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RESEARCH ARTICLE

Crisis management from a relational perspective: an analysis of interorganizational transboundary crisis networks

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Abstract
Although transboundary crises have gained relevance in an increasingly interdependent world, our understanding of the relational dynamics governing these phenomena remains limited. This paper addresses this knowledge gap by identifying common characteristics across interorganizational transboundary crisis networks and drivers of tie formation in successful structures. For this purpose, it applies descriptive Social Network Analysis and Exponential Random Graph Models to an original dataset of three networks. Results show that these structures combine elements of issue networks and policy communities. Common features include moderately high centralization, reciprocated ties, core-periphery structures, and the popularity of international organizations. Additionally, successful networks display smooth communication between NGOs and international organizations, whereas unsuccessful networks have fewer heterophilous interactions. Transitivity seems to play a role in network success too. These findings suggest that crisis networks are robust structures that reconcile bridging and bonding dynamics, thereby highlighting how evidence from relational studies could guide transboundary crisis management.

Keywords: public policy; crisis management; networks; relationality

Introduction

The increasingly decentralized, devolved, and disaggregated nature of global public policymaking has gradually eroded the capacity of state governments to handle public affairs single-handedly (Stone 2020). The growing recurrence of transboundary crises is an additional manifestation of the increasing interdependence that characterizes this changing order. Crises are defined as threats against a system whose management requires quick and effective decision-making. Crisis managers lack full knowledge of the actions needed to thwart the threat in question (Rosenthal et al. 1989). Crises are socially constructed events: hence, their labeling is not always as dependent on measurable mortality rates or damage caused as on their fit with existing narratives (McInnes 2016). Systemic threats that cross territorial and sectorial borders are referred to as transboundary crises (Ansell et al. 2010; Boin 2019). These incidents demand collaboration in networks populated by a diverse range of actors from various jurisdictions that neither have necessarily had prior contact nor share crisis management cultures (Bravo-Laguna 2021). The universe of cases includes global pandemics, migration flows, financial collapses, and climate change.

Despite the growing relevance of networked transboundary crisis management, there is insufficient work examining these operations from a relational perspective (Hafner-Burton et al. 2009). In parallel, the multitude of studies examining the management of COVID-19 has increased the number of papers that compare the management of transboundary crises across various countries (for example, see Boin and Lodge 2021; Cronert 2022); however, their empirical focus is not placed on the interorganizational networks that handle these incidents. Current exceptions to this trend have either examined incidents affecting single countries (Kapucu 2006; Nohrstedt and Bodin 2020) or rely on single case studies (Bravo-Laguna 2023a, 2023b). Therefore, our knowledge of transboundary crisis networks remains limited by a lack of comparative studies and generalizable findings.

This paper addresses these literature gaps by examining an original dataset including three interorganizational transboundary crisis networks – namely, those involved in the 2010 Icelandic ash cloud crisis, the 2014–2016 Ebola Virus Disease outbreak, and the 2019 response to Cyclones Idai and Kenneth in Mozambique – with a twofold aim. In particular, this paper identifies common characteristics of interorganizational transboundary crisis networks and assesses their tendency to be present in successful operations. These aims translate into the following research questions:

1. Which structural features characterize interorganizational transboundary crisis networks?
2. What are the main drivers of tie formation in successful interorganizational transboundary crisis networks?

This study connects the crisis management and social network literatures by providing new information on the appearance and operation of transboundary crisis networks. It also tackles a major criticism against policy network studies, namely their insufficient explanatory power (Börzel 1998; Carlsson 2000). Indeed, the paper examines whether some organizational arrangements minimize the negative effects of a crisis, whereas others cause the opposite outcome (Christensen et al. 2016b). To do so, its focus lays less on under what conditions transboundary crises are managed successfully than on what (successful) transboundary crisis networks look like. Thus, it assumes that network structure and the interactions that shape network coordination influence policy outcomes in contexts of bounded rationality (Sandström and Carlsson 2008).

Its findings show that crisis networks combine elements of policy communities and issue networks. Common features include moderately high in-degree and closeness centralization, reciprocated interactions, core-periphery structures, and highly popular and central international organizations. Additionally, successful networks display smooth communication between NGOs and international organizations, whereas unsuccessful networks have fewer heterophilous interactions. Unlike preferential attachment, transitivity seems to play a role in network success. These findings suggest that crisis networks are robust structures where trust matters; hence, they are able to reconcile bridging and bonding dynamics.

This study combines descriptive Social Network Analysis (SNA) and Exponential Random Graph Models (ERGMs). This methodological choice allows for capturing formal and *de facto* crisis management dynamics. This is a valuable aspect, given that formal protocols are frequently bypassed throughout transboundary crisis responses (Bravo-Laguna 2021). Examining three crises affecting different policy sectors helps transcend the issue focus of single-case studies to assess whether common network mechanisms travel across policy fields (Stone 2020), thereby enhancing the external validity of the findings at the expense of analytical depth (Moynihan 2009); fortunately, existing pieces have thoroughly reviewed the specificities of the crises that this paper examines[1] (Annex 1 includes brief descriptions of these). Despite their advantages, multiple-case network studies are still scarce due to their demanding data collection requirements.

Different criteria guided case selection. Firstly, the three case studies fit into the broader category of transboundary crisis, as all networks responded to threats affecting various countries and policy sectors with imperfect knowledge of the consequences of their actions. Besides, their management required coordination across several country governments, international organizations, NGOs, and private actors. Secondly, each crisis primarily affected a different policy sector, namely air transportation (ash cloud), public health (Ebola), and humanitarian aid (cyclones). Thirdly, the cases present variation in the outcome of interest in this study, namely how (un-)successfully the crisis was managed: while the 2010 Icelandic ash cloud crisis only lasted a few days, it took years to thwart the Ebola outbreak. Thus, the operations in Iceland and Mozambique are regarded as crisis management successes, whereas the managers of the Ebola outbreak response received extensive criticism. This 'most different systems design' strategy helps identify commonalities across three diverse instances of crisis networks with a high potential for generalizability to other transboundary crisis networks. Moreover, comparing two successful cases with a third negative case is a good first step to identifying determinants of network performance that future research can test further.

This paper considers 'success' to be synonymous with 'goal attainment'. In other words, successful crisis networks are hereby understood as structures facilitating specific positive outcomes that their members would find more difficult to attain on their own (Provan and Kenis 2007). Such positive outcomes entail a quick end to the systemic threat by using the minimum possible amount of time and resources, thus allowing for the fewest possible financial and human losses. Proxies such as the time or financial resources needed to tackle a crisis matter for the measurement of success (Goetz and Meyer-Sahling 2009), with time having already been used as a measure of network performance that indicates how efficiently processes are

[1]For the 2010 Icelandic ash cloud crisis, see Alemanno (2010); Christensen et al. (2013). For the Ebola outbreak, see Nohrstedt and Baekkeskov (2018); McInnes (2016). For the 2019 Cyclones Idai and Kenneth, see Bravo-Laguna (2023b).

handled (Sandström and Carlsson 2008): since these proxies vary according to the type of incident and the affected policy sectors, success is hereby measured by comparing the case study with other crises resembling them. For instance, the 2014–2016 Ebola outbreak was the first incident involving this disease that spread to several countries and large cities, and the one that took the longest time to solve in recorded history (Piot et al. 2014): comparisons with the quickly-neutralized SARS outbreaks in the early 2000s suffice to attribute its escalation to managerial negligence and deficient international coordination (Davies and Rushton 2016; Kamradt-Scott 2016).

This paper proceeds as follows. The next section presents its theoretical framework and develops hypotheses that examine drivers of tie formation in successful interorganizational transboundary crisis networks. Data and Methods describes the methodology used in this study, whereas Analysis and Results shows the results of the analysis. Finally, Conclusions concludes and suggests ways to continue this line of research.

Theoretical framework

Crises give rise to a specific type of policy network. Policy networks are structures formed by institutionalized exchange relations across actors such as state governments, private actors, and civil society organizations that participate in politics and policymaking and have interdependent interests (Börzel and Heard-Laureote 2009). Policy networks distribute tasks among such actors and coordinate collective action for problem-solving purposes. They oftentimes become involved in responses to 'wicked' problems characterized by high uncertainty (Carlsson 2000).

The (in-)stability of memberships, their permeability to non-sectoral influences, and the strength of the resource dependencies among their members explain the influence of policy networks over policy outcomes (Peterson 1995). These considerations help establish two distinct policy network subcategories, namely issue networks and policy communities: while the former feature unstable memberships, relative permeability, and weak resource dependencies, policy communities stand at the opposite end in these dimensions (Rhodes and Marsh 1992; Peterson 1995). Issue networks oftentimes emerge during debates of specific legislation, such as those leading to modifications of controversial legislative pieces (e.g., abortion law reforms). Conversely, the relatively stable set of actors that engage in Spanish agricultural policy exemplifies an institutionalized policy community.

For their part, crisis networks are problem-solving, goal-oriented structures (Carlsson 2000). This consensual, overarching crisis management goal involves solving the incident in question as soon as possible. While alignment in goals and domains allows network actors to coordinate better than they would in situations where dissensus prevails, the latter contexts occasionally facilitate the production of innovative solutions (Provan and Kenis 2007).

Crisis networks share elements of issue networks and policy communities. Specifically, crisis networks resemble issue networks when it comes to the unstable, flexible, and permeable nature of their memberships. These features facilitate quick reactions against threats (Provan and Kenis 2007). In crisis networks, actors have extensive freedom to choose their peers (Nohrstedt and Bodin 2020); indeed, the strengths of stable memberships (e.g., consistency of network outcomes) do not particularly benefit crisis networks, which are usually short-term arrangements. However, familiarity among crisis managers facilitates their successful coordination (Moynihan 2009). Finally, issue and crisis networks share their ability to produce innovative policy responses (Adam and Kriesi 2007): actors frequently need to think outside the box when facing incoming threats that render existing protocols useless. At the same time, crisis networks and policy communities are characterized by heavy resource dependencies. In particular, crisis network actors rely on one another to access information. This is specially the case during transboundary crises, which require coordination across countries and policy domains amid particularly high uncertainty (Ansell et al. 2010; Nohrstedt and Bodin 2020).

The inability of individual country governments to organize effective responses on their own distinguishes transboundary from domestic crises and forces the actors involved in transboundary crisis reactions to interact with their network peers. Indeed, such incidents typically require the participation of a wider range of actors than large-scale disasters affecting single countries. For example, transboundary crisis responses are more likely to incorporate international organizations than the reactions to domestic crises, specially when the latter affect countries with enough capacity to counter such threats by themselves. Different governmental, non-governmental, private, and scientific bodies may also participate in transboundary crisis responses. Other motivations for crisis managers to form ties with other organizations include reducing uncertainty (Galaskiewicz 1985), coordinating their efforts, and shaping quick response operations. During transboundary crises, actors use previous working relationships to maximize their sources of information. This behavior may lead to highly interconnected networks (Kapucu 2006). High network density is also associated with better communication and smoother collective action (Sandström and Carlsson 2008). Hence, this paper expects interorganizational transboundary crisis networks to have high density scores.

Transboundary crises demand robust and flexible management (Ansell et al. 2010). In this regard, Berardo and Scholz (2010) identified a trade-off between bridging (centralization) and bonding (closure and reciprocity) in policy networks. Centralization (i.e., the degree of 'concentration' of a measure on specific network actors) reduces network path length and brings efficiency to the network. While efficient, highly centralized networks with strong hierarchical dynamics are vulnerable to disruption when central nodes are affected (Hafner-Burton et al. 2009). On the other hand, closure – a network feature characterized by the presence of triangles, whereby two connected nodes A and B tend to share common connections to a third node C – and reciprocated ties provide trust, security, and stability. When risks of defection are low, bridging dynamics become preponderant; conversely, bonding is common in situations where such risks are higher (Nohrstedt and Bodin 2020).

The tangibility of the exchanged resources affects the centralization of a network. Tangible resources (i.e., with material properties) such as funding are controlled by a limited number of organizations; unsurprisingly, networks where financial flows are relevant tend to be highly centralized (Provan and Huang 2012). While tangible resource dependencies may condition crisis management (Bravo-Laguna 2023a, 2023b), coordination for these purposes is more generally driven by information exchanges. Information is an intangible resource that is not necessarily controlled by a few actors: rather, individual actors may possess particular pieces of information that help make sense of the crisis in question. While crises are traditionally associated with the concentration of executive power in a few hands and hasty decision-making at the expense of deliberative and collective managerial styles (Drennan et al. 2015), this need for gathering information from various sources suggests that transboundary crisis networks are relatively decentralized and horizontal.

In all, decentralized networks might be better equipped for handling complex, dynamic, and extraordinary situations than centralized structures, which are best suited for routine tasks (Brass 2003). Boin (2019) agrees that crisis management in centralized schemes is bound to fail unless decision-makers enjoy high political and public support. Successful communication during transboundary crises requires managerial flexibility, an expertise-based distribution of decision-making authority across public and private institutions, and the successful integration of specialized knowledge in different fields. Other valuable assets include high interdependence and trust among crisis managers. Decentralized, horizontal networks are comparatively advantageous vis-à-vis networks with strong hierarchies in these aspects (Börzel and Heard-Lauréote 2009). During transboundary crises, horizontal exchanges ensure fluid inter-institutional coordination, help stakeholders integrate into management processes, soften the unwillingness of governments to relinquish sovereignty, prevent the overburdening of decision-makers, avoid bottlenecks that delay decision-making (Drennan et al. 2015), and facilitate information exchanges (Schrama et al. 2022).

However, purely decentralized, horizontal networks have important drawbacks for transboundary crisis management. For example, the absence of clear hierarchies might complicate the rapid identification of response leaders. Additionally, prolonged bargaining among network participants may endanger quick and consensual decision-making, thus producing sluggish, inefficient, and suboptimal reactions (Börzel 1998; Feiock et al. 2012). Although crisis management structures that facilitate self-organization tend to be more successful than centralized ones, beyond a certain threshold self-organization may jeopardize crisis operations (Nowell et al. 2018; Bodin et al. 2019).

Hence, hybrid structures have emerged as mechanisms with the potential to maximize transboundary crisis response effectiveness (Christensen et al. 2016a). Such hybrid networks consist of semi-hierarchical structures combining centralized and interdependent dynamics. Being especially helpful in situations where different competencies are pooled together, hybrid crisis mechanisms have gained prominence in recent years. Thus, Ansell et al. (2010) argue that successful transboundary crisis management requires a mix of central governance and self-organization. Moynihan (2009) agrees that balancing hierarchy and centralization with flexibility is generally advantageous in network structures, and particularly beneficial in contexts of crisis. Moreover, contexts demanding transgovernmental activity tend to reconcile flexibility with effectiveness (Slaughter, 1997). For example, the Incident Command System combines hierarchical features – a central authority temporarily leading actions – with horizontal dynamics; its deployment has reduced uncertainty during crisis operations (Moynihan 2008; 2009).

Preferential attachment is a network feature that has been linked to efficient management. Networks showing preferential attachment include a small group of actors with much higher popularity than their peers: in more technical terms, they exhibit skewed power-law in-degree distributions (Siciliano et al. 2021). Highly popular actors tend to be perceived as reliable and trustworthy by their network peers (van der Heijden 2021). Hence, their presence facilitates the organization of crisis responses and reduces uncertainty, thereby providing comparative advantages for crisis management purposes vis-à-vis networks lacking this feature. Feiock et al. (2012) acknowledged the relevance of asymmetric popularity for the success of networks that coordinate information flows. For their part, core-periphery networks typically show relatively high centralization levels and include multiple central actors that are well connected with one another (forming the core of the network) and a few actors more sparsely linked (i.e., the periphery). Their stability, cohesiveness, and flexibility make them particularly apt for crisis management (Nowell et al. 2018). Following this logic:

H1A: Bridging dynamics (i.e., preferential attachment, centralized systems, core-periphery structures) predominate in successful interorganizational transboundary crisis networks.

The existence of effective communication marks the success or failure of crisis responses (Kapucu 2006). Ensuring that all network actors can be easily reached helps meet a prerequisite for successful action, namely forming a holistic picture of the crisis. Cohesion and connectivity are key features for this purpose, since information flows more quickly in networks whereby nodes keep communication channels open with as many peers as possible (Kapucu 2005). Cohesive, highly connected networks have high density values and low average path length scores. In other words, only a few steps (ties) are needed for a given actor to reach another node in those structures. Hence, this paper expects successful networks to show high density values.

Transitivity is a related property that is characteristic of networks where exchanges of information take place (Feiock et al. 2012; Vantaggiato, 2019): it consists of a tendency for two nodes that are connected through common connections to a third node to develop a tie between themselves (i.e., "the friend of my friend becomes my friend"). The literature has noted a propensity for crisis networks to form transitive triads (Bodin et al. 2019; Nohrstedt and Bodin 2020). By facilitating the formation of ties among actors that shared no connections in the past, transitivity becomes a relevant mechanism in contexts characterized by high uncertainty and limited information where preexisting arrangements determine interorganizational exchanges (Siciliano and Wukich 2016). In particular, transitive connections increase trust across the network and reduce transaction costs, as they increase the chances that actions by individual nodes are observed by their network peers (Nisar and Maroulis 2017; Siciliano et al. 2021). Reciprocity is an additional bonding mechanism that refers to the tendency for nodes to send back ties to nodes with whom they had interacted in the past. Transitivity and reciprocity have been reported to reduce uncertainty and facilitate information sharing among crisis managers, thus improving the quality of cooperation efforts under pressure. They also act as generators of interorganizational trust. Bearing this information in mind, the following hypothesis is proposed:

H1B: Bonding dynamics (i.e., transitivity and reciprocity) predominate in successful interorganizational transboundary crisis networks.

For its part, homophily (i.e., a tendency for ties to appear among actors with similar characteristics) has been identified as a driver of social relations. Similar actors tend to face fewer communication barriers, engage in more predictable behavior, and trust one another (Brass 2003; Nohrstedt and Bodin 2020). While the presence of homophily has been recorded in interorganizational networks (Siciliano and Wukich 2016), this characteristic is more common in interpersonal networks (Brass 2003; Lee et al. 2012). However, this phenomenon has barely been tested on transboundary crisis networks, which feature extremely high levels of uncertainty and require quick decision-making. Thus, transboundary crisis managers might be particularly likely to seek contact with those actors that they perceive as trustworthy, predictable, and easily accessible. Such trust-based interactions would in turn increase trust and facilitate communication across the organizations involved in a specific response. Homophily is also associated with low innovativeness, since actors connected to similar others may rely excessively on preexisting solutions to tackle policy problems (Grizzle et al. 2020). Despite the latter circumstance, the following hypothesis is proposed:

H2A: Ties tend to form among organizations of the same type in successful interorganizational transboundary crisis networks.

Fluent communication among organizations of different kinds has important advantages for transboundary crisis management. Private, scientific, governmental, international, and non-governmental organizations possess specialized expertise and unique resources that are useful in crisis operations. Moreover, different types of bodies usually possess specific pieces of information concerning the causes and impact of a crisis. Therefore, diverse networks may have greater access to richer crisis management toolboxes than more homogenous structures (Nohrstedt and Bodin 2020). Indeed, heterophilous ties predominate in contexts where full information is an asset (Siciliano et al. 2021), facilitate sense-making, and encourage the design of comprehensive response plans. Sandström and Carlsson (2008) linked heterophily with higher network performance, since heterophilous exchanges generate creative, untested, and innovative solutions: these features are particularly relevant in crises that render existing protocols and standard operating procedures useless. Hence:

H2B: Ties tend to form among organizations of different types in successful interorganizational transboundary crisis networks.

Data and methods

Data collection

Data were obtained from three surveys distributed among officials with high executive responsibilities in the management of the three crises. Vis-à-vis archival research, this data collection method has the advantage of capturing informal interactions (e.g., in-person conversations, phone calls, email exchanges) that are key for successful crisis management despite not appearing in official documents. Respondents had to identify in a pre-defined list the organizations with whom they had exchanged information and other resources throughout the crisis in question; hence, binary ties show the presence or absence of communication between organizations throughout this operation. The full questionnaire is included in Annex 2.

The pre-defined list of actors was elaborated by examining academic articles and reports on these episodes, asking experts who had researched them, and – in the case of the cyclones network – identifying the organizations that received and donated beyond certain financial amounts to the crisis response. Survey respondents could also name missing organizations that they perceived as relevant in these episodes: if more than three actors referred to a particular missing organization, it would be added to the list. Leaving the option open for survey respondents to add new actors to the node list increases the reliability of the analysis (Sandström and Carlsson, 2008). 100% of the organizations within the network boundary replied to the ash cloud and cyclones surveys, whereas 87.5% (42) of the total (48) did so in the case of the Ebola network.[2] The six actors that did not respond to the latter survey were excluded from the network. Following Metz and Brandenberger (2023), this paper checked whether missing data introduced important biases in the analysis by examining in-degree centrality scores, which are available for both non-respondent and respondent organizations alike. The mean in-degree centrality score for non-respondents (9.67) is much lower than that for respondents (17.19). Also, the highest in-degree centrality score for a non-respondent equals 13, a lower amount than the mean in-degree centrality score for respondents. This suggests that the network does not miss data pertaining to actors that drive network interaction.

The reliance of this data collection method on subjective perceptions requires testing the validity of the data through different means. Firstly, all networks show relatively high reciprocity rates: these amount to 35% (Ebola), 45.5% (ash cloud), and 47% (cyclones), respectively. Secondly, the surveys were distributed among individuals with high executive responsibilities in each crisis response, who therefore were highly likely to be aware of their organizations' activity during these incidents. Thirdly, network data were triangulated with official documents (i.e., reports, minutes of meetings) containing information about formal ties during each crisis. These documents show that the three edge lists are consistent with the identified formal ties among crisis managers. In particular, at least one survey respondent reported 91.4% of the confirmed formal ties pertaining to the Ebola network, while 40.6% of the connections were acknowledged by the two respondents involved: these figures amounted to 88.4% and 71.6% in the case of the cyclones network, and 100% and 80% in the ash cloud network, respectively.

As mentioned earlier, crises are social constructs without objectively defined temporal boundaries (Ansell et al. 2010). Therefore, this paper uses a case-specific

[2]These 42 nodes were used for the calculation of density scores and the in-degree distribution of the Ebola network. However, Phoenix Air was removed before calculating the ERGMs, as it was the only private firm in the network; one-node categories would have destabilized the model, making convergence impossible. In any case, its low activity (2) and popularity (5) scores hint that the effect of removing Phoenix on the model results is rather weak.

logic to place such boundaries. In particular, the beginning of each crisis is determined by the onset of a natural disaster or the first human death resulting from a health outbreak, whereas their end is either marked by a regulatory change that dramatically cuts financial losses (ash cloud), the end of human deaths (Ebola), or the culmination of a humanitarian operation (cyclones).

Methods

This study tests these hypotheses by combining descriptive SNA with ERGMs. In so doing, this study links the metaphorical and analytical dimensions of the idea of networks. While the former dimension includes (but is not limited to) discussions on policy networks, the latter refers to networks as the units of analysis in the SNA methodology. SNA examines networks constituted by a set of nodes (in this case, organizations involved in crisis management) and the ties connecting them – which in this paper represent exchanges of information during such operations. It is a relational methodology that highlights the relevance of connections between actors and the system where they are embedded (Emirbayer 1997; Latour 2007). This relational emphasis proves useful in crisis management studies, where analyzing systemic patterns is considered an appropriate prevention strategy (Haldane 2009).

Descriptive SNA

The SNA toolbox includes descriptive indicators that measure node centrality in the network. Closeness centrality constitutes an example: it expresses how many steps are on average necessary to connect a given node with any other node in the network. For its part, degree centrality measures how many ties go through a node. In directed networks such as those analyzed in this paper, relations in every dyad can be separated according to the sender and receiving nodes, thereby accounting for the asymmetrical nature of social relations (Nisar and Maroulis 2017). Directed ties convey information regarding the existence of a connection between two nodes and the identity of the node that reported the tie in question. Hence, degree centrality is subdivided into in-degree (i.e. the number of ties that a node receives, or how ‘popular’ the node is) and out-degree – namely how many ties a given node sends to others, or how ‘active’ the node is. Finally, betweenness centrality shows the extent to which a given actor appears in the closest path between two other nodes. Higher betweenness centrality scores reveal those actors who act as bridges connecting different groups of actors; their location in structural holes may alter their behavior in a crisis. For example, such bridging actors may experience particularly high pressure or work overload. The presence of structural holes could not be tested in additional ways, given the impossibility of dividing the networks into clearly defined communities of actors.

Other descriptive indicators pertain to the network level: hence, density measures the ratio of existing ties in the network vis-à-vis the maximum possible number of connections. As mentioned earlier, centralization reveals the degree of ‘concentration’ of a measure on specific network actors. For example, networks with high in-degree centralization include one or a few nodes with high in-degree scores and many nodes with low in-degree scores. Plus, this study includes a core-periphery metric that compares networks with an ideal core-periphery structure, as used by Nowell et al. (2018). This metric throws a value ranging between 0 and 1: the closer to 1, the stronger the resemblance between the network of interest and the ideal structure – where core nodes are connected to all remaining nodes of the network, with peripheral nodes lacking connections with any nodes other than those at the core. Finally, cliques (i.e., subsets of nodes where every node is connected to the rest) help understand crisis network performance; while they may facilitate action in situations that demand quick responses, cliques could also hinder the transmission of information across the network by excluding certain actors (Comfort and Haase 2006). Annex 3 includes lists of cliques for each network.

ERGMs

This paper also uses ERGMs to answer its research questions. ERGMs are functions of several individual, dyadic, and higher-order structural variables (Ki et al. 2020). This family of stochastic models allows for simultaneously testing the extent to which different endogenous (e.g., transitivity) and exogenous (e.g., homophily, heterophily) variables influence chances of tie formation by having significantly higher occurrences in the examined network than expected by chance alone. Unlike regression models, ERGMs are tailored to the interdependence of observations that characterize network data (Lusher et al. 2013); this means that, in network data, the existence of a given tie can be affected by preexisting ties among different pairs of actors and can itself influence the chances that a tie among a different pair of actors emerges. While the number of studies applying stochastic models to policy network data is expanding (see Berardo and Scholz 2010), those focusing on crisis networks are less frequent. In particular, the ERGM in this study is aimed at identifying structural patterns in each network. In contrast, network success is treated as the outcome of interest in this study and is not included in the ERGM models.

While ERGMs use different estimation procedures to logistic regressions, they can be interpreted in a similar way to these. Hence, coefficients show the "correspondence between a one-unit change in the predictor and the log odds of the tie existing" (Nisar and Maroulis 2017: 833). For example, the positive and significant reciprocity coefficient in Model 1 indicates that the odds of a tie appearing among two nodes that already share a tie are 4.43 times ($\exp[1.49] = 4.43$) higher than the average odds for a tie among an unconnected pair of nodes.

Individual-level Attributes and Terms. ERGMs provide additional indicators that allow for testing the hypotheses presented in the previous section. To test for homophily and heterophily, actors were classified into governments, international organizations, private bodies, NGOs, and scientific bodies. Supranational bodies were categorized by their degree of independence from their member states. Hence, highly independent bodies with extensive pooling of sovereignty (Haftel and Thompson 2006; Hooghe and Marks 2015) – such as the International Civil Aviation (ICAO) or the United Nations Population Fund – were labeled as international organizations, whereas those with lower or no independence were included in the 'government' category. Examples of the latter bodies include ECOWAS or the African Union, since many of whose decisions require a two-thirds majority vote cast by their Member State delegates.

The inclusion of this variable is justified on theoretical grounds, namely the possession by each type of organization of specialized expertise and unique resources that help make sense and respond to a crisis. Other actor attribute variables were not included in the model precisely due to the lack of solid theoretical grounds hinting at their relevance in transboundary crisis management and difficulties in operationalizing variables such as the size, country of origin, and policy sectors where the network actors focus their activity.[3] Finally, in-degree centrality terms were included for exploratory purposes, since there are no theoretical preconceptions regarding the significance of these variables in interorganizational transboundary crisis networks.

Due to the lower robustness of out-degree centrality (as opposed to in-degree)[4], this indicator was incorporated along with the term 'edges' as a control variable: 'edges' captures latent dependencies in the data; less theoretically interesting than other terms, it expresses the baseline probability of a tie arising in the network, after accounting for the remaining effects included in the model.

Dyadic and Structural Variables. Transitivity and reciprocity. The identification of positive and significant geometrically weighted shared-partner statistics (gwesp and gwesp.OTP indicators) would confirm the presence of transitivity (Schrama et al. 2022). While changing the values for their decay parameters did not dramatically alter the results, assigning values of 0.5 to these terms increased model fit. For its part, positive and significant reciprocity coefficients would confirm tendencies for reciprocity.

Preferential attachment. Testing for its presence requires several steps. The first of these involves visual inspections of in-degree distributions. Skewed in-degree distributions provide initial evidence that the networks follow a power-law distribution. Additional statistical testing would be performed if such skewed distributions were observed; the results of this exploration rendered the latter step unnecessary, though.

Comparability and omitted variable bias

To produce robust findings, network models need to be as similar as possible. The presence of NGOs, private bodies, and scientific organizations in only one or two of the networks generated variables that could not be tested across the three structures, though. Network size and density scores also need to be similar to allow for meaningful comparison, since these parameters influence other structural indicators (Faust 2006). In this regard, the sizes and density scores of the ash cloud and cyclones networks are indeed alike (N = 23 and 0.503, and N = 24 and 0.382,

[3]For example, it is unclear whether the entire government or more specific departments are relevant here. Defining the country of origin of non-state actors such as firms or NGOs is also hard. Likewise, it is easier to identify the policy sector(s) where certain organizations focus their activity in some cases (e.g., international organizations, scientific experts) than in actors without a clearly defined focus (e.g., private firms; state governments). Aside from the abovementioned aspects, space limitations exacerbate difficulties in including more variables in the model.

[4]Out-degree centrality is solely reliant on individual survey responses. In contrast, in-degree accounts for all network actors other than the node in question. Hence, the latter is less vulnerable to survey respondent bias.

respectively), whereas the Ebola network is slightly larger (N = 42). However, its density score is similar to the remaining two networks (0.418). Hence, an additional robustness check was conducted following Kourtikakis et al. (2021): it entailed reducing the size of the Ebola network by randomly sampling 24 nodes, calculating the density of the resulting network, and repeating the procedure 100 times. The average density score (0.422) was similar to the original one, with a standard deviation of 0.046. While imperfect, these metrics provide reassurance that the networks are not too dissimilar to be compared, as comparisons are hereby restricted to the identification of significant patterns across the networks.

Each model should include as many variables as possible to minimize omitted variable bias (Metz and Brandenberger 2023). Unfortunately, ERGMs are prone to convergence problems that sometimes make it impossible to include all covariates of interest at once (Lusher et al. 2013; Nohrstedt and Bodin 2020). Therefore, the analysis includes two models per network, which were built with the R packages 'sna' (Butts 2008), 'igraph' (Csardi and Nepusz 2006), and 'statnet' (Hunter et al. 2008). Annex 4 includes goodness-of-fit diagnostic tests that show that the fit of the models (especially those corresponding to the Ebola network) is imperfect, albeit reasonably good.

Analysis and results

Descriptive findings

This section begins by describing the composition of the networks. Country governments and international organizations are present in all three networks, whereas private and scientific bodies are specific to one or two of these. The presence of different types of actors illustrates that crisis networks possess elements of both policy communities and issue networks. For example, some organizations were incorporated or even created throughout the crisis response: an example of these single-purpose bodies is the United Nations Mission for Ebola Emergency Response, whose *ad hoc* creation evidences the initial failure to counter the outbreak. A second type of actor in these structures is not regularly involved in the policy communities affected by a crisis. These are the cases of the airplane engine manufacturers General Electric and Pratt & Whitney, whose input was required during the Icelandic ash cloud crisis for the discussions that led to increases in the threshold of ash concentration for flight authorizations. Finally, some networks include sector-specific organizations that are usually involved in policymaking and play central roles in the crisis in question: those are the cases of the World Health Organization (WHO) and the European Aviation Safety Agency. Annex 5 includes visual representations of the three networks.

For its part, Table 1 shows that the three networks have several things in common. For example, they show similar, moderately high density, in-degree centralization, and closeness centralization scores, especially considering the low size of the networks. At the same time, the three networks show high correlations with ideal core-peripheral structures (0.634, 0.654, and 0.735, respectively). They also have similar average path length scores, namely 1.66 (ash cloud), 1.61 (Ebola), and 1.54 (cyclones). Both the density and average path length scores corresponding

Table 1. Descriptive indicators for the networks that responded to the Icelandic ash cloud crisis, Ebola outbreak, and Cyclones Idai and Kenneth. Source: own elaboration

	Ash cloud network	Ebola network	Cyclones network
Density	0.382	0.418	0.503
Average path length	1.66	1.61	1.54
In-degree centralization	0.418	0.421	0.424
Closeness centralization	0.289	0.316	0.304
Betweenness centralization	0.172	0.054	0.076
Core-periphery model	0.634	0.654	0.735
Total number of nodes	24	42	23
Total number of ties	211	720	255

to the Ebola network (0.418 and 1.61, respectively) lie between the values of the other two structures: hence, the two successful networks do not show higher density or centralization scores than the least successful one.

Tables 2–4 include information concerning network actor centrality. Governmental actors and international organizations receive the highest centrality scores across all three networks. The latter have high degree centrality scores, and lower closeness and betweenness centrality scores. This combination suggests that international organizations develop several redundant connections. In contrast, all networks show a group of governmental actors whose high degree, betweenness, and closeness centrality scores reveal their tendency to be well connected to their peers and have direct access to various sources of information. NGOs tend to be less central. The largest cliques in the Ebola network were indeed dominated by international organizations, with a smaller presence of governmental and non-governmental organizations. In contrast, the NGO Save the Children was present in the largest cliques in the cyclones network, along with other governmental and international organizations. Finally, the largest cliques in the Icelandic ash cloud crisis network were dominated by governmental and scientific organizations, with international organizations appearing in some smaller, 4-actor cliques. This is surprising, considering the relatively high degree centrality scores of ICAO and EUROCONTROL. Private actors were absent from these larger structures too.

As mentioned in the methodology section, the first step to detect preferential attachment involves examining in-degree distributions. Figures 1–3 were included for this purpose: if preferential attachment was present in the networks, these plots would show power-law distributions, where most nodes have very few ties and a few actors concentrate the majority of them. Since the plots do not show such distributions, no further action was taken to find evidence supporting that preferential attachment drives tie formation in successful crisis networks, as H_{1A} proposes.

ERGM results

The ERGM model in Table 5 also reveals interesting information. Firstly, the *gwesp* indicators were significant and positive in the ash cloud network, significant and negative in the Ebola network, and not significant in the cyclones network. In other words, mutually tied actors were more likely to share multiple partners than

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Table 2. Centrality indicators and organization types for the actors involved in the response to the Icelandic ash cloud crisis. Source: own elaboration

Actor name	Type	In-degree centrality	Betweenness centrality	Closeness centrality
Airports Council International	Private	5	0.9	0.53
Association of European Airlines	Private	8	2.4	0.59
British Civil Aviation Authority	Government	12	18.2	0.7
Civil Air Navigation Services Organization	Private	8	15.1	0.64
Council of the European Union	Government	6	0.6	0.53
Danish Civil Aviation Authority	Government	5	5.3	0.72
EUROCONTROL	International Organization	18	16.3	0.59
European Aviation Safety Agency (EASA)	Government	18	98.7	0.85
European Cockpit Association (ECA)	Private	2	1	0.68
European Commission	Government	16	92.3	0.88
European Low Fairs Airline Association (ELFAA)	Private	2	0	0.53
General Electric	Private	4	0	0.51
Icelandic Civil Aviation Authority	Government	11	8	0.52
Icelandic Department of Civil Protection and Emergency Management	Government	7	3	0.55
Icelandic Earth Sciences Institute	Scientific Organization	5	5	0.58
Icelandic Meteorological Office	Scientific Organization	10	8	0.61
International Air Transport Association (IATA)	Private	12	16.7	0.68
International Civil Aviation Organization (ICAO)	International Organization	12	14.4	0.62
Irish Civil Aviation Authority	Government	9	8.3	0.68
Met Office	Scientific Organization	15	32.2	0.68
Méteo France	Scientific Organization	4	1.4	0.47
Norwegian Civil Aviation Authority	Government	3	3.3	0.62
Pratt & Whitney	Private	8	0.4	0.49
Rolls Royce	Private	11	10.6	0.61

Table 3. Centrality indicators and organization types for the actors involved in the response to the Ebola outbreak. Source: own elaboration

Actor name	Type	In-degree centrality	Betweenness centrality	Closeness centrality
African Development Bank (ADB)	Government	13	14.9	0.67
African Union (AU)	Government	20	9	0.51
Aspen Medical	NGO	10	0.7	0.53
Care International	NGO	14	3.8	0.51
Concern Worldwide	NGO	11	10.3	0.63
Doctors without Borders (MSF)	NGO	31	61.3	0.59
European Centre for Disease Prevention and Control (ECDC)	Government	9	0.2	0.5
European Commission	Government	22	100.4	0.85
European Community of West African States (ECOWAS)	Government	14	16	0.68
European External Action Service (EEAS)	Government	10	15.5	0.69
European Parliament	Government	6	0.6	0.53
European Union Ebola Coordinator	Government	15	46.9	0.91
French Agency of Development (AFD)	Government	7	0.8	0.56
German Corporation for International Cooperation (GIZ)	Government	12	0.6	0.51
Government of Guinea	Government	14	43.6	0.79
Government of Liberia	Government	29	15.8	0.45
Government of Sierra Leone	Government	25	110.1	0.8
Government of Spain	Government	5	1.4	0.66
International Medical Corps	NGO	18	21.4	0.73
International Organization for Migration	International Organization	17	21.7	0.82
International Red Cross and Red Crescent Movement	NGO	23	4.1	0.51
International Rescue Committee	NGO	20	33.8	0.76
Oxfam	NGO	13	0.4	0.51
Partners in Health	NGO	18	3.6	0.54
Phoenix Air	Private	5	0.7	0.35
Plan International	NGO	11	2.7	0.53
Samaritan's Purse	NGO	11	29.4	0.51
Save the Children	NGO	19	4.9	0.55
The Tony Blair Africa Governance Initiative (AGI)	NGO	8	1.3	0.57
United Kingdom Department for International Development (DFID)	Government	24	64.6	0.72

(*Continued*)

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Table 3. (*Continued*)

Actor name	Type	In-degree centrality	Betweenness centrality	Closeness centrality
United Nations Children's Fund (UNICEF)	International Organization	27	68.2	0.72
United Nations Development Programme (UNDP)	International Organization	18	28	0.74
United Nations Mission for Ebola Emergency Response (UNMEER)	International Organization	29	77.5	0.73
United Nations Mission in Liberia (UNMIL)	International Organization	16	32.1	0.87
United Nations Office for the Coordination of Humanitarian Affairs (OCHA)	International Organization	21	5.7	0.55
United Nations Population Fund (UNFPA)	International Organization	15	5	0.6
United Nations Secretary General	International Organization	10	40.2	0.93
United Nations World Food Programme (WFP)	International Organization	22	1.9	0.5
United States Agency for International Development (USAID)	Government	24	41.4	0.69
United States Centre for Disease Control (CDC)	Government	28	64.8	0.69
World Bank	International Organization	24	30.2	0.67
World Health Organization (WHO)	International Organization	34	59.3	0.61

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Table 4. Centrality indicators and organization types for the actors involved in the response to the Cyclones Idai and Kenneth. Source: own elaboration

Actor name	Type	In-degree centrality	Betweenness centrality	Closeness centrality
Canadian Government	Government	8	4.3	0.69
European Commission	Government	10	14	0.92
Food and Agriculture Organization	International Organization	12	5.7	0.69
Government of the United Arab Emirates/International Humanitarian City	Government	1	0	0.54
International Organization for Migration	International Organization	15	45.3	0.96
International Red Cross and Red Crescent Movement	NGO	13	9.2	0.63
Italian Government	Government	5	1	0.61
Japanese Government	Government	6	0	0.41
Mozambican Government	Government	20	45.4	0.67
Norwegian Government	Government	4	0.1	0.56
Oxfam	NGO	9	3	0.59
Portuguese Government	Government	7	0.1	0.52
Save the Children	NGO	11	34.4	0.92
Swedish Government	Government	8	1	0.54
United Kingdom Government	Government	13	12.4	0.81
United Nations Children's Fund (UNICEF)	International Organization	15	23.1	0.81
United Nations Office for the Coordination of Humanitarian Affairs (OCHA)	International Organization	19	18.7	0.69
United Nations Population Fund (UNFPA)	International Organization	12	18.6	0.96
United States Government	Government	14	2.9	0.54
World Bank	International Organization	11	2.6	0.61
World Food Programme (WFP)	International Organization	18	12.1	0.63
World Health Organization (WHO)	International Organization	15	15.7	0.65
World Vision International (WVI)	NGO	9	5.5	0.67

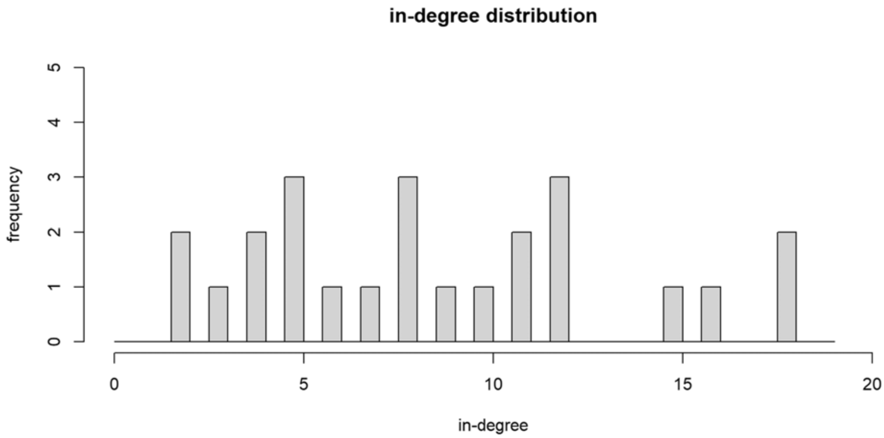

Figure 1. In-degree distribution of the network that responded to the ash cloud crisis.
Source: own elaboration.

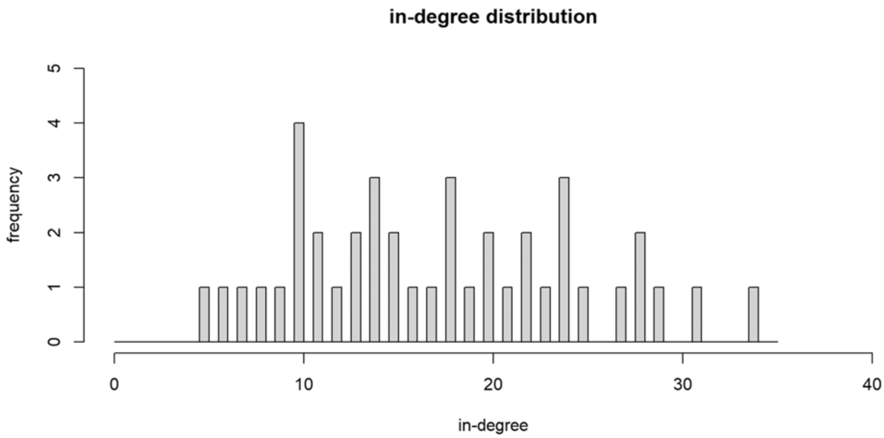

Figure 2. In-degree distribution of the network that responded to the Ebola outbreak.
Source: own elaboration.

expected by chance alone in the ash cloud network, and less likely during the Ebola response. This hints that clustered subsets are present in the former network, and absent in the latter one. This evidence partially supports H_{1B}, which expected bonding mechanisms to drive tie formation in successful networks. In contrast, the positive and significant reciprocity coefficients in all models reveal a tendency for crisis managers to send back ties to actors with whom they had interacted in the past, regardless of how effective the response was.

H_{2A} and H_{2B} tested for the presence of homophily and heterophily in the networks. While governments and international organizations tended to engage in homophilous ties in the response to Cyclones Idai and Kenneth, only scientific organizations were significantly likely to behave this way throughout the ash cloud

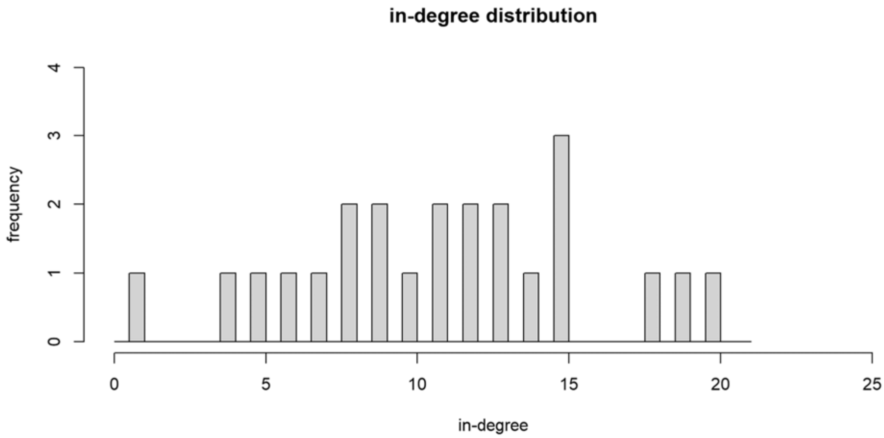

Figure 3. In-degree distribution of the network that responded to Cyclones Idai and Kenneth.
Source: own elaboration.

crisis. In other words, ties among scientific bodies were significantly likely to appear in the latter network, whereas governments tended to exchange information with one another while responding to Cyclones Idai and Kenneth. International organizations also displayed this behavior in the cyclones and Ebola networks. Finally, the homophily coefficient for NGOs in the Ebola network is significant and negative; hence, NGOs were very unlikely to exchange information with other NGOs during this response. This evidence does not back H_{2A}.

In contrast, evidence that the least successful network hosted the fewest heterophilous interactions partially supports H_{2B}. Specifically, the only significant indicators in the Ebola network have negative signs, showing that NGOs rarely communicated with governments and international organizations throughout this operation. Considering the relevant role of NGOs such as Médecins Sans Frontières in this effort – especially during earlier stages, when governmental action was limited (Nohrstedt and Baekkeskov 2018) – their disconnection and low activity might explain the unsuccessful response. In contrast, the positive indicator referring to ties between private and international organizations during the Icelandic ash cloud crisis evidences the key roles of airlines and engine manufacturers in the response: while the former stressed that a rapid resumption of flights would not compromise safety, the latter provided expertise that proved essential for determining the threshold of ash concentration levels deemed safe for airplane engines (Bravo-Laguna 2021).

Frequent and effective reporting from NGOs to international organizations was significant in the two networks where it was tested.[5] Moreover, the sign is negative in the criticized Ebola network and positive in the praised cyclones network; thus, interactions between NGOs and international organizations occurred with a lower

[5]The irrelevance of NGOs in the Icelandic ash cloud crisis excluded the possibility of incorporating actors with this profile in the network. All models used ties from international organizations to governments as their baseline categories.

Table 5. Exponential Random Graph Models for the networks that responded to the Icelandic ash cloud crisis (Models 1–2), Ebola outbreak (Models 3–4), and Cyclones Idai and Kenneth (Models 5–6). Source: own elaboration

	Ash Cloud Network (1–2)		Ebola Network (3–4)		Cyclones Network (5–6)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Edges	−4.99 *** (0.68)	−1.60 ** (0.56)	0.74 (0.56)	0.61 (0.64)	−0.68 (0.85)	0.08 (0.91)
Reciprocity	1.49 *** (0.30)	1.69 *** (0.31)	0.50 *** (0.15)	0.48 ** (0.15)	0.84 ** (0.28)	0.84 ** (0.28)
Transitivity (gwesp.0.5)					−0.31 (0.44)	
Transitivity (dgwesp.0.5)	2.08 *** (0.38)		−0.69 * (0.30)	−0.48 (0.34)		0.21 (0.42)
Homophily Gov - Gov		1.00 (0.54)		−0.07 (0.19)		0.94 ** (0.31)
Homophily NGO - NGO				−0.70 ** (0.23)		−0.37 (0.58)
Homophily IO - IO		0.73 (1.30)		0.94*** (0.24)		1.29 ** (0.41)
Homophily Priv – Priv		0.30 (0.56)				
Homophily Scien – Scien		1.55 * (0.75)				
Heterophily Priv - Gov		0.08 (0.58)				
Heterophily Scien - Gov		0.03 (0.63)				
Heterophily Gov - IO		2.30 * (0.90)		0.06 (0.22)		−0.00 (0.33)
Heterophily NGO - Gov				−0.99 *** (0.22)		−0.22 (0.38)
Heterophily NGO - IO				−0.67 ** (0.23)		0.96 * (0.46)
Heterophily Gov - NGO				−0.31 (0.20)		−0.45 (0.38)
Heterophily IO - NGO				0.06 (0.22)		0.09 (0.43)
Heterophily Priv - IO		1.67 * (0.73)				
Heterophily Scien - IO		1.21 (0.92)				
Heterophily Gov - Priv		0.26 (0.58)				
Heterophily IO – Priv		−0.55 (0.75)				
Heterophily Scien - Priv		−0.79 (0.75)				
Heterophily Gov – Scien		1.14 (0.63)				
Heterophily IO - Scien		−0.53 (0.99)				
Heterophily Priv - Scien		−0.80 (0.76)				
In-degree IOs	1.59 *** (0.39)		0.40 ** (0.13)		1.08 *** (0.23)	
In-degree	−0.05					

(*Continued*)

Table 5. (*Continued*)

	Ash Cloud Network (1–2)		Ebola Network (3–4)		Cyclones Network (5–6)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Private	(0.21)					
In-degree	0.26					
Scientific	(0.28)					
In-degree			−0.02		0.27	
NGOs			(0.13)		(0.26)	
Out-degree	−1.37 ***		0.38 **		0.97 ***	
IOs	(0.35)		(0.13)		(0.23)	
Out-degree	−0.45 *					
Private	(0.22)					
Out-degree	−0.63 *					
Scientific	(0.28)					
Out-degree			−0.69 ***		0.70 **	
NGOs			(0.13)		(0.27)	
AIC	633.6	663.5	2144	2141	644.8	650.5
BIC	672.4	736.8	2182	2201	674.4	697

Significance codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

likelihood than expected by chance alone in the former network and more likely than expected by chance in the latter case. This is consistent with previous findings, which highlight the well-functioning of the UN cluster system – and its effective coordination with NGOs working on the ground – during the response to cyclones Idai and Kenneth (Bravo-Laguna, 2023b) and the disconnection of international organizations such as the United Nations Mission in Liberia during the Ebola outbreak (Davies and Rushton, 2016). Interestingly, ties from international organizations to NGOs are not significant in either network.

Besides, in-degree coefficients for international organizations were positive and significant in all networks. This means that these actors tended to be contacted by other bodies during the three crisis responses. Along with the significance of homophilous ties among international organizations in two of the three networks, the popularity and centrality of these actors evidence their position at the highest ranks of the network hierarchy. Indeed, some of these bodies – such as the International Civil Aviation Organization (ICAO) during the Icelandic ash cloud crisis (Christensen et al. 2013) or the United Nations Office for the Coordination of Humanitarian Affairs in the response to Cyclones Idai and Kenneth (Bravo-Laguna 2023b) – are responsible for coordinating crisis responses. Therefore, they come under great scrutiny when the overall reaction is suboptimal, as the criticism against the World Health Organization (WHO) in the aftermath of the Ebola outbreak illustrates (Kamradt-Scott 2016).

Conclusions

By applying an original multiple-case network design, this paper has identified common characteristics across interorganizational transboundary crisis networks. In particular, it has shown that these networks combine elements of policy communities and issue networks, considering the coexistence of actors that participate regularly in policymaking activities with organizations that are incorporated or created *ad hoc* to manage a crisis. Interorganizational transboundary crisis networks are characterized by moderately high density, in-degree centralization, and closeness centralization levels, display a tendency for reciprocity, and resemble core-periphery structures. Within these networks, international organizations have the highest popularity scores. The literature has equated popularity with network power (Kourtikakis et al. 2021): hence, the high network power of international organizations allows them control over information flows. Although these features may distinguish transboundary crisis networks from the structures that coordinate domestic crisis responses, further research is needed to confirm this point.

For their part, NGOs and international organizations tend to communicate more frequently in successful crisis networks than in those subject to harsher criticism. This paper also shows that homophily does not drive interactions in transboundary crisis networks, as in most interorganizational networks. In contrast, heterophilous ties are less frequent in unsuccessful interorganizational transboundary crisis networks than in successful ones. The latter do not show high-density scores nor a tendency toward preferential attachment. At the same time, the possibility that transitivity is a sufficient (but not necessary) condition for successful crisis management cannot be ruled out. This combination of centralization, reciprocity, and transitivity suggests that crisis networks are robust structures where trust matters; hence, they are able to reconcile bridging and bonding dynamics. These findings inform policymaking choices during transboundary crises by suggesting the convenience of exploiting third-party contacts and enhancing communication across organizations of different types, particularly among NGOs and international organizations.

The small-n in this study, the absence of man-made incidents, and the limited comparability of the networks make generalization problematic, though. Difficulties to establish valid comparisons are exacerbated by differences in the nature of the actors involved in each episode and the limited number of examined policy sectors. Plus, the scarcity of tested actor attribute variables results in a model that fits imperfectly the analyzed network data. Additionally, the research design is vulnerable to omitted variable bias (Nowell et al. 2018). Specifically, this network study did not capture non-network variables that may affect crisis network performance, including individual actor strategies and specificities of the affected policy areas (Sandström and Carlsson 2008). In crisis networks, the effect of actor strategies is expected to be low, though, since urgent responses to existential threats leave little space for actor contestation. For its part, the failure to capture particularities of the affected policy areas can be remedied through longitudinal network studies comparing crises in the same policy sector. Longitudinal studies could indeed address pending questions, such as whether participation in crisis networks results in longer-term structural modifications to the networks and procedural changes in the involved actors.

The numerous validity tests in the paper do not invalidate objections pertaining to the subjective nature of survey responses. Moreover, respondents were not asked about other types of exchanges or crisis management tasks than simple communication to minimize the risk of response fatigue. This made it impossible to break interactions into multiple types of relationships. These limitations prevent more ambitious causal inferences from being drawn.

These findings highlight the value of studying interorganizational crisis networks for policymakers and evidence the potential of SNA in this area. Understanding what interorganizational transboundary crisis networks look like and linking structural and dyadic features with successful crisis management are essential steps for improving the performance of transboundary crisis networks. Hence, producing new studies that apply relational angles to transboundary crisis management will likely enhance the effectiveness of these operations.

This original contribution opens up a new research agenda that studies transboundary crises from a relational perspective. In-depth case studies will explore the dynamics observed in this paper in further detail and apply its insights to additional interorganizational transboundary crisis networks: these include man-made incidents threatening core state policy domains, such as security or defense. Larger-N studies could also untangle the effects of different variables (e.g., type of crisis, duration of a crisis response) on network structures, identify necessary and sufficient conditions for (un-)successful crisis management, and produce more robust links with network success. In this study, the sample was limited to three networks due to the time-consuming nature of its data collection method, that nevertheless allows for capturing both formal and informal interactions.

Different studies could expand this line of research. For example, the use of fuzzy-set qualitative comparative analysis could address an additional limitation of this study, namely the operationalization of its outcome of interest as a binary variable (i.e., successful vs unsuccessful crisis management). This could be achieved by testing the findings of this study across networks that have intermediate values in their dependent variable. However, its demanding data collection requirements would make such a survey-based project – which captures the informal dimension of crisis management – too time-consuming. Hence, its findings would be interpreted in combination with those in this paper. Finally, the use of Quadratic Assignment Procedures could help understand the extent to which crisis management networks resemble the structures set in motion for crisis preparedness purposes. These efforts will be undertaken in future research.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S0143814X24000187.

Data availability statement. Replication materials are available in the *Journal of Public Policy* Dataverse at: https://doi.org/10.7910/DVN/L8NNKN

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Competing interests. The author(s) declare no competing interests.

Ethics statement. While the sources of the data used for this paper are three surveys distributed among individuals involved in the management of transboundary crises, this paper does not meet the regulatory definition of research with human subjects because the focus of the investigation was not the opinions, characteristics, or behavior of the surveyed individuals ("about whom"). Instead, such individuals were asked to identify the bodies that their organizations cooperated with throughout the response to a specific crisis ("about what").

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