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In Case of Emergency, Don’t Break Glass: The Emergency Management Organizational Field as a Glassy Regime

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In Case of Emergency, Don’t Break Glass: The Emergency Management Organizational Field as a Glassy Regime

DISSERTATION

submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in Sociology

by

Nolan Edward Phillips

Dissertation Committee:
Professor Carter T. Butts, Chair
Professor Katherine Faust
Professor David John Frank
Professor Evan Schofer

2017
DEDICATION

To My Parents
In a multitude of ways, I would not be here with you.
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ABSTRACT OF THE DISSERTATION

In Case of Emergency, Don’t Break Glass: The Emergency Management Organizational Field as a Glassy Regime

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Doctor of Philosophy in Sociology

University of California, Irvine, 2017

Professor Carter T. Butts, Chair

The way that relations between organizations and their environments affect their structures important features of organizations. These relations can potentially induce conformity, and their environments can potentially maintain differences. Organizations dependent on a leading organization for resources are theorized to structure themselves more like the leading organization. Conversely, organizations that function in divergent social contexts are expected to structure themselves divergently. While social network analyses have offered insights into this domain, previous work typically compares organizational structures and not the mechanisms that generate them. The advent of exponential family random graph models enables the examination of the underlying mechanisms, or social forces, that produce networks such as organizational structures. However, the tools to evaluate the adequacy or assess the fit of these models have opened up new questions regarding model evaluation and adequacy assessment. The first chapter of this dissertation introduces several new methods for evaluating the adequacy of exponential random graph models using labeled rather than topological features. The second chapter advances a within-sample model validation algorithm to assess the fit of a model. These tools were used to develop exponential random graph models that are used in the third chapter, which analyzes the generative features of states’ emergency operations plans. I build a new dataset from primary source documents that delineate the organizations assigned to a standardized set of emergency support functions. I then evaluate the historical contingency of the realized emergency management networks within each state through simulation studies. These studies build upon previous work and facilitate a virtual "rerunning of history" to assess whether states form similar networks due to exogenous pressures from the federal government or whether the social substrate within each state drives observable differences. From these analyses, I postulate an interorganizational continuum that is analogous to the physical states of matter to explain the observed differences and similarities. As such, this dissertation makes several valuable contributions to both the network analytic methodology and theories of interorganizational relations.
1 Introduction

The study of social structure has been, and remains, one of the cornerstones of sociology (Durkheim 2014; Giddens 1986; Marx 1978; Weber 2009). Initial inquiries into how society emerged, changes, and persists spurred later scholars to examine the interactions between institutions and organizations (DiMaggio and Powell 1983; Fligstein 1991; Galaskiewicz 1985; Knoke 1992; Meyer and Rowan 1977; Scott 1991, 2004). As the field became increasingly interested in the relations between entities and their effects, network analytic methods emerged as natural tools for this line of social inquiry (Galaskiewicz and Marsden 1978; Granovetter 1985; Hannan and Freeman 1977, 1985; Krackhardt 1987; White, Boorman and Breiger 1976). The field of network analysis has developed immensely over the last few decades in large part due to computational advances. One of these methods, exponential family random graph models (ERGMs), identifies the generative features of (or the underlying mechanisms that produce) an observed network (Handcock et al. 2008; Hunter et al. 2008a). ERGMs have been applied widely (Faust and Skvoretz 2002; Jasny et al. 2015; Moody 2001; Wang et al. 2016), and subsequently, new directions for model evaluation have emerged. This dissertation develops several methods for assessing the adequacy of ERGMs and building off of prior comparative techniques (Faust and Skvoretz 2002) to formalize a simulation method that enables a hypothetical “rerunning of history” to assess interorganizational structures.

While organizational scholars initially focused heavily on government bureaucracies (Meyer 1968; Tolbert and Zucker 1983; Weber 2009), later scholars shifted their empirical lenses toward economic and nonprofit organizations (Powell 1990; Scott
Empirical analyses on government bureaucracies and policies shifted towards cross-national comparisons (Frank, Hironaka and Schofer 2000; Meyer et al. 1997), but within the United States, a large empirical field lies fallow. This overlooks a rich area for sociological inquiry. The United States’ federated system creates an interesting dynamic of interaction between states and Federal government organizations, producing a tension within extant organizational literature. On the one hand, neoinstitutional theories would predict organizations to be structured similarly due to the existence of a leading organization that all other depend upon for resources; on the other hand, differences in the regulatory environments and demands are expected to produce differences in structures (DiMaggio and Powell 1983; Meyer and Scott 1983; Scott 1991).

The interorganizational field of emergency management in the United States amplifies this tension since, in practice, the Federal Government places structural demands on states to facilitate coordination while simultaneously stressing local autonomy (FEMA 1996, 2008). I develop new network analytic methods to analyze this tension and assess the structural similarities across states’ emergency interorganizational networks.

1.1 Exponential Family Random Graph Models

Exponential family random graph models were developed to test hypotheses involving triadic structure while controlling for degree distribution and reciprocity effects (Holland and Leinhardt 1981). Frank and Strauss (1986) posited that these effects could be obtained by including assumptions of conditional dependence, which builds off of developments in spatial statistics (Besag 1974). The chief difficulty in examining the tie formation processes

---

1 This may be in part due to the growing field of public policy scholars, whom do analyze the United State bureaucracy (Kapucu et al. 2010; Milward and Provan 2000; O’Toole 1997).
lies in the conditional dependence within the relational structure. Scholars circumvented this issue by relying on the maximum pseudolikelihood estimator, which analyzes each edge as a logistic regression; this was the \( p^* \) model \( (\text{Strauss and Ikeda 1990; Wasserman and Pattison 1996}) \). However, these specifications provided unreliable estimates with standard errors that were underestimated because they violated the independence assumption \( (\text{Snijders 2002; Handcock 2003}) \). Additionally, these models frequently failed to reproduce graphs that closely resembled the initial network when the coefficients were used in simulations \( (\text{Snijders 2002; Handcock 2003; Hunter, Goodreau and Handcock 2008b}) \).

Prior work had shown that the maximum likelihood estimator could be approximated using Markov Chain Monte Carlo methods, though this was not initially applied to ERGMs \( (\text{Geyer and Thompson 1992}) \). These insights were later used to estimate parameters in ERGMs \( (\text{Hunter and Handcock 2006; Hunter et al. 2008a}) \). Researchers frequently use model assessment tools at the topological level (i.e.; structural features or isomorphic graphs) to evaluate how well the fitted model recapitulates the network \( (\text{Hunter and Handcock 2006; Goodreau, Kitts and Morris 2009}) \). These assessment tools are immensely valuable for networks scholars, but they obfuscate where the model is erring by providing topological rather than labeled (i.e.; the specific nodes or edges) information. Therefore, I develop a range of assessment tools that assess the model on the labeled features in my second chapter. Network analysts can use these tools to improve the fit of their model by identifying where a model is systematically erring.

For related reasons, determining the quality of an ERGM’s fit to the data is currently limited. The intrinsic relational quality of network data makes this task difficult.
Building off prior work on network imputation (Handcock and Gile 2010; Wang et al. 2016), I develop a within-sample validation technique that is similar to a jackknife. In my third chapter, I delineate the steps for systematically holding out pieces of the network and imputing the held-out data. This method facilitates the comparison of how well different ERGMs are able to reproduce the original network. Additionally, it can also show which nodes form ties in processes that differ from the rest of the model. This is similar to a leverage statistic in regression diagnostics. Finally, it can illuminate which specific edges are outliers, in a well-defined sense, and point the researcher in fruitful direction for improving their model.

1.2 The Interorganizational Field of Emergency Management

The shift from examining organizations in isolation to incorporating their broader environments, including other organizations they interact with, has led scholars to posit organizational fields (DiMaggio and Powell 1983; Scott 2004). Organizational fields establish necessary boundaries around the broader organizational environment including: the availability of resources, the regulatory constraints and the interactions between organizations. Isomorphism is a central concept in this area of research (Wooten and Hoffman 2017). Hawley (1986) established the concept of isomorphism, whereby organizations can be pushed towards conformity within a field. DiMaggio and Powell (1983) further theorized the concept by delineating the conditions within organizational fields that produce greater isomorphism. Isomorphism is not predetermined; rather, the features of and dynamics within a field can produce such a result.

The federated system of the US government can be analyzed as an interorganizational field. The states and their bureaucracies have bounded autonomy due
to constraints from the federal government. Yet, this raises a theoretical tension within organizational literature on isomorphism (Scott 1991; DiMaggio and Powell 1983). Do states conform to the Federal Government because of its central role as a resource provider or does the federated structure endow such wide latitude that states exhibit idiosyncratic rather than isomorphic structures? The fourth chapter adjudicates this tension.

Emergency management represents a particularly useful case because all states are required to produce state emergency operations plans, which delineate the organizations assigned to a range of emergency related tasks. Additionally, the states are required to adopt particular facets of an organizational structure as a prerequisite for emergency preparedness grants (DHS 2017). However, states are explicitly instructed to create plans based on their own bureaucratic capabilities that can address the disasters they are most likely to face. These contrasting imperatives elevate the tensions in the pull towards isomorphic structures and push away towards idiosyncratic structures.

To assess the affects of these competing pressures, I have meticulously collected states’ emergency operations plans, cleaned and coded them, and constructed them into two-mode networks (i.e.; two different sets of nodes). I then use exponential family random graph models to identify the underlying social forces that produce each state’s emergency management interorganizational network. I capitalize on the fact that all states incorporate a similar structure of fifteen emergency support functions into their plans, allowing me to use a common family of models across all of the states. I then perform a meta-analysis of the generative principles to assess how exogenous variables can influence how a network forms (Lubbers 2003; Moody 2001; Zijlstra, Van Duijn and Snijders 2006).
Additionally, I extend the insights of previous scholars (Faust and Skvoretz 2002; Skvoretz and Faust 2002) to develop a method that directly compares the generative features of each network across all other networks. This method produces a hypothetical “rerunning of history.” The networks arise from the interactions between systematic social forces, idiosyncratic factors, and a substrate on which these two operate. How much does each drive the outcome (i.e.; the observed network)? With simulation, we can try to answer that question. This simulation assessment speaks directly to the tension within the interorganizational field literature and empirically evaluates the effect of isomorphism. Moreover, this method has applicability that extends beyond the specifics of this case.

The dissertation makes several contributions. First, it develops several new methods for assessing the adequacy of exponential family random graph models. Second, it produces a new data set that will be of interest to network analysts as well as organizational, public policy and emergency management scholars. Third, it postulates a continuum of interorganizational relations analogous to the physical states of matter, which can be fruitfully used by organizational scholars examining the constraints within a field. Finally, this dissertation develops a new way of directly comparing the generative principles across a set of networks to ascertain what drives the observed similarities and differences.
2 Tools for Evaluating the Adequacy of Exponential Graph Models (ERGMs) Using Labeled Features

Network scholars have developed exponential family random graph models (ERGMs) to identify the generative principles of network while accounting for the dependencies within relational data (Handcock et al. 2008; Hunter et al. 2008a; Robins et al. 2007; Snijders et al. 2006). Researchers have used ERGMs to analyze: microbiological and complex brain networks (Saul and Filkov 2007; Simpson et al. 2011); adolescent friendship networks (Goodreau, Kitts and Morris 2009; McFarland et al. 2014); interactions among different species (Faust and Skvoretz 2002); echo chambers in climate policy networks (Jasny, Waggle and Fisher 2015); interorganizational networks (Broekel and Hartog 2013); and migration patterns between nations (Windzio 2017). Due to the computational intractability of using the exact probability distribution for a network, ERGMs estimate the parameters using Markov Chain Monte Carlo maximum likelihood methods (Hunter et al. 2008a; Snijders 2002), which make the use of model selection through AIC or BIC “approximate at best” (Hunter, Goodreau and Handcock 2008b, pg. 257). The issues are threefold: the calculation of the likelihood contains a lot of numerical noise, it is unclear how to compute the effective data degrees of freedom (which is needed for AICc and BIC), and we do not know if we are in the asymptotic regime (needed for all of the above). Graphical “goodness-of-fit” plots complement the models selection tools to assess how well an ERGM can recapitulate structural features of the network in simulations (Handcock et al. 2008; Hunter et al. 2008a,b). However, the current tools for assessing the goodness-of-fit of an ERGM have focused on topological features, which provides less information for assessing a model.
This chapter develops several new methods to evaluate the adequacy of a fitted ERGM by using labeled rather than purely topological (i.e.; isomorphic or structurally equivalent) features. First, it demonstrates how evaluating the model’s adequacy at the node and edge level can provide additional information and deeper insight into where a model is erring than current adequacy checks at the topologic level. Second, I extend these methods to summarize the overall fit of an ERGM to a network as graph level statistics that could be compared across multiple model specifications. I use Krackhardt’s data set on self-reported relations between managers at a high-tech machinery firm to illustrate the utility of these methods (1987).

2.1 Exponential Random Graph Models

The general ERGM representation is in equation 1 below:

$$\Pr(Y = y) = \frac{\exp[\theta^T g(y)]}{k(\theta)}$$

(1)

Where $y$ is a realization of random network $Y$; $\theta$ is the vector of coefficients; $g(y)$ is a vector of network statistics (e.g.; degree distribution or shared partners); and $k(\theta)$ is a normalizing constant, which ensures the equation is a legitimate probability distribution (Handcock 2003; Hunter et al. 2008a). The normalizing constant can contain up to $2^{n(n-1)}$ networks (for directed networks without loops), an intractably large number for most networks and the primary obstacle for inference in this model (Hunter et al 2008a).

Exponential random graph models (ERGMs) build off advances in statistical and computational methods. Holland and Leinhardt (1981) are recognized as the first to propose exponential family for social networks (Hunter et al. 2008a), which they call the $p_1$ model. This model assumes dyads (pairs of nodes) are independent such that dyads have
edges independently of all other dyads. Frank and Strauss (1986) utilize developments in spatial statistics by Besag (1974) to generalize the previous model with Markovian dependence; two dyads are dependent when they share a node, conditional on the rest of the graph. Strauss and Ikeda (1990) and later Wasserman and Pattison (1996) extend the conditional dependences. However, Snijders (2002) and Handcock (2003) show homogenous Markov graph families produce graphs (through simulations) with bimodal distributions, where graphs are nearly complete or empty; neither reproduces the original network well. Geyer and Thompson (1992) had previously shown how the likelihood could be approximated using Markov Chain Monte Carlo methods in a different context, and their insights were later incorporated by others (Hunter and Handcock 2006).

The use of simulations to estimate the model also enabled simulations of the estimated parameters. Since it was already shown that models failed to produce realistic networks (Snijders 2002; Handcock 2003), graphical goodness-of-fit assessments were developed to evaluate the adequacy of the thetas (Hunter et al. 2008 a,b). These adequacy plots illustrate how well the thetas reproduce network’s features by simulating networks. However, the features typically employed (such as, the degree distribution or minimum geodesic distance) are purely topological. This provides an excellent adequacy check of the overall structure of the network, but it obfuscates where the model is erring. Since the goal is to model inhomogeneities in networks’ structures, focusing on the labeled features provides deeper insight into the adequacy of a mode. For example, a model may systematically under or over predict particular nodes’ edges. By examining the labeled features, the tools developed in this chapter illuminate how well the model can reproduce the original, labeled network, which can aid researchers in developing better fitting
ERGMs as key features can be assessed more easily. Additionally, these tools could be used to examine hypothetical situations where edges are added or deleted from the original network to assess the impact, if any, that these additions or deletions have. There is a real need for additional tools to further assess the adequacy of a fitted ERGM that can be used to improve the fit of a model.

2.2 Data

To demonstrate the utility of these model assessment tools, I use Krackhardt’s data set of managers within a high-tech machinery firm (Krackhardt 1987). Krackhardt’s data set consists of twenty-one individuals’ self-reported relations of advice seeking, friendship, and whom they report to. It also includes each individual’s age, department, level within the firm, and tenure at the firm. I recode level within the firm from three values (CEO, upper and middle management) to two values (upper and lower management). I fit an exponential family random graph model with dyadic dependence on the directed friendship network. Ties are not assumed to be reciprocated, and though individuals frequently report mutual friendship ties, this is not always the case. These tools could also be used with undirected or two-mode networks.

I fit the model using the R package “ergm” which is part of the statnet suite of packages (Handcock et al. 2008, 2017); I also use the R package “network” to create the network plots (Butts 2008). I include in the model: edges (the baseline propensity of tie formation); edge covariates for the advice and reports to relations; dyad covariates for absolute differences in individuals’ levels within the firm, ages, and lengths of tenure; homophily within departments (without distinctions made between the departments);
geometrically weighted outdegree; intransitive ties; and mutual ties. The thetas of the model are shown below in Table 2.1.

Table 2.1: ERGM Fit to Friendship Network Data

<table>
<thead>
<tr>
<th>ERGM Term</th>
<th>Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edges</td>
<td>-0.26457</td>
<td>0.29658</td>
</tr>
<tr>
<td>Edge Covariate: Advice Network</td>
<td>0.40259</td>
<td>0.21749</td>
</tr>
<tr>
<td>Edge Covariate: Reports to Network</td>
<td>1.94026**</td>
<td>0.63748</td>
</tr>
<tr>
<td>Absolute Difference in Level</td>
<td>-0.84768***</td>
<td>0.24092</td>
</tr>
<tr>
<td>Absolute Difference in Age</td>
<td>-0.089**</td>
<td>0.03225</td>
</tr>
<tr>
<td>Absolute Difference in Tenure</td>
<td>0.04117*</td>
<td>0.01698</td>
</tr>
<tr>
<td>Nodematch Department (diff=F)</td>
<td>0.49728*</td>
<td>0.23756</td>
</tr>
<tr>
<td>Geometrically Weighted Outdegree</td>
<td>-2.46357***</td>
<td>0.49689</td>
</tr>
<tr>
<td>Intransitive Ties</td>
<td>-0.20379***</td>
<td>0.04701</td>
</tr>
<tr>
<td>Mutual Ties</td>
<td>1.75877***</td>
<td>0.3667</td>
</tr>
</tbody>
</table>

Significance: p < .001 ***; .01 **; .05 *
Null Deviance 0 on 420 Degrees of Freedom
Residual Deviance -255 on 410 Degrees of Freedom
AIC: -206.9; BIC: -164.6

The results in Table 2.1 show that edges are not widely present; there are only 102 ties out of a possible 420 (since there are no loops) for a network density of 0.24. We also see that individuals, overall, report more friendship ties with: the person they report to, people that are at their same level within the firm, those that are similar in age, and employees that work in the same department, but not with those that have been at the company for the similar amounts of time. Additionally, the results show that friendship ties are highly likely to be mutual (reciprocated) and that intransitive ties (i.e.; person $i$ reports a friendship with person $j$, who reports a friendship with person $k$, but $k$ does not report a friendship with person $i$) are not very likely (Holland and Leinhardt 1972; Wasserman and Faust 1994).
Now, we have a model fit to the data, but how well does the model recreate the original network from simulations? Where is the model more accurate and where does the model err? Are these errors systematic?

Before examining the model adequacy tools, a quick note on model adequacy compared to model selection is in order. Model adequacy focuses on what features of the data can the model reproduce consistently; model selection focuses on how well the model fits the data. Researchers should consider both when choosing which model to present as results. For model adequacy, it is important to note that model should get right what it can get right (Gelman et al. 2014). While this may seem obvious, researchers should have reasonable expectations for a model’s adequacy. If a case or edge results from odd circumstances, then one should not expect the model to reproduce this case well. Relatedly, it is worth pointing out that the tools developed below are asking far more of an ERGM than conventional metrics, and are more applicable for particular networks. Rather than evaluating the model’s ability to reproduce purely topological features, these methods focus on the labeled features; hence, the model needs to get the exact edges correct and not the general structural features. These assessments are more relevant for smaller networks or when enough covariates are included in the model to distinguish effectively between specific nodes and edges.

2.3 Model Adequacy for Nodes’ Degrees

The current goodness-of-fit package shows how well a model is able to reproduce a network’s topological features (Hunter et al. 2008b), but this output obfuscates which nodes’ ties are reproduced well or poorly in networks simulated by the model’s thetas. Since the model includes the geometrically weighted outdegree term, I focus on how well...
the model is able to reproduce each node’s indegree (i.e.; reported friendship ties to an individual). Figure 2.1 below is the current goodness-of-fit plot.

**Figure 2.1: Current Goodness-of-Fit Plot for Nodes’ Indegree**

The figure illustrates how well 100 simulated networks from the fitted model’s thetas reproduce the indegree values of the original network. The proportions of nodes for indegree values are on the y-axis. The black line shows the proportion of nodes for each value from the original network. The grey lines connecting circles depict the ninety-five percent simulation interval, and the boxplots for each value illustrate the distribution of nodes’ indegree from all of the simulations. Ideally, a researcher would like to see the black line pass through the median of each boxplot; however, this is an unrealistic expectation. Thus, network scholars strive to have the true value stay within the interquartile range of each value.
While these plots are immensely useful (and remain a tremendous contribution to the field), they do not enable a researcher to distinguish easily between which nodes’ degrees are and are not reproduced well by the simulations. These plots do not differentiate between which nodes have what indegree values in the simulations. For example, a node may have an indegree of four in the original network but never have that value in any of the simulations. Thus, despite the figure showing that the proportion of nodes with an indegree of four is well reproduced by the simulations, one of the nodes with that value may never actually have that value reproduced since the plot summarizes the information at the topological level. Similarly, the plot shows that the mode indegree value of five is not well covered by the simulations, but we do not know if some nodes consistently have an indegree of five in the simulations, while others do not, or if different nodes that do not have an indegree of five in the original network frequently have that value in the simulations. Therefore, it is useful to look at each node’s degree distribution from the simulations separately.

Figures 2.2 and 2.3 below illustrate the labeled adequacy of the same model. In both plots, the nodes are arranged on the x-axis by their indegree in the original network. Figure 2.2 purposefully mimics the current goodness-of-fit plots, while Figure 2.3 highlights each node’s coverage by the simulations. Similar to Figure 2.2, the black line in Figure 2.3 displays node’s degree from the network. The shaded grey area is the ninety-five percent simulation interval for each node’s indegree. For each node: the vertical line displays in the interquartile range; the circle is the median; and the color for these are based on the coverage of the simulations in relation to a node’s true value, where green represents
coverage within the interquartile range, orange within the ninety-five percent simulation interval, and red as outside of the ninety-five percent interval (as an open interval).

The two figures illustrate that the model fits the data better for nodes that are closer to the mean indegree, while the simulations generated by the model’s thetas do not reproduce well nodes’ indegrees that are at the two ends of the distributions (particularly those with low indegree). Additionally, the figures show that the ninety-five percent simulation intervals consistently fail to reproduce the indegree of node 9. Comparing these plots to Figure 2.1, underscores the utility of examining node’s statistics separately. Figure 2.1 shows that nodes with an indegree of six (the same as node 9) are within the interquartile range of simulated networks, which could lead researchers to conclude erroneously that their model fits nodes with an indegree of six well. Instead, Figures 2.2 and 2.3 show that additional or different terms should be used in the model to reproduce the indegree of node 9 more consistently. For the purpose of demonstrating the utility of these new diagnostic tools, I use the same model throughout the paper rather than adjusting the model to fit the data more accurately.
Figure 2.2: Labeled Goodness-of-Fit Diagnostics with Boxplots

![Boxplot Diagram](image1)

Figure 2.3: Labeled Goodness-of-Fit Diagnostics with Colored Simulation Intervals

![Diagram with Colored Intervals](image2)
2.4 Model Adequacy for Edges

While Figures 2.2 and 2.3 illustrate how well each node’s statistics are reproduced by the simulated networks, they do not shed light on the model’s ability to recreate nodes’ specific edges that are present in the original network. Put another way, the simulations may reproduce the correct degree statistic for a node, but this could result from the simulations consistently placing edges that are absent in the network. To assess this possibility, it is useful to look at the edge probabilities derived from the change scores along with whether or not these edges are present or absent in the network. Figures 2.4 and 2.5 below elucidate the relationship between edges’ probabilities and their presence in the network.

In both figures, the nodes are ordered on the x-axis by their indegree in the network. The edge probabilities are shown on the y-axis in Figure 2.4, and the rank ordered probabilities are on the y-axis in Figure 2.5. The edge probabilities are found by exponentiating the conditional log-odds of a tie occurring (the sum of the products of the model’s thetas and the changes to the network’s statistics if the edge were present versus) and dividing it by one plus the exponentiated conditional log-odds (Handcock et al. 2008; Hunter et al. 2008). To compute the change statistics, I use the R package “ergm.changestats” (Butts 2016), which greatly improves the speed of compiling each edge’s change statistic.

These figures indicate whether the model predicts the presence of nodes’ edges that are present in the original network at higher rates than edges that are absent. Edges that are present in the original network are colored green, while edges that are absent are red. Ideally, one would like to see the present edges with higher probabilities than the absent edges, such that the figure would depict a clear separation between the green and red
circles. The rank ordered probabilities are similar to recall plots used for logistic regression models, as present edges’ probabilities may be low but are still higher relative to the absent edges’ probabilities. Returning to node 9, the figures show that overall the correct incoming edges have higher probabilities. This suggests that the model lacks a term to increase the probabilities of these edges and have them realized in the simulations. Yet, it remains unclear which edges specifically the simulations do not realize and why.
Figure 2.4: Edge’s Probabilities for each Node, Colored by Presence or Absence

![Figure 2.4: Edge’s Probabilities for each Node, Colored by Presence or Absence](image)

Figure 2.5: Edge’s Probabilities Rank Ordered for each Node, Colored by Presence or Absence

![Figure 2.5: Edge’s Probabilities Rank Ordered for each Node, Colored by Presence or Absence](image)
To examine which edges are and are not realized in the simulations, I have created a network plot (Figure 2.6 below) that illustrates the percent of simulations that include each edge. The edges are colored based on their presence (green) or absence (red) in the original network. The transparency of each edge is equal to the percent of simulations that realize an edge. Also, the edges are curved in this plot so that the indegree and outdegree ties between two nodes can be seen.

Figure 2.6: Network Image of Edges Realizations from All Simulations
If all of the simulations reproduced the original network exactly, then only green edges would be displayed in the plot. From the figure above, this is obviously not the case: it is worth noting that is immensely difficult to replicate the exact network in all simulations. Furthermore, one does see many green edges; especially, considering the network’s density is less than 0.25. Admittedly, it is a bit difficult to tell the percent of realizations for some of the edges (particularly those in the middle of the plot). However, this is easily remedied by utilizing the interactive option for a network plot, which is already included as part of the network package (Butts 2008 and 2015), or by plotting only a few node’s edges at a time. The former enables researchers to alter nodes’ coordinates in the plot to inspect more closely the relationship between specific nodes; while the latter, enables a researcher to examine a subset of nodes’ ties without all of the other edges displayed.

Alternatively, one could examine the true and false, positive and negative realizations in the simulated networks as separate plots. These networks plots show: edges present in the network that are in the majority of the simulations (true positive); edges absent in the network that are in the majority of the simulations (false positive); edges absent in the network that are not in the majority of the simulations (true negative); and edges present in the network that are not in the majority of the simulations (false negative). The threshold set to thin the number of edges displayed could be set to any value. Figure 2.7 below shows these plots with a threshold of sixty-five percent. All of the plots use the same coordinates for the nodes.
The figure displays a tremendous amount of information. The “True Positive” panel shows that only twelve of the 102 edges from the original network are realized in more than sixty-five percent of the simulations, while fifty of the edges from the original network are in the “False Negative” panel. This demonstrates that additional terms should
be added to the model that can better distinguish between edges (such as, including multiple features with node match). The “False Positive” panel shows ties that the simulations consistently recapitulate. These ties are especially problematic, and a researcher should focus on including terms to rein these in as the dependency between ties (due to the inclusion of mutuality in the model) can lead to additional edges being wrongly realized. Finally, the “True Negative” panel shows that the simulations accurately do not include many of the edges that are absent in the network: 258 of the 318 absent edges. Examining the true and false, positive and negative realizations can aid researchers in identifying systematic errors produced by the simulations and provide insights on how to improve their initial model.

An alternative way to diagnose potential problems with terms included in a model is to examine the relationships between the predicted probabilities of each edge based on the characteristics of the edge that are included as terms in the model. For a well-fitted model, we should expect to see separation between the probabilities for edges and nulls. However, it is not quite that simple since this captures a marginal effect of term absent of other factors that can affect the edge’s probability. A positive coefficient for a statistic indicates that higher values of the statistic are associated with higher conditional edge probabilities than there would be with lower values of this statistic, but if the higher values of the statistic are correlated with other terms that lower the edge probability, then the separation will not be as clear. Thus, this information can illuminate which terms should be altered, either by using a different term to capture that relationship or by creating interaction effects within covariates. Figure 2.8 below shows the edge probabilities and values for each edge for all of the terms in the model. Again, the green circles represent edges that are present in the
model while the red circles represent nulls. The solid black lines with embedded dashed color lines show the means for bivariate terms and LOWESS curves for interval terms. The points are jittered to ease interpretability. Interpreting Figure 2.8 requires one to refer back to the coefficients from the model. For example, the plot for the mutual ties shows good separation between edges that are and are not mutual and whether or not the edge is present or absent. The model found this distinction to be highly significant and impactful. On the other hand, the scatter plot for nodes that work in the same department does not show clear separation. Many nodes in different department have ties, while many nodes in the same department do not. This suggests that homophily within departments differs, so one should assess whether or not differentiating homophily within departments improves the fit of the model. Moreover, this underscores the importance of using alternative methods to evaluate a model’s fit other than an approximate AIC. Changing the node match term from equal homophily to differential homophily will add more terms to the model, which will in turn increase the number of parameters and alter the AIC (potentially increasing it) even though the inclusion of these terms may improve the adequacy of the model. Altering the shape or color of the points by other attributes of the edge can enhance the utility of these plots. This would show interactions that a researcher should include in a model to determine if the interaction improves the overall fit. Once could also plot the probabilities based on terms not included in the model to determine if they provide greater separation between present and absent edges.
Figure 2.8: Scatter Plots of Edges’ Predicted Probabilities for Each Term In the Model
2.5 Model Adequacy for the Entire Network

Up until now, the focus has been on how to assess and improve the fit of the model by examining where the model can reproduce the labeled network well and where it cannot. At this point, I am going to zoom out from the edge and node level to assess the overall ability of a model to reproduce the original network via simulations. First, I will show how hamming distance can be used to evaluate the fit of a model. Then, I delineate several accuracy scores for networks.

Hamming distance measures the similarity between networks by taking the sum of the numbers of edge deletions and additions to make the networks identical (Butts and Carley 2005). Therefore, hamming distance provides a graph level statistic that can be used to evaluate how closely simulated networks (from the fitted model’s thetas) resemble the original network. Additionally, one could use the hamming distance to assess if the simulated networks generated by one model’s coefficients more closely resemble the original network than another model. In below, the hamming distances of 100 networks simulated from the fitted model are shown in a histogram. The figure also displays the means of the Hamming distances for networks generated by the model (green line) and a null model (red line). The null model only includes an edge term, so it is equivalent to a Bernoulli graph (i.e.; each edge has an equal probability of being present).
Figure 2.9 shows that the networks simulated from the fitted model have an average Hamming distance that is about twenty-five less than networks simulated from the null model. Additionally, the mean Hamming distance for networks generated by the null model is within the distribution of Hamming distances for networks generated by the fitted model, albeit in the upper tail. One would like to see greater separation between the two distributions as this suggests that our fitted model does not reproduce the original network (via simulations) much better than a null model, though this distinction is dependent on the size of the network. When evaluating a model’s fit using Hamming distances, one should keep in mind that the null model will have lower Hamming distances, relative to the size of the network, in more dense networks. This is because the null models for more dense
networks have less of a chance of placing an edge incorrectly. The increase in the number of edges creates fewer opportunities for an edge to be realized inaccurately. Finally, this approach could be used to evaluate if one model is better at reproducing the original network than another model. This provides an alternative way to compare models.

Hamming distance provides one graph level statistic that summarizes the accuracy of a model in order to facilitate model selection, but other statistics can be computed that prioritize different aspects of the model’s fit. Table 2.2 below shows the root mean square error (RMSE) and F1 score for the fitted and null models. The RMSE value summarizes the overall error of the simulated networks from the fitted model’s thetas compared to the original network. The RMSE is found using the formula below:

$$RMSE = \sqrt{\frac{\sum (\hat{Y}_{i,j} - Y_{i,j})^2}{n}}$$

(2)

where: $Y_{i,j}$ equals the value of edge $Y_{i,j}$ from network Y; $\hat{Y}_{i,j}$ is the fraction of simulations that realize the edge; and $n$ is the total number of possible edges (i.e.; the number of dyads) in network Y. RMSE, like hamming distance, focuses on the overall error of the model. However, unlike hamming distance, RMSE ranges from zero to one (where lower values indicate less error), which can facilitate comparisons across networks of different size. A researcher interested in fitting a model to multiple networks can use this to assess the absolute errors across all of the networks. Alternatively, one could compute a model’s F1 score, which prioritizes a model’s ability to recall correctly the present edges relative to the false positives. It also ranges from zero to one, but here higher values indicate more accurate models. The formula for the F1 score is shown below:
\[ F_1 = 2 \cdot \frac{p \cdot r}{p + r} \]  

(3)

where: \( p \) (precision) equals the number of correct positive results divided by the number of all positive results; and \( r \) (recall) equals the number of correct positive results divided by the number of positive results that should have been returned.

Table 2.2: Summary Statistics of Model’s Fit

<table>
<thead>
<tr>
<th></th>
<th>Full Model</th>
<th>Null Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Hamming Distance</td>
<td>128.77</td>
<td>152.78</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.39</td>
<td>0.42</td>
</tr>
<tr>
<td>F1 Score</td>
<td>0.36</td>
<td>0.25</td>
</tr>
<tr>
<td>AIC</td>
<td>-206.9</td>
<td>-113.9</td>
</tr>
</tbody>
</table>

Table 2.2 shows that the networks simulated from the full model’s thetas more accurately reproduce the original network than the null model. The overall error is lower for the full model, as indicated by the RMSE values and mean hamming distance, and the weighted error is also lower, as indicated by the F1 scores. These additional network statistics are useful for summarizing the overall fit of a network. Moreover, a researcher could use these statistics to assess the fit of different models to the same network. By using different measures, the researcher can assess different aspects of the models’ fit. Furthermore, since the model’s thetas are approximate maximum likelihood estimates found using a stochastic algorithm based on Markov Chain Monte Carlo, the thetas will not be identical when run multiple times (Hunter et al. 2008a). One could evaluate the stability of the model specified by running the same model multiple times on the network and comparing the variances of the summary statistics. If the statistics vary widely across
the runs, then this would indicate a poorly fitted model as the model is drawing divergent coefficients from the parameter space.

2.6 Conclusion

This chapter delineates several tools that can assist network researchers in multiple ways. First, several of the methods shown move beyond the current goodness-of-fit tools by examining a model’s adequacy based on the labeled rather than the topological features of a network. These methods can be gainfully employed to discern where a model is systematically erring, and they provide ways to assess if different terms could potentially improve a model. Second, the utility of alternative ways to assess model fit as a summary statistic is demonstrated. These methods can be used to compare models for a single network or compare a model’s fit across a set of networks. All of these tools can assist network scholars in developing better fitting exponential family random graph models. This area has lagged behind the growing application of ERGMs by the community. Moreover, developing suitable models can be daunting for the uninitiated, and I hope these methods make ERGMs more accessible to neophyte network researchers. The above methods will be publicly available as an R package soon. Finally, these tools create opportunities for researchers to assess hypothetical situations and their impacts on how networks form.
3 Held-Out Predictive Evaluation (HOPE) of Exponential Family Random Graph Models

As pointed out in the previous chapter, researchers currently rely on an approximated AIC or graph level goodness-of-fit plots to assess the fit of an exponential random graph model (ERGM). However, the assumptions for justifying the AIC are not met for two interrelated reasons. First, the observations are not independent or identically distributed (Hunter et al. 2008b). Second, the effective sample size from which the ERGM draws from is intractably large except for the smallest of networks (Goodreau et al. 2009). As a result, the likelihood function cannot be evaluated directly. Therefore, there is a real need for alternative ways to assess the fit of an ERGM.

For other statistical models, cross-validation techniques are fruitfully used to assess how well the results from a model generalize to an independent data set. Typically, this is done by partitioning the data set into a training set (which the model is fit to) and test set (where the model is evaluated). Alternatively, a model can be fit to one data set and then evaluated on a comparable data set. However, the intrinsic relational aspect of network data precludes such a simple partitioning and comparable data are not often available. Using techniques developed by Handcock and Gile (2010) and Wang et al. (2016), I develop a within-sample validation method for exponential random graph models that supplies information on: how well the model is able to estimate held out data; where the model performs poorly based on held-out data, which indicates an idiosyncratic edge formation process for a node; and a graph level summary of the accuracy of the imputations. Taken together these assessments can assist researchers in improving models and facilitate the comparison of fit across multiple models.
3.1 Held-Out Predictive Evaluation (HOPE)

Handcock (2002) introduced the idea that methods for addressing latent missing data in non-relational data sets (Rubin 1976) can be applied in network contexts. Handcock and Gile (2010) apply this to ERGMs, and Wang et al. (2016) build off this to assess network imputation schema on missing data from the In-School Survey of Adolescent Health. They refer to their cross-validation method as Held-Out Predictive Evaluation or HOPE (Wang et al. 2016). I build off their method to develop a model assessment algorithm for ERGMs.

First, I set all of the edges for a single node to missing. Then, I fit an ERGM to the altered network. Third, I simulate networks from the newly fitted ERGM while holding all original edges constant, so only the missing edges are simulated or imputed. Next, I summarize the edge realizations from these simulations for the node’s edges that were initially held out. Finally, I repeat this process for all nodes in the network. In order to assess my previous model, I use the same terms for the third step as the ERGM fit in chapter 2. This process is similar to a “jackknife” technique; although, I am not estimating the parameters of the model based on the held-out data. Instead, I am using the held-out data to evaluate how well the model can recapitulate the “missing” edges.

Holding out data corrupts model performance in two ways. First, the effects of the held-out edges are not accounted for in the parameter estimates. Second, the values cannot be used to predict tie formation internally. This is precisely what makes the method so powerful. Better fitting models will be able to reproduce the held-out edges more accurately without having that data initially. Edges that are formed in ways that differ from the model will not be imputed with high accuracy. This could signal a deficiency within the model and point to aspects of ties that the researcher should include in their model (if
the issue is systemic). Alternatively, if the model imputes most edges with high accuracy and a small portion with much lower accuracy, then HOPE indicates that these ties are formed due to a divergent process. Either way, this information is useful to a researcher.

3.2 HOPE for Nodes

The HOPE routine can be used to assess the relative influence of a node within a network. If a node has a lower accuracy score relative to all other nodes, then the node impacts the edge formation process of the entire network more than a node whose held out edges can be predicted more accurately. This is due to the amount information “stored” in the node’s edges – how much it contributes to the generative process compared to when its edges are absent. Below shows the percentage of simulations that include an edge for each node; this is for 100 simulations. The figure illustrates this for incoming edges for each held-out node. Similar to the plots in the previous chapter, green circles indicate edges that are present in the original network, and red indicates edges that are absent.
The figure illustrates that overall incoming edges are imputed with high accuracy under this model. For most nodes, present edges (green circles) are realized more frequently than null edges. However, the figure also shows that several nodes have lower imputation accuracies. For example, node 7 has three null edges that are imputed with higher frequency than any present edges. This suggests that other generative features in the model would expect these three edges to be present and that node 7 has a tie formation process.
that diverges from the other nodes. The above information could be examined in a figure that separates the nodes by attributes (similar to Figure 2.8) to assess what features drive the differences. Heuristically, an ideal fit would have all of the green circles towards the top of the graph and the red circles would be at the bottom.

The imputation accuracy can also be summarized for each node. This illuminates which nodes are more or less influential in the network’s formation process, similar to a leverage analysis in regression model. A node that has a lower accuracy score relative to all other nodes indicates that the node’s edges are formed in a more idiosyncratic fashion than the rest of the model, which can have profound effects on network formation and diffusion processes (particularly in models with many dependency terms). Figure 3.2 below is based on the imputation accuracy for in and out ties. The sizes of the nodes are scaled based on the accuracy using root mean squared error, and the ties are the edges present in the original network.

The figure illustrates the differences in how well the model imputes a node’s edges. The figure also shows that the error is not simply driven by degree. For example, nodes 13 and 7 both have a total degree of three, yet node 13’s edges are imputed with far more accuracy than node 7. Thus, the plot shows which nodes form ties in ways that differ from the full model because the thetas from the model fit to the network with all other edges yield less accurate imputations of that node’s edges.
3.3 HOPE for Networks

At the network level of evaluation, the HOPE routine indicates how well the model captures the tie formation process. A better accuracy score for an entire network after using the HOPE routine demonstrates that the model captures the network’s tie formation process better than a model with a worse accuracy score. This could be used to compare different models fit to the same network or evaluate a model on a similar network.

In order to compare the HOPE routine results from the full model to the null model (with only an edge term), we must control for the changes in the number of edges in the network based on which node is held out. The network with held-out data by node will have differing numbers of edges due to the degree distribution. For example, if a node with a degree of twenty is held out of the network compared to a node with a degree of
two, the first ERGM will be fit to a network with eighteen less edges than the second. Without controlling for this, the null model would predict differing numbers of edges and bias the comparison. After running the HOPE routine for each node with the full and null models, I compute the RMSE for the entire network. This is done only on the imputed edges, as the rest of the edges remain constant for the simulations.

The RMSE for the full model is 0.37 while the null model is 0.45. Compared to the RMSEs when simulating the entire networks in chapter 2, the RMSEs from the HOPE routine are lower for the full model but actually increases for the null model. If the RMSE were higher for the full model, this would indicate a poorly fit model as the model fails to recapitulate the held-out edges more accurately even when provided additional information (i.e.; the other edges). The null model’s higher RMSE is due to the stochastic process. This shows that the full model is much better at reproducing the original network than the null model when the rest of the network is used as a constraint, which one would expect.

3.4 Conclusion

Evaluating network models is inherently difficult due to the relational dependencies in the data, which precludes many statistical methods that are available to other models. The HOPE routine provides a useful diagnostic to evaluate the fit of an exponential random graph model by using a within sample validation technique. Thus, network analysts can use HOPE to evaluate and compare ERGMs. Moreover, HOPE can be used to assess the amount of information contained in specific nodes or subsets of edges. This aspect can assist researchers in improving their models by identifying edge formation processes that differ from their model.
HOPE is computationally expensive however. The routine requires an ERGM to be fit with each node’s edges held-out. HOPE could be usefully extended for larger networks by holding out subsets of nodes or random subsets of edges. The exact proportions for yielding accurate assessments are beyond the scope of this paper and would be a fruitful next step in furthering the assessment of ERGMs.
4 Analyzing the Structure of the Emergency Management Organizational Field

Organizations are an intrinsic part of contemporary society (Zald and McCarthy 1987; Perrow 1991; Scott 2004). Due to their importance, scholars have sought to understand the differences among and interactions between organizations (Galaskiewicz 1985; Hannan and Freeman 1986; Meyer and Scott 1991; Mizruchi and Galaskiewicz 1993; Contractor, Wasserman and Faust 2006; Wooten and Hoffman 2017). Researchers have theorized organizational fields as a way to place boundaries around the relevant organizations and limit the scope of analysis (DiMaggio 1986; Wooten and Hoffman 2017). DiMaggio and Powell define organizational fields as “those organizations that, in the aggregate, constitute a key recognized area of institutional life: key supplies, resource and product consumers, regulatory agencies, and other organizations that produce similar service or products” (1983, p. 148). The concept of organizational fields provides insights into why organizations become more similar or distinct within a field by examining (1) the relations between organizations and (2) the features of the field that the organizations inhabit (Hannan and Freeman 1977; Galaskiewicz 1979; Burt 1987; Uzzi 1999; Pfeffer and Salancik 2003; Holloway et al. 2017). Hawley (1986) defines the push towards conformity as isomorphism, where the conditions of an organizational field constrain organizations, potentially causing them to become more similar. Scholars have applied these two concepts widely to analyze the emergence of an organizational field encompassing art museums (DiMaggio 1991), the effects of isomorphic pressure on nation-states (Meyer et al. 1997; Frank, Hironaka and Schofer 2000), and biotechnology firms’ collaboration networks (Powell 1996). While organizational sociologists had historically held an interest
in the United States’ bureaucracy (Meyer 1968, 1972; Tolbert and Zucker 1983), their interest has largely shifted towards firms and nonprofit organizations (Scott 2004). This overlooks a ripe opportunity to assess organizational field’s effects that can induce conformity versus idiosyncratic features that perseverate differences.

The federated government system of the United States can be treated as an organizational field where each state has a large amount of authority and responsibility within its jurisdiction, but all states are also embedded within and dependent upon the Federal Government. Emergency management in the United States provides a rich case to assess the effects of the competing pressures towards conformity (from the federal government) and towards distinctiveness (from states’ divergent political and ecological environments). The Federal Government and all states regularly release Emergency Operations Plans\(^2\) (EOPs) that are applicable to all types of disasters. These plans delineate which organizations are responsible for a standardized set of fifteen emergency support functions (ESFs), such as communications, mass care and community recovery (DHS 2004, 2008, 2011a). States must adhere to this structure in order to be eligible for federal preparedness grants, which totaled more than $1.6 billion for the 2016 fiscal year (Moynihan 2005; DHS 2017). Within this imposed structure, each state possesses the autonomy and authority to decide which organizations are included in their EOP and their ESF responsibilities as well as which ESFs are part of their plan (though very few deviate from the prescribed fifteen ESFs). The numbers, scale (e.g.; city, county, state, and

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\(^2\) The Federal Government labeled initially their plans as Federal Response Plans and later as the National Response Framework. Some states refer to their plans as “Comprehensive Emergency Plans” or “Emergency Response Frameworks”; I refer to all of these as Emergency Operations Plans (EOPs), since the majority of states use that term.
national) and sector (e.g.; government, private and non-profit) of organizations in states’ EOPs vary drastically. Additionally, states’ EOPs frequently focus on specific types of disasters that the state experiences more often (Tierney 2012). As a result, the overall structures of states’ EOPs can differ substantially while simultaneously exhibiting many similarities in substructures: the underlying social forces, generative mechanisms, can produce divergent networks.

Figure 4.1 below illustrates this duality by representing the 2011 Federal Response Plan and five states’ EOPs as two-mode networks – networks with two different sets of nodes (Wasserman and Faust 1994). The blue circles are organizations, and the orange squares are emergency support functions. The lines connecting nodes denote organizations’ assignments to ESFs; in network terminology, these are ties or edges. The differences between these networks are readily apparent. Yet, the six networks also exhibit structural similarities. All but Texas’ 2012 EOP have subgraphs (subsets of the network) where an ESF has many connections to organizations that have no other ties. Across the different networks, several of these subgraphs include the same ESF; for example, Georgia and Massachusetts’ EOP networks contain this feature for ESF 12 (energy). This substructure indicates that the ESF requires specialized organizations whose capacities are not applicable to other ESFs. Additionally, the figure demonstrates that the majority of the organizations are assigned to multiple ESFs, which indicates that most organizations in SEOPs have capacities that are applicable to multiple ESFs. Taken together, these facets suggest that states generate EOPs with structural similarities to varying degrees. This raises several questions that are the focus of this chapter: How comparable are the underlying, generative mechanisms across states? Why do these mechanisms converge or
diverge across states? How similar would states’ Emergency Operations Plans be if they were generated by different states’ mechanisms?

Network scholars have developed exponential family random graph models (ERGMs) to account for the dependencies within relational data and identify the underlying social forces, or mechanisms, that generate an observed network (Handcock et al. 2008; Hunter et al. 2008a; Robins et al. 2007; Snijders et al. 2006). ERGMs are widely applicable because of their ability to model structural dependencies within networks. Researchers have used ERGMs to analyze: microbiological and complex brain networks (Saul and Filkov 2007; Simpson et al. 2011); adolescent friendship networks (Goodreau, Kitts and Morris 2009; McFarland et al. 2014); interactions among different species (Faust and Skvoretz 2002); echo chambers in climate policy networks (Jasny, Waggle and Fisher 2015); interorganizational networks (Broekel and Hartog 2013); and migration patterns between nations (Windzio 2017). The general ERGM representation is in equation 1 below:

$$\text{Pr}(Y = y) = \frac{\exp[\theta^T g(y)]}{k(\theta)}$$

Where $y$ is a realization of random network $Y$; $\theta$ is the vector of coefficients; $g(y)$ is a vector of network statistics (e.g.; degree distribution or shared partners); and $k(\theta)$ is a normalizing constant, which ensures the equation is a legitimate probability distribution (Handcock 2003; Hunter et al. 2008a).
Figure 4.1: Network Images of Federal and State Emergency Operations Plans
From equation 1, the conditional log-odds of a tie can be found:

$$\logit[\Pr(Y_{ij} = 1|Y^c)] = \theta^T \Delta[g(y)]_{ij} \quad (2)$$

Where $Y_{ij}$ is a dyad in $Y$; $Y^c$ is the rest of the network; and $\Delta[g(y)]_{ij}$ is the change in $g(y)$ when the tie between $Y_{ij}$ is present. Equation 2 means that each element of $\theta$ indicates the effect of changes in the network’s statistics per unit from a particular edges’ presence or absence on the conditional log-odds of the observed network (Hunter et al. 2008b). I use ERGMs first to determine the social forces that generate states’ emergency management organizational networks. I then meta-analyze the social forces to assess the ubiquity of the effects from the Federal Government’s isomorphic pressure.

The thetas can also be used to simulate random networks to assess a model’s ability to recapitulate important structural features of the original network (Goodreau, Kitts and Morris 2009; Handcock et al. 2008). Additionally, the thetas can be altered to evaluate hypotheticals, such as how different are simulated networks from the original if homophily (the tendency of similar nodes to have ties) is stronger or weaker. To demonstrate this, I simulate 74,500 networks with varying levels of isomorphic pressure from the 2011 Federal Response Plan. First, I fit an ERGM to a network with the same number of nodes and edges with a term for edge covariate shared partners. This term creates a network statistic equal to the number of shared partners between emergency support functions (i.e.; an organization has a tie with two ESFs) that is weighted by the number of shared partners between the same two ESFs in the 2011 Federal Response Plan. ESFs with more shared partners have higher weights relative to those with fewer shared partners. Then, I simulate 500 networks at different theta values – isomorphism pressure from the federal
government. Intuitively, a higher theta value on this term increases the conditional probability of a tie that connects ESFs with more shared partners in the 2011 Federal Response Plan; subsequently, higher thetas will increase the similarity between the simulated networks and the original. I compare the simulated networks to the original using Hamming distance, which is the sum of the number of edge deletions and additions to make two networks identical (Butts and Carley 2005). Figure 4.2 below illustrates this relationship.

The theta values are on the x-axis; the hamming distances are on the y-axis. The curve indicates the mean Hamming distance (as the orange line) and the ninety-five percent simulation interval (as the grey region) of the 500 simulations for each value of theta. The five network images surrounded by dashed circles are subgraphs of the simulated networks with mean hamming distance values. The subgraph from the original network is surrounded by a dashed rectangle. The figure shows that higher theta values do produce networks that are more similar to the original network, which is further substantiated by the subgraph network images. It also shows that theta values greater than 0 rapidly reduce the hamming distances and that the variation in these networks is smaller compared to theta with large, negative values. Most importantly, the figure demonstrates the ability to evaluate empirically the effects of isomorphism.
The ability to simulate networks with different thetas can be extended to compare the generative features across a set of networks. Faust and Skvoretz (2002) use this approach to assess the similarities in tie probabilities across forty-two networks of different species and relations. I build off their insight by identifying the generative features of thirty-seven states’ emergency operations plans and then use each state’s generative features to simulate 1,000 networks for all of the other states as well as themselves. This simulation approach artificially “reruns history” to address how a state’s emergency operations plan would be
expected to appear if the generative principles (or social forces) of other states created its network while maintaining the same organizational features (or substrate). Moreover, this method illuminates how the conflicting pressures toward isomorphic emergency operations plans (caused by the Federal Government’s centralized role) contra idiosyncratic plans (due to the differences between states ecological environments) operate across the states. How ubiquitous are the effects of the Federal Government’s isomorphic pressure? How idiosyncratic are states’ remaining generative mechanisms and organizational substrates?

The rest of the chapter proceeds as follows. First, I briefly provide additional background on emergency management within the United States. Then, I review relevant organization literature. Next, I elaborate on the data and methods that I use to answer the three central questions of this chapter: How comparable are the underlying, generative mechanisms across states? Why do these mechanisms converge or diverge across states? How similar would states’ Emergency Operations Plans be if they were generated by different states’ mechanisms? After that, I present the results followed by a discussion of their implications for interorganizational fields. I then conclude the chapter with potential next steps that can build upon this research.

4.1 Emergency Management in the United States

Initially, the United States government responded to emergencies on an ad hoc basis. The federal government has only more recently taken on a more pivotal and central role in emergency management. Subsequent legislation solidified its authority and established “guidelines” that later became requirements for states. Importantly, these requirements include institutional and structural features to coordinate multiple organizations for effective responses to disasters that are codified into plans. However, the Federal
Government insists, “all incidents begin and end locally” (DHS 2011b, p. 2), and its intention is “not to command the response, but rather to support the affected local, tribal, and/or state governments” (FEMA 2017). These facets make studying the field of emergency management interesting because the federal government imposes requirements to address coordination issues caused by the uncertainty of disasters while simultaneously bestowing wide latitude to states on how exactly that coordination occurs.

The first federal disaster relief act occurred after a fire ravaged Portsmouth, New Hampshire in 1802 (FEMA 2010). Improvised federal responses continued through the beginning of the 20th century, and Congress passed 128 separate laws related to disaster relief as a result (FEMA 2003). The Federal Government was not officially authorized to address major disasters until 1950 when Congress passed the Federal Disaster Assistance Program (Baca 2008). Importantly, the program – as well as all subsequent Federal disaster legislation – conferred authority to the President in deciding whether or not provide a state supplementary Federal assistance.

The Disaster Relief Act of 1974 established the Presidential disaster declaration process, and the 1988 Robert T. Stafford Disaster Relief and Emergency Assistance Act expanded the amount of resources that the President can dispense (FEMA 2010; US Congress 1988). Under the Stafford Act, the Governor of a state experiencing a disaster must first appeal to the Federal Government for additional assistance, and then the President approves or denies the appeal (Comfort 1999; Reeves 2011). The President’s approval leads to a disbursement of funds to the affected state and spurs into action a host of Federal agencies that assist states with their response to a disaster. Section 402 of the Stafford Act states that the President may “direct any Federal agency, with or without
reimbursement, to utilize its authorities and the resources granted to it under Federal law … in support of State and local assistance response and recovery efforts, including precautionary evacuations…” (US Congress 1988).

Concurrently, coordination during and after disasters remained problematic. External organizations (besides federal agencies) and individuals frequently converge on a disaster site seeking to help, but they can complicate recovery efforts (Butts, Acton, and Marcum 2012; Drabek and McEntire 2002). In 1979, the National Governor’s Association requested that President Carter centralize federal emergency management to ameliorate this; later that year, he consolidated several, separate federal programs and agencies related to disaster management under the new Federal Emergency Management Agency (FEMA 2010). To facilitate coordination further, the 1988 Stafford Act also tasked FEMA with developing a Federal Response Plan, which was first released in 1992 (FEMA 1999). The plan established the coordinating structure for federal agencies responding to disasters and was designed to be applicable to all potential disasters. The structure includes lines of authority and organizational relationships (designating the lead or primary organization), for a standardized set of emergency support functions (ESFs). The ESFs are the:

Federal coordinating structures for building, sustaining, and delivering the response core capabilities. … The Federal ESFs bring together the capabilities of Federal departments and agencies and other national-level assets. ESFs are not based on the capabilities of a single department or agency, and the functions for which they are responsible cannot be accomplished by any single department or agency. Instead, Federal ESFs are groups of organizations that work together to deliver core capabilities and support an effective response (DHS 2016a).
The standardized set consists of fifteen ESFs\(^3\): transportation; communications; public works; firefighting; emergency management; mass care; resource support; public health; urban search and rescue; oil and hazardous materials; agricultural and natural resources; energy; public safety and security; community recovery; and external affairs (DHS 2004, 2008, 2011a). When the President approves a governor’s request for federal assistance, it activates the Federal plan.

The Federal Government encouraged states to develop analogous operations plans so organizations from different levels of government could work together more effectively during disasters. FEMA released guides for how states can develop their plans. Their first guide, released in 1996, begins by stating, “One goal of the Federal Emergency Management Agency (FEMA) is to develop, in partnership with State and local governments, a national emergency management system that is comprehensive, risk-based, and all-hazard in approach. Crucial to this system are emergency operations plans (EOPs)…” (FEMA 1996, p. forward). The same guide emphasizes that the numbers and types of ESFs in SEOPs can vary, but some states may choose to “mirror” the federal plan to simplify coordination.

In 2005, the guideline became more rigid as states were required to incorporate the National Incident Management System (NIMS) within their SEOPs to qualify for federal preparedness grants and funding (NIMS Integration Center 2007). NIMS includes the Federal Government’s approach for responding to disasters. To be NIMS compliant, states’ plans must include a hierarchical division of labor detailing organizations’

\(^3\) The 1992 and 1999 Federal Response Plans contained twelve emergency support functions. The number of functions expanded to fifteen in the 2004 plan, and the 2016 plan, which is the most recent, also has fifteen.
responsibilities during emergencies (FEMA 2006). A state can accomplish this by adopting the ESF structure or providing a crosswalk between their unique structure and the fifteen ESFs in the federal plan (FEMA 2008). All states conform to this requirement, and many states specifically reference their adherence to NIMS in their plans.

However, as Figure 4.1 above illustrates, states’ plans evidence heterogeneity despite the Federal Government’s strict requirements that one would expect to induce homogeneity, or isomorphism. Next, I review literature on organizational fields and interorganizational relations that provide insight into this puzzle.

4.2 Organizational Fields and Interorganizational Relations

Research on organizations initially focused on markets and hierarchies. The market structure consists of firms competing with one another while seeking to maximize their efficiency and is associated with neoclassical, microeconomic theory (Smith 1976). Conversely, hierarchies contain distinct boundaries between organizations with vertical lines of interaction and minimal autonomy; it is associated with theories of the firm or bureaucracy (Taylor 1914; Tirole 1988; Weber 2009). In both cases, analysis focused on the phenomena occurring within the boundaries of an organization; they were closed systems (Scott 1991, 2004). Scholars increasingly recognized that these two structures did not adequately describe a large portion of the empirical world. Attention had shifted towards how organizations seek to manage uncertainty (Coase 1937; Williamson 1981) and the relations between organizations (Granovetter 1985; Galaskiewicz 1985; Burt 1987) leading scholars to analyze populations of organizations (Hannan and Freeman 1977, 1986) and assess the effects of their institutional environments (Meyer and Rowan 1977; DiMaggio and Powell 1983). These are open systems, where organizations respond to
their environments (regulatory structures, availability of resources and other organizations) more than internal factors (Scott and Davis 2007).

The shift in emphasis towards relations between organizations led Powell (1990) to term these “networks” structures. Network structures are composed of interdependent organizations that mutually enhance one another’s capabilities; the relations are more horizontal and interdependent (as opposed to hierarchical), and autonomy is constrained by the organizational field (Galaskiewicz 1985; Kapucu, Arslan, and Collins 2010; Powell 1990; Thoereli 1986). The organizational field approach bounds the system to the relevant set of organizations that affect organizations embedded within it.

Research using this perspective accounts for organizations’ governance structures as a result of uncertainty in transactions by causing organizations to establish ties horizontally and vertically (Galaskiewicz 1985; Gulati and Gargiulo 1999; Williamson 1981). Organizations facing greater uncertainty are more likely to formalize their structures (Leblebici and Salancik 1982). Formal organizations are organizations with a broad range of responsibilities that must be stable and unify all its constituent parts; they typically have internal horizontal ties (i.e.; divisions at similar levels) and vertical, hierarchical ties differentiating levels of authority (Lune 2010). Conversely, informal organizations develop more naturally and lack authoritative structures; they are more akin to friendship networks (Krackhardt 1992). Informal organizations can emerge within or span across organizations. The informal connections across organizations can facilitate repetitive interactions and potentially become formalized (Gulati and Gargiulo 1999; Powell, Koput and Smith-Doerr 1996). The frequency of the interactions will influence how the relation is structured (Laumann, Galaskiewicz and Marsden 1978).
Within an organizational field, organizations influence one another based on availability of resources, status and the strength of enforcement mechanisms (Mizruchi and Galaskiewicz 1993). DiMaggio and Powell (1983) posit that higher levels of dependence on a single entity for resources, more frequent transactions, and the lack of alternative organizational models will all generate greater isomorphism among organizations in the field. Though some argue that the decentralized system in the United States make authority weaker, the Federal Government can induce structural similarity and policy adoption through funding (Scott 1991). For example, Pfeffer and Salancik (2003) find that organizations more dependent on the United States’ government for revenues conform faster to affirmative action policies. Conversely, Quirke (2013) demonstrates that “patchy” organizational fields consist of heterogeneous organizations (primarily at the periphery) as well as “clusters of homogeneity” due to weak regulatory environments, shifting demands, and multiple institutional logics that legitimate alternative organizational models.

The research on organizational fields identifies mechanisms that would increase isomorphism among organizations; several of these are present within emergency management field. States’ emergency operations plans are highly formalized and standardized to address immensely uncertain conditions. States depend on the Federal Government for resources during major emergencies. The Federal Government imposes a general, structural prerequisite for emergency preparedness grants. All would predict high levels of isomorphism with in the organizational field of emergency management in the United States. Conversely, some facets of the field would lead one to expect lower levels of isomorphism. The structural requirements for states’ emergency operations plans only address the emergency support functions; they are silent on the organizational side. The
Federal Government states this is intentional since states have different bureaucratic structures and operational needs. As a result, states adopt the ESF structure, but can evidence high levels of heterogeneity in which organizations are part of their plans and which ESFs those organizations are assigned. The methods used in this chapter evaluate the products of this tension.

**4.3 Data & Methods**

The primary dataset consists of thirty-seven states’ emergency operations plans (SEOPs) from thirty-seven states. The earliest plan was released in 2005, and the most recent was released in 2014. Each plan delineates organizations’ assignments to emergency support functions (ESFs) in a table or list. I create an adjacency matrix for each plan with this information, which I then convert into a two-mode network. The first mode is organizations, and the second is ESFs. For all organizations, I use organizations’ websites or government documents to code each organization’s scale and type based on Tierney’s (2003) definitions, which others have used since (Butts et al. 2012). The categories of organizations’ scale include: city, county, state, interstate, regional, and international. The types of organizations are: government, not-for-profit, for-profit, and government-private partnerships. I also dichotomously code the alignment between organizations’ quotidian tasks and the ESFs based on the federal plans’ descriptions (DHS 2004, 2008, 2011a). Additionally, I create matrices of organizations’ ESF assignments from the three federal plans. These three plans are not analyzed directly; information from these plans are used as terms in the exponential random graph models.

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4 Four SEOPs had to be dropped due to singularity when fitting ERGMs. The four plans are: Alabama 2012, Iowa 2010, Texas 2012, and Virginia 2012.
4.3.1 Exponential Family Random Graph Models

Exponential family random graphs models (ERGMs) are fit to each of the thirty-seven states’ emergency operations plans as two-mode networks using the ergm package in R (Handcock et al 2017; Hunter et al. 2008a). The thetas correspond with the network features specified in the model. As equation 2 shows, positive thetas indicate network features that increase the conditional log-odds of a tie, absent all other features. Thus, the thetas identify the underlying mechanisms of tie formations in the observed network.

From the three federal plans, I create two covariates to assess the effects of isomorphic pressures from the Federal Government. The first term, which was used to generate the simulated networks in Figure 4.2, is the numbers of shared partners between ESFs. Shared partners are organizations assigned to two ESFs for all pairs of ESFs. This represents the amount of overlap between ESFs in the federal plan; ESFs with more shared partners are more closely related. I use the weighted version of this term, so ESFs with more shared partners (rather than just one shared partner) are considered; this term is from the “ergm.bipartiteExtra” package (Butts 2015). To use this term, I created a square matrix for each of the federal plans such that the lower right hand corner contained the numbers of shared partners between ESFs divided by the total number of ESFs in that plan5. I then link one of the three matrices to each of the states’ networks based on the year the states’ plan was released. If a state plan and federal plan were released in the same, then I used

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5 The three federal plans include different numbers of organizations. There are thirty-two organizations in the 2004 plan, thirty-six in the 2008 plan, and forty-eight in the 2011 plan. Dividing by the total number of organizations in each plan controls for the changes in numbers over time.
the previous federal plan since this is the federal plan that was in effect when the state was creating its plan.

The second term I derive from the three federal plans relates to the numbers of organizations assigned to each ESF (or ESFs’ degrees). ESFs’ degrees capture the scope of a task; tasks with higher degrees are broader and require more organizations to complete the task effectively. Similar to the first term, I divide each ESF’s degree by the number of organizations in the plan, and I link these numbers to each state’s plan. In all of the ERGMs, I include: edges (the baseline propensity of ties), the two terms derived from the federal plans, a term for organizations’ task alignment with ESFs, and terms for each organization type and scale included in a state’s plan. Government and state are the reference categories for type and scale and are not in any of the models. Additional terms for each are only included if they are present in a state’s plan.

4.3.2 Meta-Analysis of ERGM Coefficients

The second set of analyses assess why isomorphism differs across states. I use weighted least squares regression to meta-analyze the two federal isomorphism thetas that the ERGMs identified in the first analyses. Many others have used similar approaches to examine contextual effects on sets of networks’ tie formation processes (Lubbers 2003; McFarland et al. 2014; Moody 2001; Snijders and Baerveldt 2003; Zijlstra, Van Duijn and Snijders 2006). Each theta is separately regressed on: historical exposure to hazards, recent hazards, numbers of organizations in plans, years of plans, Governors’ political party affiliations and its alignment with the President’s party, size and population of states. Historical exposure to hazards is measured as the number of emergency declarations by a state between 1990 and 1999 and recent hazards as the number of declaration in the three
years prior to a plan’s release. These data are from FEMA’s website (FEMA 2016). The numbers of organizations and years of plans come directly from the states’ plans. Governors’ political parties are from Ballotpedia (Ballotpedia 2017). The states’ land area in kilometers squared and populations are from 2010 US Census (US Census 2012). The descriptive statistics are in Table 4.1 below.

Table 4.1: Descriptive Statistics for Independent Variables in Meta-analyses

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disaster Exposure</td>
<td>11.78</td>
<td>8.43</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>Disaster Recency</td>
<td>6.70</td>
<td>5.65</td>
<td>0</td>
<td>32</td>
</tr>
<tr>
<td>Year of Plan</td>
<td>2011.24</td>
<td>2.33</td>
<td>2005</td>
<td>2014</td>
</tr>
<tr>
<td>Number of Organizations</td>
<td>52.27</td>
<td>36.36</td>
<td>8</td>
<td>144</td>
</tr>
<tr>
<td>Size of State(^1)</td>
<td>11.66</td>
<td>1.07</td>
<td>9</td>
<td>14</td>
</tr>
<tr>
<td>Population of State(^1)</td>
<td>15.06</td>
<td>1.05</td>
<td>13.24</td>
<td>17.43</td>
</tr>
<tr>
<td>Party Alignment</td>
<td>0.43</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

\(^1\) indicates logged transformed variables

4.3.3 Comparing Networks Using Simulations

The final set of analyses asks: how similar would the networks of states’ emergency operation plans be if the same generative features were present? I develop new techniques in order to do this that build off of the insights of Faust and Skvoretz (2002; see also Skvoretz and Faust 2002). Their key insight was that despite a set of networks’ surface level differences they could in fact be structured similarly. They fit exponential family random graph models (therein called p\(^*\) model) to forty-two networks from four different kinds of species with different relation types. Then, they calculate the predicted tie probabilities for each network using all of the networks’ estimates. Finally, they compare
the sets of predicted tie probabilities using correspondence analysis and find that the types of relation, rather than the kinds of species, possess more similar structural features.

However, the method has some limitations. At the time there was not a way to assess how well networks simulated from the estimates parameters would reproduce the observed network. Only more recently have Markov chain Monte Carlo methods been incorporated to estimate maximum likelihood functions (Hunter and Handcock 2006; Snijders 2002) though Geyer and Thompson (1992) proposed the idea much earlier for other exponential family models. The recent advances computationally and statistically enable maximum likelihood estimates of parameters for exponential random graph models with nodal covariates (Snijders 2002; Hunter and Handcock 2006; Hunter et al. 2008a). Nodes’ attributes are potentially important to understanding differences in the networks of states’ emergency operations plans. For example, one would expect that government organizations have more ESF assignments than non-profit or for-profit organizations.

I use the most recent version of exponential random graph models in the R package “ergm” to fit my models in the first analyses (Handcock et al. 2017). To compare all of the networks’ social forces and social substrates, I use each of the generative features, the thetas, for one network and simulate 1,000 networks on all of the networks’ substrates. This produces 1,369,000 networks. For each pair of social forces and substrates, I compare the 1,000 simulated networks to the true network that the social substrate corresponds with using Hamming distance. For example, the social forces identified for Alaska’s 2011 network were used to simulate 1,000 networks on the social substrate of Arkansas’ 2013 network. I find the hamming distance of each simulated network and the true Arkansas 2013 network. This approach enables an artificial “rerunning of history” to ask: how
similar would Arkansas’ 2013 network be if the generative features of Alaska’s 2011 network produced it?

The simulated graphs could be assessed in numerous ways. I chose two that focus on (1) the ubiquity of the social substrate and (2) the interaction between the social forces and substrates. The first asks: how well can the social forces in other states recapitulate networks compared to its own social forces? Unique networks will be poorly reproduced while more general networks will be more accurately reproduced overall. To assess this, I normalize the mean Hamming distances for all pairs by the mean and standard deviation of the networks produced by its own social forces and substrate. The second asks: how ubiquitous are the social forces when accounting for the number of nodes in the social substrate? This analysis facilitates a comparison of the social forces controlling for the social substrates. Social forces that can better recapitulate networks irrespective of the order of the network are more general. To evaluate this, I divide the mean Hamming distance for each pair by the number of possible edges in that network. Both analyses are presented as heat maps in the results section.

Taken together, these two analyses directly address the sources of differentiation and similarity between the structures of states’ emergency operations plans: do similar social forces or social substrates drive the observed phenomena? Moreover, other network scholars could gainfully utilize these methods to assess structural similarities in other sets of networks. However, one should carefully consider whether the baseline density should be held constant or if the expected degree should be held constant or scaled with the order of the network. Standard ERGMs maintain baseline densities consistent with the size of the network, which may not be reasonable for particular contexts (Butts and Almquist
Krivitsky et al. (2011) suggest that networks of social relations between individuals (such as sexual partners or friendships) should include the offset term since it is unreasonable for the number of ties to scale with the size of the network. This is not the case for the networks of states’ emergency operations plans since states assign organizations to varying numbers of ESFs irrespective of the numbers of organizations in their plans.

4.4 Results

4.4.1 Exponential Family Random Graph Models

The results of the exponential family random graph models fit to each of the network representations of states’ emergency operations plans are shown below in Table 4.2 through Table 4.8. I chose to display the results in this way because states’ emergency operations plans include different kinds of organizations in scale and type, and the conflicting combinations of particular effects are noteworthy. These distinctions would be lost if the thetas were shown using box plots or a similar summary figure.
Table 4.2: Exponential Random Graph Models Results for States’ Emergency Operations Plans

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</thead>
<tbody>
<tr>
<td>Shared Partners</td>
<td>1.090***</td>
<td>1.245***</td>
<td>0.331*</td>
<td>0.837***</td>
<td>-2.445</td>
<td>0.980***</td>
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<tr>
<td>ESF Degree</td>
<td>0.947</td>
<td>-0.101</td>
<td>4.169***</td>
<td>2.081**</td>
<td>0.482</td>
<td>-0.750</td>
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<td>Task Alignment</td>
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<td>2.298***</td>
<td>1.219***</td>
<td>1.537***</td>
<td>2.501***</td>
<td>2.116***</td>
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<td>City</td>
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<td>-</td>
<td>-</td>
<td>-0.660</td>
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<td>County</td>
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<td>-0.469</td>
<td>-0.475</td>
<td>-</td>
<td>-0.003</td>
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<tr>
<td>Interstate</td>
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<td>-0.691</td>
<td>-0.491</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Regional</td>
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<td>-0.441</td>
<td>-0.26</td>
<td>-</td>
<td>-</td>
<td>-0.114</td>
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<tr>
<td>National</td>
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<td>-0.451**</td>
<td>-0.405*</td>
<td>0.116</td>
<td>-</td>
<td>-0.194*</td>
</tr>
<tr>
<td>International</td>
<td>-</td>
<td>-</td>
<td>-0.329</td>
<td>-</td>
<td>-</td>
<td>0.027</td>
</tr>
<tr>
<td>Type</td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>Non-Profit</td>
<td>-0.041</td>
<td>-0.231</td>
<td>-0.398*</td>
<td>-0.280</td>
<td>-</td>
<td>0.033</td>
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<tr>
<td>For-Profit</td>
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<td>-0.200</td>
<td>0.488</td>
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<td>Government-Private</td>
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<td>-</td>
<td>-0.099</td>
<td>-</td>
<td>-</td>
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<tr>
<td>AIC</td>
<td>855.547</td>
<td>1258.881</td>
<td>1881.651</td>
<td>693.479</td>
<td>195.461</td>
<td>1513.685</td>
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</tbody>
</table>

Significance levels: *** .001; ** .01; * .05
Table 4.3: Exponential Random Graph Models Results for States’ Emergency Operations Plans

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<tbody>
<tr>
<td>Shared Partners</td>
<td>0.172</td>
<td>1.347***</td>
<td>1.086***</td>
<td>0.932***</td>
<td>1.385***</td>
<td>1.162***</td>
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<tr>
<td></td>
<td>(0.265)</td>
<td>(0.079)</td>
<td>(0.088)</td>
<td>(0.115)</td>
<td>(0.098)</td>
<td>(0.069)</td>
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<td>ESF Degree</td>
<td>2.847***</td>
<td>-0.219</td>
<td>4.131***</td>
<td>0.697</td>
<td>-3.379***</td>
<td>2.222***</td>
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<td></td>
<td>(0.498)</td>
<td>(0.592)</td>
<td>(0.803)</td>
<td>(0.546)</td>
<td>(0.827)</td>
<td>(0.654)</td>
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Significance levels: *** .001; ** .01; * .05
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Significance levels: *** .001; ** .01; * .05
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Significance levels: *** .001; ** .01; * .05
Table 4.6: Exponential Random Graph Models Results for States’ Emergency Operations Plans

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Significance levels: *** .001; ** .01; * .05
Table 4.7: Exponential Random Graph Models Results for States’ Emergency Operations Plans

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<th>Organization Covariates</th>
<th>Task Alignment</th>
<th>Scale</th>
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<td></td>
<td>2.661***</td>
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<table>
<thead>
<tr>
<th>Type</th>
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<th>For-Profit</th>
<th>Government-Private Partnership</th>
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<tbody>
<tr>
<td></td>
<td>-0.060</td>
<td>-0.501*</td>
<td>-</td>
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<tr>
<td></td>
<td>(0.187)</td>
<td>(0.243)</td>
<td>(0.368)</td>
</tr>
<tr>
<td></td>
<td>-0.115**</td>
<td>-0.928</td>
<td>-</td>
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<tr>
<td></td>
<td>(0.368)</td>
<td>(0.799)</td>
<td>(1.024)</td>
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</thead>
<tbody>
<tr>
<td></td>
<td>(0.337)</td>
<td>(0.326)</td>
<td>(0.446)</td>
<td>(0.799)</td>
<td>(0.605)</td>
</tr>
</tbody>
</table>

| AIC       | 726.580   | 726.800   | 570.238   | 111.327   | 215.174   |

Significance levels: *** .001; ** .01; * .05
Table 4.8: Exponential Random Graph Models Results for States’ Emergency Operations Plans

<table>
<thead>
<tr>
<th></th>
<th>VT2009</th>
<th>WA2011</th>
<th>WI2010</th>
<th>WY2008</th>
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<tbody>
<tr>
<td><strong>Isomorphism</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shared Partners</td>
<td>0.813***</td>
<td>0.683***</td>
<td>1.194***</td>
<td>0.783***</td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.147)</td>
<td>(0.109)</td>
<td>(0.176)</td>
</tr>
<tr>
<td>ESF Degree</td>
<td>2.276***</td>
<td>2.770***</td>
<td>-1.274</td>
<td>-0.153</td>
</tr>
<tr>
<td></td>
<td>(0.655)</td>
<td>(0.757)</td>
<td>(1.199)</td>
<td>(0.979)</td>
</tr>
<tr>
<td><strong>Organization Covariates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task Alignment</td>
<td>2.366***</td>
<td>2.338***</td>
<td>2.694***</td>
<td>1.951***</td>
</tr>
<tr>
<td></td>
<td>(0.368)</td>
<td>(0.539)</td>
<td>(0.485)</td>
<td>(0.371)</td>
</tr>
<tr>
<td><strong>Scale</strong></td>
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<td></td>
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<tr>
<td>Interstate</td>
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<td>-</td>
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<tr>
<td>Regional</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.319</td>
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<td></td>
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<td></td>
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<td>(0.732)</td>
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<tr>
<td>International</td>
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</tr>
<tr>
<td><strong>Type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Profit</td>
<td>-0.153</td>
<td>-0.340</td>
<td>-0.262</td>
<td>-0.052</td>
</tr>
<tr>
<td></td>
<td>(0.158)</td>
<td>(0.440)</td>
<td>(0.294)</td>
<td>(0.382)</td>
</tr>
<tr>
<td>For-Profit</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Government-Private Partnership</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Edges</td>
<td>-3.125***</td>
<td>-2.666***</td>
<td>-2.250***</td>
<td>-2.319***</td>
</tr>
<tr>
<td></td>
<td>(0.343)</td>
<td>(0.314)</td>
<td>(0.582)</td>
<td>(0.469)</td>
</tr>
<tr>
<td>AIC</td>
<td>879.194</td>
<td>751.281</td>
<td>272.428</td>
<td>414.125</td>
</tr>
</tbody>
</table>

Significance levels: *** .001; ** .01; * .05

The most consist result is the effect of organizations’ task alignment with an emergency support function. Alignment between the two significantly increases the probability of a tie. This is not surprising; in fact, it would be worrying if this relation were absent. Additionally, the results show that state organizations and governmental agencies
have higher tie probabilities. Both are the reference categories for scale and type, respectively; the nearly uniform negative (and occasionally significant) thetas for the other categories of organizations evidence this. While national organizations have lower tie probabilities than state organizations overall, the effect is generally smaller and nonsignificant compared to more local organizations (e.g., city or county). The contrast is more apparent for the type of organization. Nongovernmental organizations only have seven positive thetas and never reach significance compared to thirty-five negative thetas, ten of which are significant. For these organizations, task alignment drives their tie formations, and they are bound within their domain.

The models identify federal isomorphic pressure as a strong social force that significantly increases ties’ probabilities overall, though with some interesting caveats. The ESF shared partner effect is stronger and more consistent across models. The social force significantly increases the probability of a tie in thirty of the models, and has a significant negative effect in only one (Maine’s 2008 plan). These ties bridge tasks, potentially linking organizations beyond their quotidian tasks. In the models with negative thetas or smaller magnitudes of positive thetas, the task alignment thetas are stronger. The three networks evidencing the strongest, positive effects of alignment on the probability of ties (North Dakota 2012, Montana 2012, and Massachusetts 2013) have insignificant thetas for shared partners and two are negative.

The second isomorphism term is the number of organizations assigned to each emergency support function (i.e., the node’s degree). This can be interpreted either as the broadness of a function (it takes many organizations to complete it) or a prioritization of a function (more organizations should be assigned to it). Regardless, the term captures the
percentages of organizations assigned to each function from the active federal plan; functions with more organizations yield higher edge probabilities (when the term is positive). In twenty-three of the models, the term is positive with significance in eighteen; it is negative in fourteen models with significance in three. When both terms significantly increase ties’ probabilities, then federal isomorphism is a stronger social force that greatly influences the formation of ties within that network. This is the case for fifteen of the thirty-seven networks.

Overall, the ERGMs find strong effects of federal isomorphic pressures on states’ emergency operations plans, manifesting as generative features that increase the probabilities of particular ties. Yet, these effects are not ubiquitous and exhibit heterogeneity. The meta-analysis of the isomorphism thetas will assess if exogenous features correlate with these differences.

### 4.4.2 Meta-Analysis

The isomorphism thetas from the ERGMs are analyzed using weighted least squares; the weights are the standard errors in the ERGMs. Each term is regressed on state and plan features. The results are shown below in Table 4.9. Surprisingly, the results evidence minimal relation, and the F-statistic indicates the lack of a linear relationship for the analysis of ESF degree thetas.
Table 4.9: Meta-Analysis of Federal Isomorphism Thetas

<table>
<thead>
<tr>
<th></th>
<th>Shared Partners</th>
<th>ESF Degree</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Disaster Exposure</strong></td>
<td>-.011</td>
<td>.033</td>
</tr>
<tr>
<td></td>
<td>(.009)</td>
<td>(.049)</td>
</tr>
<tr>
<td><strong>Disaster Recency</strong></td>
<td>-.017</td>
<td>.113</td>
</tr>
<tr>
<td></td>
<td>(.009)</td>
<td>(.078)</td>
</tr>
<tr>
<td><strong>Year of Plan</strong></td>
<td>.029</td>
<td>.037</td>
</tr>
<tr>
<td></td>
<td>(.022)</td>
<td>(.247)</td>
</tr>
<tr>
<td><strong>Number of Organizations</strong></td>
<td>-.001</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>(.001)</td>
<td>(.012)</td>
</tr>
<tr>
<td><strong>Size of State(^1)</strong></td>
<td>-.009</td>
<td>.108</td>
</tr>
<tr>
<td></td>
<td>(.042)</td>
<td>(.416)</td>
</tr>
<tr>
<td><strong>Population of State(^1)</strong></td>
<td>.080</td>
<td>.058</td>
</tr>
<tr>
<td></td>
<td>(.051)</td>
<td>(.552)</td>
</tr>
<tr>
<td><strong>Party Alignment</strong></td>
<td>-.152</td>
<td>-.375</td>
</tr>
<tr>
<td></td>
<td>(.089)</td>
<td>(.966)</td>
</tr>
<tr>
<td><strong>Intercept</strong></td>
<td>-58.875</td>
<td>-75.961</td>
</tr>
<tr>
<td></td>
<td>(43.633)</td>
<td>(491.498)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Residual Standard Error</th>
<th>Multiple R-squared</th>
<th>Adjusted R-squared</th>
<th>F-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.975</td>
<td>.371</td>
<td>.219</td>
<td>2.439*</td>
</tr>
<tr>
<td></td>
<td>3.310</td>
<td>.152</td>
<td>-.052</td>
<td>.744</td>
</tr>
</tbody>
</table>

*Significance levels: *** .001; ** .01; * .05
\(^1\) indicates logged variables

The analysis of shared partners’ thetas find no variables significant (though number of recent disasters and political party alignment at the .1 level). The direction of recent disasters is particularly noteworthy since these disaster declarations lead to interactions between states’ emergency management organizations and the Federal Government. This is the opposite of what DiMaggio and Powell (1983) hypothesized would induce greater isomorphism. Political party alignment between Governors and the President indicates a weak, negative relationship where states structure their plans less like the Federal Government if they are not the same party. For states with Republican Governors, this
affect is attenuated by the positive (though insignificant) effect of plans released in later years. The model was also specified with an interaction between the two and with a dummy variable for Republican Governors. In the first, the interaction term was insignificant; in the second, the dummy variable was also negative, significant $p < .1$. It also worth noting that the number of organizations in states’ plans and historical experiences with disasters (the number of emergency declarations between 1990 and 1999) are insignificant.

The model of the thetas for isomorphism with ESFs’ degree should not be given much credence, since the F-statistics failed to reject the null that there is not a linear relationship. Both models were run removing two outliers, which did not alter the results. I also specified the weights by regressing the absolute values of the residuals on the fitted values (once using standardized and second using unstandardized thetas), but these all produced similar results. Taken together, the meta-analysis of the thetas associated with isomorphism fail to find strong correlations between variables operationalizing federal isomorphic pressures and states’ features. This suggests that features of the states to not drive the idiosyncrasies or similarities found in the parameters.

4.4.3 Comparing the Social Forces across Substrates

The final set of analyses assesses the historical contingency of the generative mechanisms that produce states’ emergency operations plans by taking the social forces for each plan and simulating them across all of the plans. This new method directly compares the similarity of the social forces and the ubiquity of the substrates. Consensus networks are generated by consensus forces. They should reproduce other networks well and be reproduced well by other forces. Dissensus forces would be the opposite. For each combination of social forces and substrate, I simulate 1,000 graphs. Each simulation is
then compared to the true network to find the Hamming distance. Each cell in the figures is the mean value of each pair.

The first figure compares how well the social forces of all other networks reproduce the network compared to its own social forces; it is below in Figure 4.3. Each row (the substrate) is standardized by the self-simulations (the social forces simulated on its own network), so the diagonal is equal to zero for all networks. All other cells in a row are colored by their z-scores from the self-simulations. The sum of the z-scores are in the margins of each row, indicating how well other social forces reproduce the network compared to its own social forces. Higher sums indicate that other social forces do not reproduce that network as well as its own.

The figure shows large variations in the networks produced by other social forces compared to its own social forces. In most cases, the self-simulations have the lowest z-score in a row, but in a few cases, different social forces do a better job of recapitulating the original network than its own social forces. For example, the social forces for Montana 2012 and North Dakota 2012 are frequently lower than the z-scores on the diagonal. Yet, others’ social forces reproduce their own networks poorly. However, the comparison of social forces across context should be done carefully. The z-scores in a row could be high because the generative mechanisms very poorly reproduce the original network or because the self-simulations reproduce its own network quite well. In spite of this caveat, it is quite clear that there are large differences in how well the different social forces reproduce other networks.
Figure 4.3: Self Social Forces Compared to Others
To account for differences in how well the self-simulations recapitulate its network, the remaining figures normalize each cell by the number of possible edges in the network. This enables comparison across networks’ substrates as well as social forces despite differences in the numbers of organizations. On this scale, lower values indicate simulations that are closer to the original network (colored red), shown below in Figure 4.4. The values in the margins are the sums of the normalized hamming distance for each social force (vertical) and substrate (horizontal). The rows and columns have been rearranged by the row sums; the diagonal cells are still the self-simulations. The rescaling reverses the observed ability of different social forces to recreate the Massachusetts and Colorado plans. In the first figure, Massachusetts had the highest row sum and Colorado the lowest. Normalized by the number of possible edges, Massachusetts now has the lowest row sum, and Colorado is in the middle.

This figure also illustrates heterogeneity in how closely the simulated networks resemble the original. Many substrates consistently yield networks close to their original, regardless of the social forces acting upon them. Yet, others illustrate patterned differences. The lower part of the figure contains the networks that are reproduced poorly overall, but the effect is inhomogeneous. This indicates structured variations in the interactions between the social forces and substrates. The location of Utah 2005 in the figure further evidences heterogeneity. Even though its social forces recapitulate other networks quite well (it has one of the lowest column sums), its own network is poorly recreated by other states’ social forces.
Figure 4.4: Comparison of Simulated Networks Sorted by Row Sums

Normalized Hamming Distance

Social Forces

Substrate
The next figure permutes the matrix based on how well the social forces recapitulate all of the other networks (by the column sums); it is below in Figure 4.5. This figure also shows ordered differences. The social forces with the worse overall accuracies are failing to reproduce many of the same networks. Interestingly, the latter are from the networks whose social forces are among the most accurate in reproducing all of the other networks. Cleavages within the figure are becoming evident.

A few networks have more ubiquitous social forces (though not necessarily substrates), while other have more idiosyncratic social forces coupled with more idiosyncratic substrates. Subsets of the networks fail to reproduce well many of the same networks, but within their subsets, these social forces reproduce the networks with better precision than elsewhere. This points to dissensus within the organizational field and is juxtaposed to the high level of consensus observed in other areas of the figure. The upper left quadrant illustrates that some states’ social forces are more general, and these generative mechanisms recapitulate more accurate networks in almost all of the substrates. This begs the question: what are driving these observable differences and similarities?
Figure 4.5: Comparison of Simulated Networks Sorted by Column Sums
The last two figures permute the matrices by the federal isomorphism thetas and the number of organizations in a state’s plan respectively. The first examines how much of the underlying variations are accounted for by states’ isomorphism with the federal plan (through the numbers of shared partners between ESFs). In Figure 4.6 below, the raw thetas are sorted from smallest to largest. The second assesses the effect of different numbers of organizations in states’ plans: do the states’ with similar numbers of organizations recapitulate each others’ networks more accurately? In Figure 4.7, the matrix is permuted by the numbers of organizations, fewest to most.

The first figure shows that differences between the substrates more than the social forces produce the observed heterogeneity. The accuracy of the simulated networks cluster more by the former than the latter. Additionally, the figure evidences that networks produced by social forces with higher levels of federal isomorphism are less accurate across all of the substrates than social forces with lower levels of isomorphism. The second figure illustrates that the greatest source of heterogeneity are the plans that have organizations in the middle of the distribution. The corners of the figure depict more accurate recapitulations, meaning that substrates with the fewest and most organizations are reproduced with higher accuracy. The blue in the middle of the figure shows that when the numbers of organizations do not overly constrain the observed structures (by having very few or many organizations) the differences in the simulated networks are greatest. Here, the lower accuracy scores are clustered by substrate more than social forces. This suggests that the structure is more fixed at the ends of the distribution of organizations: there is greater contingency in the networks produced when the numbers of organizations does not overly constrain the possible networks.
Figure 4.6: Comparison of Simulated Networks Sorted by Isomorphism Thetas
Figure 4.7: Comparison of Simulated Networks Sorted by Numbers of Organizations

Social Forces

Normalized Hamming Distance

Substrate

NV2012 (13.1)
MT2012 (10.6)
ND2012 (10.1)
TN2012 (10.3)
CT2011 (10.2)
ME2008 (15.9)
MI2012 (15.3)
WI2010 (14.9)
UT2005 (16.9)
OK2007 (16.1)
OR2014 (13.1)
WY2006 (14.9)
NE2014 (12)
MD2010 (12)
IO2010 (14.8)
SD2011 (13.7)
CO2013 (13.8)
WA2011 (7.6)
HI2009 (15.2)
LA2014 (13)
IL2014 (12.1)
MS2012 (12)
NV2014 (12.6)
PA2012 (14.2)
AK2011 (16.9)
MO2014 (13.6)
VT2009 (15.4)
SC2011 (5.9)
IN2009 (15.2)
GA2013 (11.6)
ID2012 (11.3)
KY2013 (9.9)
AR2013 (10.2)
DE2006 (16)
FL2012 (13.8)
CA2013 (11.9)
MA2013 (8.2)
Taken together, these figures have clearly shown that there is not a universal plan that all states are adopting. If this were the case, then all of the cells would be closer to the same color. The figures also evidence a weaker than expected relationship between how well a state’s social forces can reproduce other networks and how well its network can be reproduced by the other social forces. This lends credence to the idea that these networks are not predetermined; rather, they are the manifestations of loosely shared social forces interacting with different local environments, which produce heterogeneous networks. Furthermore, the figures evidence underlying structural differences. There are social forces that consistently recapitulate the true networks well regardless of the substrates, while others consistently do so less accurately. Relatedly, there are several substrates that other social forces do not reproduce well. The differences are not well accounted for by differences in federal isomorphism. They appear to relate more to the numbers of organizations that are included in states’ plans. States’ plans with fewer or more organizations, compared to distribution across states, recapitulate each others’ networks better than states that are in the middle of the distribution. The tails are more constrained by the underlying generative mechanisms (particularly task alignment), while the middle of the distribution produces more heterogeneous interactions. Thus, while much of the social forces are similar, they generate different networks as a result of the substrates.

4.5 Discussion

The results demonstrate a surprising level of heterogeneity given the homogenous forces. The exponential random graph models identify consistent social forces across the forty-seven networks overall. The differences in thetas related to federal isomorphism do not
correlate with differences in states’ features or mechanisms that previous theoretical works would expect to induce higher levels of isomorphism (DiMaggio and Powell 1983). In particular, the lack of a relationship between the number of disaster declarations historically and recently with federal isomorphism thetas runs counter to theoretical expectations of what induces isomorphism within an organizational field. Finally, the plots comparing how well social forces recapitulate the networks across all substrates evidence differences are primarily a result of different substrates. Several social forces consistently reproduce the original networks in most substrates, while other networks are not reproduced well. This is surprising since the thetas are overall quite similar. The final set of analyses further show that the differences are structured less by the degree of isomorphism, which previous theory would lead one to expect induces conformity, but rather by the numbers of organizations in a plan.

The heterogeneity links with the degree of elaboration in emergency operation plans by different states. States with very few organizations simply check the box that they have adopted the incident command structure and related national incident management system to be in compliance. Others delineate far more detailed plans that specify responsibilities for organizations. To disregard these differences would be tantamount to ignoring the internal processes that influence how states structure their plans. These differences shed light on how states view their responsibilities for creating their plans. Moreover, the numbers of organizations are consequential for understanding why the social forces recapitulate networks in some substrates better than others. The fact that the final plot shows high accuracy in the corners of the plot with low accuracy in the middle highlights the fact that the imposed structure from the Federal Government constrains the
possible network configurations when the numbers of organizations are great or small. Yet, when the numbers of organizations are in the middle of the distribution, the networks that states form exhibit greater heterogeneity because more possible combinations exist: the environment is less fixed.

Taken together, this unearths a quandary within the interorganizational literature. The generative features are quite homogeneous, which should lead to isomorphism in the generative features across the networks – as shown by the ERGMs, but the simulations evidence underlying structural heterogeneity. On the other hand, this heterogeneity is not associated with differences across the states’ features, which aligns with neoinstitutional arguments that intrinsic differences, functional requirements, account for less of the variation (DiMaggio and Powell 1983; Tolbert and Zucker 1983); yet the differences in states’ substrates, which organizations are included in a plan, interact with the social forces differently. This suggests that interorganizational structures need theoretical elaboration.

4.5.1 Theorizing a Glassy Regime

As previously noted, organizational scholars primarily classify the field into three structures: hierarchies, networks and markets (Galaskiewicz 1985; Kapucu, Arslan, and Collins 2010; Powell 1990; Thoreli 1986). Hierarchies contain distinct boundaries between organizations with vertical lines of interaction and minimal autonomy (Simon 1976). Network structures are composed of interdependent organizations that mutually enhance one another’s capabilities; the relations are more horizontal, and autonomy is constrained by the organizational field (Powell 1990). The market structure consists of firms competing with one another while seeking to achieve their own goals and is associated with neoclassical, microeconomic theory (Galaskiewicz 1985). One of the key
distinctions between these three structures is the nature of the constraining relations between organizations operating within each structure. As Powell (1990, p. 301) puts it, “Markets, hierarchies, and networks are pieces of a larger puzzle that is the economy. The properties of the parts of this system are defined by the kinds of interaction that takes place among them. The behaviors and interests of individual actors are shaped by these patterns of interaction.” Thus, to understand better the impacts that structuration has on organizations within a particular field, scholars should focus on the nature of the interactions inherent to a structure and how these interactions inhibit or enable organizations’ actions.

Scholars have theorized that the types of interactions that occur within an organizational structure can be arrayed from highly constraining (hierarchies) to minimally constraining (markets) along a continuum (Powell 1990; Thoreli 1986). Analogously, the physical states of matter can be arranged along a continuum of highly constrained interactions within a rigid structure in the solid state to the virtually unconstrained interactions that occur in a gas state. Viewing organizational structures in this manner is useful in two ways. First, this view places the wide range of theoretical frameworks for organizational structure in a broader context. It views the competing frameworks not as antithetical to one another, but rather as describing distinct regimes that exhibit divergent behaviors. The second advantage of this approach is that it arranges these regimes in an ordered fashion based on the degree that organizations’ actions are bound by uniform, enduring interorganizational relationships that are intrinsic to the structures.

At one end of the spectrum, organizations are assumed to be autonomous agents pursuing their own interests. In a market, organizations may interact, but these interactions
are nonconstraining and viewed as fleeting. Organizations interact when they need to obtain or disperse goods, but there is minimal – if any – inertia in these connections: organizations seeking to minimize costs may alter their exchange partners for every interaction (Smith 1976). Because the interactions are episodic, classical, microeconomics theory views the organizations as independent units whereby any interactions can be “averaged out” by the market. In the interorganizational literature, this assumption has been somewhat relaxed as contracted transactions are included (Williamson 1981). However, this literature still regards the bulk of these interactions as only bounding firms weakly and ephemerally to most partners: at most, it is often assumed that only a pair of organizations become locked into a relationship. The key point is that these organizations are operating almost entirely independent of the rest of the organizations within the field. Analogously, organizations in the market regime act like particles in a gas phase. They do interact, but again these interactions are episodic and nonconstraining on future interactions. Just as in the physical case, the ephemeral nature of the interactions within this interorganizational regime makes it theoretically tractable, and a great deal is known about how organization act in this regime.

At the opposite end of the spectrum, the earliest theories about bureaucratic structures viewed them as entirely rigid, command and control systems with an essentially fixed structure and no local autonomy (Weber 2009). Similarly, some economic theorists argue that firms act as “agents” and will exhibit high levels of control to maximize production and profits while reducing uncertainty in procuring resources (Taylor 1914; Tirole 1988). In this regime, the hierarchical structure of interorganizational ties (e.g.; the authority structure) is viewed as a static structure that fully constrains individual
organizational units’ actions, and the bulk of these structures are quite homogeneous with a few organizations at the top that control the lower levels. This is analogous to a crystalline solid, where particles are fixed in their positions by a systematic pattern of rigid bonds to their partners. Just as the solid acts like a unitary object, bureaucratic systems in this “crystalline regime” can be treated as singular entities (as firms often are by the majority of economic theory) whose internal structure and the behavior of its subunits can be disregarded. Although this “crystalline regime” is at the opposite end of the spectrum from the “gasy regime”, it is quite tractable and has been theorized greatly.

As organizational scholars sharpened their focus, it became evident that many systems in the real world did not fit cleanly at either end. Powell (1990, p. 299) asserts that “[b]y sticking to the twin pillars of markets and hierarchies, our attention is deflected from a diversity of organizational designs that are neither fish nor fowl, nor some mongrel hybrid, but a distinctly different form.” Economic sociologists and neoinstitutionalists pointed out that many groups of organizations were composed of units with persistent and more constraining ties to other organizations than could be accounted for by a “gasy” model of organizations (Williamson 1981). They described a regime where constraining interorganizational relationships were highly dynamic, but also longer lasting such that they could not be “averaged out” (as is often the case with markets or hierarchies). As such, these ties are more consequential and strongly influence organizations’ behaviors. For example, they can lead to repeated interactions between organizations as the familiarity can produce trust (Powell et al. 1996). Analogous to the states of matter, these organizational scholars were describing a “liquid” phase, where particles are locally constrained by their previous interactions, but the interacting partners can change
dramatically over time. The “liquid” phase is much more difficult to analyze than the “gassy” or “crystalline” phases because the interactions are consequential, which necessitates the use of more sophisticated methods (e.g.; dynamic network models). They key point is that the “liquid regime” represents a qualitatively divergent behavioral pattern than the “crystalline” or “gassy” regimes.

While the three regimes cover a lot of ground, there are other regimes or “phases” that organizational populations can occupy. In the case of government bureaucracies – particularly those in federated systems, such at the United States – we observe that organizations are bound into enduring, semi-rigid authority structures, but the organizations also have considerable freedom to act within those structures. This freedom entails not only the ability to make decisions and set local policy, but also the freedom to engage in interactions of variant lengths of time with organizations both inside and outside the bureaucracy. Furthermore, there is considerable heterogeneity in the authority structures themselves in terms of the degree that ties are constraining and even in the formal structure of the authority network (i.e.; different levels of elaboration or spans of control in different parts of the system). Therefore, this type of organizational structure is poorly approximated by the “crystalline regime” of a unified, homogenous structure that acts as a singular unit. Simultaneously, this structure is also poorly approximated by the “liquid regime” of an organizational field where organizations are bound together by a continuously shifting network of moderately constraining interactions. Rather, it represents a distinct regime. The physical analogy remains applicable because this also happens in physical systems: systems with particles that are bound together by enduring ties that are relatively but imperfectly constraining and
structurally heterogeneous manifest as amorphous solids and are often referred to
generically as “glassy” (Varshneya 2013, p.14). While a population of organizations in
the "glassy regime” is still bound together into a long lasting whole, its members have
substantial local degrees of freedom, which must be taken into account to understand its
behavior.

Figure 4.8 below illustrates the spectra for both the organizational and physical
states of matter structures. Both are arranged in a continuum based on the nature of the
constraining interactions among the entities. Autonomy is highest in market (gas)
structures and lowest in hierarchical (solid) structures. Similarly, interdependence among
the organizations will be lowest in market structures and highest in hierarchical structures.
The rigidity of the structure will be more obdurate in hierarchical structures and more
chaotic in market structures. Glassy regimes lie between the hierarchical and network
structures. The organizations will be more constrained and more hierarchical than in
network structures, but the structure will also be more flexible and amenable to change
than a hierarchical structure. Furthermore, organizations in a hierarchical structure are
nearly homogenous while those in a market structure can be far more heterogeneous, and
the organizations in a glassy regime will be more homogenous than those in a network
organizational structure.
Figure 4.8: Interorganizational Structures as States of Matter
The physical analogy can be applied further. In all of the physical phases, libration movement occurs between molecules where an object with a nearly fixed orientation repeatedly rotates. These rotations are constrained by the molecules’ interactions with its neighbors, but overtime the partners can change and the preferred orientation will also change. Analogously, we can think of the organizational behaviors and the degree to which these behaviors constrain future actions for an organization. In the “gas” phase, interactions turn over on the time scale of the librations (or faster), and do not constrain the molecules in a path-dependent manner. By contrast, interaction in a liquid last longer than the librations, and from the analogy, it is worth noting that inter-firm relations in a “liquid” field are long-lasting relative to the individual decision and behaviors of the organizations involved: thus, constraining future interactions. One can also consider how magnetic fields reorient the intrinsic spins of particles. This corresponds with exogenous pressures on organizational fields, whereby a change outside of the organizational structure (e.g.; a new government regulation, like the structural requirement in states’ emergency operations plans) can alter the behaviors of the organizations.

Public policy scholars have eschewed the study of hierarchical structures and focused more on network structures as a result of the increasing trend towards nonstate entities providing public goods (Henry, Lubell, and McCoy 2011; Provan and Milward 1995; Salamon 1987). These scholars emphasize that this form of governance implies collective rather than individual decision making (Ansell and Gash 2008) with top-down chains of command being replaced by horizontal decentralization and coordination (Robinson 2006). They view that “in general, the internal authority structure of collaborative institutions tend to be less hierarchical and stable, and more complex and
fluid, than those found in traditional bureaucracies” (Emerson et al. 2001, p. 15). This has made the conventional theory of bureaucratic structures inapplicable to the network setting (O’Toole 1997). However, in the move away from hierarchical structures, some of these scholars have overstated the decline of bureaucratic influences. McGuire (2006) asserts that collaborative governance can occur without the government as the main actor or even as a participant. This overlooks an important facet of organizational structuration. Even if government entities were not directly involved, they shape the regulatory environments that the collaborative networks occupy. By shaping the environments, the government bureaucracy is constraining and enabling the nonstate entities’ actions; a facet that aligns with the organizational field perspective (DiMaggio and Powell 1983).

The emphasis on the decentralized nature of collaborative governance with more horizontal than vertical ties has further pushed public policy scholars away from hierarchies. Playing off the idea of a hollowed corporation that has replaced internal production with subcontractors, Milward and Provan assert that the “central government has become hollowed out as power is devolved to state and local governments” (2000, p. 360, emphasis in original). Yet, this again overlooks the role of the federal government in shaping the general field. I agree with Milward and Provan that local governments have gained more power in planning and implementing policies, but within each state there are also hierarchies. Thus, the field should be examined holistically to account for the multiple levels of government. This is an aspect of the glassy regime. Part of the structure is determined at higher order levels, but much more is determined at lower levels. In the case of emergency management, the federal government can orient the field and influence the structure, but the state governments determine more of the structure. The glassy regime
incorporates the idea that vertical ties can exhibit varying degrees of influence based on where the entities are located within the overall regime. It also views the interactions as more enduring with perseverating impacts that are longer than in the case of the “liquid” phase. The analogous spectrum presents a useful typology for analyzing organizational structures and the impact that the structure has on the organizations inhabiting it.

The elaboration is necessary because glassy regimes organize in a manner that is not well captured by the hierarchical or network structures. Powell (1990) includes formal rules and status hierarchies as mixes of network forms, but when the formal rules and embedded hierarchies alter the way that the organizations relate to each other, then elaboration is needed. The Federal Government imposes the structure of the emergency support functions on state but also provides states wide latitude in how the structure is implemented into their emergency operations plans. The bounded autonomy evidences the similarities in the generative features (form the ERGMs) and the differences from the simulations (when the social forces are simulated across the substrates). The glassy regime accounts for multiple layers of hierarchical (or vertical) ties and moves towards a multilevel network (Contractor et al 2006). Thus, substrates drive the differences in the simulations. If this was purely a hierarchical form (from the Federal Government), then the differences across substrates would be inconsequential: the heat maps would display similar colors for all cells.

The liquid phase, or network form, of interorganizational structures possess a “medium” degree of flexibility and the normative basis is “complementary strengths” (Powell 1990). This is certainly true for many interorganizational networks, but it is simply not the case for the field of emergency management. The flexibility across states is limited,
though present, and the normative basis contains organizations’ relations outside the field of emergency management. The Governor and the state organizations tasked with emergency management decide which organizations are assigned to which tasks, and whether organizations are the lead, or primary organization, or a support organization. This is not collective governance or group decision making (Ansell and Gash 2008).

Organizational scholars frequently view horizontal ties as competing interactions as well as potentially collaborative (Scott 1991). In glassy regimes, there exist a multitude of vertical ties in order to coordinate organizations for uncertain events, such as disasters. The emergence of firms is attributed to organizations seeking to minimize uncertainty (Galaskiewicz 1985; Powell 1990; Scott 1991), so it is not surprising that more hierarchical structures emerge in this environment. Simultaneously, these structures need built in flexibility in order to cope with the range of uncertain events that can occur. This create an intrinsic tension between overly rigid structures (hierarchies) that cannot adapt to all situations and more nebulous structures where organizations cannot be coordinated effectively. In the aftermath of Hurricane Katrina, the Red Cross had a large bridging role, linking a wide range of organizations (Butts et al. 2012). This aligns with its organizational capacity and experience in disaster recovery.

The predictable way of structuring emergency operations plans was deliberate by the Federal Government: it wanted a uniform structure so nonstate entities could connect with states’ organizational response. The network form, liquid phase, views collaborations yielding further collaborations, but this is not the same process when the collaborations are dictated by government policy. If the emergency management interorganizational networks were recreated for each disaster based on previous interactions, then precious
time would be wasted and the structural form would vary more for disasters occurring within the same state. Moynihan asserts that:

The [Incident Command Structure] illustrates the possibility of switching between centralized and more decentralized forms of network governance consistent with task demands. During crises, network governance is highly centralized. But between crises, the ICS does not exist. Crisis response networks are loosely affiliated and follow a shared governance model. In precrisis periods, responders can build working relationships and trust and improve their understanding of mutual capacities and the principles of the ICS, thereby laying the groundwork for an integrated response during the actual crisis. Crisis networks therefore suggest the fluidity of network governance. In this policy area, network governance does not evolve incrementally but cyclically, changing in rapid fashion in response to environmental conditions that give rise to specific task demands. (2009, pg. 911)

However, the structures clearly still exist as evidenced by organizations ability to organize consistently and quickly into the same structure delineated by states’ emergency operations plans.

4.6 Conclusion

Glassy regimes are present in fields where: (1) an exogenous organization, perhaps organizations, influences the structure of the lower-level entities but with local autonomy; (2) the degree of uncertainty necessitates formalization, but also adaptability or flexibility; (3) relations endure longer than the requisite task, typically through formal rules (e.g.; government policies); and (4) horizontal ties denote interdependence for completing tasks but not shared decision making or competitive relations. While more cases will be needed to fully flesh out the details and implications of interorganizational fields as phases of matter, this cases provides a first cut at formalizing those distinctions and offers several methods for assessing which regime a field belongs to. I would expect glassy regimes to be applicable to other interorganizational structures that do not have the means of controlling high-levels of uncertainty but still need standardized interorganizational
relations. This could potentially be applied to hospital emergency rooms or large multinational, financial firms that afford considerable autonomy to local branches. Fitting an ERGM to the interorganizational networks (the relations, not the liquid phase) would provide insights into the degree that the entities share generative features. The terms and magnitude of coefficients would likely differ based on its regime type. I would expect that shared partnerships in task assignments would be higher among glassy regimes than liquid phases and hierarchical relations outside of the specific network would also manifest in the interorganizational one. These are preliminary theoretical distinctions and further work can build off this framework.

This chapter presents a comprehensive examination of the structuration within the emergency management interorganizational field. To do so, it utilized advanced network analysis methodologies and builds upon extant ideas (Faust and Skvoretz 2002) to develop new ones. Through this process, this chapter also conceptualizes interorganizational structures as continuum analogous to the phases of matter. While previous scholars have organized interorganizational structures (Galaskiewicz 1985; Powell 1990), the case presented here does not fall neatly within the prior theorizations. Thus, the new methods and theoretical conceptualization lay fertile ground for future work to explore these aspects further.
5 Concluding Matters

In this last chapter of my dissertation, I highlight the key contributions from the three chapters, recognize their limitations, and suggest areas of future research than can build of this work.

5.1 Key Contributions

- **Labeled model adequacy methods**: The second chapter develops and demonstrates the utility of several model adequacy methods for exponential family random graph models. Researchers can use these methods to better diagnose issues with their models and ultimately develop better ones. The range of tools cover edge, node and graph level assessments, which together provide a more encompassing package of techniques than are currently available.

- **Labeled model assessment tools**: The third chapter extends previous work on network imputation methods to delineate an algorithm that is related to a jackknife in statistical methods. The relational aspect of network data precludes many statistical diagnostics; yet, this chapter demonstrates how a held-out predictive evaluation (HOPE) technique can provide information equivalent to a leverage statistic in regression analyses or be used to evaluate the adequacy of a model within its own data. Moreover, this tool circumvents inherent issues with relying on an estimated maximum likelihood estimate for model selection.
• **New data set**: The collection, cleaning and coding of states’ emergency operations plans was a major endeavor. This data set is derived from primary documents and supplemented by great efforts to gather additional information on the organizations included in states’ plans. These data will be released in the future and will be of great interest to a range of scholarly communities.

• **Novel comparative method**: The third chapter extends previous scholars insights (Faust and Skvoretz 2002) to generate a new way of comparing the underlying, generative features that produce a network. Network comparison has historically been stuck in descriptive statistics, so this method opens a wide range of scholarly pursuits. By directly comparing the social forces across social substrates, more rigorous theory testing and building can be achieved.

• **Interorganizational field dynamics as a spectrum**: Prior works have moved away from a spectrum to a tripartite distinction. The third empirical chapter posits a spectrum of interorganizational relations analogous to the states of matter. Doing so views the differences along a continuum, as opposed to discrete categories, suggesting that fields can undergo phase transitions due to changes in their environments. Though this is a nascent theoretical conceptualization, it present a useful typology for arranging the distinctions between interorganizational field (beyond economic fields) that can be extended and evaluated further.
5.2 Limitations

- **Labeled Networks:** The model adequacy and assessment tools developed in chapters 2 and 3 are best suited for smaller networks with distinguishing covariates. Otherwise the labeled distinctions cannot be included in a model and will inhibit labeled comparisons.

- **State Emergency Operations Plans Data set:** The data unfortunately do not include all fifty states, nor do they include organizational authority structures. Both would greatly improve the current data set. The former was precluded by states unwilling to provide their plans, and the latter by the sheer magnitude of collecting these data. Additionally, data with multiple plans for states would provide a longitudinal dynamic that could better capture the underlying processes. Some of these aspects have been addressed already, and the data set that will ultimately be released will include these facets.

- **Glassy Regimes and Interorganizational Fields:** The conceptualization of interorganizational fields as a continuum only examined one area on the spectrum. Additional analyses of different regimes could provide richer comparisons to bolster the conceptualization.

5.3 Future Directions

- The labeled model adequacy and assessment tools can be extended for valued networks rather easily; extending them to multiplex networks would be more difficult but fruitful. Developing these tools for assessing the adequacy of multilevel network models presents a further opportunity.
As suggested earlier in this chapter, empirically evaluating different fields within the interorganizational field spectrum would provide deeper insights into its theoretical utility. Moreover, the comparative methods developed here should be analyzed across regimes to evaluate the different outcomes. Relatedly, developing statistical summary statistics for comparing networks’ generative features present a fruitful direction going forward.
6 Bibliography


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