, 401-425.

Zaccarin, S., Rivellini, G., 2010. Modeling Network Data: An Introduction to Exponential Random Graph Models, in: Palumbo, F., Lauro, C.N., Greenacre, M.J. (Eds.), Data Analysis and Classification. Springer, Berlin, pp. 297-305.