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Mechanisms of Control in Emergent Interorganizational Networks

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The delegation of decision-making capacity from one actor to another—known variously as authority or control—is a central phenomenon of organizational sociology. Despite its theoretical and practical significance, however, the dynamics of control within disrupted settings (such as disasters) remain poorly understood. Here, we shed light on this question by a reexamination of historical data on multiorganizational disaster response networks, using recently developed statistical methods for robust inference from error-prone informant reports. Specifically, we test competing hypotheses about the relationship of control during the response process to the structure of interorganizational communication. We find that both the realized and normative response hierarchies are likely shaped by coordination among both nonadjacent alters and along indirect channels. Our results suggested that the communication structure of these networks is consistent with a control at a distance model of command. This article makes a substantial contribution to understanding the role of network structure in the emergence of control between organizations in disrupted settings. Additionally, our innovative approach to network inference will guide researchers in dealing with error-prone data in their own research on policy networks.

KEY WORDS: organizations, social control, social networks, disaster response, authority

Introduction

A central phenomenon of human organization is the emergence of *control* relations, that is, relationships in which one actor transfers his or her decision-making capacity to another (Coleman, 1990; Weber, 1958). Indeed, it has been argued that the existence of such relations is one of the defining characteristics of organizations per se (see, e.g., Perrow, 1970; Porter, Lawler, & Hackman, 1975). If "organization" is (in the words of Galbraith, 1977) "that 'something' which distinguishes any collection of 50 individuals in Kennedy International Airport from the 50 individuals comprising a football team in the National Football League," one of its core elements is clearly the willingness of organizational members to systematically cede control to other members of the group. Coincident with control relations between individual actors, control of one organization over another involves the controller organization to, in Kirsch's (1996) words, "regulate or adjust behavior" of the controllee organization.

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While the emergence of institutionalized control relations (or *authority* relations) has been a target of intensive study at least since Spencer (1874), much remains to be learned regarding the emergence of *ad hoc* control over short timescales. This is particularly true at the interorganizational level, where formal authority relationships frequently overwhelm or obscure other factors (Agranoff & McGuire, 2001; Weber, 1958). Observations of interorganizational control relations during periods of relative stability are thus effective at revealing the structure and long-term evolution of formal authority but are of limited use in illuminating how control relations arise where the influence of such authority is attenuated (or altogether absent). Since the latter condition must precede the former, understanding the structural conditions in which *ad hoc* control relations arise can potentially shed light on the circumstances in which formal authority structures initially develop. More pragmatically, *ad hoc* control also acts as a "fallback" mechanism for interorganizational collaboration within settings wherein formal authority relations are ineffective or disrupted (Roethlisberger & Dixon, 1939). Moreover, *ad hoc* control facilitates task performance and role fulfillment when formal authority is ineffective. Thus, following Agranoff and McGuire's (2001) question of the role power plays in interorganizational networks, understanding the emergence of *ad hoc* control relations is of both practical and theoretical importance for the sociology of organizations.

Given the prevalence of formal authority structures in routine settings, the study of *ad hoc* control is more easily conducted in nonroutine settings, such as disasters. Sociologists have long observed that disasters disrupt existing social structures and practices, thereby providing researchers with an opportunity to examine mechanisms that are difficult to observe in everyday settings (Drabek, 1986; Quarantelli, 1987). As events disrupt daily routines, they also trigger the emergence of social structures than deviate from routine and/or planned patterns of interaction (Drabek & McEntire, 2002; Dynes, 1970; Quarantelli, 1996). Examination of the organizational response to disasters thus offers a glimpse into the processes by which routine social structure is reorganized and/or restored. In particular, a common effect of disasters is to render temporarily ineffective the conventional lines of authority among organizations; this is particularly true in the immediate postimpact period, during which organizations and their members must rapidly mobilize and respond within an uncertain (and often infrastructure-degraded) environment. During this period, individual and organizational task performance requires the flexible combination of planning and improvization, including the creation of novel mechanisms of coordination and control (Comfort, 2007; Dynes, 1994; Neal & Phillips, 1995, Waugh, 1993). By studying *ad hoc* control relations during the immediate postimpact period, we thus gain the opportunity to test competing theories regarding the processes by which such structures develop and operate.

Employing the emergent multiorganizational network (EMON) as a research site has a rich history in organizational sociology (Drabek & McEntire, 2002; Majchrzak, Jarvenpaa, & Hollingshead, 2007; Stallings & Quarantelli, 1985; Trainor, 2004, Waugh, 1993, Weick & Roberts, 1996). EMON has long been characterized as a response to the breakdown in authority and communication lines entailed in disasters (Drabek & McEntire, 2002; Tierney, Lindell, & Perry, 2001; Trainor, 2004).

However, little is known about the structural mechanisms that facilitate command relations in EMONs. Indeed, the ways in which organizations delegate decision-making capacity and issue commands in the context of an emergent network represent a remarkable occlusion in the literature, given the emphasis on communication and coordination. We shed light on that question in this article.

This article follows the strategy outlined earlier, examining emergent control in disaster response networks to shed light on the development of *ad hoc* control relations. Our data are composed of a collection of networks from seven remote-area search and rescue operations from late twentieth century disasters in the United States, collected by Drabek, Tamminga, Kilijanek, and Adams (1981). To borrow a term from Provan, Fish, and Sydow (2007), we take a "whole network" approach by utilizing the Drabek studies at the network level of analysis. By doing so, we emphasize the contributions of each individual organization only as they relate to the overall process by which control mechanisms arise (Provan et al., 2007; Provan & Milward, 1991). Employing recently developed methods for analysis of error-prone network data within a Bayesian framework, we evaluate the relationship between the structure of interorganizational communication and organizations' prominence in the control structure (as evaluated by organizational informants). This relationship, in turn, is used to assess several theories regarding the process by which *ad hoc* control operates. Thus, we also make a methodological contribution by taking an analytic approach that bridges what Zaheer and Soda (2009) call "the structure of outcomes" with the "outcomes of structure." We used a novel model to infer the structure of communication in EMONs. We then used those networks to model how authority relations arise within the structure. This approach is general enough for many applications where ties are drawn based on informant accounts and there is uncertainty about the underlying network. Our analyses suggest that control in these networks involved both direct interaction and use of indirect contacts. As we argue later, this finding is of both theoretical and practical import.

Command, Control, and Authority in Disaster Response

Organizational practices employed in response to disasters and other extreme events fall broadly under the rubric of *emergency management* (Auf der Heide, 1989). The normative structure of emergency management in the United States (and the developed nations more generally) is based on a bureaucratic model, whereby response activities among a relatively decentralized collection of agents are coordinated through a centralized decision-making apparatus (Schneider, 1992; Takeda & Helms, 2006). The exercise of authority occurs "downwards" through the structure, with each agent answerable in principle to a single superordinate agent (a principle known as *unity of command*). As with most other modern organizations, authority relations within response organizations allocate power on a positional rather than a personal basis (Uhr & Fredholm, 2006; Weber, 1958). The design of these relations—and their effective use to coordinate activities during the response process (Comfort & Kapucu, 2006)—constitutes a family of tasks known collectively as *command and control* problems. Given that disasters typically involve rapid deployment of multiple units from disparate locations in a turbulent environment, it is perhaps unsurprising that effective command and control has been argued to be a core challenge for emergency management policy (Comfort, 2007; Iannella & Henricksen, 2007).

In principle, command and control problems may be solved by a combination of *a priori* policies and standard operating procedures. Unfortunately, however, the heterogeneous and often unpredictable environments encountered during disasters can dramatically limit the effectiveness of such systems, as Weick (1993) observed during the Mann Gulch fire. Where conventional structures and routines no longer suffice, novel (or, as we have used the term earlier, *ad hoc*) arrangements must be developed in response to changing circumstances (Mendonca, Beroggi, & Wallace, 2001; Webb, 2004). Failure to establish effective *ad hoc* control structures under such conditions can lead to conflict between organizations (e.g., due to task interference), failure to complete critical objectives (e.g., due to vital tasks being overlooked or unassigned), inefficiency (e.g., due to repeated performance of the same tasks by multiple actors), or other problems (e.g., underutilization of available personnel). Unfortunately, this process is made difficult by the limitations of interorganizational communication during disasters, differences in mission and procedures across organizations, and the short timescales within which solutions must be implemented. The development of *ad hoc* control structures is thus a form of "collective improvization" in which simultaneous adjustments by multiple actors within a heterogeneous environment converge to a solution that is beyond the capacity of any one actor to completely anticipate or determine.

The presence of explicitly articulated command and control concepts in disaster response within the United States may be tied back to the origins of emergency management as a distinct field of organizational practice. Prior to the creation of the Federal Emergency Management Agency in 1979 under Executive Order 12127, U.S. civil disaster response was situated largely within the Department of Defense, with additional support distributed across the Department of Commerce and the Department of Housing and Urban Development. Much of the emergency preparedness capability in the United States prior to this event stemmed from post-World War II civil defense programs. Following several devastating disasters in the mid-twentieth century (Hurricanes Carla, Betsy, and Camille; the Alaska earthquake in 1964; and the San Fernando earthquake in 1971), the U.S. government identified the need for a new independent civil agency to prepare and respond to natural hazards (Nicholson, 2003).

In contemporary emergency management, the influence of civil defense and military rigor are still apparent as former military personnel find civilian positions in paramilitary organizations, such as fire and police, and emergency management (Brooks, 2005; Nicholson, 2003). As neo-institutionalist theories would predict (DiMaggio & Powell, 1983), this exchange has promoted a certain degree of isomorphism between organizations in the military and emergency management fields. Among the practices to have diffused from the former to the latter field is a tendency for emergency response plans to be founded on a core model of hierarchical communication and coordination structures, regulated by a central authority. This hierarchical model is intended to direct actions to lower level actors based on decisions made by high-level actors, with the latter basing their decisions in part on information passed "up the chain" from units in the field. Such systems can have numerous benefits in terms of efficiency (Bavelas, 1950) and robustness to loss of noncentral units (Carley, 1992), but these benefits come at the cost of increased dependence on core units, and a rise in delays and errors stemming from the need to transmit critical information through multiple intervening parties in order to arrive at a decision (Drabek, 1985). The limitations of centralized solutions to command and control problems during disaster response have led some researchers (e.g., Dynes, 2003; Neal & Phillips, 1995; Wenger, Quarantelli, & Dynes, 1990) to call for increased use of decentralized decision making structures; the tension between the flexibility and low latency of local autonomy versus the efficiency and global robustness of centralized control is a core issue in the debate over how response operations should be structured.

Communication Network Structure and Control

Explicitly structural concepts such as kinship ties, resource flows (Phillips, Garza, & Neal, 1994), roles (Kreps, 1987, 1989; Kreps & Bosworth, 1993, 1994, 1997), and emergent behavior have been utilized by disaster researchers for several decades (Quarantelli, 1984, 1996; Stallings & Quarantelli, 1985); however, relatively few quantitative studies of communication or control structures appear in the early literature of the field. Following the 1976 Big Thompson River flood, Thomas Drabek began to study the relationships of interagency coordination and relationships (Drabek, 1985, 2002). In the disasters that followed (the Wichita Falls tornado in 1979, Hurricane Frederic in 1979, and Mount St. Helens in 1980), Drabek (2002) asserted that the measures then used to assess complex social phenomena arising in the aftermath of these events were woefully inadequate. Subsequently, Drabek and his colleagues conducted several studies that aimed to map the social relations of the multiorganizational networks that emerged among disaster response organizations (Drabek, 1985, 2002; Drabek et al., 1981; Gillespie & Colignon, 1993; Gillespie, Sherraden, Streeter, & Zakour, 1986). Following this line of research, Drabek (1987) argued that disaster response activities at the interorganizational level can be characterized via EMONs—the structured patterns of relationships among organizations collaborating during the response process.

In 1978, Drabek began collecting data on EMONs resulting from remote-area search and rescue (SAR) operations mounted in response to seven different natural and anthropogenic disasters. The intent was "to prepare a set of case studies in which the multiorganizational responses could be documented" (Drabek, 1983, p. 279). Several studies focused on specific events and provide preliminary analyses (Adams, Drabek, Kilijanek, & Tamminga, 1980; Kilijanek, Drabek, Tamminga, & Adams, 1979; Tamminga, Drabek, Kilijanek, & Adams, 1979). These provide additional insights into local events, such as the July 1979 tornado that struck Cheyenne, WY (Drabek, Tamminga, Kilijanek, & Adams, 1982). The accumulated results of these studies were published by Drabek et al. (1981) and constitute the largest single collection of response operations with systematically collected and directly comparable network data to date.

The diversity of the events covered by Drabek et al. (1981)—flash floods in Texas; tornadoes in Lake Pomona (KS), Wichita Falls (TX), and Cheyenne (WY); Hurricane Frederic in Jackson County (MS); the eruption of Mount St. Helens (WA); and the report of a lost hiker on Mount Si (WA)—enable the comparison of EMON structures across context. The researchers collected data on each event in a systematic and consistent manner. While the dyadic relational information reported by in this work is limited to interorganizational communication, the authors also provide information regarding the extent to which each organization was judged by other network members to play a central role in decision-making and control activities during the initial response (Drabek et al., 1981). This information potentially makes it possible to test a number of competing hypotheses regarding the mechanisms of control employed during the early phases of each event by relating each organization's observed role in the control structure to the communication, which would be needed to obtain that role given the assumed control mechanism. We follow that strategy here.

We draw from past research and social theory to provide insight on how the realized network structure of interorganizational communication might generate control relations. Control relations are related to positions of centrality in networks, which have a long history of study in organizational science and in sociology, more generally (Bonacich, 1987; Freeman, 1979; Ibarra, 1993). *Prima facie*, we would expect that organizations that communicate with a lot of other organizations to play central roles in delegating authority and exerting control over the whole network. Tsai (2002) found that organizations with more ties tended to share knowledge more frequently in his study of 24 business units in a large petrochemical firm; however, the more direct control exerted by the headquarters on its subunits, the less frequently the subunits shared knowledge. This suggests that direct control, insofar that it is related to the number of ties an organization has, may hinder the communication flow in the whole network, dampening the efficacy of delegating authority.

An accumulation of direct ties alone may not give rise to control relations. Rather, organizations that occupy structurally advantageous positions, such as brokers, may be the key to the flow of authority over an interorganizational network. Brokers, as gatekeepers of information and resources between two otherwise nonadjacent actors, may gain authority over the actors they stand between (Burt, 1992, 2005; Gould & Fernandez, 1989). Additionally, Granovetter's (1973) famous "weak ties" propositions lead us to expect that indirect ties channel control relations broadly across the network. This is a reasonable expectation in our case because emergent interorganizational disaster response networks tend to have sparse features (Butts, Petrescu-Prahova, & Cross, 2007; Lind, Tirado, Butts, & Petrescu-Prahova, 2008), which means that not all organizations are directly tied to the central players (Bevc, 2010). In the following section, we spell out these arguments as a set of competing and complementary hypotheses.

Hypotheses. In this section, we describe our hypotheses about the relationship between communication network structure and the emergence of *ad hoc* control relations. We begin by briefly summarizing the theoretical argument outlined earlier. As we have suggested, realization of control during nonroutine conditions creates a concomitant communicative burden. Trivially, one actor cannot transfer control of his or her actions to another unless he or she has some mechanism for receiving direction from the superordinate alter. Likewise, effective control of a subordinate alter may be impossible unless ego is able to obtain information about the alter's current status and environment. Thus, the communication network must permit some communication between superordinate and subordinate actors for control to be realized. Where the amount of information to be conveyed is minimal, communication may be indirect, that is, actors may pass messages to one another through third parties. Since such mediation is likely to induce both delays and errors, however, control may be easier to maintain when messages are relayed through as few third parties as possible (and when multiple, redundant channels are available for message exchange). When the need for rapid information exchange is substantial, moreover, any degree of indirect communication is unlikely to prove sufficient for effective control. In such circumstances, direct ties between superordinate and subordinate actors may be required for control to be realized. By turns, it is reasonable to expect that the demand for control is itself partially dependent upon communication: two actors who are in direct contact can potentially resolve conflicts among themselves, while actors without such contacts may be expected to benefit from management by a third party that is mutually accessible to both (i.e., a *broker* [Gould & Fernandez, 1989] or a *least upper bound* [Krackhardt, 1994]).

Figure 1 presents an illustrative summary of how our proposed mechanisms relate to opportunities for communication. The solid lines connecting source

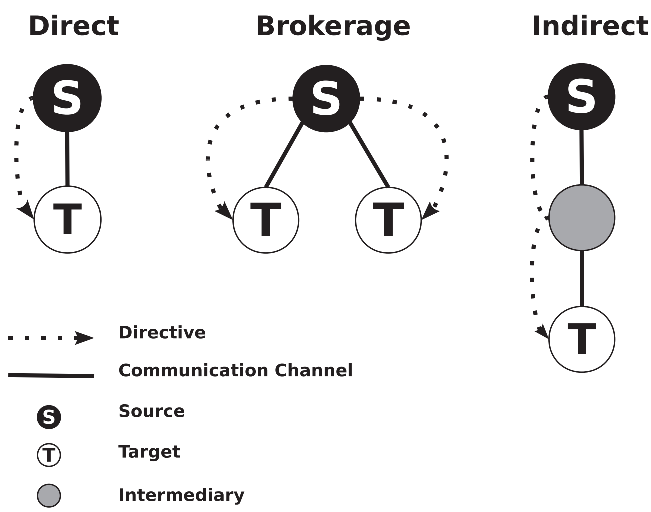

Figure 1. Three Basic Mechanisms for Control Exercise within Communication Networks.

organizations to their targets represent communication channels (i.e., interorganizational ties over which communication may take place). The dotted lines represented hypothetical directives sent from source organizations to targets through the communication network. Since the transfer of decision-making capacity from target to source requires (at minimum) the flow of imperative information from source to target, structures of the forms shown here constitute *necessary preconditions* for the mechanisms of direct, brokered, and indirect control (respectively). Organizations satisfying these preconditions with respect to a larger set of potential targets have (*ceteris paribus*) a wider range of control opportunities and are predicted to exercise greater control in practice than organizations with fewer such opportunities. By comparing each organization's structural opportunities for direct, brokered, and indirect control (as revealed by the communication network) with that organization's observed level of control exercise, we can thus infer the extent to which each mechanism is active within a given network. This leads immediately to three basic hypotheses regarding control activities within undirected interorganizational communication networks:

Hypothesis 1 (direct control): The extent of control exercised by any given organization will be positively related to the number of other organizations to which it is directly tied.

Hypothesis 2 (indirect control): The extent of control exercised by any given organization will be positively related to the number of other organizations to which it is indirectly tied via redundant, short paths.

Hypothesis 3 (brokerage): The extent of control exercised by any given organization will be positively related to the number of pairs of organizations to which it is directly tied and which are not directly tied to one another.

Clearly, these hypotheses are not exclusive of one another: for instance, organizations with many direct ties will by definition be tied to many alters via short communication paths (though it is possible to obtain the latter state without the former). For this reason, we describe hypotheses 1–3 as *inclusive* hypotheses—they constitute assertions regarding communication and control which follow from, but do not uniquely identify, the putative underlying mechanisms. To better narrow the field of possible options, we also posit a set of *exclusive* hypotheses that specify the cases in which only direct, indirect, brokered, or suitable combinations of these effects are present.

Hypothesis 4 (direct control only): Hypothesis 1 holds, and the extent of control exercised by any given organization does not increase with indirect ties or brokerage after conditioning on the number of direct ties.

Hypothesis 5 (indirect control without brokerage): Hypothesis 2 holds, and the extent of control exercised by any given organization does not increase with brokerage after conditioning on the number of organizations to which it is tied via redundant, short paths.

Hypothesis 6 (brokerage only): Hypothesis 3 holds, and the extent of control exercised by any given organization does not increase with direct or indirect ties after conditioning on the number of brokerage relationships.

Hypothesis 7 (brokerage and direct control only): Hypotheses 1 and 3 hold, and the extent of control exercised by any given organization does not increase with indirect ties after conditioning on the number of direct ties and brokerage relationships.

Hypothesis 8 (all mechanisms): Hypotheses 1–3 hold, and none of hypotheses 4–7 hold.

To summarize, if direct contact enhances opportunities for control, then hypothesis 1 should be found to hold within realized disaster EMONs. If indirect contact and/or brokerage enhance control, then hypotheses 2 and 3 (respectively) should be supported. If the communicative demands of effective control are so strong that only direct communication will suffice—and if demand effects for mediation are inactive, then hypotheses 1 and 4 will be supported; alternately, direct contact with appreciable brokerage demands would lead to the combination of hypotheses 1, 3, and 7. Brokerage demands alone should produce observations satisfying hypotheses 3 and 6, but the correlation between brokered pairs and direct ties may lead to a spurious observation of hypothesis 1 as well. Similarly, the use of mediated communication will clearly produce support for hypothesis 2, with hypothesis 1 arising as a by-product: if messages can be relayed, they can also be passed directly, and hence, our putative mechanism does not predict a case in which indirect ties are predictive without a direct tie effect. Nevertheless, it is entirely possible for indirect communication to be important without the presence of brokerage demands, in which case we expect to observe hypotheses 1, 2, and 5. Finally, it is conceivable that all mechanisms discussed here (direct communication, indirect communication, and brokerage demands) are in play. In this case, we would observe support for hypotheses 1–3, without observing support for hypotheses 4–7, a possibility we designate as hypothesis 8. While these hypotheses do not exhaust the set of possible alternatives (e.g., the case of hypothesis 2 without hypothesis 1 noted earlier), they do describe the set of alternatives that are plausible given the system under study.

To assess the previous hypotheses on observed EMON data, it is of course necessary to more precisely define what is meant by "direct" and "indirect" ties, as well as "brokerage." Here, we employ familiar concepts from social network analysis (degree, eigenvector centrality, and Gould–Fernandez brokerage scores) to measure these features of the communication network. Our measures of control are composed of the command and decision rank score variables constructed by Drabek et al. from informant assessments of organizational activities during the initial response period. We now turn to a consideration of these measures (and related methodological issues).

Data and Methods

As indicated earlier, our data were drawn from Drabek et al.'s (1981) study of interorganizational networks arising from seven events occurring between 1978 and

1980. All events involved remote-area SAR operations but varied considerably by scale and location. Drabek et al. interviewed managers from participating organizations shortly after each event, but before response efforts were completed; in addition, they collected self-administered surveys from managers of all organizations believed to be involved in the response. The data derived in each case can thus be considered a complete census of responding organizations (in the sense of Wasserman & Faust, 1994). Responses were collected from 137 organizations. The information collected on the networks included communication interactions between organizations, which provides the basis for our independent variable (i.e., the network). Importantly, Drabek et al. validated their coding of the networks both internally, through traditional diagnostics, and externally, by soliciting feedback on the networks from informants who were present at the disaster sites and involved in the responses. We improved upon this confirmation with our network inference model (as described later).

Although historical, the Drabek et al. study was precedent setting insofar as it was the first comparative, quantitative research on disaster response networks, and it remains the largest collection of response network data collected using standardized (i.e., cross-case comparable) methodology. Indeed, collecting new data from this domain was costly, difficult (Stallings, 2003)—and sometimes, dangerous as applied demographer Swanson learned (Henderson et al., 2009)—time-consuming, and authorities have been quick to deny access to organizational informants and primary resources (Tierney, 2006). Thus, the Drabek et al. data set is a valuable resource to the field of policy networks as new data are scarce even as disaster response networks have grown. Moreover, the additional information on organizational activities captured by Drabek et al. allowed us to examine mechanisms of command and control which cannot be studied using more recent data sets. On the other hand, innovations in network analytic methods also permitted more extensive investigation of the Drabek et al. data than was possible when the data were first collected. As such, we were here able to leverage new methods to obtain new answers from a classic data set.[1]

Network Data

Each of the seven networks in the Drabek et al. data set is recorded as a valued directed graph (digraph), where an edge from organization i to organization j indicates the extent of communication from i to j as judged by an informant from organization i. The values of the edges were determined by asking informants (here, organizational managers) the following question regarding communication during the response period:

> During this time period, how often was there direct communication between your organization and each of the other organizations that you knew was involved in some aspect of the SAR activity?

- 1 = continuously
- 2 = about once per hour

- 3 = every few hours
- 4 = about once a day or less
- no communication.

For purposes of the present study, the extent of communication was of less importance than the *possibility of control* afforded by such ties; moreover, informants' ability to reliably determine frequency of communication (versus whether some communication occurred) is somewhat questionable. For these reasons, we dichotomized all edge reports at level 4 (i.e., separating those dyads with some communication from those with no communication) prior to further analysis. After dichotomization, then, ties in the resulting networks represent *any* communication between organization *i* and organization *j*.

Although recorded as a digraph, it should be noted that the underlying relation in the Drabek et al. networks (direct communication between organizations) is, in fact, undirected; the data are thus not a true digraph (in which edges reflect directional relations from a sender to a receiver) but a simple graph (in which edges reflect mutual relations) with two observations per edge. Such a data structure can be thought of as an extremely local component of a cognitive social structure (CSS) design (Krackhardt, 1987) in which (to use the terminology of Butts, 2008) own-tie reports are obtained from each actor. In contrast to many designs, the one used by Drabek et al. thus provides a small amount of redundant information regarding communication ties. While this information is far less than would be present in a full CSS design, it nevertheless is sufficient to permit some treatment of measurement error using the network inference methods of Butts (2003).

Any data arising from field research are susceptible to errors either in recording or informant accounts; disasters, however, are especially challenging because of the higher level of situational uncertainty in these settings than in routine contexts. Pragmatically, errors in the present case may be divided into two types: false positives (i.e., an informant reports that two organizations communicated when no communication was present) and false negatives (i.e., an informant fails to report communication that actually occurred). While knowledge of informant error rates is limited, it is reasonable to expect (following Butts, 2003; Freeman, Romney, & Freeman, 1987) that errors within this setting will occur more often from forgetting and lack of knowledge regarding realized communications than from false reports of communications which did not occur. Using Bayesian methods, we make use of this prior knowledge to supplement information on accuracy, which can be gleaned from the datum itself; these methods simultaneously allow us to infer the underlying communication structure in a way that accounts for reporting error. This is discussed in more detail in the Network Inference section.

Derived Measures. To evaluate hypotheses 1–8, we required formal notions of direct communication partners; communication partners reachable via redundant, short paths; and communication partners for whom ego serves as a bridge or broker. These quantities are neatly captured by three widely used notions of centrality (Wasserman & Faust, 1994) within the social network literature. Trivially, the number of direct communication partners for a given organization corresponds to its *degree* in the underlying communication network. The capacity to reach many other organizations via numerous short paths is well-expressed by *eigenvector centrality* (Bonacich, 1972), and the number of pairs of otherwise nonadjacent organizations with which an organization communicates corresponds to the *total brokerage score* of Gould and Fernandez (1989). These three indices, then, were used as our measures of direct contact, indirect contact, and brokerage for the analyses that follow (all network statistics were computed using the sna package for R; Butts, 2008).

Command and Control Data

The Drabek et al. data set contains two organization-level variables, command rank and decision rank, which assess the involvement of each organization in command and control activities during the response. Both variables are constructed from responses to questions asked of organizational informants during field interviews. Informants were shown a list of the organizations involved in the response (collected *a priori*) and were asked the following:

1. Command rank: "If there was an overall *chain of command* overseeing activities *in the area* where search-and-rescue operations were carried on, rank in order up to six organizations that were at the top of the chain of command. More than one organization may receive the same ranking. If there were less than six, name only those in the chain of command."
2. Decision making rank: "Thinking in terms of the major decisions affecting the *overall* search and rescue operation, rank in order the organizations that made the key decisions. If several were equally important, rank them equally."

The decision rank and command rank questions were closed-ended insofar as the informants were limited to choosing, at most, six organizations from the initial response; any organizations that were involved in the response but not on the list (i.e., during a subsequent phase) were coded as "unrated."

We argued that command rank serves as a measure of the *authority structure* of the response, while the decision-making rank is a measure of (potential *ad hoc*) *control*. That is, command rank highlights organizations identified as occupying relatively solidified command roles within the response, while decision-making rank captures the realized exercise of control *per se*. As might be expected, Drabek et al. (1981) found that both variables were highly correlated ($R = 0.93$) and, further, that perceptions of who was in command correlated highly with normative expectations (i.e., from response plans). The high correlation, however, is not sufficient to conclude that these tap into the same control process—and we agree with Drabek that they are unique measures and worthy of unique treatment. Although Drabek et al. (1981) did not provide the raw dyadic rankings, they did supply the aggregated ranks for each organization, standardized with a simple weighting procedure that allows the ranks to be compared from event to event.[2] We employ these measures in our analyses.

As noted earlier, a number of the organizations in each network were unrated on one or both of command rank and decision-making rank. Drabek et al. effectively treated these as having ranks of 0 in their data analyses. Command rank was unrated for 37/134 or 28 percent of the organizations and decision making rank was unrated for 35/134 or 26 percent of the organizations. Since unrated organizations were excluded due to nonparticipation in the initial phase of the response, one can correctly argue that they should have minimal command and decision-making rank. However, our hypotheses as articulated in hypotheses 1–8 pertain to the roles of organizations that are, in fact, present and active in the response; we do not make predictions for organizations that are not present. For this reason, we considered all unrated organizations to be missing for purposes of command and decision-making rank scores and excluded them from all relevant analyses. Given that unrated organizations were inactive during the initial phase of interaction, we also calculated network measures only for the induced subgraph of rated organizations. All informants' reports are useful for purposes of error estimation, however, and reports from unrated organizations were hence included when conducting network inference.

Analysis

We employed Bayesian methods to assess our research hypotheses. Our procedure is outlined as follows (and explained in detail in the Appendix). First, we employed a network inference model to take a sample of five hundred draws from the posterior distribution of each communication network, drawing on past research regarding EMON structure and reporting errors to set the necessary priors. Collectively, the posterior communication networks draws then represent the likelihood of ties between organizations, given the distributions of the false positive and false negative reporting errors. We used these posterior draws to estimate informant error rates and to compute the joint posterior distributions of degree, eigenvector, and brokerage scores for organizations within each network. Thus, the network inference model allowed us to account for informant discrepancies in the network in a principled manner. That is, the network inference model accounted for error in our data arising from discrepancies between informant accounts of the communication relationships between respective organizations.

The resulting marginalized posterior distributions of each communication network were the data used in our statistical analysis. To evaluate hypotheses 1–3, we then calculated the posterior predictive distributions for the respective correlations of the command and decision rank with each of the three centrality scores; these were aggregated by sign (e.g., by negative or positive value) to yield the marginal posterior predictive probability that each hypothesis holds for each EMON. To evaluate hypotheses 4–8, we conducted linear regression of the command and decision rank on the matrix of centrality scores from each posterior draw. The resulting joint distribution of coefficients (together with the marginal correlations previously computed) was then employed to calculate the marginal posterior predictive probability for each of the last five hypotheses on each EMON. Thus, to satisfy a particular test, the probability of a positive correlation coefficient was calculated from the marginal correlations (a gross estimate) for hypotheses 1–3 or the probability of a positive correlation, net of competing factors and given some conditionals, for hypotheses 4–8.

In comparison with older methods, this scheme has several advantages. First, it allows us to draw conclusions regarding the control/communication relationship in each EMON, which are appropriately adjusted for our uncertainty regarding the true network. Second, we are interested in estimating the probability each of our hypotheses holds rather than frequentist alternatives such as p values (which suffer from a range of both conceptual and practical problems; Robert, 1994). The Bayesian approach provides these answers. Third, rather, we are interested in the signs of the (*ceteris paribus*) network structure coefficients rather than their order or size. Thus, simple robust regression of the dependent variables on the matrix of posterior network statistics is sufficient to test our hypotheses and we can avoid the complications of endogeneity, model degeneracy, and other issues that may arise from alternative approaches (i.e., exponential random graph models). Finally, our approach does not depend upon asymptotic arguments (e.g., the central limit theorem) for its justification, which is a significant concern given the small sizes of the EMONs being studied. For readers unfamiliar with Bayesian data analysis, an accessible introduction is provided by Gelman, Carlin, Stern, and Rubin (1995).

Network Inference. To evaluate our research hypotheses, we must first infer the seven communication networks on which they depend. To this end, we draw from the joint posterior distribution of each network using a network inference model from the family derived by Butts in his 2003 *Social Networks* methods piece. Specifically, we employ a pooled error model with a Bernoulli graph prior; due to the limited quantity of data from each informant, estimation of informant-specific error rates is not possible here (because not all informants reported on all organizations in each disaster). Our approach improves upon the mutual agreement methods of verifying ties because we are able to incorporate error stemming from both false positive and false negative reports of ties whereas prior methods could not. A total of five hundred posterior draws were taken using a Gibbs sampler with five independent chains, and a burn-in of five hundred iterations (convergence was checked using the potential scale reduction measure of Gelman & Rubin, 1992).[3]

Priors for the network inference model were selected to be weakly informative, per the guidelines in Butts (2003). The graph prior employed for each communication network is a homogeneous Bernoulli graph with expected mean degree approximately equal to the mean degrees of organizations from the two Hurricane Katrina EMONs recently studied by Lind et al. (2008). The latter networks are of similar size and general composition to those of the Drabek et al. data, suggesting them as a reasonable starting point; employing a mean degree parameterization allowed us to avoid biases due to differences in network size. Error rate priors were set to be diffuse Beta distributions, with most mass below the 0.5 mark. Priors were chosen to essentially prohibit perverse inferences (prior probability of less then 0.0001) since these cannot plausibly arise within the pooled data context. Prior mean error rates were chosen to be similar to the rates estimated by Butts (2003) for the advice network of Krackhardt (1987). The latter case involves communication about pragmatic matters in an organizational setting and (while not an exact parallel) provides the best currently available basis for setting error rate priors in this instance.

The result of the network inference model fit is a sample from the joint distribution of the communication network and associated error rate parameters for each event. As described earlier, we employed these draws to obtain the corresponding posterior distribution of centrality scores for each organization. These scores were, in turn, associated with the command and decision rank scores of Drabek et al. using correlations and robust linear regressions to obtain the posterior predictive distributions of correlations/partial correlations needed for hypothesis testing. A more detailed, technical summary of these procedures is provided in the included Appendix.

Results

Figure 2 displays the marginalized posterior network draws for each of the seven Drabek et al. EMONs. The vertices in this figure are scaled by expected degree—thus, organizations believed to have more communication partners appear larger in the display. The edges in this figure are shaded by likelihood, with more probable ties being darker. As explained earlier, these posterior network draws are

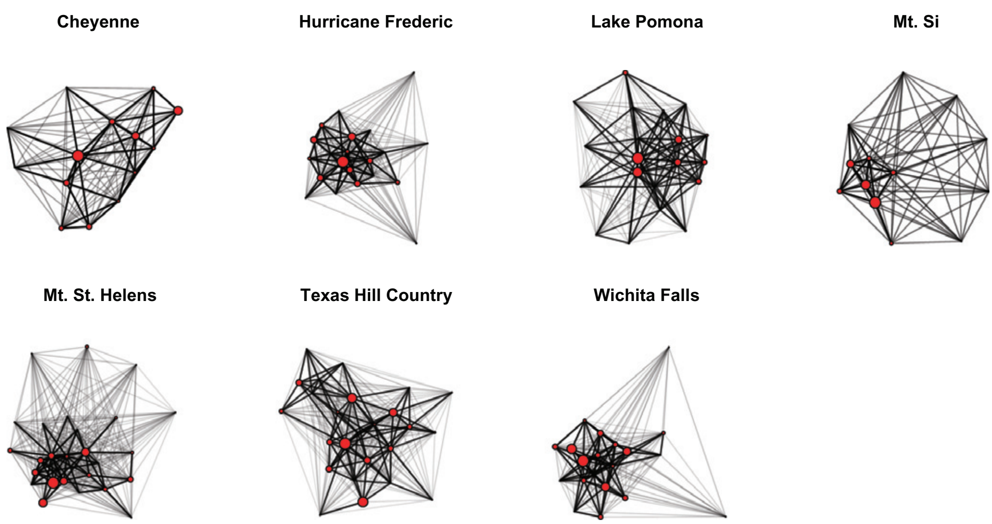

Figure 2. Posterior Communication Networks of Seven Disasters Investigated by Drabek et al. (1981). The Vertices (Organizations) Are Scaled by Their Expected Degree and the Ties Are Shaded Proportionally to Their Likelihood, with Darker Lines Indicating Higher Probability of a Tie between Two Nodes.

Table 1. Summary Statistics for Posterior Draws

	Network size	Network density	2.5% Lower PI	97.5% Upper PI
Cheyenne, WY, tornado—1979	14	0.4426	0.4385	0.4468
Jackson County, MS, Hurricane Frederic—1979	21	0.2953	0.2927	0.2978
Lake Pomona, KS, tornado—1978	20	0.3279	0.3249	0.3309
Mt. Si, WA, remote search and rescue—1978	13	0.4565	0.4519	0.4610
Mount St. Helens eruption, WA—1980	27	0.2180	0.2162	0.2198
Texas Hill Country flood—1978	25	0.2521	0.2500	0.2542
Wichita Falls, TX, tornado—1979	20	0.3206	0.3177	0.3235

PI, probability interval.

the "data" used in the statistical analyses that evaluate our hypotheses. Table 1 presents the network size and the average posterior density with 95 percent probability intervals. Smaller networks tend to be more dense, which is consistent with the idea that mean degree is relatively stable across events. The probability intervals of the mean posterior network density are very narrow, indicating that the posterior draws have relatively compact distributions.

Along with the networks themselves, we can also examine the posterior marginals of the associated error rate parameters. We expected that the posterior false negative rates would be, on average, higher than the posterior false positive rates. This was true for all but disaster 3, the Lake Pomona, KS, Tornado. Figures 3 and 4 show density plots of the posterior marginals for error probabilities by network. It is immediately apparent from these plots that the error rates are relatively high for some networks; in particular, disaster 4 has a fairly high false negative error rate distribution compared with others in this sample (minimum = 0.266, median = 0.489, maximum = 0.697). This case is unusual in that it involves not a disaster response per se but the search for a lone hiker reported to have gone missing on Mt. Si in Washington State. Many organizations that reported to the scene were not fully engaged in the search process, which may have led some informants to underestimate the extent of communication activity within the response network.

Turning to our research hypotheses, we first consider the inclusive hypotheses 1–3. Respectively, these assess the extent to which each EMON shows the structural signals compatible with control via direct interaction (hypothesis 1), indirect interaction (hypothesis 2), or brokerage (hypothesis 3). Operationally, we define a structure as satisfying one of these hypotheses for the command or decision rank measure if the corresponding structural index (degree, eigenvector centrality, or total brokerage) is positively correlated with the rank measure in question. Table 2 shows the marginal posterior predictives for the truth of hypotheses 1–3 on each EMON structure; the number in the i, j cell of this table can be interpreted directly as the marginal probability that the hypothesis of row i holds for the network of column j (given the data and modeling assumptions). For example, the value in the first row and first column of results for command rank in Table 2 is 0.97, which is the probability that the number of direct ties is positively correlated with command rank in the interorganizational communication network during the response to the Cheyenne, Wyoming, Tornado of 1979. As is evident from Table 2, all of the inclusive

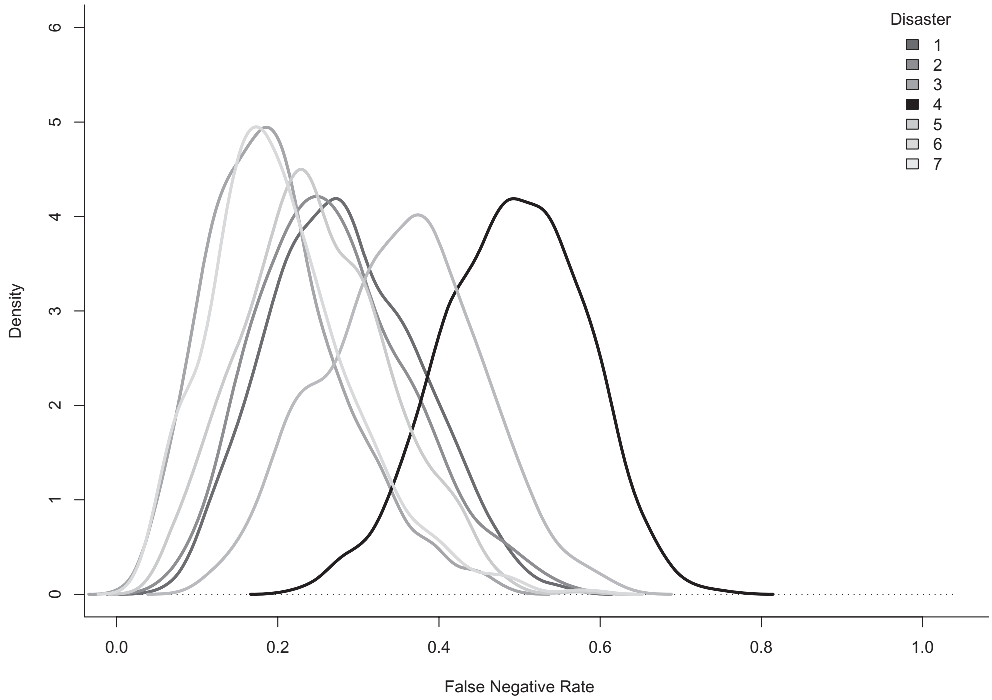

Figure 3. Marginal Posterior Distribution of False Negative Rates, by Network.

hypotheses are inferred to hold with very high probability for nearly all cases (the lone exception being the brokerage hypothesis for decision rank on the Wichita Falls EMON). This tells us immediately that the Drabek et al. EMONs display the basic structural signatures of direct interaction, indirect interaction, and brokerage-based interaction for both authority and *ad hoc* decision making. While this does not guarantee that all three are in active use, it gives us reason to proceed with an examination of hypotheses 4–8.

Hypotheses 4–8 all combine logical dependencies on one or more of hypotheses 1–3 with additional conditions relating to the conditional effect of one or more structural indices controlling for other factors. Here, we operationalize this in terms of partial correlations (implemented in practice via the distribution of coefficients for a regression of command or decision rank on the three structural indicators). For instance, a given posterior draw satisfies hypothesis 4 if the correlation between the appropriate rank score and degree is positive and if the coefficients for eigenvector centrality and brokerage-given degree are less than or equal to zero. Taking the mean fraction of draws simultaneously satisfying this condition yields the posterior predictive probability that hypothesis 4 holds. Table 3 provides the marginal posterior predictives for hypotheses 4–8 and can be read in the same manner as Table 2. It is immediately evident that the probabilities here are much lower than those of Table 2, a fact that arises naturally from the more restrictive nature of these hypotheses (and, relatedly, the larger number of viable alternatives).[4]

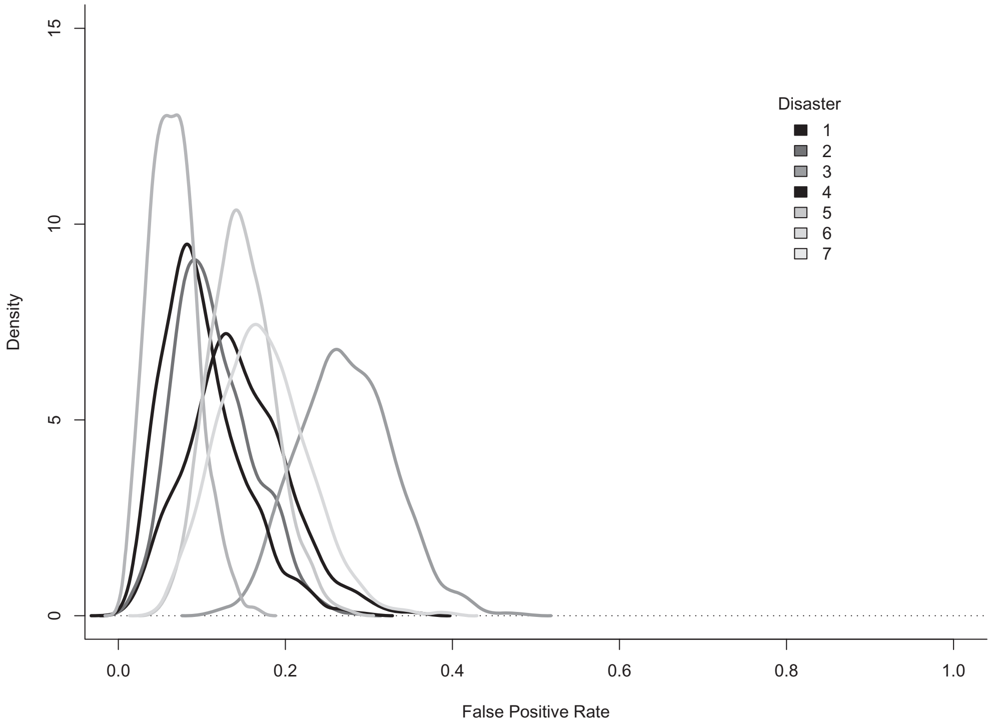

Figure 4. Marginal Posterior Distribution of False Positive Rates, by Network.

Table 2. Marginal Posterior Predictives for Hypotheses 1–3

	1	2	3	4	5	6	7
Command rank							
Hypothesis 1 (direct)	0.97	0.95	0.95	0.92	0.98	0.95	0.92
Hypothesis 2 (indirect)	0.96	0.95	0.94	0.92	0.98	0.93	0.94
Hypothesis 3 (brokerage)	0.96	0.91	0.92	0.85	0.97	0.96	0.84
Decision rank							
Hypothesis 1 (direct)	0.98	0.92	0.94	0.91	0.97	1.00	0.78
Hypothesis 2 (indirect)	0.98	0.93	0.93	0.91	0.97	0.99	0.85
Hypothesis 3 (brokerage)	0.97	0.84	0.92	0.86	0.95	1.00	0.56

The values of each cell in the table report the marginalized probability that the respective hypothesis holds in each of the seven disasters.

Considering Table 3, the most salient observation is almost surely the clear rejection of hypotheses 6 (brokerage only) and 8 (all mechanisms) for both authority and *ad hoc* decision making. These hypotheses have an extremely low probability of being true in any of the seven networks, indicating that neither the action of brokerage in and of itself nor the combination of all three mechanisms provide a satisfactory account of the Drabek et al. data. This strongly suggests that some other factor is involved. On the question of *which* factor, the data are rather more equivocal: some networks show substantial probability mass on a single hypothesis (e.g.,

Table 3. Marginal Posterior Predictives for Hypotheses 4–8

	1	2	3	4	5	6	7
Command rank							
Hypothesis 4 (direct only)	0.15	0.28	0.34	0.46	0.16	0.06	0.22
Hypothesis 5 (indirect/direct only)	0.18	0.41	0.36	0.50	0.41	0.12	0.45
Hypothesis 6 (brokerage only)	0.06	0.05	0.03	0.00	0.02	0.07	0.02
Hypothesis 7 (brokerage/direct only)	0.39	0.44	0.48	0.46	0.21	0.22	0.23
Hypothesis 8 (all mechanisms)	0.01	0.01	0.01	0.01	0.02	0.01	0.00
Decision rank							
Hypothesis 4 (direct only)	0.15	0.26	0.32	0.45	0.14	0.21	0.19
Hypothesis 5 (indirect/direct only)	0.18	0.39	0.35	0.49	0.36	0.27	0.52
Hypothesis 6 (brokerage only)	0.07	0.04	0.02	0.00	0.01	0.05	0.01
Hypothesis 7 (brokerage/direct only)	0.34	0.33	0.48	0.47	0.22	0.45	0.15
Hypothesis 8 (all mechanisms)	0.00	0.01	0.01	0.01	0.03	0.06	0.00

The values of each cell in the table report the marginalized probability that the respective hypothesis holds in each of the seven disasters.

Table 4. Relative Posterior Predictives for Hypotheses 4–8 (All Alternatives Excluded)

	1	2	3	4	5	6	7
Command rank							
Hypothesis 4 (direct only)	0.19	0.24	0.28	0.32	0.19	0.13	0.24
Hypothesis 5 (indirect/direct only)	0.22	0.34	0.30	0.35	0.50	0.25	0.49
Hypothesis 6 (brokerage only)	0.08	0.04	0.02	0.00	0.02	0.15	0.02
Hypothesis 7 (brokerage/direct only)	0.49	0.37	0.39	0.32	0.26	0.46	0.25
Hypothesis 8 (all mechanisms)	0.01	0.01	0.01	0.00	0.02	0.02	0.00
Decision rank							
Hypothesis 4 (direct only)	0.21	0.25	0.27	0.31	0.18	0.20	0.22
Hypothesis 5 (indirect/direct only)	0.24	0.38	0.29	0.34	0.47	0.26	0.59
Hypothesis 6 (brokerage only)	0.09	0.04	0.02	0.00	0.02	0.04	0.01
Hypothesis 7 (brokerage/direct only)	0.45	0.32	0.40	0.33	0.28	0.43	0.17
Hypothesis 8 (all mechanisms)	0.01	0.01	0.01	0.01	0.04	0.06	0.00

hypothesis 5 on the Wichita Falls tornado). Comparison among hypotheses 4–8 *per se* is facilitated by examining the relative posterior probabilities of each hypothesis, that is, the posterior predictive of each hypothesis relative to the total probability of the hypothesis set. Relative probabilities (expressed as fraction of total probability mass) are shown for hypotheses 4–8 in Table 4. As the table makes clear, the two leading contenders across all seven EMONs are hypothesis 5 (control via indirect contacts without a brokerage effect) and hypothesis 7 (control via direct contacts with a brokerage effect). Rankings are generally consistent across networks, with hypothesis 7 being more likely to hold for both rank measures in EMONs 1, 3, and 6, and hypothesis 5 more likely to hold in EMONs 4, 5, and 7 (EMON 2 shows a reversal between command and decision rank scores, but this appears to be due to the fact that both hypotheses are about equally likely to hold for this network). By contrast, hypothesis 4 (control only via direct interaction) does not seem to be a viable candidate (except perhaps in EMON 4, where it still falls behind H5). As such, we can be reasonably confident that neither direct communication alone nor brokerage ties are adequate to account for the exercise of control within the Drabek et al. data set, on the one hand, and on the other, that the triple combination of direct, indirect, and brokered contact is not necessary to explain the patterns that are observed. We note that, as discussed earlier, a combination of structures are correlated with the control measures. Either indirect contact or brokerage is critical along with direct influences, but the evidence cannot differentiate which of the two is more critical.

It is useful to recontexualize these findings in terms of the original data and at the level of the organization, rather than at the level of network. We draw from the largest disaster in our data set, the Mt. St. Helens eruption, as a setting for our example. The organization with the greatest command rank and decision-making rank in that emergent disaster response network was the Cowlitz County Sheriff's Department (both scores equal 40). Consistent with our results, this organization did not have the most direct ties to other organizations (or highest degree) but was indeed situated structurally in indirect contact with many organizations (with high eigenvector centrality). This case highlights the principal theoretical contribution of our study. The Cowlitz County Sheriff's department was thus clearly *in control* of the disaster response not through its direct contact with all other organizations but because it could reach others through short paths in the communication network.

Discussion

Our data and hypotheses address how networks are structured, managed, and governed to accomplish the difficult task of emergency response. These are tasks for which networks are especially well-suited, although there are contingencies that arise, which prevent cooperation from all relevant actors to accomplish short- and long-term recovery goals. The task of establishing control in an emergent network of organizations remains one of the critical challenges for responsible parties involved in the response (Moynihan, 2009; Quarantelli, 1988). In particular, our findings expose the structural mechanisms implicated in what Provan and Kenis (2007) referred to as "modes of network governance" as they related to this problem by testing hypotheses about the relationship between three types of network centrality (degree, brokerage, eigenvector) and two measures of authority relations (command and decision-making ranks). Our results are consonant with the theory that network governance more effectively arises through sparse local structures such as indirect communication or a combination of direct and brokered communication—or a "midrange" model of governance between a few leading organizations and a full network administrative organization (Provan & Kenis, 2007, p. 234). Furthermore, that we can take a comparative perspective on this issue makes a major contribution to the study of organizational networks and informs policy across a range of possible crisis scenarios.

While our findings regarding the possible mechanisms underlying control exercise in emergent networks speak to a long-standing theoretical concern within the sociology of organizations, they also have practical implications for public policy. In particular, the issue of command and control has been central to a number of contemporary critiques of emergency management practices motivated by experience with recent large-scale disasters like Hurricane Katrina (Neal & Webb, 2006). It has been argued that the current bureaucratic, centralized model of command and control doctrine is ill-equipped to handle such large-scale catastrophes and is, moreover, ineffective in facilitating interorganizational communication (Britton, 1991; Drabek & McEntire, 2003; Neal & Phillips, 1995). Specifically relevant for command and control, Waugh (1994, p. 254) refers to the centralized response system as "an ill-chosen strategy that overlooks the 'emergent' quality of much of the typical disaster response."

Waugh (1994), along with others, noted that centralized authority restricts flexibility, decision making, and mutual aid. Carley and Harrald (1997) suggested that experience will enable flexible organizations to outperform their centralized or hierarchical counterparts by adapting faster through individual learning. Certainly, effective decision making is enhanced by the ability to draw on previous experience, have access to available information, and manage one's own events, all things that are more easily achieved when interacting directly with other organizations (Carley, 2002; Flin, 1996; Klein, 1993; Weick & Roberts, 1996). Our results suggest, however, that direct interaction alone is not the critical element in driving control within emergent interorganizational networks. Rather, we find that realized control patterns are, in fact, compatible with "action at a distance" (in the sense of influence over nonadjacent organizations) and with control, which is contingent upon nondyadic properties such as brokerage roles. While our findings are not in disagreement with calls for more flexible, decentralized control systems, accordingly, they do suggest that a focus on direct interaction among organizations as either a necessary or a sufficient means of attaining this objective is potentially problematic.

Our results are also consistent with the notion that overly centralized authority structure is too risky, and indeed impractical, during disaster responses. If these actors cannot arrive at the scene quick enough, or if communication channels are disrupted, we have shown that the formal control structure, which is typically top-down and direct, is replaced by an *ad hoc* structure that relies more on percolation through the network to facilitate authority relations. As information and communication technology advances, however, central command should consider adopting these systems into their control strategies (Burkhardt & Brass, 1990). One policy recommendation from our results, then, is to focus on diffuse strategies that exploit connections between actors who have few ties to those with many ties. While focused on information broadcasts rather than the dissemination of authority relations, Sutton, Palen, and Schlovski (2008) showed that the so-called "back-channel" communication structure (peer-to-peer networks, Facebook, Twitter) that is outside the typical Incident Command System may offer support to disaster managers. Despite the fact that there is still risk of disruption to these systems—they typically exploit the same structural mechanisms to relay information over a personal network as we find at play in the delegation of control during disaster responses and should be deployed as part of disaster managers' communication infrastructure. Disaster managers have typically been skeptical of the efficacy of these systems and their potential to foster rumoring and false information, but policy aimed at training managers in the proper use of this technology will help to alleviate those concerns. We recommend adoption of these systems to help maintain the formal control relations mandated by response plans and to assist in the emergence of *ad hoc* control relations when formal structures break down (Burkhardt & Brass, 1990).

Our findings generalize to emergent networks in other situations where organizations must collaborate during periods of uncertainty, such as in mergers and economic crises (Fendt, 2005). Research reflecting upon the process by which control relations is resolved during organizational uncertainty point to "optimal mixing" (March, 1991) and "balancing" (Bradach, 1997) of authority positions rather than a sole actor issuing directives (De Witt & Meyer, 1999). The results presented here inform this line of work that indeed, direct interaction alone is not sufficient for generating control relations but that more collaborative network structure involving both direct and indirect relationships is warranted.

Conclusion

Decision-making structures, whether seen in terms of "authority," "command," or "control," are integral features of social relations within modern organizations (Coleman, 1990; Weber, 1958). In conventional settings, decision-making structures are often "frozen" into predetermined and well-defined forms. However, in the context of disrupted settings such as disasters, organizations are faced with challenges that can undermine both the ability to exercise control over others and the normative acceptance of such control. Where organizations must work together in response to such disruptions, new "*ad hoc*" control structures often emerge in tandem with other facets of the multiorganizational network. Here, we have utilized data on communication and control among organizations to uncover some of the structural mechanisms which are—and are not—implicated in this process.

While direct interaction would seem to be the most natural basis for control exercise, our data do not support the contention that this alone can explain control within multiorganizational response networks. Rather, we find that direct interaction mediated by brokerage roles, or indirect interaction alone, provides a better accounting of which organizations actually exercise control within the networks studied here. This finding is consonant with recent work by Tsai (2002) and Ghoshal, Korine, and Szulanski (1994), which challenged the long-held assertion that centralization is key to coordinating across interdependencies in organizational networks (Egelhoff, 1982). On the other hand, we do not find evidence that favors brokerage alone or a joint combination of brokerage and indirect interaction; thus, the data employed here seem to suggest that one or the other of these factors is critical within any given setting. Although current data do not allow further discrimination between these alternatives, it does nevertheless substantially narrow the range of plausible theories to be winnowed by further research. One possible direction for future work is to study the evolution of the process through time. For instance, do authority relations change as the communication network moves from more central to more brokered structures as Provan and Kenis's (2007) propositions about network governance predicted? Our results certainly suggest that—at least within the emergent network context—neither highly central nor highly brokered, communication structures are implicated in the network governance process as stand-alone mechanisms of control.

Finally, many policy network studies collect data under uncertain circumstances or are otherwise exposed to sources of error—such as in the disaster response scenarios studied here and in the emerging economies scenarios studied by Lee et al. (this issue). The methods we employed here (and detailed in the Appendix) offer a very general framework for policy researchers to use in handling error-prone data. As Robins et al. (this issue) point out, the ERGM framework for missing edge data is still under development; our approach offers both an alternative and a complementary solution to this problem.

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Notes

1. All of the data used here can be reproduced from Drabek et al. (1981) and are conveniently bundled with Butts, Handcock, and Hunter (2008) network package for the R Statistical Computing System.
2. The weighting procedure is described in detail in Drabek et al. (1981). The ranks were reverse-weighted, summed, divided by the number of organizations minus 1, and multiplied by 10. Thus, in a case with 20 organizations, the maximum score would be $10 * \sum \frac{(19 \times 6)}{19} = 60$.
3. Posterior simulation was performed using the bbnam function of the sna package for R (Butts, 2008).
4. Note that the column values here need not sum to 1 since the hypothesis set does not contain all possible alternatives (as explained in the Hypotheses section) and since the operationalization used here allows a single draw to support multiple hypotheses in some cases. This is in contrast with Table 4 in which the columns do sum to 1, within rounding, because all alternatives were excluded.

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Appendix

Network Inference Model

Although Bayesian analysis is in increasing use throughout the social sciences (see, e.g., Gill [2007] for an introductory treatment with numerous applications), some readers may be unfamiliar with its application to the problem of network inference (i.e., inferring the structure of a social or other network from incomplete and/or error-prone data). With this in mind, we, here, provide additional technical detail on the procedure employed in generating the joint posterior communication networks for our study. Our focus here is on our specific case; we refer readers to section 2.3 of Butts (2003) for more general background on the Bayesian network inference model. Additionally, we refer readers to Gamerman (1997) and Gelman et al. (1995) for accessible introductions to Markov chain Monte Carlo (MCMC) simulation and Bayesian inference more generally. Our notation follows that of Butts (2003).

For our analysis of the seven Drabek et al. emergent multiorganizational network networks, we used Butts's (2003) Bayesian network inference model for pooled error probabilities. Such a model is appropriate when integrating multiple reports of unknown accuracy, as is the case with our data, and when the number of independent reports from each informant is insufficient to support reliable estimation on a per-source basis. Under this model, the accuracy of reports regarding each communication network is governed by a pair of false negative and false positive error probabilities. These error rate parameters are uncertain, and (jointly with the networks themselves) are estimated from the data.

Prior Distributions. To employ this model, we must specify two prior distributions for each network: the joint prior distribution of the error parameters and the joint prior distribution of the network itself. Our prior distribution on each communication network, as explained in the text, is obtained by fixing the expected mean degree (i.e., expected number of ties per organization) and taking all edges as *a priori* independent and identically distributed. This is equivalent to a *homogeneous Bernoulli graph prior*, a simple, weakly informative prior that can be expressed as follows. For a communication network on N organizations, let Θ be the true adjacency matrix; that is, Θ is an $N \times N$ matrix such that $\Theta_{ij} = 1$ if the ith organization communicates with the jth organization, with $\Theta_{ij} = 0$ otherwise (since communication is in this case reciprocal,

Table A1. Network Prior Hyperparameters (φ), by Network

	Network						
	1	2	3	4	5	6	7
φ	0.461	0.300	0.316	0.500	0.231	0.250	0.316

Θ is symmetric; diagonal entries are ignored). Obviously, we do not know the true state of Θ and thus treat it as a random variable with probability mass function:

$$p(\Theta \mid \phi) = \prod_{i=1}^{N} \prod_{j=i+1}^{N} [\Theta_{ij}\phi + (1-\Theta_{ij})(1-\phi)] \tag{1}$$

where φ is a *hyperparameter* expressing the *a priori* probability of a tie between two organizations. For mean degree $\bar{d}$, this corresponds to $\phi = \bar{d}/(N-1)$. Here, we choose $\bar{d} = 6$ based on prior work on similar networks by Lind et al. (2008), leading to the φ values shown in Table A1. Note that the use of this prior specification does *not* imply that the expected number of ties per organization in Θ is actually equal to $\bar{d}$; rather, this serves as an initial "guess," with the final estimate depending primarily on the observed data. Likewise, the use of a Bernoulli graph prior (in which edges are independent) does not imply that all edges in the underlying network are in fact independent, but only that we do not *force* any particular dependence assumptions on the network on an *a priori* basis. Dependency between edges (e.g., transitive closure bias; Holland & Leinhardt, 1972) can still arise from the data.

In addition to the network priors, we must specify priors for the error rate parameters, e^+ and e^-. The e^+ parameter for any given network expresses the probability that an informant might err by falsely indicating communication between two organizations that do not, in fact, communicate. Likewise, the e^- parameter indicates the probability that an informant might err by falsely indicating that two organizations do not communicate when, in fact, they do. Since we obviously do not know these probabilities, we treat them as random variables. As before, we employ weakly informative independent priors based on findings from previous research; specifically, we model e^+ and e^- separately for each network, with independent beta priors for each parameter. Thus, for a given network, we have

$$p(e^+, e^-) = \text{Beta}(e^+ \mid \alpha^+, \beta^+)\text{Beta}(e^- \mid \alpha^-, \beta^-) \tag{2}$$

where α^+, β^+ and α^-, β^- are the respective hyperparameters for e^+ and e^-. Here, we choose hyperpriors $\alpha^+ = 4$, $\beta^+ = 20$ and $\alpha^- = 4$, $\beta^- = 12$ based on previous work by Butts (2003). The resulting prior distributions are shown in Figure 5. As can be seen, both allow for the possibility that error rates could range quite widely, although rates greatly in excess of 0.5 are seen as *a priori* unlikely. Prior means for both distributions are shown with dotted lines: that for e^- is slightly higher, reflecting the observation that false negatives (errors of omission) are typically more common than false positives (errors of commission). As with the network priors, it should be stressed that

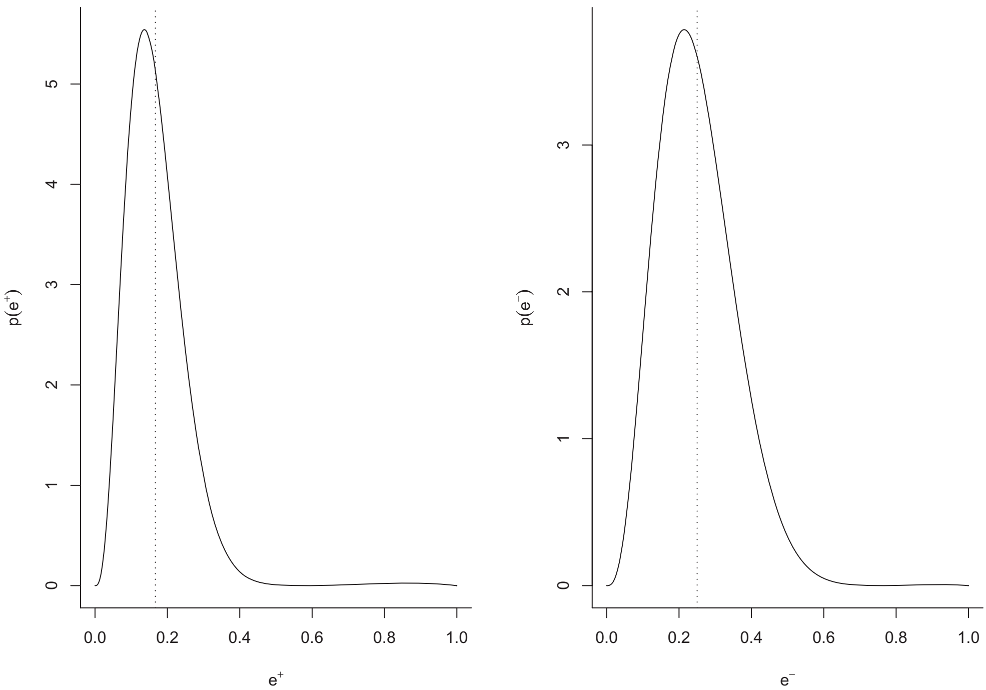

Figure 5. Prior Densities for Error Parameters (with Prior Means).

these distributions should be interpreted as initial expectations based on first principles and past research—actually estimated error rates are based primarily on the observed data.

Posterior Simulation. For each communication network in the Drabek et al. (1981) data set, our observations can be summarized by an $N \times N \times N$ data array Y, such that $Y_{ijk} = 1$ if the informant for organization i reports the presence of a communication tie between organizations j and k. Since reports were collected only for informants' organizations' own ties, only cells of the form Y_{iij} and Y_{jij} are used here; others are ignored. Following Butts (2003), the likelihood of Y is given by

$$p(Y \mid \Theta, e^+, e^-) = \prod_{i=1}^{N} \prod_{j=i+1}^{N} p(Y_{iij} \mid \Theta_{ij}, e^+, e^-) p(Y_{jij} \mid \Theta_{ij}, e^+, e^-), \quad (3)$$

where Θ, e^+, and e^- are as given earlier, and where

$$p(Y_{ijk} \mid \Theta_{jk}, e^+, e^-) = \Theta_{jk}\left[Y_{ijk}(1-e^-) + (1-Y_{ijk})e^-\right] + (1-\Theta_{jk})\left[Y_{ijk}e^+ + (1-Y_{ijk})(1-e^+)\right] \quad (4)$$

is the likelihood of a single edge report. It follows from Bayes' theorem that the joint posterior of Θ and the error parameters given Y has the form

$$p(\Theta, e^+, e^- \mid Y) \propto p(Y \mid \Theta, e^+, e^-)p(\Theta)p(e^+)p(e^-) \quad (5)$$

$$= \mathrm{Beta}(e^+ | \alpha^+, \beta^+)\,\mathrm{Beta}(e^- | \alpha^-, \beta^-) \times \prod_{i=1}^{N}\prod_{j=i+1}^{N} p(\Theta_{ij} \mid \phi)p(Y_{iij} \mid \Theta_{ij}, e^+, e^-)p(Y_{jij} \mid \Theta_{ij}, e^+, e^-). \quad (6)$$

Although this expression is too complex to be treated analytically, we may easily examine the posterior properties of Θ (the communication structure) via posterior simulation (Gelman et al., 1995). Specifically, we use the algorithm described later to take multiple draws from the marginal posterior distribution of Θ (or, alternately, the error parameters), using these to conduct our analyses. See Gelman et al. (1995), Gamerman (1997), or Gill (2007) for extensive treatments of this approach.

Gibbs Sampler Algorithm. Butts (2003) provided an iterative algorithm for simulating draws from the joint posterior. This algorithm (known as a Gibbs sampler) proceeds as follows:

1. **procedure** Draw $\Theta, e^+, e^- \mid Y$
2. Draw $\Theta^{(1)}$ from $p(\Theta \mid \varphi)$
3. Draw $e^{+(1)}$ from $p(e^+ \mid \alpha^+, \beta^+)$
4. Draw $e^{-(1)}$ from $p(e^- \mid \alpha^-, \beta^-)$
5. $i{:} = 2$
6. repeat
7. Draw $\Theta^{(i)}$ from $p(\Theta \mid e^{+(i-1)}, e^{-(i-1)}, Y, \varphi)$
8. Draw $e^{+(i)}$ from $p(e^+ \mid \Theta^{(i)}, e^{-(i-1)}, Y, \alpha^+, \beta^+)$
9. Draw $e^{-(i)}$ from $p(e^- \mid \Theta^{(i)}, e^{+(i)}, Y, \alpha^-, \beta^-)$
10. $i{:} = i + 1$
11. **until** $\Theta^{(\cdot)}, e^{+(\cdot)}, e^{-(\cdot)} \sim \Theta, e^+, e^- \mid Y$
12. **return** $\Theta^{(\cdot)}, e^{+(\cdot)}, e^{-(\cdot)}$

This procedure makes use of the full conditional distributions of Θ, e^+, and e^-, which are derived in the previous reference.

Given a series of draws from the algorithm, we then use $\theta^{(\cdot)}, e^{+(\cdot)}, e^{-(\cdot)}$ to generate posterior network quantities (degree, eigenvector centrality, and Gould–Fernandez raw brokerage) and conduct our marginal and robust regression analyses. As noted in note 3 of this article, simulation for this study was performed using the bbnam() function of the sna package for R (Butts, 2008) in the statnet software suite (Handcock, Hunter, Butts, Goodreau, & Morris, 2003); likewise, the data are packaged with the network package for R (Butts et al., 2008) and can be called within the R environment using data (emon).