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Policy communication in times of public health crisis: Longitudinal network modeling of U.S. politician-health agency interactions during the COVID-19 pandemic

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ABSTRACT

Severe public crisis such COVID-19 pandemic entail coordinated communication between politicians and public health agencies. The study explores how and why U.S. politicians share messages from health agencies on social media during COVID. Proposing a multi-theoretical, multi-level (MTML) framework to understand the phenomenon, we draw upon the Advocacy Coalition Framework and Crisis and Emergency Risk Communication theory and conceptualize politicians' public health communication as serving the dual functions of policy and risk communication. With bipartite longitudinal network modeling, our analysis finds a fragmented national message-sharing network deprived of central federal leadership and clustered around state-level actors such as local health agencies and state governors. The politicians' party affiliation and positions on COVID-19 policies significantly impacted whether they would help distribute messages from public health agencies. Health agencies' message features such as expression of certainty and use of analytical words also influenced politicians' message sharing patterns. These findings suggest the pandemic communication is both a policy advocacy and a risk and crisis communication process. This integrated theoretical approach offers explanations of information sharing dynamics between politicians and health agencies, two major information sources for the public.

1. Introduction

When faced with COVID-19 pandemic, one of the worst public health crises in the 21st century (John Hopkins University, 2020), the widespread misinformation regarding its cause and solution not only endangers individuals' health choices but also thwarts large-scale public health efforts. For example, many people believe that bleach is an effective treatment for the coronavirus (Reimann, 2020). The lack of relevant knowledge (Li et al., 2022) and the politicization of the pandemic (Robertson et al., 2021) further obstruct the debunking of pandemic-related misinformation. To simultaneously address the pandemic-infodemic, communication is an indispensable component in disseminating scientific evidence, informing policy arguments, and facilitating coordination (Atouba & Shumate, 2010).

Informing the public timely and accurately is a key step in combating the pandemic-infodemic. Public health agencies cannot single-handedly deliver effective public health messages and motivate sufficient public compliance without the support from other prominent social actors such as elite politicians (Robertson et al., 2021). Especially when a public health crisis is heavily politicized (Zhou et al., 2023), politicians are important communicators. Political elites occupy central roles in the hierarchy of influence on traditional and digital information systems (Shoemaker & Reese, 2013) as their institutional positions allow them to influence other elites, who in turn affect the media and the public (Entman, 2003). During the pandemic, politicians' messages and actions powerfully influence news agenda and shape public opinion in profound ways (e.g., Robertson et al., 2021; Zhou et al., 2023). Therefore, the public health agencies' pandemic communication can be more effective if the politicians offer support and share messages consistent with agencies' stances.

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Previous literature has explored how public agencies (Kim et al., 2021; Malik et al., 2021) and the government (Zhou et al., 2022) might increase public engagement in the communication process during the pandemic. However, little is known about what factors drive politicians' spread or neglect of public health agencies' messages, two important information sources for many. Understanding the information-sharing pattern between politicians and health agencies complements the landscape of pandemic information ecology and offer insights into how the public received their messages. The current research thus fills this research gap by identifying the factors that explain how politicians share public health agencies' messages during the pandemic.

We draw from a social network perspective with a multi-theoretical, multi-level (MTML) framework (Monge & Contractor, 2003), which brings together complementary theories to offer holistic explanations. Focusing on social-mediated communication, we argue that a network approach is required to understand the dynamics between groups of actors as numerous studies have demonstrated that information sharing dynamic is governed by the relationship among communicators as (e.g., Borgatti et al., 2009; Heaney & Rojas, 2008; Henry, 2011; Malinick et al., 2013). In addition, it is unrealistic to assume that politicians' communication of health messages are driven by any single reason. It is likely that public health and political interests intertwine and co-shape their communication choices. Nevertheless, communication theories and research are often segmented by boundaries of subfields, making MTML a useful perspective to integrate multiple theoretical perspectives to explicate complex social realities.

Guided by MTML, we integrate the Advocacy Coalition Framework (ACF) (Jenkins-Smith & Sabatier, 2003; Sabatier & Jenkins-Smith, 1988) and Crisis and Emergency Risk Communication (CERC) framework (Reynolds & Seeger, 2005; Seeger et al., 2010) to explain the dual logic of politicians' sharing of health messages in a networked fashion. Specifically, ACF suggests that politicians' communication patterns are governed by their political ideologies and public policy positions; whereas CERC postulates that their communication should be based on the needs to enhance the publics' certainty and sensemaking in times of crisis. This integrated framework helps us better account for the intertwinement of policy advocacy and public health communication in politicians' communication behavior on social media, the essential communicational channel for information dissemination during the pandemic (Kim et al., 2021; Zhou et al., 2023).

Utilizing a large dataset from Twitter, we operationalized our message-sharing networks as bipartite networks between health agencies and politicians as they are two types of entities driven by different operational logic. We applied Stochastic Actor-Oriented Model (SAOM) to model the longitudinal evolution of politicians' sharing of messages from health agencies.

The rest of this article starts from explicating why an MTML framework is essential to explain the communication ties between politicians and health agencies. Specifically, we unpack the ACF and the CERC and develop hypotheses and research question from respective theories. Then, we provide details of data collection, network construction, and modeling strategies followed by the results of empirical network modeling. Finally, we discuss how our integrated theoretical perspective offers insights into the complexities of the communication over COVID-19 among politicians and health agencies. Directions for future research of bridging distinctive scholarly traditions and limitations of this study are also reflected.

2. A multi-theoretical multi-level network approach to social-mediated communication

We situate our study of politicians' sharing of public health agencies' messages on social media within a social network perspective. Social networks refer to any types of social entities (e.g., individuals, organizations, countries) and the relationships among them. With growing popularity across disciplines, social network research has emerged as a field consisting of distinctive theories and methodologies (Scott & Carrington, 2011). The uniqueness of the network perspective is its focus on the emergence, maintenance, and decline of connectivity and flows among communication actors (Borgatti et al., 2009; Monge & Contractor, 2003).

In our study, we conceptualize politicians' tweeting of messages from public health agencies as a two-mode network, which is a network formed by two types of entities and the relationships between them (Malinick et al., 2013). Politicians and heath agencies are conceptualized as two different entities as the former has motivations to politicize the issue than merely communicating risks as evidenced by recent studies (e.g., Zhou et al., 2023). While scholars have identified the different mechanism through which politicians and health agencies engage with the public separately during the pandemic (Kim et al., 2021; Zhang & Cozma, 2022; Zhou et al., 2023), how politicians retweet certain health agencies' messages is less known. The communication process may depend on a range of factors such as their relationship with specific health agencies and how their peers have responded to these agencies. This complex and dynamic process is an admixture of public health risk and policy advocacy communication. Theoretically, the complexity of the situation requires theories that account for different set of factors. The MTML approach is therefore valuable as the structural tendencies of a complex network are unlikely to be explained by a single theory, and require an integration of multiple theories.

The MTML framework has been to understand interorganizational networks (Atouba & Shumate, 2010) and scholars consistently support the value of integrated theories (Malinick et al., 2013). In our study, we incorporate two theoretical frameworks to address different dimensions of the communication process. Methodologically, we recognizes the differences between the two types of entities while modeling their interdependencies. In addition, communication networks are not static entities. As the pandemic continued to evolve, so did health agencies' recommendations and politicians' positions on response policies. Recent developments in computational methods have advanced two-mode network analysis over time and thus allow us to examine how evolving conditions could shape changes in the networks and communication outcomes (Ripley et al., 2020). In the following sections, we introduce two complementary theories to guide our study.

2.1. *Politicians' political advocacy networks on social media*

The political advocacy coalition framework (ACF hereafter) was developed by Sabatier and Jenkins-Smith (1988, 2003)to explain how coalition networks with different political interests compete over complex policies. ACF posits that at any given time, different stakeholders would take interest in a wide range of policies. Policy stakeholders of the same policy issue form a policy subsystem (Pierce et al., 2017). The concept of networks is central to ACF (Weible, 2005). According to ACF, promoting and implementing public policies such as COVID-19 responses often require coordination among policy stakeholders connected by complex relationships. Different coalitions could exist within, between, and outside of political parties. ACF assumes that stakeholders cluster together based on shared beliefs and interests and that such clustering pattern empowers these actors' advocacy (Jenkins-Smith & Sabatier, 2003; Sabatier & Jenkins-Smith, 1988).

Within-coalition networks are crucial for like-minded stakeholders to build trust, access resources (e.g., intelligence, expertise, and advice), and coordinate their actions against competing coalitions (Heaney & Rojas, 2008; Weible, 2005), which can be formal or informal. For example, actors can "join" a coalition by communicating with other members, developing common strategies, and coordinating actions to achieve shared goals. Between competing coalitions, networks provide the crucial infrastructure to win the competition and expand the influence of specific coalitions (Yang et al., 2021). ACF suggests that the formation and competition between these coalition networks could determine policy processes and outcomes. Previous studies have mapped the network structure of advocacy coalitions (Heaney & Rojas, 2008) and showed that coordination and information exchanges occur primarily within coalitions (Weible, 2005).

ACF identifies three main antecedents that shape network formation: party affiliation, access to resources, and policy core beliefs. We further expand on each of the antecedents below.

2.1.1. Party affiliation

According to ACF, party affiliation could shape a coalition network based on several mechanisms. First, party affiliation may influence actors' relationship building based on the mechanism of homophily. Homophily refers to the tendency of networked actors to interact with others of similar backgrounds (McPherson et al., 2001). Among politicians, studies found that they are significantly more likely to engage with those who share identical party affiliations than their political opponents (Valle et al., 2018).

Second, a party can be viewed as a network of cooperating actors whose interests tend to align with one another (Koger et al., 2009). The COVID-19 pandemic occurred concurrently with the 2020 Presidential Election, which featured divisive campaigns. It is likely that in this polarizing political environment (Robertson et al., 2021; Zhou et al., 2023), party affiliation could powerfully shape politicians' behaviors out of political goals and personal interests. Party affiliation has been found as a strong and consistent predictor of how policy networks interact and form coalitions both online and offline (Valle et al., 2018). Research shows that political interactions are effective indicators for classifying the ideological orientations of both political actors and ordinary people (Barberá, 2015).

When it comes to how party affiliation influences politicians' retweeting of health agencies' messages, the homophily effect cannot be directly modelled as the interactions occur between politicians and health agencies. However, due to the public visibility of politicians' tweets, other politicians could still watch how their party members tweet and conform to such party norms. As such, we expect that party affiliation guides politicians' message sharing behaviors on social media.

H1. Politicians are more likely to share messages from health agencies if those agencies' tweets were retweeted by politicians of the same party than those of a different party.

2.1.2. Access to resources

Gaining access or control of critical resources could affect the outcomes of policy advocacy (Weible, 2005). Therefore, in the process of building coalition networks, actors are motivated to gain access to resources to strengthen coalitions, elevate status, and achieve political goals (Sabatier & Weible, 2007). Studies have examined the impact of resources on coalition building. Henry (2011) examined coalitions in California regional planning and found that the formation of a policy coalition network can be explained by both actors' similarity in ideology and resource-seeking behaviors. On the other hand, politicians who have access to more resources are likely to be more active in building coalitions (Sabatier & Weible, 2007).

ACF recognizes that a variety of resources could shape politicians' decisions in terms of who to connect with. Such resources include political positions, public opinions, information, financial resources, and leadership. In this study, we consider the impact of both politicians' and health agencies' political or institutional positions and financial resources. Politicians may hold different political positions (parliamentary politicians vs. governors) which could be backed by different levels of financial support. Health agencies also have different institutional positions (i.e., different levels of jurisdictions ranging from sub-state, state, to regional, and federal) and corresponding budgets.

ACF suggests that politicians with more resources are in favorable positions to develop new network ties. It is likely that they are more willing to share messages from health agencies. Moreover, actors with more resources can be attractive partners in coalition networks because the connection with resourceful actors could potentially provide access to critical resources and elevate one's own status (Sabatier & Weible, 2007). Since health agencies possess different levels of resources, sharing messages from resourceful agencies may connect politicians with important allies and elevate their status. We propose the following hypotheses.

H2a. Politicians with more financial resources are more likely to share messages from health agencies.

H2b. Politicians are more likely to share messages from health agencies that possess more financial resources.

In addition, politicians may hold different political positions (parliamentary politicians vs. governors). Although ACF recognizes these positions as different, the theory does not predict which type of positions are more favorable or how politicians in different positions behave. Therefore, to explore if politicians with different political positions retweet differently, we propose the following research question.

Research Question (RQ)**:** How do politicians with different political positions share messages from health agencies with different levels of jurisdictions?

2.1.3. Policy core beliefs

Policy core beliefs refer to normative and causal perceptions about a policy subsystem (Jenkins-Smith & Sabatier, 2003; Sabatier & Jenkins-Smith, 1988). ACF conceptualizes that policy positions could evolve and change throughout the advocacy process. This concept thus is valuable for understanding the evolution of politicians' communication patterns regarding COVID-19 response policies.

Policy core beliefs are the principal glue for holding advocacy coalitions together and provide a rationale for coordinating behaviors to influence policies. For instance, in terms of how to respond to COVID-19, there are competing perspectives on appropriate public policies. While some politicians argued that the public needed to practice strict "stay-at-home" policies, others were more concerned about the health of the economy and pushed for reopening. ACF suggests that actors sharing the same policy core beliefs are likely to form coalitions, and dominant coalitions are more likely to translate their goals into policy than minority coalitions (Jenkins-Smith & Sabatier, 2003; Sabatier & Jenkins-Smith, 1988).

Although ACF assumes that policy core beliefs are difficult to change, the framework also acknowledges that policy learning occurs through exposure to new information and new contacts (Grossback et al., 2004). This means politicians' COVID-19 public policy beliefs may gradually evolve and influence their network positions. Politicians are more likely to relay the same messages that are consistent with their own policy beliefs, and such policy positions could change over time. Hence, we propose.

H3. Over time, politicians are more likely to share messages from health agencies that are congruent with their own COVID-19 policy positions on social media.

So far, we have discussed a theoretical framework that could explain political actors' relationship-building behaviors related to policy. However, the COVID-19 is also a public health crisis, which requires politicians to work with health agencies and communicate crisis and risk-related facts. We now turn to the Crisis and Emergency Risk Communication Model.

2.2. Crisis and Emergency Risk Communication on social media

In times of public health crises, public health agencies are expected to effectively convey health risks and threats to individuals and communities, and provide a framework for the public to understand and respond to them (Austin et al., 2012). The Crisis and Emergency Risk

Communication theory (CERC, Reynolds & Seeger, 2005; Seeger et al., 2010; Veil et al., 2008) offers valuable insights on key elements of risk communication. According to CERC, when communicating about public health risks, communicators should help "the public, agencies, and other stakeholders to make sense of uncertain and equivocal situations and make choices about how to manage and reduce the threats to their health" (Veil et al., 2008).

Most importantly, the CERC model argues that reducing uncertainty and improving sensemaking could improve communication outcomes. Uncertainty refers to "having a number of possible alternative predictions or explanations" (Berger & Calabrese, 1975). Uncertainty reduction is the action of increasing the ability to predict and explain ongoing crises (Berger & Calabrese, 1975). Sensemaking is an individual's ability to make sense of their circumstances (Weick, 1995). Uncertainty reduction and sensemaking could be enhanced through the manipulation of communication messages (Reynolds & Seeger, 2005). Guided by CERC, previous literature has examined how leading health agencies engage with the public during the pandemic on social media (Malik et al., 2021). However, how the messages might engage with elite communicators such as politicians is less studied. In this study, we propose that health agencies' messages with linguistic features that may reduce the public's uncertainty and sensemaking may attract more engagement from politicians.

2.2.1. Use of certainty expression

Crisis events concerning public health can place consequential stress and uncertainty on the population. Effective communication from health agencies is critical to aid in the arising threat and uncertainty. The CERC model highlights uncertainty reduction as a key communication goal during the initial event phase and maintenance phase of a crisis. The process should allow the audience to obtain a basic understanding of what happened so that they may act properly (Reynolds & Seeger, 2005). Messages that express high levels of certainty may enhance people's belief in these messages and intentions to adopt the advocated behaviors (Han et al., 2007). As such, elected officials may share messages that express a high level of certainty to help their followers and constituents to better make sense of the crisis. Therefore, we propose.

H4. Politicians are more likely to share messages from health agencies that express higher levels of certainty.

2.2.2. Sensemaking

During crises, messages that encourage sensemaking should help the public understand the scope of a crisis, accommodate the unexpected, and seek relevant information (Weick, 1995). Sensemaking messages as those that "contained information about the number of people infected, the number of deaths, the spread of the virus, vaccine development, and the likelihood of human-to-human transmission" (Vos & Buckner, 2016, p. 304). Sensemaking requires the use of scientific evidence in an analytical and accurate way. For example, in a study that examined how health agencies use Twitter to help publics make sense of H1N1, Vos and Buckner found that tweets containing numerical evidence and analytic language are significantly more likely to be retweeted. As pinpointing the scientific evidence in the tweets in a large-scale corpus is hardy feasible, we choose the use of number as one of the two indicator of sensemaking. As such, we propose that politicians are more likely to retweet health agencies when their messages contain more numbers or analytic language.

H5. Politicians are more likely to share messages from health agencies that use more numbers and analytic words.

3. Method

3.1. Data

Our bipartite (politician-health agency) network was extracted from a large public COVID-19 Twitter dataset (Chen et al., 2020).[1] The data were collected between January 22 and October 31, 2020. We chose this time period because the first COVID cases emerged on January 21. COVID-related topics remained a salient topic on social media until the U.S. presidential election took away its spotlight in early November 2020. Twitter was selected as it is one of the major platforms for politicians and health agencies to communicate with the public (Zhang & Cozma, 2022). To construct the network, we started with a list of 581 U.S. official Twitter accounts of legislators and governors and 83 health agencies including The Centers for Disease Control and Prevention (CDC) and state- and regional-level of public health departments in the U.S. (see Appendix B).[2] Next, we collected all tweets and retweets that originated from the list of politicians and health agencies from the COVID-19 Twitter dataset. A tie was identified when a politician retweeted a message sent by a health agency. The network was directed because we were interested in the formation and dissolution of retweeting behavior.

To examine the longitudinal evolution of the bipartite network, we broke down the network into three periods: 1) January 22 – February 29, 2) March 1 – June 12, and 3) June 13 – October 31. The three periods were divided based on observations of critical events and validated by quantitative network change patterns. To explore network change patterns, we extracted the network on each day and calculated the Jaccard index[3] of every pair of networks in two adjacent days. A shift in the scale of the Jaccard index indicates a statistically significant change in network between two periods. See Appendix C for details of the Jaccard analysis. Fig. 1 shows the pipeline of data processing, which was conducted in R 4.2.3.

We aggregated all ties within each period. If a politician *i* retweeted a health agency *j* during the first period, we defined a tie linked *i* to *j* in the first period. If *i* did not retweet *j* in the second period, there would be no tie between *i* and *j* during the period. Fig. 2 shows the visualization of the retweet networks for three periods (the figures were generated by the Python library Matplotlib). Additionally, we investigated the distribution of ties in our networks and discovered, by and large, the distribution of tie strength is largely sparse. We have included a figure of the distribution of tie strength in Appendix D.

3.2. Measures

3.2.1. Party affiliation

Politicians' political affiliation was extracted from Campaign Finance Institute (2020) . This variable is a categorical variable with 1 = Republican ($N = 272$, 46.8%) and 2 = Democratic ($N = 305$, 52.5%). As we are focusing on party affiliation alignment, we coded third-party ($N = 3$, 0.5%) and nonpartisan ($N = 1$, 0.2%) as missing for better data interpretation.

[1] The COVID-19 Twitter dataset (Chen et al., 2020) contained tweets that are related to coronavirus. Data collection started on January 22, 2020, and is still ongoing as of early March 2021. For the list of 76 keywords and phrases and date for data collection, see Appendix A. The details of data collection and data hydrating can be found on Github repository https://github.com/echen102/COVID-19-TweetIDs. Users need either Hydrator or Twarc to retrieve the original tweets based on the tweet IDs stored on the repository.

[2] The list was compiled from resources including HHS Organizational Chart and State & Territorial Health Department Websites.

[3] The Jaccard index measures the similarity between the successive networks, with a higher Jaccard index signaling more similar structures between two networks (Ripley et al., 2020).

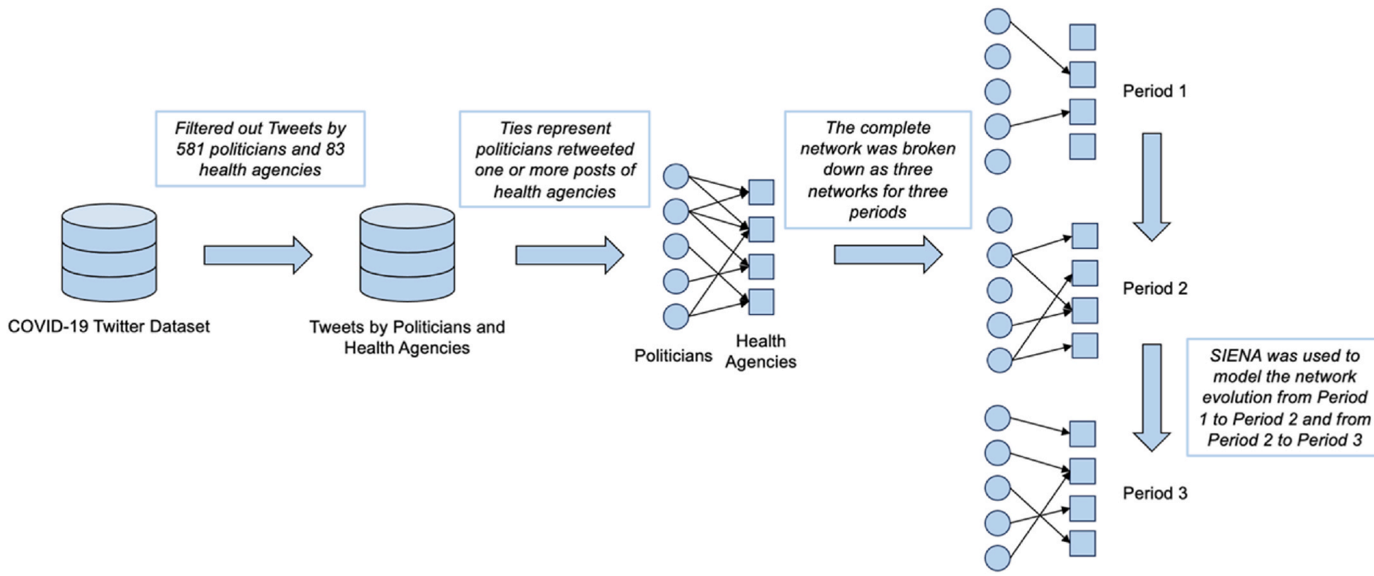

Fig. 1. Data processing pipeline.

3.2.2. Access to resources

This variable include three indicators. ***Political Position.*** *Politicians* were categorized based on their positions as governor or legislators, which included House Representatives and Senators. A dummy variable was created: 1 = Legislator ($N = 531$), 0 = Governor ($N = 50$). ***Level of Jurisdiction.*** *Health agencies* were categorized into four ordinal groups to reflect their level of jurisdiction: 1 = Sub-state ($N = 3$, 3.6%), 2 = State ($N = 48$, 57.8%), 3 = Regional ($N = 10$, 12.0%), 4 = Global or federal ($N = 22$, 26.5%). ***Financial Resources.*** For *politicians*, we obtained raw records of campaign donations they received from the Campaign Finance Institute (2020) . The campaign finance was calculated as the sum of money raised in a politician's most recent election year (2020 excluded). Since the raw number was highly skewed, we performed a log transformation on this variable ($M = 14.73$, $SD = 1.10$). *For health agencies*, we searched for the amount of budget (in billion) for the recent fiscal year. A log transformation was performed on this variable to reduce skewness ($M = -0.06$, $SD = 2.52$). The budget data for the ten regional Offices of the Assistant Secretary for Health (OASH) were missing because they were not publicly available.

3.2.3. Policy position

We examined politicians' and health agencies' policy core beliefs as their policy positions expressed through tweets. Social media can be used to broadcast beliefs and policies and influence followers (Barberá, 2015). Following Kleinnijenhuis and de Nooy (2013), the current study measured policy positions by two steps (details in Appendix E).

3.2.4. Expression of certainty and sensemaking

We measured the three message-level variables applying the Linguistic Inquiry and Word Count (LIWC) 2015. LIWC is a program gauging linguistic and psychological features of texts based on built-in dictionaries (Tausczik & Pennebaker, 2010). Expressions of certainty can be detected through linguistic patterns (Szarvas et al., 2012). Previous research has shown that LIWC can produce a reliable measure of certainty in communication (Himelboim et al., 2020). Therefore, certainty in tweets was measured by the percentage of words reflecting certainty in LIWC's built-in dictionary (e.g., always, never).

Sensemaking is measured by two indicators: (1) use of numbers was calculated as the percentage of numbers in tweets; (2) use of analytic language was measured using LIWC's built-in metric, which captures the extent to which the text contained words reflecting formal and logical thinking (Tausczik & Pennebaker, 2010). Like policy positions, only the first two periods' measures were needed in the SIENA model. Thus the three measures were calculated for period 1 (certainty: $M = 0.27$, $SD = 0.86$; number: $M = 0.80$, $SD = 2.05$; analytical thinking: $M = 35.98$, $SD = 45.11$) and period 2 (certainty: $M = 0.93$, $SD = 1.13$; number: $M = 2.72$, $SD = 2.74$; analytical thinking: $M = 76.76$, $SD = 30.89$).

3.2.5. Covariates

We also controlled for the number of cases per 100 K residents, state unemployment rate, and accounts' Twitter information. ***Number of Cases per 100K Residents.*** As politicians might react accordingly in line with the severity of the pandemic in their jurisdiction, we control for the number of confirmed cases in each state which was retrieved from the Johns Hopkins University Coronavirus Resource Center (2020). This variable was also time-variant and logged due to high skewness. The descriptives for each period were: period 1 ($M = 0.43$, $SD = 0.92$), period 2 ($M = 10.65$, $SD = 1.52$). Since the variable was aggregated at the state level, politicians in the same states shared identical values. ***State Unemployment Rate.*** We used the official unemployment rate from the U.S. Bureau of Labor Statistics (2020). The pandemic has presented serious economic challenges to each state. Relief funding and stimulus checks are all hot debate topics along with the development of COVID-19 response policies. Therefore, we included the unemployment to account for the economic impact potentially due to COVID-19 (Li et al., 2021). The variable was time-variant. The means and standard deviations for each period were: period 1 ($M = 3.55$, $SD = 0.69$), period 2 ($M = 4.37$, $SD = 1.10$). ***Twitter Account Information.*** To control for actors' overall activity on Twitter, we extracted number of followers ($M = 10.56$, $SD = 1.44$) and number of friends ($M = 6.66$, $SD = 1.27$) for each account. These account-related measures can also exert influence over the engagement on Twitter, which is the key outcome element in the current study. The variables were logged due to high skewness.

It is necessary to note that while both ACF and CERC help to identify exogenous variables that could shape the chance of tie formation, MTML recognizes that networks, once form, their evolutions may also be influenced by endogenous variables (also known as structural effects) that are characteristics of relations within the networks (Monge & Contractor, 2003). In our models, we also controlled for important structural effects: politician activity, health agency popularity and transitivity. Fig. 3 illustrates the relationship among the variables especially how different set of variables were derived from ACF, CERC, and social network theory under the guidance of MTML.

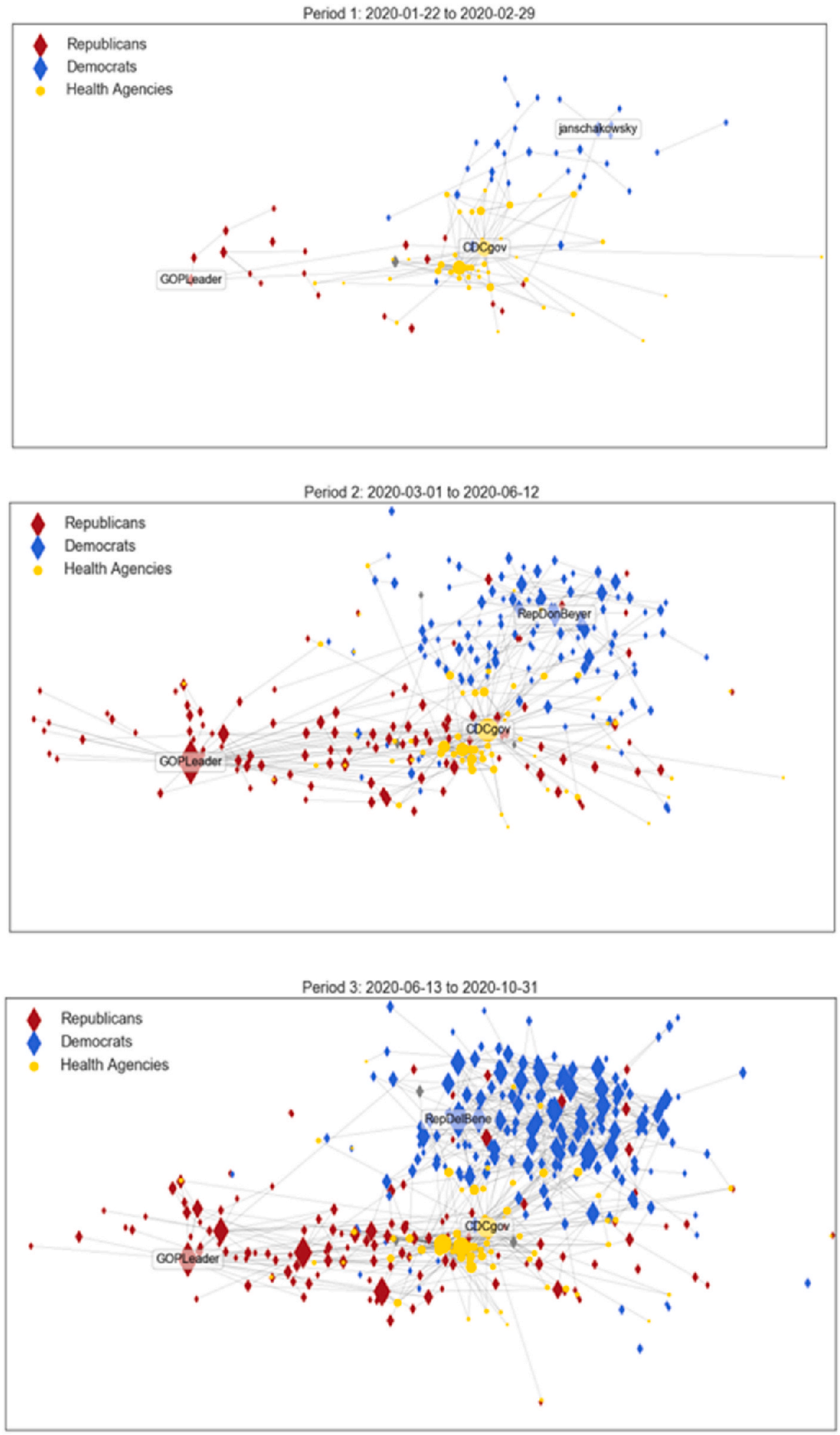

Fig. 2. Politicians-health agencies retweeting networks at three periods in COVID-19 pandemic.

3.3. Analytical procedure

To analyze the longitudinal dynamics in the bipartite network, we employed the Stochastic Actor-Oriented Model (SAOM) in SIENA (Simulation Investigation for Empirical Network Analysis) (Snijders et al., 2010). We chose SAOM for two reasons. First, the model estimates network evolution based on both endogenous structural effects and exogenous actor characteristics. Second, SAOM assumes that actors know each other and can make decisions on tie formation autonomously. This corresponds to the politician-health-agency Twitter network as American politicians actively use Twitter and their attention to public health agencies should have increased during the COVID-19 pandemic. The outcome variables were the three politician-health agency message-sharing networks. In two-mode network analysis, only

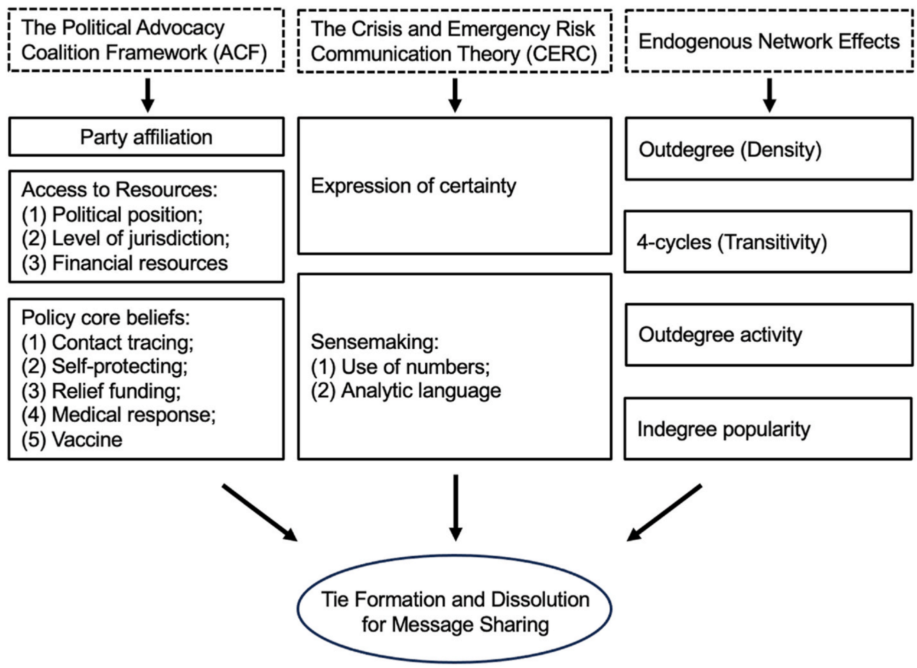

Fig. 3. Variables derived from ACF, CERC, and social network theory under the MTML framework (control variables omitted).

one type of actor can change the outgoing ties. In our case, only the politicians could send out ties (i.e., retweet messages from health agencies on Twitter). Please see Appendix F for details about our model specification. The R package RSiena (Ripley et al., 2020) was used to simulate and estimate the models.

4. Results

4.1. Network descriptives and endogenous network effects

The three networks each contained the same 664 actors (581 politicians and 83 health agencies). The density of the networks rose from period 1 to period 2, and increased slightly from period 2 to period 3 (period 1 = 0.002; period 2 = 0.005; period 3 = 0.006). Average degrees showed a similar pattern (period 1 = 0.151; period 2 = 0.456; period 3 = 0.535), so did the number of ties (period 1 = 88; period 2 = 265; period 3 = 311). These results suggest that the interactions over COVID-19 related topics between health agencies and politicians increased as the COVID-19 situation in the U.S. worsened. Furthermore, tie change patterns demonstrated that the distances and Jaccard indices between periods also climbed over time (period 1 - > period 2: distance = 275, Jaccard = 0.124; period 2 - > period 3: distance = 358, Jaccard = 0.233). This indicates that the message-sharing networks of the three periods have notable changes.

Table 1 summarized the results of our SIENA models, with Model 1 reporting results testing the ACF framework (H1 to H3) and Model 2 displaying results testing the CERC framework (H4 and H5). The full model combining both frameworks is reported in Model 3. The overall maximum convergence ratios for all models were smaller than 0.18 and the convergence of t-ratios for all reported estimates were smaller than 0.03 in absolute values, suggesting excellent convergence for all models (Ripley et al., 2020). Wald-type tests for joint significance were also performed. Overall, the significant chi-square statistics for the models provided strong evidence that the network dynamics between politicians and health agencies on Twitter depended both on the endogenous network effects and exogenous covariates informed by ACF and CERC.

The significant and positive rate parameters suggested that, on average, there were more changes in how politicians shared messages from health agencies during period 1 than in period 2. The outdegree density parameters were negative across all models, suggesting that politicians generally did not retweet health agencies. Three structural effects were significant across models. The significant 4-cycles (transitive closure) effect showed that retweeting behaviors by other politicians would affect how connected politicians retweet health agencies. Both indegree popularity and outdegree activity effects were significant, demonstrating “the richer get richer effect” in tie formation. In addition, the inclusion of the three endogenous effects improved our models' good-of-fit compared with the null model (See Appendix G).

4.2. Hypothesis testing

H1 proposed that politicians from the same party would share the messages from the same health agencies. We tested this hypothesis using the ego-in-alter distance 2 similarity parameter (*simEgoInDist2*), which measured if politicians with the same party affiliation tended to retweet the same health agency. This is similar to homophily effects in one-mode networks. The positive and significant ego-in-alter distance 2 effect supported H1 (Table 1 Model 1), showing that politicians retweeted the same health agencies as others from their own party did.

H2 hypothesized that the financial resources were predictive of tie formation. According to Table 1 Model 1, there was no significant effect for the amount of campaign finance of a politician; H2a is rejected. However, the amount of annual budget for health agencies significantly predicted network ties formation, indicating that health agencies with more financial resources were preferred by politicians on Twitter. Thus H2b was supported.

Our RQ asked how actors' political positions affected tie formation. We found that being a House representative or Senator decreased the odds of retweeting a health agency while governors are more likely to share messages from health agencies. For the health agencies, the level of jurisdiction was significantly associated with the chance of being retweeted. Local health agencies were more likely to be retweeted compared with state and national agencies. These patterns revealed a tendency towards local clustering, where state governors were more likely to retweet local health agencies whereas national-level agencies were less retweeted by politicians.

H3 postulated that politicians' are more likely to share messages from the health agency with congruent COVID-19 policy positions. We

Table 1
Estimated stochastic actor-based models for two-mode network (politicians = 581, health agencies = 83, periods = 3)[a].

	Model 1 (ACF)		Model 2 (CERC)		Model 3 (Full)	
Effects	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
Rate function						
Rate (period 1)	2.379***	.293	2.468***	.357	2.787***	.437
Rate (period 2)	2.228***	.183	2.699***	.268	2.203***	.181
Endogenous network effects						
Outdegree (density)	−6.353***	.168	−6.171***	.163	−6.541***	.173
4-cycles	.061***	.024	.062***	.015	.060*	.015
Outdegree activity	.462***	.050	.281***	.044	.394***	.045
Indegree popularity	.019***	.003	.014***	.002	.015***	.002
Exogenous network variables: ACF						
Party affiliation homophily	1.534***	.197			1.643***	.211
Politician resources						
Campaign finance	.044	.057			.026	.056
Political position	−.858***	.192			−.826***	.186
Health agency resources						
Level of jurisdiction	−.634***	.118			−.335***	.131
Budget	.105***	.022			.066***	.020
Politicians $\times$ health agency policy position						
Contact tracing	1.951*	.892			1.943*	.912
Self-protection	1.474*	.654			1.173*	.591
Relief funding	1.043*	.410			.845*	.382
Medical response	1.323	.810			1.000	.747
Vaccine	2.580*	1.125			2.240*	1.020
Exogenous network variables: CERC						
Health agency						
Certainty			.301***	.075	.297***	.078
Use of Numbers			.001	.024	−.026	.024
Analytics			.024***	.005	.025***	.004
Politician						
Certainty			−.022	.062	−.045	.064
Use of Numbers			.024	.027	.007	.030
Analytics			.002	.004	.006**	.002
Covariates: Politician						
COVID-19 case	−.025	.042	−.100**	.039	−.092*	.046
Unemployment rate	.147*	.061	.171**	.063	.152*	.061
Twitter followers	.049	.051	−.148**	.051	.054	.051
Twitter friends	.261***	.049	−.081	.055	.252***	.048
Covariates: Health agency						
COVID-19 case	−.055	.040	−.025	.035	.019	.042
Unemployment rate	.113	.074	.108	.066	.084	.071
Twitter followers	.589***	.057	.308**	.045	.461***	.052
Twitter friends	−.336***	.069	−.304***	.070	−.312**	.064
Wald χ^2 statistics (*df*)	162.65***(9)		20.96***(3)		210.75***(16)	

Note: ***$p < .001$, **$p < .010$, *$p < .050$, †$p < .100$.
[a] Convergence *t*-ratios for all effects $< |0.03|$.

tested this hypothesis on five core policies: policies related to 1) contact-tracing, 2) self-protection, 3) relief funding, 4) medical response, and 5) vaccination. An interaction term between the policy belief of politicians (*egoX*) and that of health agencies (*alterX*) was added for each of the policies (Table 1 Model 1). A positive interaction score means politicians were more likely to retweet the messages from health agencies with a similar position on the same policy. The results suggested that the similarity of core beliefs in all policies, except for medical response, were significant and positive predictors of politicians' retweeting of health agencies. Therefore, H3 was supported.

Results showed that ACF theory could explain the dynamics of retweeting network evolution. The parameters could be interpreted in probabilistic terms (Ripley et al., 2020). A density coefficient of −6.353 suggested that the baseline conditional probability of a politician retweeting a health agency was 0.002. The similarity of positions on vaccine-related policies had the strongest effect, which increased the chance of message sharing by a politician from 0.002 to 0.022. We also found that legislators tended not to retweet health agencies compared to governors (estimate = −0.858, $p < .001$) while health agencies at the local-level (estimate = −0.643, $p < .001$) or with larger amount of budget (estimate = 0.105, $p < .001$) were more likely to be retweeted.

Table 1 Model 2 presents the results of testing H4 and H5. Supporting H4, results, suggested that health agencies with higher levels of expression of certainty (estimate = 0.301, $p < .001$) tended to be retweeted. H5 tested if the use of numbers and analytical words in messages promoted politicians' message sharing. The results lent partial support to H5. Using numbers when talking about COVID-19 was not significantly associated with politicians' message sharing (estimate = 0.001, $p > .050$). Yet, health agencies with more analytical tones in their message garnered more retweets from politicians (estimate = 0.024, $p < .001$).

Informed by the MTML framework, variables from both ACF and CERC were further integrated into one full model (Table 1 Model 3). The results remained consistent with previous models but the model explained more variance, suggesting that ACF and CERC provide a complementary explanation to account for the dynamics of the message sharing network.

5. Discussion

In this study, we propose a multi-theoretical and multi-level (MTML) framework to explain communication processes centered around a politicized public health crisis. Specifically, we focus on U.S. politicians' sharing of health agencies' messages on Twitter during the COVID-19 pandemic as an example. Bringing together insights from the advocacy coalition framework (ACF) (Jenkins-Smith & Sabatier, 2003; Sabatier &

Jenkins-Smith, 1988) and the Crisis and Emergency Risk Communication (CERC) framework (Veil et al., 2008), we conceptualized that politicians' message-sharing behaviors are driven by the dual process of advancing their policy interests and dutifully conducting risk communication.

Recent studies have embarked on explaining how the public receive and share information from governmental agencies, politicians, and public health agencies during the pandemic (Kim et al., 2021; Li et al., 2022; Malik et al., 2021; Zhou et al., 2022). However, we know little about how elite communicators such as politicians share information from health agencies. Our study fills this research gap by revealing that politicians' message-sharing behaviors are explained by policy advocacy and risk communication at the same time. A summary of the results can be found in Table 2.

5.1. Fractured policy advocacy during COVID-19

Overall, the bipartite network containing U.S. politicians and health agencies illustrated a structural tendency of the political divide and state-level clustering. The political divide is driven both by divergence in politicians' party affiliations and COVID-19 response policies. In terms of party affiliation, our analysis reveals a significant tendency for politicians to share messages from health agencies with whom their in-group partisans have established retweeting ties. This pattern of retweets contributes to the formation of distinctive information sources and distribution networks that distinguish different public policy coalitions. This result resonates with findings from Zhou et al. (2023), which suggests U.S. politicians largely politicized the discourse about COVID-19 vaccine on social media. Given that the ideological divide in local politics can sway public engagement of vaccine information (Zhou et al., 2022), the partisan information sharing may also influence public engagement of policy communication.

Consistent with predictions derived from ACF (Jenkins-Smith & Sabatier, 2003; Sabatier & Jenkins-Smith, 1988), we found that politicians' position in COVID-19 response policies could significantly drive their message-sharing patterns. Specifically, we identified five major policies: contact tracing policies, self-protection policies, government funding policies, medical response policies, and vaccine development and rollout policies. With the exception of medical response policies, we found agreement on most of these policies drives tie formation. In other words, politicians agreeing with health agencies on those policies are more likely to retweet their messages, likely using health agencies' messages as evidence to support their own policy positions. Although ACF has been widely supported by studies looking at politicians' voting patterns (Heaney & Rojas, 2008; Pierce et al., 2017; Weible, 2005), to our best knowledge, this is the first study to demonstrate the influence of politicians' policy positions on their social-mediated communication patterns. This finding contributes new insights into our understanding of the political divide among politicians. That is, the observed political divide on social media is not simply driven by dichotomized ideological differences but also fuelled by nuanced disagreement on various public policies.

Table 2
Summary of results.

Hypotheses or Research Question	Results
H1: Politicians are more likely to share messages from health agencies if those agencies' tweets were retweeted by politicians of the same party than those of a different party.	Supported
H2a: Politicians with more financial resources are more likely to share messages from health agencies.	Rejected
H2b: Politicians are more likely to share messages from health agencies that possess more financial resources.	Supported
RQ: How do politicians with different political positions share messages from health agencies with different levels of jurisdictions?	Governors more likely to retweet; local agencies were more likely to be retweeted.
H3: Over time, politicians are more likely to share messages from health agencies that are congruent with their own COVID-19 policy positions on social media.	Supported
H4: Politicians are more likely to share messages from health agencies that express higher levels of certainty.	Supported
H5: Politicians are more likely to share messages from health agencies that use more numbers, statistics, and analytic words.	Partially supported

Importantly, we also observed that the network tends to cluster around state-level actors. What we mean here is that not only state-level health agencies are more likely to get retweeted, state governors, in comparison to legislators, are also most likely to retweet health agencies in general. Moreover, among health agencies with different jurisdictions, local and state-level health agencies are far more likely to be retweeted, controlling for state-level COVID-19 financial impact (i.e., unemployment) and case numbers per capita. This result is particularly important as previous research also found that the COVID-19 vaccine communication is politicized differently across government agencies' jurisdiction levels (Zhou et al., 2023). This may reflect the different functions these politicians serve in the U.S. political system. While governors mainly serve as the heads of the executive branch of each state, senators (representing whole states) and congressmen/women (representing districts) serve the legislative branch. As such, it makes sense that the governors were more likely to share information from health agencies as a function of their offices. Our results thus offer a more nuanced understanding of information sharing pattern among politicians beyond treating them as a homologue in previous research (Zhou et al., 2023).

In addition, in the U.S, there is a deep-rooted anti-federalist sentiment that dates back to the founding days of the nation (Cornell, 1990). While the phenomenon is understandable, it presents considerable challenges to the handling of a pandemic for two reasons. First, the COVID-19 virus does not respect state boundaries. The lack of coordinated responses may continue to create inconsistencies in public health policies and create hot spots for transmission. Second, federal-level health agencies such as CDC have access to considerable scientific information and up-to-date knowledge on variants of the virus and vaccines, and response measures. However, we found that federal-level health agencies did not appear to be retweeted by politicians from different states. For federal-level health agencies' messages to fall through the cracks of information diffusion, it may delay speedy responses to emerging epidemic conditions. As such, policy-makers may consider certain levels of mandate that require elected officials to retweet federal level health agencies in the current and future national health crises.

5.2. Risk communication during COVID-19

To further look at what type of health agencies' messages were more likely to be shared, we draw from the CERC (Veil et al., 2008), and examined linguistic features of messages that drove politicians' retweets. According to CERC, messages that contain a higher level of certainty or use more numbers and scientific evidence may help to boost the public's certainty and sensemaking. Consistent with previous literature (Malik et al., 2021), our analysis showed that both linguistic features that allow uncertainty reduction and sense-making were powerful predictors for politicians' messages sharing behavior over time. Importantly, the use of analytic language is likely to be shared by politicians, which may further help mitigate the negative impact of emotion in discerning accurate scientific information during crisis (Li et al., 2022).

Consistent with previous risk communication research (Austin et al., 2012), we found that message linguistic features could elicit different responses. While previous studies tend to focus on the general public's responses to only a few leading health agencies (Malik et al., 2021), our study examined politicians' retweeting behaviors with a wide range of health agencies. Our finding has implications for future health agencies' social-mediated crisis and risk communication. Since politicians will continue to command considerable influence on social media and the public, public health agencies should proactively incorporate message features that drive politicians' retweets and leverage their influence to reach out to the public who are concerned about misinformation in risk communication context (Zhang & Cozma, 2022).

5.3. Conclusion, limitations, and future research

An important contribution of our study is that we illustrate that the complexity of social crisis requires social scientists to adopt more holistic theoretical angles by removing arbitrary boundaries between subfields of social science, and bring relevant theories together in a meaningful way. Using the current study as an example, ACF emphasizes power dynamics in the policy communication process. Meanwhile, public policy communication often deals with and is informed by knowledge and expertise from scientific domains such as medical science. The original ACF thus could not adequately explain how concerns for the publics' understanding of risk would play a role in the process of public policy communication. On the other hand, the CERC framework focuses on the ideal component of risk communication, with the assumption that government agencies and politicians would work seamlessly to communicate effective messages. However, the realities of the COVID-19 pandemic remind us that public health messages are often influenced by political considerations in public policy communication.

By integrating the two theories under MTML, we conceptualize the politicalized health risk communication as a process where considerations for political interests and public health both shape network formation and evolution. The process involves message framing and dissemination. While public health agencies' institutional logic imprint their messages, once such messages enter the networks of politicians, the dual logic of policy coalition advocacy and risk communications both shape how far and where such messages disseminate in political networks. The integrated framework thus reveals insights neither theory could fully provide. It is important to note that our proposed framework is not only useful for analysing the previous pandemic, but could be applied to studies of future COVID-19 waves or other types of major societal crises because similar dual logic may continue to govern how politicians communicate.

Our study has limitations. Our sample focused on politicians' retweets of health agencies. It is likely that politicians also share health agencies' messages on other platforms. With additional data collected from multiple platforms, future studies may examine if communication patterns show differences across platforms. Though we focused on the early stage of the pandemic, the proposed theoretical framework and method is applicable to later COVID-19 waves once additional data is available. Moreover, we only studied message senders' behaviors without considering how the publics may respond to politicians' tweets. Future studies may adopt multiple perspectives and compare if the publics' responses differ when they receive similar messages from different politicians, and if a coordinated communication approach could improve communication outcomes. In short, the COVID-19 pandemic has laid bare many problems in the current political and public health communication system. Continued research is needed to identify existing issues and provide recommendations for coping with future challenges.

Credit author statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The link to the dataset has been shared in the paper.

Appendix A

Keywords and Added Date for Data Collection on Twitter[4]

Coronavirus 1/28/2020	Social Distancing 3/13/2020	staysafestayhome 3/18/2020
Koronavirus 1/28/2020	SocialDistancing 3/13/2020	stay safe stay home 3/18/2020
Corona 1/28/2020	panicbuy 3/14/2020	trumppandemic 3/18/2020
CDC 1/28/2020	panic buy 3/14/2020	trump pandemic 3/18/2020
Wuhancoronavirus 1/28/2020	panicbuying 3/14/2020	flattenthecurve 3/18/2020
Wuhanlockdown 1/28/2020	panic buying 3/14/2020	flatten the curve 3/18/2020
Ncov 1/28/2020	14DayQuarantine 3/14/2020	china virus 3/18/2020
Wuhan 1/28/2020	DuringMy14DayQuarantine 3/14/2020	chinavirus 3/18/2020
N95 1/28/2020	panic shop 3/14/2020	quarentinelife 3/19/2020
Kungflu 1/28/2020	panic shopping 3/14/2020	PPEshortage 3/19/2020
Epidemic 1/28/2020	panicshop 3/14/2020	saferathome 3/19/2020
outbreak 1/28/2020	InMyQuarantineSurvivalKit 3/14/2020	stayathome 3/19/2020
Sinophobia 1/28/2020	panic-buy 3/14/2020	stay at home 3/19/2020
China 1/28/2020 4/24/2020	panic-shop 3/14/2020	stay home 3/19/2020

(*continued on next page*)

[4] Retrieved from: https://github.com/echen102/COVID-19-TweetIDs/blob/master/keywords.txt.

(*continued*)

Coronavirus 1/28/2020	Social Distancing 3/13/2020	staysafestayhome 3/18/2020
covid-19 2/16/2020	coronakindness 3/15/2020	stayhome 3/19/2020
corona virus February 3, 2020	quarantinelife 3/16/2020	GetMePPE 3/21/2020
covid June 3, 2020	chinese virus 3/16/2020	covidiot 3/26/2020
covid19 June 3, 2020	chinesevirus 3/16/2020	epitwitter 3/28/2020
sars-cov-2 June 3, 2020	stayhomechallenge 3/16/2020	pandemie 3/31/2020
COVID—19 August 3, 2020	stay home challenge 3/16/2020	wear a mask 6/28/2020
COVD December 3, 2020	sflockdown 3/16/2020	wearamask 6/28/2020
pandemic December 3, 2020	DontBeASpreader 3/16/2020	kung flu 6/28/2020
coronapocalypse 3/13/2020	lockdown 3/16/2020	covididiot 6/28/2020
canceleverything 3/13/2020	lock down 3/16/2020	COVID_19 September 7, 2020
Coronials 3/13/2020	shelteringinplace 3/18/2020	
SocialDistancingNow 3/13/2020	sheltering in place 3/18/2020	

Appendix B

We composed a list of health agencies and their official Twitter handles (see Appendix-Table 1), including one international agency World Health Organization and 83 U.S. agencies. The U.S. agencies are divided into four levels: sub-state, state, regional, and federal.

As for the sub-state and state levels, we identified one health agency for each state and Washington D.C. according to two resources (CDC, 2020; Ensign, 2019). If an agency has the highest jurisdiction regarding the state's health decisions, it was coded as state level; otherwise, it was coded as sub-state level. When two different health agencies were identified for the same state, we decided to include the one with higher jurisdiction. For example, when the New Hampshire Department of Health and Human Services and its Division of Public Health Services were both selected and active on Twitter, the latter one was excluded given the lower jurisdiction. However, there is one exception where we included the Maine Center for Disease Control and Prevention (Maine CDC) instead of the Maine Department of Health and Human Services (Maine DHHS) for the reason that Maine CDC was much more active (more followers and tweets in total) and shared more COVID-19 relevant information than the Maine DHHS on Twitter. In this case, the Maine health agency was coded as sub-state level.

As for regional and federal levels, we included the U.S. Department of Health and Human Services and all COVID-19 relevant organizations under its umbrella when official Twitter accounts existed (HHS Digital Communications Division, 2008). The exclusion criteria are: (1) not directly relating to COVID-19 (i.e., Agency for Toxic Substances and Disease Registry), (2) involving no public engagement responsibility (i.e., Assistant Secretary for Administration). More than one Twitter handle was kept on our list depending on representativeness and relevancy for salient organizations like the Centers for Disease Control and Prevention (CDC). In the CDC case, we included its official Twitter source @CDCgov and the handle for its Center for Preparedness and Response (CPR), @CDCemergency.

List of Health Agencies

No.	Twitter Account ID	Health Agencies	Level
1	146,569,971	Centers for Disease Control and Prevention (CDC)	Federal/Global
2	15,134,240	National Institutes of Health (NIH)	Federal/Global
3	24,959,108	Substance Abuse and Mental Health Services Administration	Federal/Global
4	44,034,613	Health Resources and Services Administration (HRSA)	Federal/Global
5	44,783,853	Department of Health & Human Services (HHS)	Federal/Global
6	44,957,814	Agency for Healthcare Research and Quality (AHRQ)	Federal/Global
7	455,024,343	Surgeon General (Head of United States Public Health Service Commissioned Corps) PHSCC	Federal/Global
8	911,306,494,536,224,000	Indian Health Service (IHS)	Federal/Global
9	14,499,829	WHO	Federal/Global
10	138,530,516	Office of Disease Prevention and Health Promotion (ODPHP)	Federal/Global
11	538,456,752	Office of the Assistant Secretary for Health (OASH)	Federal/Global
12	137,450,696	Office of the Assistant Secretary for Preparedness and Response (ASPR)	Federal/Global
13	208,120,290	Food and Drug Administration (FDA)	Federal/Global
14	59,769,395	National Institute of Allergy and Infectious Diseases (NIAID)	Federal/Global
15	106,895,787	National Library of Medicine (NLM)	Federal/Global
16	70,837,868	Centers for Medicare & Medicaid Services (CMS)	Federal/Global
17	820,236,583	Administration for Community Living (ACL)	Federal/Global
18	1,337,539,945	Administration for Children and Families (ACF)	Federal/Global
19	2,827,049,413	Office for Civil Rights (OCR)	Federal/Global
20	291,759,889	Office of Inspector General (OIG)	Federal/Global
21	39,250,316	National Institute of Mental Health (NIMH)	Federal/Global
22	108,638,625	Office of the National Coordinator for Health IT (ONC)	Federal/Global
23	2,363,238,127	HHS-Region 5 Chicago	Regional
24	2,910,903,323	HHS-Region 3 Philadelphia	Regional
25	3,177,403,355	HHS-Region 10 Seattle	Regional
26	407,228,333	HHS-Region 1 Boston	Regional
27	414,860,556	HHS-Region 7 Kansas City	Regional
28	418,859,255	HHS-Region 4 Atlanta	Regional
29	426,033,838	HHS-Region 8 Denver	Regional
30	431,100,994	HHS-Region 9 San Francisco	Regional
31	460,473,395	HHS-Region 2 New York	Regional
32	460,534,166	HHS-Region 6 Dallas	Regional
33	1,019,591,965,766,119,425	Wyoming Department of Health	State
34	111,630,094	Arkansas Department of Health	State

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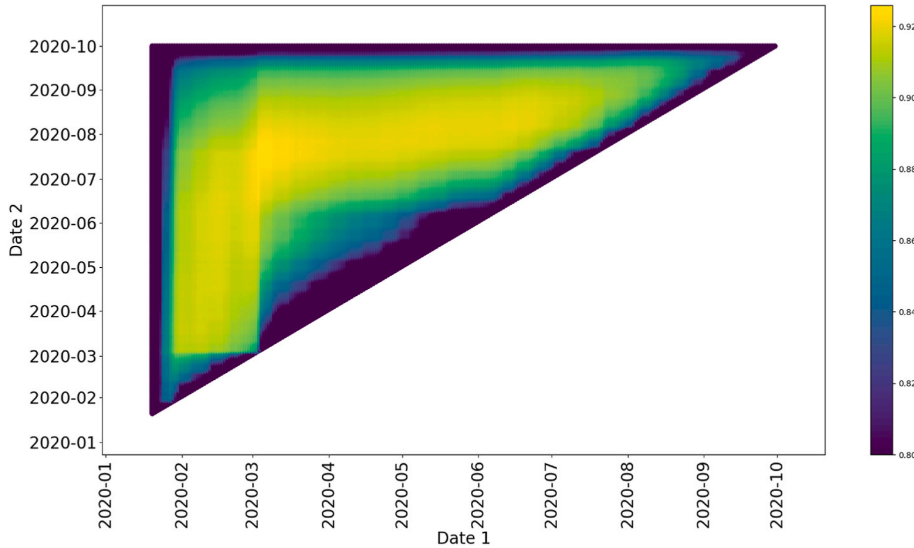
No.	Twitter Account ID	Health Agencies	Level
35	117,793,973	District of Columbia Department of Health	State
36	123,926,499	New York State Department of Health	State
37	1,465,196,934	New Mexico Department of Health	State
38	151,175,266	Oregon Health Authority, Public Health Division	Sub-State
39	16,100,741	Mississippi State Department of Health	State
40	1,667,792,120	North Carolina Department of Health and Human Services	State
41	16,952,753	Arizona Department of Health Services	State
42	176,892,371	Louisiana Department of Health	State
43	188,369,254	Virginia Department of Health	State
44	19,797,326	Alaska Department of Health and Social Services	State
45	209,599,290	South Carolina Department of Health and Environmental Control	State
46	2,339,177,324	Kentucky Department for Public Health	State
47	2,353,731,720	West Virginia Department of Health and Human Resources, Bureau for Public Health	Sub-State
48	23,711,785	Massachusetts Department of Public Health	State
49	25,149,628	Minnesota Department of Health	State
50	252,114,970	New Jersey Department of Health	State
51	2,535,616,304	South Dakota Department of Health	State
52	26,042,513	New Hampshire Department of Health and Human Services	State
53	61,562,609	Maine Department of Health and Human Services, Center for Disease Control and Prevention	Sub-State
54	293,028,988	Wisconsin Department of Health Services	State
55	296,814,488	Florida Department of Health	State
56	318,509,758	Idaho Department of Health and Welfare	State
57	3,218,464,527	Pennsylvania Department of Health	State
58	323,311,059	Alabama Department of Public Health	State
59	325,113,018	Georgia Department of Public Health	State
60	331,244,103	Colorado Department of Public Health and Environment	State
61	33,934,492	California Department of Public Health	State
62	35,239,459	Rhode Island Department of Health	State
63	35,789,875	Connecticut State Department of Public Health	State
64	35,820,178	Vermont Department of Health	State
65	36,099,461	Utah Department of Health	State
66	36,790,269	Iowa Department of Public Health	State
67	3,996,166,572	Montana Department of Public Health and Human Services	State
68	44,961,877	Maryland Department of Health	State
69	454,138,567	Oklahoma State Department of Health	State
70	47,356,175	Delaware Division of Public Health	Sub-State
71	57,338,289	Michigan Department of Health and Human Services	State
72	584,069,282	Indiana State Department of Health	State
73	59,545,968	Washington State Department of Health	State
74	65,677,968	Nebraska Department of Health and Human Services	State
75	68,412,042	Texas Department of State Health Services	State
76	70,775,228	Kansas Department of Health and Environment	State
77	71,652,085	Illinois Department of Public Health	State
78	76,761,964	Missouri Department of Health and Senior Services	State
79	78,450,167	Hawaii State Department of Health	State
80	815,379,032	North Dakota Department of Health	State
81	84,678,363	Tennessee Department of Health	State
82	90,422,822	Ohio Department of Health	State
83	910,239,254,894,088,192	Nevada Division of Public and Behavioral Health	Sub-State

Appendix C

Jaccard Indices Based on Two Breakpoints.

Note. X-axis represents the two-mode Twitter messaging sharing network in the preceding day, and the y-axis indicates the network in the following day. Yellow colors signal larger shifts in Jaccard Indices, which indicates significant changes between successive networks.

We used March 1 as the first time point to break down our network because CDC announced the state of emergency after the first fatal COVID-19 case in the United States on that day (CDC, 2020). This choice is supported by a large increase in the Jaccard index that occurs around the date. The Jaccard index stayed relatively stable after March 1 until it started to drop on June 12, which was chosen as our second breakpoint for our network analysis. Starting from June 13, new infections surged and the second peak in COVID-19 cases emerged (CDC, 2020). These breakpoints are consistent with temporal locations identified in studies that utilized the same dataset, investigating the 2020 USA Elections (Chang et al., 2022).



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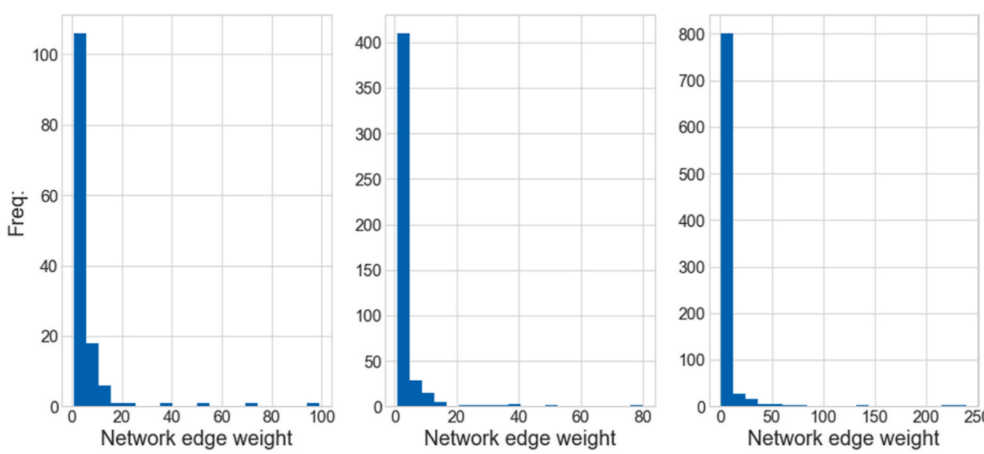
Appendix D

Distribution of tie strengths across three periods.

Since the three waves vary in length, we also calculated daily interaction volumes in each network to provide a direct comparison of the connectivities in the three networks: Wave 1 (37 days): 687 total interactions, 136 unique interactions, 18.56 tweets per day. Wave 2 (106 days): 1361 total interactions, 470 unique interactions, 12.84 tweets per day. Wave 3 (141 days): 5218 total interactions, 872 unique interactions, 37.01 tweets per day.



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Appendix E

Policy position.

Following Kleinnijenhuis and de Nooy (2013), the current study measured policy positions by two steps. First, we applied topic modeling with Latent Dirichlet Allocation (Blei et al., 2003) to extract topics from tweets in our example. We identified five major policies discussed by politicians in their tweets: policies related to 1) contact-tracing; 2) self-protection (e.g. social distancing and mask mandates); 3) relief funding, 4) medical response (e.g. supplying testing kits and personal protective equipment (PPE) for healthcare professionals), and 5) vaccination. To avoid missing any significant policies related to COVID-19, we also created a bigram of words co-occurrence and manually checked the word pairs that occurred more than 10 times in our dataset. The five policies were covered by the bigram list and no additional policies were identified. Then, we built a policy dictionary based on the LDA results and the bigram list. A tweet was assigned to a policy or multiple policies if it hits one or more keywords of the policy category/categories. The dictionary can be found in Appendix-Table 2.

Keywords and Descriptive Statistics of Policy Positions

Policies	Keywords	Period 1			Period 2		
		N	*Mean*	*SD*	*N*	*Mean*	*SD*
Contact tracing	“contact tracing”, “in contact with”, “contact tracer”, “been exposed”, “monitor your health”, “monitor your symptoms”, “seek medical care”, “signs and symptoms”, “close contact"	12	0.16	0.46	50	0.11	0.54
Self-protection	“stay-at-home”, “stay home”, “away from others”, “social distancing”, “keep distance”, “physical distancing”, “six feet”, “6 feet”, “avoid crowds”, “nonessential travel”, “avoid travelers”, “self-isolate”, “self-quarantine”, “avoid contact”, “quarantine”, “avoid travel”, “recently returned”, “hygiene”, “avoid touching nose”, “touch mouth”, “hand sanitizer”, “wash hand”, “mask”, “wear a mask”, “wear masks”, “cover cough”, “cover sneeze”, “cover”, “throw used tissues”, “disinfect”, “take your temperature”, “wear glove”, “cloth face covering”, “surgical mask”, “n95 mask”, “preventive measures”, “precautions”, “protect yourself”, “fresh air”, “ventilate"	37	0.06	0.46	194	0.23	0.47
Relief funding	“emergency funding”, “funding”, “funds”, “federal fund”, “bill”, “money”, “supplemental funding”, “relief package”, “relief fund”, “stimulus package”, “stimulus check”, “paycheck”, “unemployment insurance”, “unemployment benefits”, “unemployment aid”, “healthcare insurance”, “insurance coverage”, “health insurance”, “direct payments”, “recovery grants”, “financial assistance”, “assistance program”, “response package”, “CARES Act”, “HEROES Act”, “TRACE Act”, “ENCORES Act”, “HEALS act”, “resource”, “economic security”, “defer tax”, “financing”, “SNAP”, “affordable”, “financial support”, “cover the cost"	35	−0.04	0.57	267	0.24	0.43
Medical response	“test”, “get tested”, “getting tested”, “testing”, “community testing”, “testing kits”, “testing sites”, “screening”, “diagnostics”, “diagnostic test”, “personal protective equipment”, “PPE”, “ventilator”, “ICU”, “equipment”, “medical supplies”, “frontline”, “health professionals”, “nurses”, “healthcare professionals”, “monitor”, “first responder”, “long term care”, “longtermcare”, “contact tracing”, “swab"	62	0.13	0.32	264	0.30	0.40
Vaccination	“vaccine”, “antibody”, “vaccinations”, “treatment”, “immune”, “mRNA”, “viral vector”, “vector vaccine”, “BioNTech”, “Fosun Pharma”, “Pfizer”, “Moderna”, “NIAID”, “dose”, “shot”, “clinical trials”, “Phase 3″, “AstraZeneca”, “Janssen”, “Novavax"	17	0.10	0.50	69	0.30	0.40

Next, we performed sentiment analysis using VADER (Valence Aware Dictionary for Sentiment Reasoning) on tweets related to the aforementioned policies. VADER is a dictionary-based sentiment method commonly applied by researchers (Hutto & Gilbert, 2014). The score ranged from −1 to +1 with positive scores indicating a more positive attitude on a certain policy. If a node (i.e., a politician or health agency) had multiple tweets about the same policy, the sentiment scores for each tweet were averaged to reflect the general attitude of the node toward that policy. If a node did not mention a policy, we coded the variable's policy position as missing. Note that nodes' policy positions may change across the time periods. When there are changing explanatory variables across different time periods, SIENA model uses the value of the variable in the preceding period to predict the network change in the following period (Ripley et al., 2020). Because we have three time periods in the analysis, only policy positions in the first two periods were measured. In general, politicians and health agencies talked more about policies responding to COVID-19 with more positive attitudes in period 2 than in period 1.

Appendix F

Model specification.

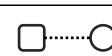
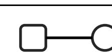
We used the function below to estimate the effects of both endogenous and exogenous effects as a linear combination of the probability of the network change at the level of the focal actors:

$$f(x_{ij}) = \sum_k \beta_k s_{ijk}(x_{ij}) + \sum_l \beta_l e_{il}(x_{ij}) + \sum_m \beta_m \alpha_{jm}(x_{ij}) + \varepsilon \tag{1}$$

where k, l, and m were the number of parameters β, s were the structural effects, e represented the effects of politicians' characteristics of politicians, α represented the effects of health agencies' attributes, and ε was a random error term. A significant β suggests that the network tends to change in direction with its corresponding effect (Snijders et al., 2010). For simplicity, the rate and density effects were omitted in the function as they were included in the model as baseline parameters akin to the intercept of a traditional regression model (Ripley et al., 2020). The rate effect for each period specified the frequency at which politicians retweeted health agencies. The outdegree density parameter captured the general propensity for politicians to retweet health agencies.

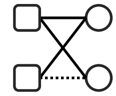
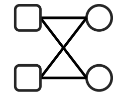
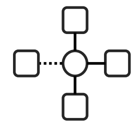
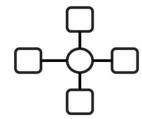
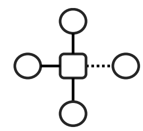
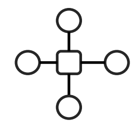
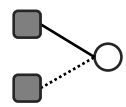
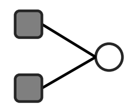
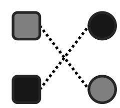
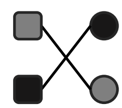
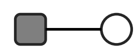
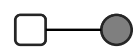
Though not hypothesized, we also included three common network structural effects in the model. Transitive closure (4-cycles) measured whether retweeting the same health agency increases the chance of a pair of politicians retweeting more health agencies together in the future. Indegree popularity measured the tendency that a popular health agency retweeted by many politicians retweeting attracted other politicians to retweet it. Outdegree activity measured the tendency that a politician actively retweeted many health agencies. The exogenous variables, or network effects driven by attributes of politicians and health agencies explained above, were added in the model for hypothesis testing. Table 3 summarizes all the effects, and their configurations and mathematical definitions in our model.

Summary of Endogenous Local Network Effects and Exogenous Actor-Specific Covariates

Parameter	Short name of effects	To control for	Configuration (t_1)	Configuration (t_2)	Definition
Outdegree (density)	*density*	Overall tendency to retweet health agencies			$\sum_j x_{ij}$

(continued on next page)

(*continued*)

Parameter	Short name of effects	To control for	Configuration (t_1)	Configuration (t_2)	Definition
4-cycles (transitive closure)	*cycle4*	Tendency for pairs of politicians to retweet the same health agencies			$\frac{1}{4}\sum_{i_1,i_2,j_1,j_2} x_{i_1j_1}x_{i_1j_2}x_{i_2j_1}x_{i_2j_2}$
Indegree popularity	*inPop*	Tendency for politicians to retweet health agencies that received many retweets			$\sum_j x_{ij}(\sum_{h\neq i} x_{hj} + 1)$
Outdegree activity	*outAct*	Tendency for politicians who retweet many health agencies to retweet another health agency			x_{i+}^2
Party ego-in-alter distance 2 similarity	*simEgoInDist2*	Tendency for politicians from the same party to retweet the same health agencies			$\sum_j x_{ij}(sim(v)_{ij} - \widehat{sim^v})$
Policy attitudes (funding, self-protection, medical response)	interaction between *egoX* and *altX*	Tendency for politicians to retweet health agencies with similar attitudes on policies			$v_i x_{ij}\sum_j v_j x_{ij}$
All the other covariates for politicians	*egoX*	Tendency for politicians with certain characteristics to retweet health agencies			$v_i x_{ij}$
All the other covariates for health agencies	*altX*	Tendency for health agencies with certain characteristics to be retweeted by politicians			$\sum_j v_j x_{ij}$

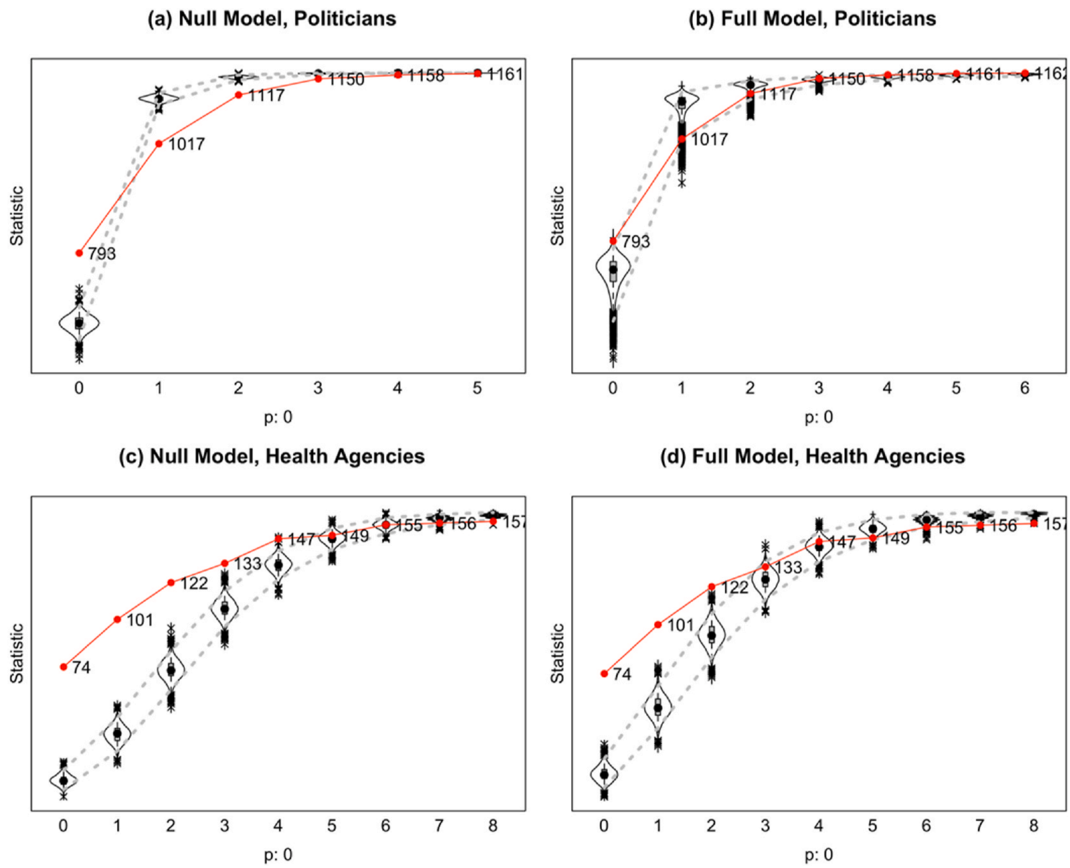
Note: Dark squares and circles represent politicians and health agencies with a specific attribute. White squares and circles represent politicians and health agencies under endogenous effects. Dash lines represent ties not yet existing. Solid lines represent existing ties. For details of each parameter in the effect definition, see (Ripley et al., 2020).

Appendix G

Goodness-of-fit Diagnostic Plots for Degree Distribution of Politicians (a-b) and Health Agencies (*c*-d).

Note. Observed values are indicated by numbers connected by a red line. The simulated statistics are represented by the violin plots. Dotted lines give 95th percentile bands. The *p*-value for the Mahalanobis distance-combination is given at the bottom.

Violin plots illustrate the observed degree distribution and the simulated statistics during the estimation. The null model only includes the transitive closure (4-cycles) and the model fit is less satisfactory. The fit significantly improves after three additional endogenous network structural effects (indegree popularity, outdegree activity, and out-in-degree assortative) are included in the full model (see (b) and (d)). The better fit is reflected by the red line being closer to the mean of the simulated networks.



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