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Communication Across the Spectrum of Hazards and Disasters



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"Communication Across the Spectrum of Hazards and Disasters"

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Sociology

by

Scott Leo Renshaw

Dissertation Committee:
Chancellor's Professor Carter T. Butts, Chair
Professor Emerita Katherine Faust
Associate Professor Rachel Goldberg
Professor David Schaefer

2022

# DEDICATION

This dissertation is dedicated to the teachers and mentors who have guided me to seek information, understanding, and to reach further than I thought possible. This could not have been accomplished without you.

Thank you.

*"And it's only the giving that makes you, what you are."*
– Wond'ring Around, Jethro Tull

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And finally, to my dog Potoroo. If you're reading this... *Wow, who taught you how to do that? What a good boy!*

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- Sutton, Jeanette, **Scott Leo Renshaw**, & Carter T. Butts. (2020) ”COVID-19: Retransmission of Official Communications in an Emerging Pandemic.” *PLoS ONE*, 15(9). DOI: `https://doi.org/10.1371/journal.pone.0238491`
- Sutton, Jeanette, **Scott Leo Renshaw**, & Carter T. Butts. (2020) ”The First 60 Days: American Public Health Agencies’ Social Media Strategies in the Emerging COVID-19 Pandemic” *Health Security*, 18(6), 454-460. DOI: `https://doi.org/10.1089/hs.2020.0105`
- Olson, Michelle, Jeannette Sutton, Sarah Vos, Robert Prestley, **Scott Leo Renshaw**, & Carter T. Butts. (2019) ”Build Community Before the Storm: The National Weather Service’s Use of Social Media.” *Journal of Contingencies and Crisis Management*, 27(4), 359-373. DOI: `https://doi.org/10.1111/1468-5973.12267`
- Sutton, Jeanette, **Scott Leo Renshaw**, Sarah Vos, Michelle Olson, Robert Prestley, Ben Gibson, & Carter T. Butts. (2019) ”Getting the Word Out, Rain or Shine: The

Impact of Message Features and Hazard Context on Message Passing Online." *Weather, Climate, and Society*, 11, 763-776. DOI: `https://doi.org/10.1175/WCAS-D-19-0021.1`

- Vos, Sarah, Jeanette Sutton, Yue Yu, **Scott Leo Renshaw**, Michelle Olson, Ben Gibson, & Carter T. Butts. (2018) "Retweeting Risk Communication: The Role of Threat and Efficacy." *Risk Analysis*, 38(12), 2580-2598. DOI: `https://doi.org/10.1111/risa.13140`

- Arthur, Mikaila Mariel Lemonik, & **Scott Leo Renshaw**. (2017) "Waking Yourself Up: The Liberatory Potential of Critical University Studies." *Radical Teacher*, 108(1), 5-12. DOI: `https://doi.org/10.5195/rt.2017.353`

- **Renshaw, Scott Leo**, & Roger Clark. (2017) "Boy Problem? Girl Problem?: A Century of Gender Inequality in American Education Viewed Through General Social Survey Data." *International Review of Modern Sociology*, 43(1), 79-93. **(Special Issue on Gender Inequality)** DOI: `https://www.jstor.org/stable/44510055`

# ABSTRACT OF THE DISSERTATION

“Communication Across the Spectrum of Hazards and Disasters”

By

Scott Leo Renshaw

Doctor of Philosophy in Sociology

University of California, Irvine, 2022

Chancellor’s Professor Carter T. Butts, Chair

This dissertation investigates several instances of the micro-communication landscape across the spectrum of hazards, from the quotidian to the exotic, by offering a deeper understanding into the communication process via retransmission and communication dynamics. Chapter 2 focuses on hazard communication during quotidian and atypical hazards in the context of the National Weather Service’s use of Twitter from 2009-2021. We investigate several micro-structural, content, and style related message features to understand the properties that make a message more likely to be retransmitted. Chapter 3 looks into communication occurring in the range of exotic and atypical end of the spectrum by studying public-health communicators on Twitter during the first eight months of the unfolding coronavirus disease 2019. Finally, Chapter 4 focuses solely on the exotic end of this spectrum in an investigation of 17 communication networks during the unfolding events of the 2001 World Trade Center Disaster. We model 17 dynamic radio networks to understand the role that the social mechanisms of preferential attachment, Institutionalized Coordinator Roles, and conversational inertia play in the communication process of a disrupted environment. This dissertation provides a holistic overview of hazard communication across this spectrum, providing into the kinds of micro-communication strategies and processes that are unfolding. We hope it inspires future research in this area of critical importance.

# Chapter 1

# Introduction

In hazard and disaster communication, the strategies leveraged by communicators will depend heavily on the context of the hazard at play, particularly relating to the frequency of the event (i.e., how often does this kind of hazard occur) and the familiarity of the hazard (Fischer, 1998; Drabek, 1986). For instance, the National Weather Service reporting information regarding a rain shower in Portland, Oregon, will utilize different communication strategies compared to those used during an imminent tornado touchdown in Wisconsin. Some hazards, like rain in a place like Portland, Oregon are frequent, and well-known/experienced by those who live there, connoting a quotidian aspect to that hazard. Tornadoes in the Mid-West are an atypical hazard, in that while they are something that happens several times each year, they are not as commonly occurring as rain in Portland. On the other end of this spectrum of frequency and familiarity are hazards or disaster events that occur nearly once in a decade or "once in a lifetime." These once in a lifetime hazard events can be characterized as exotic hazards. For natural hazards, this may include severe tsunamis or even events like the so-called impending "big one" earthquake[1] In a health-risk context, we might use a similar framework where the risk of the common cold or sunburn is a fairly

[1]The last earthquake of that magnitude (7.8 or higher on the Richter scale) last occurred in 1906.

quotidian kind of threat. On the other side of the spectrum, we have events like pandemics, such as the coronavirus disease 2019, which are more exotic in nature and represent a more significant threat to human populations.

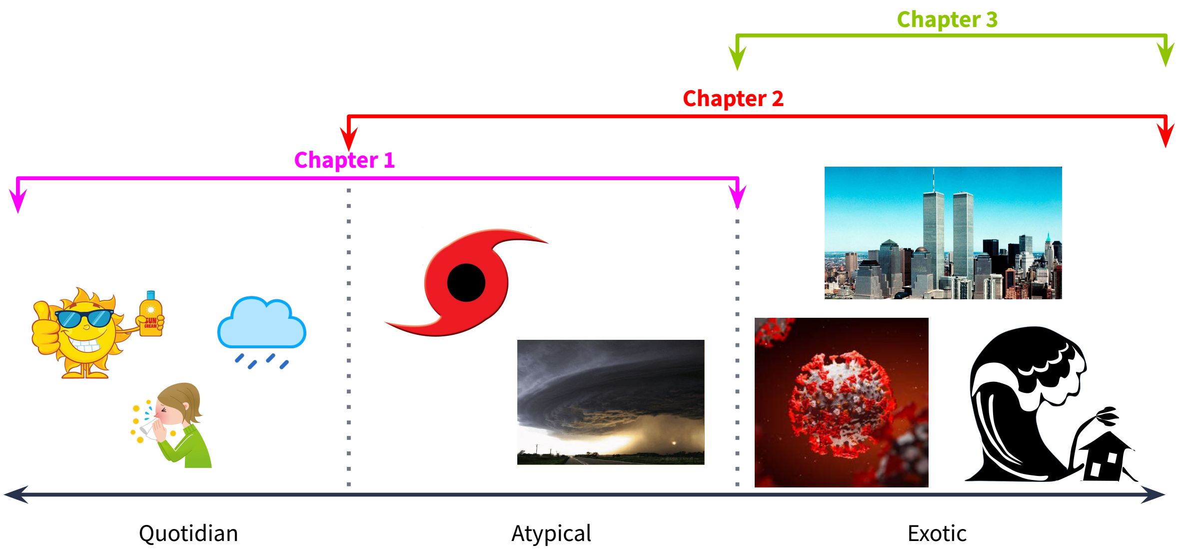


Figure 1.1: Spectrum of hazard frequency, from quotidian, atypical, to exotic events and threats. Quotidian threats here are indicated by hazards like sunburns, the common cold, and rainy weather, which represent hazard events that are not rare or uncommon. Atypical threats are represented here by hurricanes and a forming tornado since these events, while more uncommon, still tend to occur with enough frequency on a yearly cycle. Finally, exotic hazards include the coronavirus disease 2019, tsunamis, and events like the 2001 World Trade Center disaster.

This dissertation presents three chapters that investigate various aspects of the micro-communication landscape of hazards and disasters across this spectrum of frequency/familiarity. Figure 1.1 visualizes the framework in order to highlight the general scope of each chapter in the dissertation in reference to the spectrum. The novelty of this dissertation is not the framing of hazards on a spectrum[2], the novelty of this dissertation lies within its ability to investigate several instances of the micro-communication landscape across the spectrum of hazards, from the quotidian to the exotic, by offering a deeper understanding into the

[2]These kinds of framing/organizational schemes for hazards and disasters has been done historically in the sociological literature with Fischer 1998 and Drabek 1986, and to some extent, Perrow's "Normal Accidents" 1999

communication process via retransmission and communication dynamics. Chapter 2 investigates hazard communication during quotidian and atypical hazards in the context of the National Weather Service's Twitter communications from 2009-2021. This chapter investigates several micro-structural, content, and style related message features to understand the properties that make a message more likely to be retransmitted. Chapter 3 looks into communication occurring in the range of exotic and atypical ends of the spectrum by looking at public-health communicators during the first eight months of the unfolding coronavirus disease 2019. Public health, emergency management, and governmental officials communicating during this time had to first contend with an exotic event/threat, the likes of which would be more similar to the Spanish flu of the early 20th century. However, over time, aspects relating to the familiarity of the threat become normalized ("the new normal"), thus becoming atypical, but no longer exotic. This study is the first of its kind to analyze image textual content through a large scale Optical Character Recognition (OCR) analytic approach. Finally, Chapter 4 focuses solely on the exotic end of this spectrum in an investigation of 17 communication networks during the unfolding events of the 2001 World Trade Center Disaster. We model 17 dynamic radio networks to understand the role that social mechanisms of preferential attachment, Institutionalized Coordinator Roles, and conversational inertia play in communication in a disrupted environment. This chapter takes it a step further by providing the first of its kind, Relational Event Modeling simulation study, allowing for the identification of mechanisms in how they shape the formation of hub-structures found in these communication networks. By providing a holistic view of hazard communication across this spectrum of frequency and familiarity, can we provide insight into the kinds of micro-communication strategies and processes, how they are similar or dissimilar, and how the communication landscapes may change or be altered depending on where it falls on the spectrum.

# Chapter 2

# Writers of the Storm: An Examination of National Weather Service Communications from 2009 to 2021

## 2.1 Abstract

This study is the first to investigate the entirety of a federal organizations use of a communication medium from the experimental use to the official adoption of the medium, charting the communication over a 12 year period. We constructed and analyzed an original dataset containing a census of over 2.8 million communications by 152 national, regional, and local Weather Forecast Offices (WFOs) from the National Weather Service from 2009 to 2021. From this data we are able to model the likelihood of retransmission based on various micro-structural, content, and style related message features to understand the properties that

make a message in this hazard communication space more likely to be passed on. Results indicate that traditional "rumoring" theories, ala Allport and Postman (1947) & Shibutani (1966), that individuals are likely to share information that is salient to them individually and provides clarity in times of ambiguity, hold true with some caveats relating to the special contexts of the Online Social Network. Our results underscore the need for further examination of organizational communication practices across and within time and hazard periods differences so that communications can best "get the word out."

## 2.2 Introduction

During times of imminent threat, strategic real-time information and alerts can help prevent human causalities by increasing the public's awareness of potentially lifesaving instructions (National Weather Service, n.d.b). Due to the costs involved in not receiving this critical information, it is of the utmost importance that we understand the factors that amplify or attenuate these communications. Over the course of the last century, these messages have undergone continuous transformations in reference to media of the time. Historically, formal information of this kind was broadcast unidirectionally through means of public-address systems including radio, television, and sirens (Mileti, 1999). In our era of instant communication, Online Social Networks (OSNs) have become a new avenue for organizations to disseminate important information. Unlike old public-address systems, OSNs have an inherent mix of formal and informal forms of communication that range from public-addresses (one-to-many), to public conversations (one-to-one). A renewed investigation of message amplification and attenuation in this medium would help us better understand how an organization adopts and grows in their use of a communication medium.

While there has been increased research and work in the areas of message passing (Allport and Postman, 1947; Shibutani, 1966; Scanlon, 1971), social amplification (Kasperson et al., 1988, 2010), and especially in contexts relating to hazards and disasters (Danzig et al., 1958a; Sutton et al., 2015a; Vos et al., 2018), they often begin from the vantage point focused on a single historic event, or a collection of past events with similar attributes that leave little to no discussion regarding official organization messages in times of non-events, that is, periods in which strictly risk-related communications are not present, but other forms of communication are. From this gap, a more holistic and systematic understanding of official organizations' communication can be developed that includes message passing relating to hazards, and to the quotidian. A systematic overview and analysis of official organizations' communication, especially in investigating potential retransmission differences within formal and informal communication types, would help bridge many of understandings in disparate hazard communication contexts.

This study investigates the social amplification of official communications by the National Weather Service (NWS) on the OSN, Twitter. This research is the first of it's kind to provide a systematic overview of all official communications over a several year period for a multi-organizational federal agency on a single medium. Due to the breadth of the communication histories utilized here, we can investigate the properties of message passing across hazard and non-hazard event times. This allows for a more general perspective on the influences of these mechanisms without an event selection bias, thereby broadening our knowledge about message passing and retransmission across all hazard events and non-events alike. Additionally, because of the significance of the information provided in these communications, this study is also able to provide practical policy recommendations for the National Weather Service and similar kinds of emergency management agencies.

## 2.3 Literature Review

### Rumoring

Early social science research investigated the passing of information communications from person to person, typically called rumoring, to better understand how information diffuses and what social and psychological factors may influence the message passing process (Caplow, 1947; Allport and Postman, 1947). Allport and Postman's 1947 study proposed a formula in which a rumor's intensity is equal to the rumor's importance to the individual times the ambiguity of information available surrounding the topic or event that the rumor pertains to. This means that a message has an increased likelihood of being passed if the information is salient to the individual and if that information provides clarity in times of ambiguity (Allport and Postman, 1947; Shibutani, 1966; Rosnow, 1980; Starbird et al., 2016). Anxiety has also been found to be a compounding factor for rumor transmission; findings show that anxiety further amplifies the likelihood of a message being passed on (Anthony, 1972; Rosnow, 1980; Walker and Beckerle, 1987). From the early literature it is clear that events that are highly salient to an individual and lead to informational ambiguity and anxiety are important factors in influencing people to pass on rumors.

### Disasters and Social Amplification

Given that the social mechanisms of rumoring and message passing become excited during times of ambiguity and anxiety, it is understandable that researchers would leverage the context of hazards and disasters to study rumoring, message passing, and social amplification. In this field, a hazard is defined as an extreme, but low-probability event, (usually natural or meteorological) that has the potential to cause disaster (Mileti, 1999). Disasters are serious disruptions to the functioning of a community that exceed its capacity to cope using its own resources (IFRC, n.d.) and have large costs to human life and infrastructure (Mileti, 1999). For example, a hurricane, a hazard, that greatly impacts human life and infrastructure, would be referred to as a disaster event. Studies in the hazards and disaster literature have focused on the social networks of individuals and the chains of message passing involved in receiving information related to an event (Scanlon, 1971, 2007; Erikson et al., 1978). These studies have found that individuals are more likely to receive information from those who share similar demographic characteristics, those whom they are in close personal contact with (such as family and coworkers), and often those who were closest in proximity to the occurring event (Greenberg, 1964).

Early research, like Danzig et al. (1958a), described the significant role that official local organizational structures like the fire department, police, and civil defense headquarters play in information transmission during times of uncertainty. These organizations became the primary agents for the communication of official information as well as correcting circulating misinformation for the public (Danzig et al., 1958a). In the social amplification of risk literature, individuals and organizations like these are considered to be acting as stations of amplification, i.e., positions situated within social networks where the perception of risk is either amplified or attenuated (Kasperson et al., 1988, 2010). Therefore, an emphasized aspect of the social amplification of risk literature is how risk messages are presented. Within the communication process, information becomes imbued with various signals, including images, signs, and symbols that, to those receiving the message, "interact with psychological, social, institutional, or cultural processes in ways that intensify or attenuate perceptions of risk" (Renn, 1992). Without a deeper understanding of these signals officials in organizations and institutions tasked with communicating lifesaving information might be unintentionally muddying their messages, ultimately reducing their potential reach to audiences.

## Message Retransmission on Online Social Networks

While risk communications are often generated by official organizations and institutions, this does not mean that the public plays the role of passive recipient. Similar to the rumoring literature, the social amplification of risk literature interpolates all individuals as potential stations of amplification who participate in the generation, interpretation, and passing on of risk signals (Kasperson et al., 1988). In the past two decades with the rapid proliferation of Internet-enabled hand-held devices, along with the birth of new communication media such as Facebook and Twitter, individuals now have an unprecedented ability to participate in the generative and interpretive process of mass communication (Panagiotopoulos, 2016; Chong and Choy, 2018). Research on message retransmission on OSNs has found that messages or other media content shared by peers increase information saliency to the individual. Additionally, the more times an individual is exposed to a message, the ability to induce behavioral change becomes greater (Centola, 2010; Lerman and Ghosh, 2010), which is particularly salient for organizations who share livesaving information.

On the OSN Twitter, the mechanism of message passing is called "retweeting," a process by which users can repost or "share" the message to their extended social networks (Kwak et al., 2010). Therefore, on this medium, all users are quite literally stations of amplification in that they decide what messages they want to socially amplify, passing along information publicly to friends and family. Literature in this area investigates the effects of properties of the medium, including tweet micro-structure (the building blocks of the tweet, including media or hashtags for instance), individual user attributes (including their number of followers), as well as message properties like the choice of style and content (Bongwon and Hong, 2010; Arabshahi et al., 2015). The micro-structure of a tweet is the collection of message features, or building blocks, inherent to the medium which are used in constructing a message. For example, the choice by an individual to use a hashtag, reply to others, or include pictures or videos all represent micro-structural properties that affect the retransmissability of a message. It has been found that some user attributes, like having a larger number of followers (i.e., a larger initial audience size for the message to be retransmitted by) and micro-structural properties, like hashtag inclusion (pre-existing channels or conversation around a topic) are both associated with higher likelihoods for retransmission. However, the inclusion of URLs (i.e., links to external sources of information) and mentions (i.e., the singling out of another user) have been found to significantly decrease the likelihood that a message will be passed on (Kouloumpis and Moore, 2010; Sutton and Butts, 2014). For properties relating to message content, researchers have found that the use of certain message styles have a greater likelihood for retransmission. The use of instructional information, especially terse messages with directive language used to emphasize and or intensify words or statements has been found to be much more likely to be retransmitted (Genes and Chary, 2014; Sutton et al., 2015b).

## This Study

With message passing being especially intensified during periods of ambiguity and anxiety, hazard and disaster events provide a suitable context for investigation. Hazards and disasters can provoke anxiety, are often marked by their ambiguity (e.g., varying hazard strengths, differences in times needed to react, etc. local recent histories of threats of a similar kind, etc.), and are salient to individuals' whose properties, and more importantly, their lives, are often in the line of fire of these events. Individuals in these potentially hazardous or disastrous events often attempt collective sense-making based on available information and look toward official governmental organisations to provide clarity in times of ambiguity (Shibutani, 1966; Danzig et al., 1958a). To understand social mechanisms related to message passing of an official governmental organization in an information-rich communication environment, we have chosen here to investigate the official communications of the Untied States' National Weather Service (NWS) agency on the OSN Twitter ("Timeline" NOAA, n.d.).

The NWS is an official governmental agency that provides weather forecasts, watch, and warning information for the United States. Due to its size, the United States faces one of the widest ranges of potential weather hazards. With this in mind, the NWS is comprised of 122 local forecast offices across six geographical regions to appropriately provide necessary information and services(“Organization” NOAA, n.d.). As of 2013, all NWS offices use Twitter in an official capacity, using it to formally disseminate meteorological information related to natural hazards, while also informally interacting with their audiences (“Timeline” NOAA, n.d.).

The prior literature on message passing informs us that messages that can clarify ambiguity, are personally salient, reduce anxiety, and are a part of an ongoing collective communication process have a greater likelihood of being retransmitted. In this study we are looking at a host of properties and features that lead to the amplification or attenuation of National Weather Service communications from 2009 to 2021. Many of these properties are motivated by prior literature in the hazard and disaster communication space, while others are coded through deductive and inductive coding and knowledge of the National Weather Service communication context.

## 2.4 Methods

### Data

For this study, an original dataset was constructed containing a census of communications ($n$ = 2,801,446) from January 1st 2009, to December 31st 2021, published by the 150 national, regional, and local Weather Forecast Offices (WFOs) from the National Weather Service. NWS Twitter accounts were chosen based on a continually updated list of active NWS accounts, maintained by the main national NWS account. These data were collected through the Twitter Application Programming Interface (API) using the AcademicTwitteR R statistical programming language package (Barrie, 2021) as part of a data collection infrastructure maintained by the Hazards, Emergency Response, and Online Informal Communications (HEROIC) group from the University of California, Irvine.

To measure the number of times a message was passed on to others, we use the count of retweets for each tweet provided in the tweet meta-data. Retweeting is an effective choice to quantify how many times the message was retransmitted because the act of retweeting itself means that an actor has decided to pass this message on to their extended social network. The Twitter API provides a measure of the cumulative retweet count at the time of the query, along with other tweet relevant meta-data. To test the research questions at hand, we use covariates that relate to the attributes of the account, micro-structural properties and content features of the message. Many of the covariates investigated here are provided within the tweet's meta-data (e.g., the number of followers for an account, what hashtags were used in the message if any, etc.) while others were coded using regular expressions (e.g., the inclusion of an exclamation point or question mark).

## Micro-Structural Properties

When a user is constructing a message to send out to their followers, there are decisions around what kind of micro-structural properties of the message they may want to include. These building blocks in the construction of a message include: hashtags, URLs, pictures and videos (media), mentions, and replies – are of the properties we test here.

On OSNs, a commonly used feature for those wanting to participate in the discussion of a larger topic of interest is through the use of hashtags in their messages. Using a *hashtag* on Twitter connects a message to a larger channel of communication using a specific word or string of words. For example,the hashtags #hurricanemathew and #florida would link to two separate communication channels about Hurricane Matthew and the State of Florida, thereby connecting messages with an ongoing conversation around those same hashtags. In this way, hashtags act as a forum for users, in which active sense-making can occur, especially during times of ambiguity and anxiety.

Two ways in which additional information can be communicated on Twitter are through the use of URLs and media attachments. *URLs* (Uniform Resource Locators) on Twitter indicate the sharing of a web resource, or web-page, which if clicked, will redirect the user away from Twitter and onto another website. *Media* represents the inclusion of a picture or video embedded in a tweet. Commonly, NWS media ranges from weather radar projections, to detailed infographics containing bite-sized, but potentially lifesaving, information. Unlike URLs, media attachments do not direct users away from Twitter. Both URLs and Media covariates are selected because they provide potentially clarifying or anxiety-reducing resources, whether it be by providing links to supplemental resources (outside the Twitter OSN), or in the palatable form of an infographic.

While Twitter's main discourse is by design one-to-many, there are also ways in which users can converse one-to-one in a public form. A *mention* is the act of directly tagging another user through their username or online handle. For example, directly mentioning "@NWSTulsa" would notify NWS Tulsa on Twitter that a user had mentioned them in a new tweet. A similar property to mentioning on Twitter is replying. *Replying* indicates that a given message was an answer or reaction to another user's tweet. If NWS Tulsa were to respond to the tweet that directly mentioned them, then this message would be marked as a reply in the meta-data. Both mentions and replies are communicative acts that represent a narrowing of the audience, from one-to-many to one-to-one, and thereby limits the potential for broader conversation around that message. These messages would have less salience to a general audience even if the information contained in the message is of general interest.

As these properties are either present or absent, we construct covariates that represent 0 if they are not included, and 1 if they are.

## Lexicon Development for Content

It is apparent from the message passing and social amplification of risk literature that how a message is conveyed (i.e., the content of the message) can make the message more or less salient to individuals. Therefore, in the context of official NWS messages, being able to make general distinctions about message themes is important to understanding how they may affect message passing.

A standard approach to understanding important keywords, phrases, and frequently used terminology within a specified communication domain is through building a topic lexicon. Lexicons are a specialized dictionary constructed to assist in identifying key terms, topics, and words used in a specific corpus. The use of lexicons and dictionaries have been leveraged in previous studies; from identifying crisis-specific keywords that are relevant in an emerging disaster Olteanu et al. (2014); Imran et al. (2014), as well as the early months of the unfolding COVID-19 virus (Sutton et al., 2020; Renshaw et al., 2021). We build off prior studies to develop a lexicon specific to National Weather Service communications, which will aid in the discovery of common content themes and topics by these organizations.

The lexical categories were constructed by a multi-step deductive/inductive coding scheme, implemented as follows. First we created a list of all of the uniquely uttered single words character strings from each tweet, into a single vector of all unique words and phrases from the entire corpus of 2.8 million messages. This results in a set of 63,410,090 unique terms. A term frequency-inverse document frequency (TF-IDF) analysis was then conducted, where the "document" is each unique month-year combination, (for example: 01/2019, 02/2019, 03/2019), which resulted in 156 month-year periods ("documents") of all tweets produced in that month-year combination. Through this process we are able to discover high contrast terms that are frequently used in particular month-year periods – this is extremely important when we understand the context of the kinds of communication occurring in the National Weather Service space. Meteorological terminology and weather reporting is highly seasonal in nature. Further, a coding scheme using TF-IDF is particularly well suited for discerning the use of named events for hurricanes (like Hurricane Matthew) versus replying to someone named Matthew – if we have a high contrast use of Matthew in a particular year/month period we know not only that utterances of "Matthew" has increased in this period, but we can also cross-reference the period to determine whether there was indeed an event named Matthew in that month-year period.

We then selected the top 100 high contrast words from each month-year period through this TF-IDF discovery process, resulting in a list of 1303 unique words. We then went through each of the keywords and identified emergent categories, while cross-referencing terminology to known NWS glossary guides (National Weather Service, n.d.a). In situations like proper nouns, like Matthew, sample tweets containing the word were referenced to understand the contextual use of the terms[1] These emergent lexical categories were identified as the following: Meteorological Technical Information (e.g. forecasting, nowcasting, etc.), Bureaucratic, Weather, NWS Office References, Community, Hazards, Marine, Weather Modeling, Time-related Keywords, Space & Space Weather, Holidays, International Locations, US Government, Expertise, Social Media, Demographic, and Named Weather Events. These categories are explained further in Table 2.1 with specific examples below.

In line with the literature of Shibutani (1966) and Allport and Postman (1947), these themes are relevant to the present research because messages containing hazard keywords, named-events, demographic details, and other categories may provide information that is pertinent to individuals, which may relieve unclarity in times of anxiety. Message content relating

[1] For Named Weather Events, we generated our Regex code to match only to tweets that contained the named event & the utterance of tropical, hurricane, or cyclone or if the named event was used in a hashtag (#Matthew)

purely to quotidian or non-emergency contexts, like community, holidays, bureaucratic, and space & space weather may not have the same kind of importance that is likely to be shared by followers compared to other more "important" information shared by these accounts.

## Content Style

In addition to these lexical categories, it can be argued that not merely what is said, but how it is said is of relevance. To that end, we have added several covariates that may help speak to a certain level of style in terms of content presentation, something that has been seen as important in the Amplification of Risk frameworks (Kasperson et al., 1988, 2010; Starbird et al., 2016). We have a dichotomized covariate for whether the message included exclamation points, and questions marks. Exclamation points indicate imperative, directive messages which are often related to actionable declarations. The use of this punctuation may heighten the salience of the message to the audience, thereby intensifying their decision to retransmit. Question marks indicate that a question is being asked to the audience, which may be potentially pertinent to individuals, increasing the messsage's saliency.

Prior literature on retransmission, specifically in reference to hazards, has found that the use of ALL CAPS in communication increases the likelihood of message passing (Olson et al., 2019). The use of upper case for large portions of text is normally used to indicate significance, as if to imply that the person is yelling or announcing something. In the hazard context, the use of all uppercase is often done in combination with automated weather warning announcements, where large proportions of the text in the message, especially the part that is of the utmost significance to the viewer, is emboldened using this tactic. To understand how this effect may work, we have constructed 3 covariates to measure the ratio of upper case words compared to the total number of words used – with categories $\geq 25\%$ & $< 50\%$ ALL CAPS, $\geq 50\%$ &$< 75\%$ ALL CAPS, and $\geq 75\%$ ALL CAPS. These three categories, with the baseline comparison $<$ 25% ALL CAPS, should tell us the relative impact that using ALL CAPS has on the potential for retransmission. Following the literature, we may suspect that the use of upper case may increase relative to the increase in the proportion of all caps used in a given message, with statements with more than 75% ALL CAPS having the greatest positive influence on message passing.

Finally, a term has been added that indicates the "source" of a communication. On Twitter, as part of the meta-data, there is information as to the device or source that the tweet has come from. For instance, a common social media management software "HootSuite" is commonly used by some organizations (including the NWS) to post content to multiple OSNs with one push of a status button. To understand how the content style influences message passing, we have utilized a dichotomous variable for whether a post was shared from the "source" called "NWSBot." NWSBot is a service utilized by NWS meteorologists to automate the posting of warning and watch product data – this highly standardized product information includes warnings and watches for even trivial events like light rain and fog (for example: "RNK continues Wind Advisory for Bland, Smyth, Tazewell [VA] and Mercer [WV] till 12:00 PM EDT https://t.co/9F5kRsFr"). The use of the NWSBot provides a convenience for the meteorologists, but may have a cost in terms of retransmission – individuals may disregard these highly standardized and often unimportant communications, likening it to a Bot that cried wolf. Perhaps users are desensitized to these automated communications, and may prefer more "human" styles of communication.

## Controls

To control for temporal elements and other idiosyncrasies within the organizational structure at the National Weather Service (especially in terms of posting style etc.), we have added several fixed effects to account for some of these issues. Because the data takes place over

Table 2.1: Lexicon Set: Definitions, Frequencies, and Examples

| **Lexicon Category** | **Category Description** | **Keyword Examples** | **# of Keywords** | **% of Corpus** |
|---|---|---|---|---|
| Meteorological Technical Information | Technical meteorological terminology used to describe future and ongoing weather conditions. | outlook, forecast, closure, conditions, hwo (Hazardous Weather Outlook). | 86 | 63.7% |
| Bureaucratic | Keywords that discussed organizational functioning at NOAA and the National Weather Service broadly. | economic, pledge, payroll, project, budget. | 67 | 1.4% |
| Weather | Terminology used in the description of non-hazardous meteorological events. | chill, fog, accumulations, dry, wx. | 61 | 67.6% |
| NWS Office Reference | References to specific National Weather Service Weather Forecast Offices, including their abbreviations. | noaa, okx, bmx, bos, jax | 52 | 13% |
| Community | Terminology regarding discussion, conversation, or other community building programs. | q&a, discussion, tweetchat, commemorate, owlie (Owlie's Weather-Ready Educational Activities). | 33 | 9.7% |
| Hazards | Keywords and terminology referencing severe hazardous events and their impacts. | tsunami, radiation, ef3 (Enhanced Fujita Scale Tornado), fatalities, FEMA | 52 | 30% |

| Lexicon Category | Category Description | Keyword Examples | # of Keywords | % of Corpus |
|---|---|---|---|---|
| Marine | Words relating to ocean, sea, and other marine life - including animals, occupations, and transportation. | boating, dolphin, fishery, coral, ship. | 31 | 6.5% |
| Weather Modeling | Technical information pertaining directly to scientific models in weather hazard prediction. | visualization, predicts, dual-pol (Dual Polametric Radar), gis (Geographic Information System), cfs (Climate Forecast System). | 22 | 4.2% |
| Time-related Keywords | Language pertaining to event timing. | morning, tonight, weekend, 24x7, est (Eastern Standard Time). | 25 | 57.2% |
| Space & Space Weather | Terminology relating to general space information and space weather reporting (like geomagnetic storms, eclipses, and meteor sightings). | geomagnetic, satellite, smg (Spaceflight Meteorology Group), supermoon, Perseid (A meteor-shower associated with the comet Swift-Tuttle). | 22 | 1.1% |
| Holidays | References to holidays and cultural events. | Halloween, Thanksgiving, Veterans, solstice, merry. | 14 | 1.1% |
| International Locations | References to international locations and countries. | Korea, Ireland, Belize, Bahamas, Japanese. | 14 | 0.3 % |

| Lexicon Category | Category Description | Keyword Examples | # of Keywords | % of Corpus |
|---|---|---|---|---|
| U.S. Government | Words relating to specific organizations and individuals in the United States. | senate, gov, whitehouse, uss, national. | 11 | 1% |
| Expertise | Keywords that reference someone's formal title or role. | Dr., expert, scientists, deputy, weatherperson. | 10 | 0.28% |
| Social Media | Terms of and relating to social media platforms. | blog, podcast, tweet, facebook, app. | 9 | 0.52% |
| Demographic | References to demographic categories or groups. | women, kid, male, baby, child. | 5 | 0.06% |
| Named Weather Events | References to specific named weather events, most often referencing Tropical Storms and Hurricanes, but occasionally other hazardous events like blizzards. | Matthew, Bonnie, Arthur, Sandy, Katrina. | 90 | .8% |

the course of thirteen years, within a period the Twitter communication medium and the official use of it by organizations greatly matured since 2009, temporal controls are fairly crucial for the generalizability of the results. In this vein, we have included fixed effects for 24 hours of the day, seven days of each week, each of the twelve months in a year, and a term for each year within the study period. For these fixed effects the reference categories are as follows; 5 am UTC, Wednesday, and 2013 – 2013 was selected in particular because it is the year in which the National Weather Service as an organization adopted Twitter in an "official" capacity, with prior years calling their use of the service "experimental."

To account for variation in NWS account's behavioral and characteristic differences in their communication styles (e.g., certain accounts that post more frequently than others, or service larger populations) we utilize two sets of controls including a dummy variable for the **State** the NWS office serves (National/No State for National, Rivercrest Warning, and Regional Accounts), and a dummy variable for **Region**, indicating which of the 6 Regions (or National) an office serves within. We use the state of Washington and the Eastern Region as the reference category. Finally, the *follower count* represents the natural log of the number of followers of the account, which controls for how many people were potentially "attending" to the message upon it's original posting.

## Negative Binomial Regression

For communications published by the NWS between 2009 and 2021 the median retweet count among the 2.8 million NWS messages is low, with 75% of messages being retweeted less than 5 times. This accords with prior work on modeling retransmission on twitter (Sutton et al., 2015b; Vos et al., 2018; Sutton et al., 2020), in which the majority of messages do not go on to be retransmitted. Considering this, we conduct a negative binomial regression to model the count of retransmission. This method is used for skewed count data, account for unobserved heterogeneity in the transmission process which manifests as over-dispersion relative to a Poisson process. We performed a negative binomial regression using the R statistical programming language and the MASS package (Venables and Ripley, 2000). An interpretation of the resulting model would be as follows: for a particular message feature, like the inclusion of **hashtags**, if positive would indicate an increase in the likelihood of retransmission, *ceteris paribus*. If the coefficient was negative, it would indicate an attenuation or decrease in the likelihood of retransmission. For a more in-depth discussion of using negative binomial regression to model message retransmission, please see Sutton et al. 2020.

## 2.5 Results

Results for the negative binomial regression of retweet count, as seen in Table 2.3. The $\beta$ coefficients represent logged multiplicatives of the expected retweet count for micro-structural properties and content characteristics while controlling for time and other organizational-structure related idiosyncrasies. Since these are the logged multiplicative of the expected retweet count, we can compare relative effect sizes as seen in Figure 2.1. Using the Akaike Information Criterion (AIC) score as a measure of goodness of fit, we find that the final model score is 13,131,597 which is more informative than an empty model with an intercept of 1, which had an AIC score of 15,009,243. After rerunning several other models without controls, the resultant model was selected because it was found that the combination of temporal and organizational fixed effects improved the overall AIC score. In visualizations we compare the raw $\beta$ coefficient values, but in our presentation of findings we opt to use a % change of a covariate, with all else remaining equal, represented by the $\exp(\beta)$ coefficient.

| Table 2: Retransmission of National Weather Service Communication from 2009 to 2021: Negative Binomial Regression Model | | | | |
|---|---|---|---|---|
| | Estimate | Std. Error | Rate Multiplier | Sig. |
| (Intercept) | -6.11 | 0.06 | 450.24 | *** |
| *Account Properties* | | | | |
| log(Follower Count) | 0.71 | 0 | 1.03 | *** |
| *Microstructural Properties & Style* | | | | |
| Incl. URLs | -0.44 | 0.01 | 0.55 | *** |
| Incl. Hashtag | 0.21 | 0.01 | 0.23 | *** |
| Incl. Mention | -0.13 | 0.01 | 0.14 | *** |
| Incl. Reply | -2.64 | 0.02 | 13 | *** |
| Incl. Question Mark (?) | 0.03 | 0.01 | 0.03 | *** |
| Incl. Exclamation Point (!) | 0.26 | 0.01 | 0.29 | *** |
| Incl. Media | 0.59 | 0.01 | 0.81 | *** |
| Incl. NWSBot | -0.3 | 0.01 | 0.36 | *** |
| ALL CAPS >=25-50% | -0.46 | 0.01 | 0.58 | *** |
| ALL CAPS >=50-75% | 0.32 | 0.02 | 0.38 | *** |
| ALL CAPS >=75-100% | 1.86 | 0.08 | 5.42 | *** |
| *Lexical Categories* | | | | |
| Meteorological Terminology | -0.08 | 0 | 0.08 | *** |
| Bureaucratic | -0.11 | 0.02 | 0.11 | *** |
| Weather | -0.05 | 0.01 | 0.05 | *** |
| NWS Office Abbreviations | -0.46 | 0.01 | 0.59 | *** |
| Community | -0.04 | 0.01 | 0.04 | *** |
| Hazard | 0.33 | 0.01 | 0.38 | *** |
| Marine & Ocean | 0.12 | 0.01 | 0.13 | *** |
| Weather Modeling | 0.15 | 0.01 | 0.16 | *** |
| Time-related | -0.06 | 0 | 0.06 | *** |
| Space & Space Weather | 0.58 | 0.02 | 0.78 | *** |
| Holidays | 0.13 | 0.02 | 0.14 | *** |
| International Locations | 0.54 | 0.03 | 0.72 | *** |
| U.S. Government | -0.03 | 0.02 | 0.03 | N.S. |
| Expertise | -0.02 | 0.04 | 0.02 | N.S. |
| Social Media | -0.06 | 0.03 | 0.06 | * |
| Demographic | 0.28 | 0.07 | 0.32 | *** |
| Named Weather Events | 1.09 | 0.02 | 1.98 | *** |
| Named Weather Events Hashtags | 1.26 | 0.08 | 2.52 | *** |
| *Period Effects – Year* | | | | |
| 2009 | -3.71 | 0.36 | 39.69 | *** |
| 2010 | -1.66 | 0.11 | 4.28 | *** |
| 2011 | -0.69 | 0.04 | 1 | *** |
| 2012 | -0.9 | 0.02 | 1.45 | *** |
| 2014 | 0.41 | 0.01 | 0.51 | *** |
| 2015 | 0.44 | 0.01 | 0.55 | *** |
| 2016 | 0.43 | 0.01 | 0.53 | *** |
| 2017 | 0.47 | 0.01 | 0.59 | *** |
| 2018 | 0.43 | 0.01 | 0.54 | *** |
| 2019 | 0.42 | 0.01 | 0.53 | *** |
| 2020 | 0.43 | 0.01 | 0.53 | *** |
| 2021 | 0.48 | 0.01 | 0.61 | *** |
| *Period Effects – Month* | | | | |
| January | 0.19 | 0.01 | 0.21 | *** |
| February | 0.16 | 0.01 | 0.17 | *** |
| March | 0.06 | 0.01 | 0.06 | *** |
| May | -0.11 | 0.01 | 0.12 | *** |
| June | -0.08 | 0.01 | 0.09 | *** |
| July | -0.09 | 0.01 | 0.09 | *** |
| August | -0.03 | 0.01 | 0.03 | ** |
| September | 0.14 | 0.01 | 0.15 | *** |
| October | 0.01 | 0.01 | 0.01 | N.S. |
| November | -0.01 | 0.01 | 0.01 | N.S. |
| December | 0.11 | 0.01 | 0.11 | *** |
| *Period Effects – Time of Day* | | | | |
| 12 am UTC | -0.04 | 0.02 | 0.04 | ** |
| 1 am UTC | -0.02 | 0.02 | 0.02 | N.S. |

Table 2.3: NWS Negative Binomial Regression

| | | | | |
|---|---|---|---|---|
| 2 am UTC | 0.05 | 0.02 | 0.05 | ** |
| 3 am UTC | 0.06 | 0.02 | 0.06 | ** |
| 5 AM UTC | -0.12 | 0.02 | 0.13 | *** |
| 6 AM UTC | -0.17 | 0.02 | 0.18 | *** |
| 7 AM UTC | -0.33 | 0.02 | 0.4 | *** |
| 8 AM UTC | -0.23 | 0.02 | 0.26 | *** |
| 9 AM UTC | -0.1 | 0.02 | 0.11 | *** |
| 10 AM UTC | -0.04 | 0.02 | 0.04 | * |
| 11 AM UTC | 0 | 0.02 | 0 | N.S. |
| 12 PM UTC | 0.01 | 0.02 | 0.01 | N.S. |
| 1 PM UTC | 0.02 | 0.02 | 0.02 | N.S. |
| 2 PM UTC | 0.03 | 0.02 | 0.03 | N.S. |
| 3 PM UTC | 0.05 | 0.02 | 0.05 | ** |
| 4 PM UTC | 0.01 | 0.02 | 0.01 | N.S. |
| 5 PM UTC | 0.03 | 0.02 | 0.03 | * |
| 6 PM UTC | 0.05 | 0.02 | 0.05 | ** |
| 7 PM UTC | -0.03 | 0.02 | 0.03 | N.S. |
| 8 PM UTC | -0.03 | 0.02 | 0.03 | N.S. |
| 9 PM UTC | -0.01 | 0.02 | 0.01 | N.S. |
| 10 PM UTC | -0.06 | 0.02 | 0.06 | *** |
| 11 PM UTC | -0.06 | 0.02 | 0.06 | *** |
| *Period Effects – Day of Week* | | | | |
| Monday | 0.07 | 0.01 | 0.08 | *** |
| Tuesday | 0.04 | 0.01 | 0.04 | *** |
| Wednesday | 0.01 | 0.01 | 0.01 | N.S. |
| Friday | -0.02 | 0.01 | 0.02 | * |
| Saturday | -0.03 | 0.01 | 0.03 | *** |
| Sunday | -0.04 | 0.01 | 0.04 | *** |
| *NWS Organization – Region* | | | | |
| Alaska Region | 0.66 | 0.12 | 0.93 | *** |
| Central Region | -2.36 | 0.04 | 9.63 | *** |
| National | -0.75 | 0.03 | 1.11 | *** |
| Pacific Region | 0.22 | 0.06 | 0.24 | *** |
| Southern Region | -1.59 | 0.04 | 3.92 | *** |
| Western Region | -0.23 | 0.06 | 0.25 | *** |
| *NWS Organization – Office Location* | | | | |
| Alabama | 1.04 | 0.06 | 1.83 | *** |
| Alaska | -0.61 | 0.13 | 0.85 | *** |
| Arizona | 0.02 | 0.02 | 0.02 | N.S. |
| Arkansas | 0.75 | 0.06 | 1.11 | *** |
| California | 0.13 | 0.02 | 0.14 | *** |
| Colorado | 2.3 | 0.06 | 9.01 | *** |
| Florida | 1.11 | 0.06 | 2.02 | *** |
| Georgia | 1.52 | 0.06 | 3.56 | *** |
| Idaho | 0 | 0.03 | 0 | N.S. |
| Illinois | 2.64 | 0.06 | 13.01 | *** |
| Indiana | 2.64 | 0.06 | 12.96 | *** |
| Iowa | 2.12 | 0.06 | 7.36 | *** |
| Kansas | 1.97 | 0.06 | 6.14 | *** |
| Kentucky | 2.01 | 0.06 | 6.49 | *** |
| Louisiana | 0.99 | 0.06 | 1.7 | *** |
| Maine | -0.46 | 0.06 | 0.58 | *** |
| Maryland | 0.22 | 0.06 | 0.24 | *** |
| Massachusetts | -0.44 | 0.06 | 0.55 | *** |
| Michigan | 2.25 | 0.06 | 8.5 | *** |
| Minnesota | 1.98 | 0.06 | 6.21 | *** |
| Mississippi | 1.35 | 0.06 | 2.85 | *** |
| Missouri | 2.36 | 0.06 | 9.6 | *** |
| Montana | -0.23 | 0.02 | 0.25 | *** |
| Nebraska | 2.06 | 0.06 | 6.84 | *** |
| Nevada | 0.1 | 0.02 | 0.1 | *** |
| New Jersey | 0.24 | 0.06 | 0.26 | *** |
| New Mexico | 1.07 | 0.06 | 1.92 | *** |
| New York | -0.17 | 0.06 | 0.19 | ** |
| National / No Specified State | 0.36 | 0.05 | 0.43 | *** |
| North Carolina | -0.19 | 0.06 | 0.21 | *** |

| | | | | |
|---|---|---|---|---|
| North Dakota | 1.61 | 0.06 | 4.01 | *** |
| Ohio | 0.4 | 0.06 | 0.48 | *** |
| Oklahoma | 1.33 | 0.06 | 2.78 | *** |
| Oregon | 0.27 | 0.02 | 0.3 | *** |
| Pennsylvania | 0.13 | 0.06 | 0.13 | * |
| Puerto Rico | 0.91 | 0.06 | 1.48 | *** |
| South Carolina | -0.62 | 0.06 | 0.86 | *** |
| South Dakota | 1.66 | 0.06 | 4.28 | *** |
| Tennessee | 1.14 | 0.06 | 2.11 | *** |
| Texas | 1.1 | 0.06 | 2 | *** |
| Utah | -0.26 | 0.02 | 0.29 | *** |
| Vermont | -0.09 | 0.06 | 0.1 | N.S. |
| Virginia | -0.19 | 0.06 | 0.21 | *** |
| West Virginia | 0.09 | 0.07 | 0.09 | N.S. |
| Wisconsin | 2.04 | 0.06 | 6.69 | *** |
| Wyoming | 1.63 | 0.06 | 4.11 | *** |

Observations: 2,801,445; AIC: 13,131,597

Dispersion Parameter: 6.9;

* P < 0.05, ** P < 0.01, *** P < 0.001.

*Note: The rate multiplier is the exponentiated absolute value of the beta coefficient – 1.*

## Controls

Figure 2.1 provides effects for year periods from 2009 to 2021 with 2013 as the comparison year. 2013 is used as the comparison year because it marks the first year in which the National Weather Service as an organization transitioned their use of Twitter as an experimental communication medium, to an official medium.

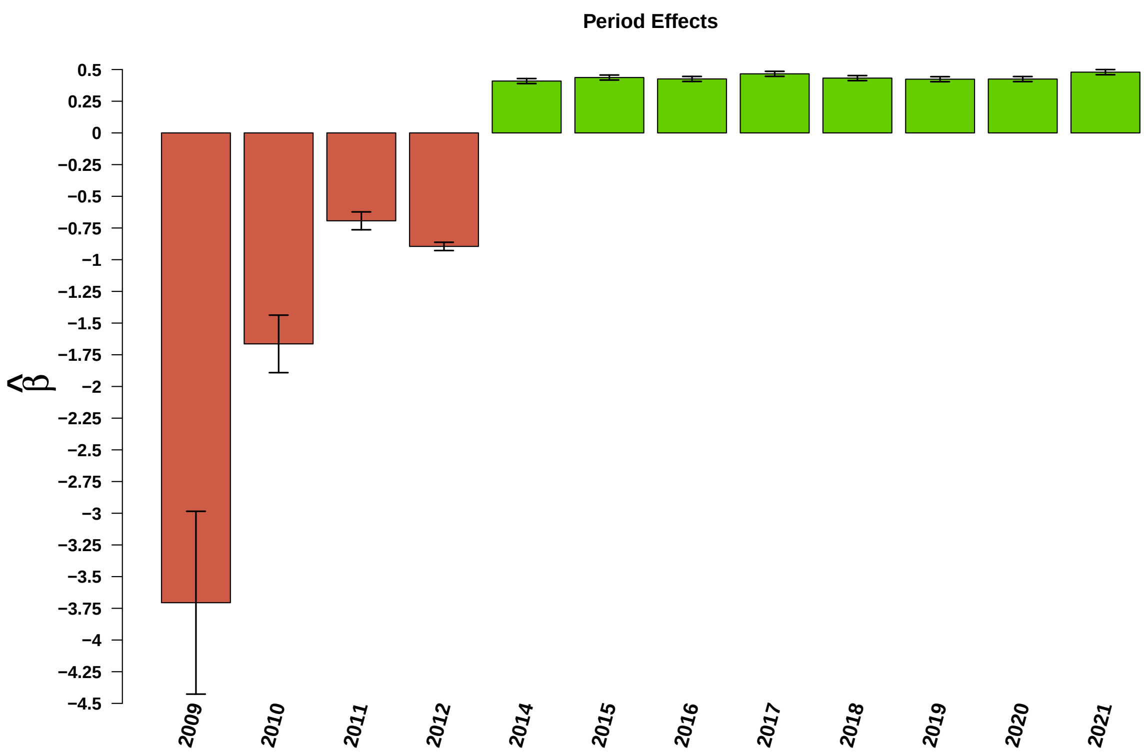


Figure 2.1: Negative Binomial plotted beta coefficients for year controls.

We find that in their experimental phase that the relative expected count of retransmission starts low and slowly rises between 2009 and 2012 – from -3969% lower in 2009 than 2013, to -145% lower in 2012. Post transition, we find that the likelihood of message passing increases in the years after officialization, rising ever so slightly from 51% in 2014 to 61% in 2021. Other date and time controls can be seen in Table 2.3.

## Microstructural Properties

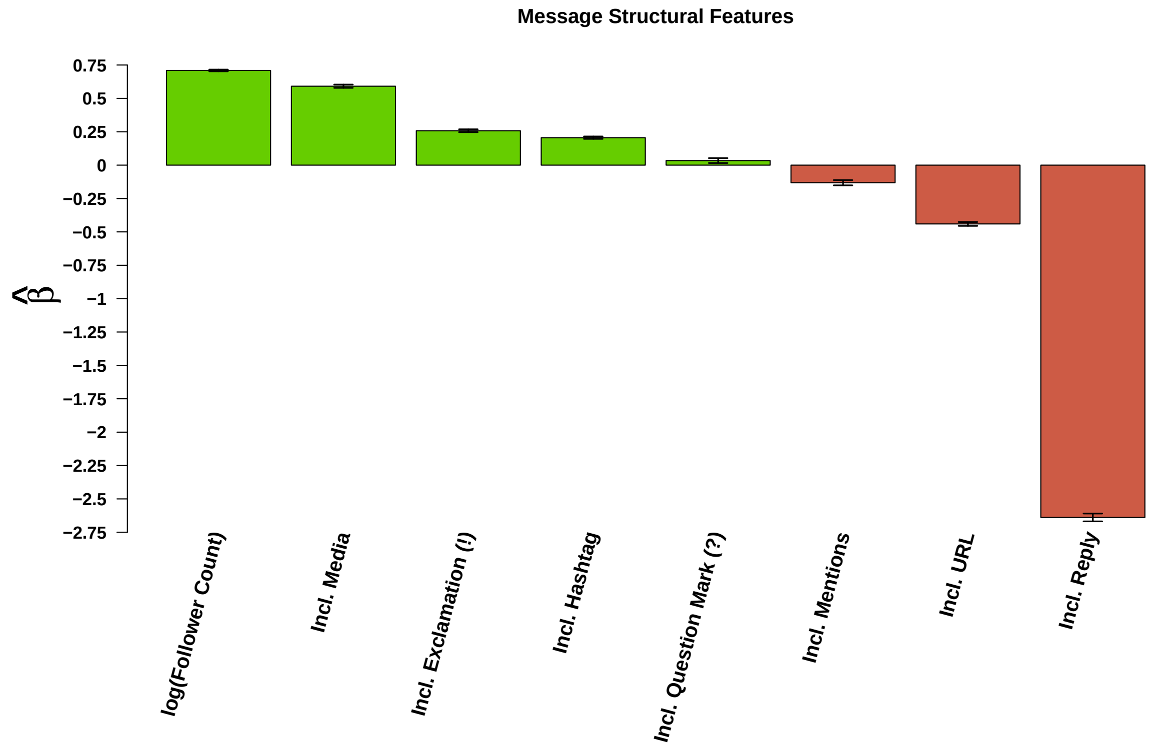


Figure 2.2: Negative Binomial plotted beta coefficients for microstructural properties.

In terms of microstructure, visualized in Figure 2.2 we find that, like prior findings, the log of the Follower Count is one of the greatest structural features for amplification – the more followers one has, the more likely a message is to be retransmitted - with an increase to the likelihood of transmission at 103%. The use of media, exclamation points, hashtags, and question marks are also all found to increase retransmission by 84%, 29%, 23%, and 3% respectively. Using external URLs or hyperlinks that direct users off of the platform is found to be the second largest microstructural attenuator for retransmission for National Weather Service communications – with URL inclusion decreasing the likelihood of being passed on by 55%. Finally, the use of mentions and replies, i.e. singling out and directly communicating with another user, greatly reduce the retransmission by 14% when using mentions broadly, and a massive 1300% decrease when the NWS account replies directly to a user.

## Lexical Keyword Content

In Figure 2.3 we find several topics tend to have greater likelihoods of amplifying a given communication. Utilizing named storm hashtags and referencing named weather events increases likelihood of retransmission by 198% and 252%, respectively. Discussion of international locations, hazard keywords, demographics, and weather models are all found to positively influence message passing from 72%, 38%, 32%, to 16%.

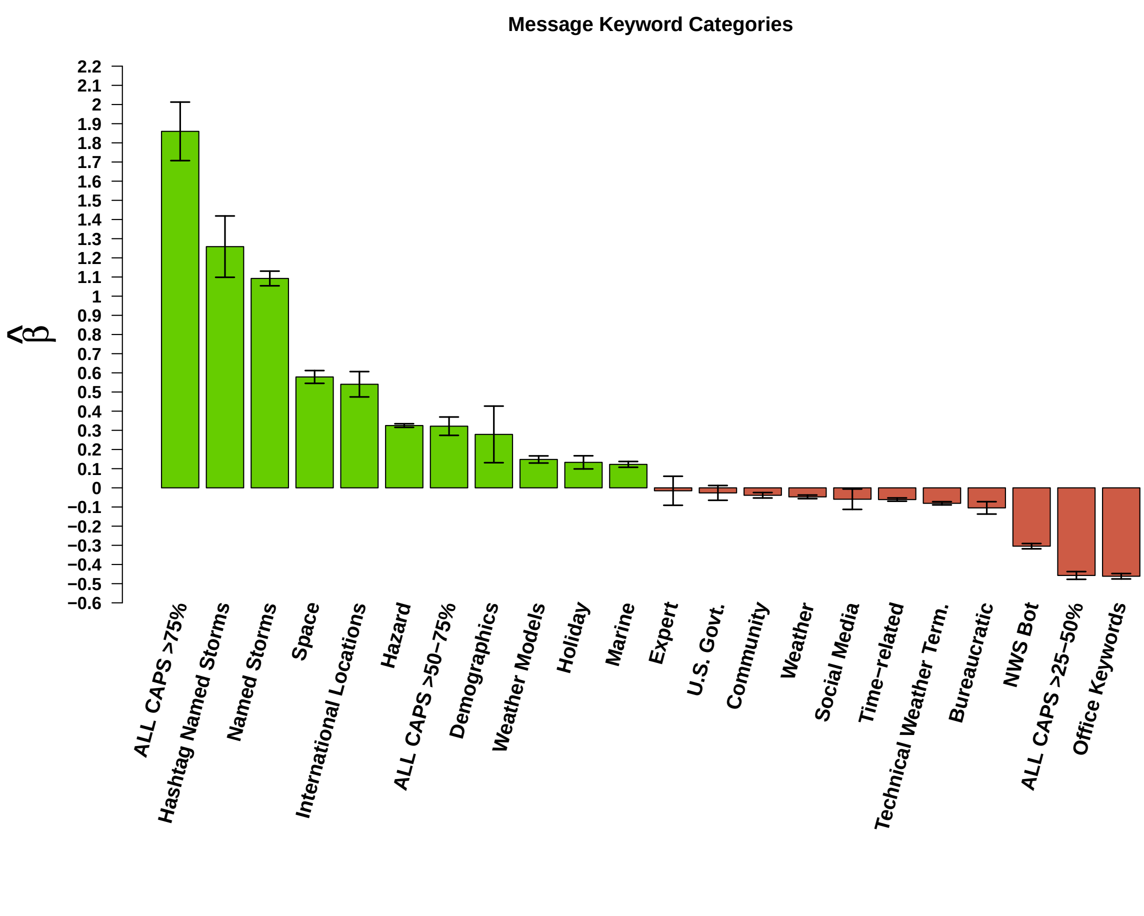


Figure 2.3: Negative Binomial plotted beta coefficients for content and style.

Keyword use relating to Space & Space Weather, Holidays, and the lexical category Marine, also positively influence retransmission from 78%, 14%, and 13%. Communication that focuses on community (4%), use of quotidian weather terms (5%), time-related terms (6%), and other technical weather terminology (8%) all negatively influence retransmission. Finally, the use of bureaucratic language (11%), the use of intra-office communication jargon and abbreviations (59%), and Social Media references (6%) all appear to decrease the potential for message passing.

Two lexical categories were found to have no statistically significant relationship between message passing for NWS accounts. The reference of experts through titles and roles (Dr., deputy, scientists), and references to U.S. Government (senate, whitehouse, gov) were not detected to have any impact on message passing likelihoods.

## Content Style

Figure 2.3 also depicts the plotted beta coefficients for content categories and features from greatest positive influence to greatest negative impact. Here we find that when comparing a message to a tweet that has less than 25% of the words capitalized (i.e., the message contains fairly standard capitalization practices and is not being used to add emphasis) that the use of ALL CAPS in more than 75% percent of the words leads to one of the strongest single variable, increasing the likelihood for transmission from the baseline by 542%. Messages that contain more than 50% but less than 70% of their words capitalized also get a modest increase, with a likelihood at 38%. However, messages that are lukewarm with their capitalization, having anywhere from 25% to less than 50% of their words capitalized see a decrease retransmission by 58%. Finally, we find that the use of the NWSBot, an application used to automate the posting of watch and warning product information on Twitter, is found to decrease the likelihood of being passed on by 36%.

## 2.6 Discussion

Through a systematic overview of retransmission for an entire census for a federal organization's communication over more than a decade of time, we are able to more deeply understand several of the social mechanisms of message passing, how they work in this particular Online Social Network context. Guided by the early tenants of Allport and Postman (1947) and Shibutani (1966), we found that microstructural and content features that tend to provide information that may reduce anxiety and decrease unclarity, or allow for users to participate in the public sense-making, will have increased likelihoods of retransmission. For the National Weather Service, the use of hashtags to connect with pre-existing channels of communication, or forums for public sense-making, is one of the largest amplifiers of message passing – hashtags generically are found to increase message passing by 23%, ceteris paribus, while hashtags linked to named-weather events are found to increase the retransmission of NWS communications by a whopping 252%. By tapping into an ongoing channel for communication on an emergent and salient topic for individuals, it is abundantly clear that NWS communications are able to reach a much broader audience on average leveraging that context, in effect widening their ability to reach those outside their immediate followers. Further, it is clear in this study that the use of quickly digestable forms of information like photos and videos are also found to increase message passing by 81%. Compared to URLs, which also may direct users to critical information, it appears that within the eco-system of Twitter, individuals are more likely to share items that they stay on the medium for – where using a URL reduces relative message passing by 55%.

We find clear evidence that any micro-structural properties that tend to lead to message narrowing, lead to decreases in the potential for retransmission. Unlike a rumor that may be passed on because it has unique salience to a few particular individuals, the kinds of information the National Weather Service is interested in getting the word out about, are communications that are broadly salient to individuals – i.e., those in the line of a hurricane, or those who will may be at risk of experiencing flooding. We find that the use of microstructural properties that – whether intentionally or not – lead to narrowing of an audience, that of mentioning and replying, is found to reduce message passing by 14% and 1300% respectively.

Replying, in particular, is the largest attenuator for a non-control covariate. This accords with prior findings, where narrowing messages leads to less overall traction. Part of the job of NWS communicators is to respond and answer questions in the public forum from their constituents, sometimes this is pointing users to weather-ready resources in preparation for a hurricane, or merely thanking a user for submitting a photo they took. In some of these contexts, information that is provided may in fact be useful or interesting to a general population, yet because of the use of this microstructural feature, less people will ultimately be reached. It is important in these contexts to consider the generality of the communication to the general audience, forego the direct mentioning or make two separate tweets, one for the individual, and another for the general population.

In line with Allport and Postman (1947), we found that audiences were more likely to pass information that use exclamation points (!), where holding everything else equal, the mere use of an exclamation point, indicating an order, directive, or emphasizing an emergency aspect to a communication, was found to increase message passing by nearly 30%, nearly 10 times more impactful than using question marks that do not provide the same kind of stylistic emphasis. Another way National Weather Service accounts use emphasis is through the use of ALL CAPS in their messaging. We find that when 75% or more of the words in a tweet are in ALL CAPS, that the likelihood of being passed on increases by 542% – the single largest amplifying effect among any microstructural or content features. Even using some extra capitalization as emphasis, anywhere from 50% to less than 75% of the words having capitalization, increases message passing by nearly 40%.

Finally, the use of lexical categories, or content/topic categories that were salient and could potentially reduce unclarity in the NWS audience included communications on Named Weather Events (198%), International Locations (72%), Hazards (38%), and Demographic groups (32%) were all found to increase the potential for retransmission.

## 2.7 Future Directions

While it is evident from the study that the major axis of interest from audiences in their decision to pass information on is how the content and style relate to hazard contexts and help users in their active sense-making, there are some lexical themes that do not fall so cleanly under this main thrust. We find that outside of the emergency context that the use of keywords around Space & Space Weather, Marine & Ocean, and Holidays increase message passing by 78%, 13%, and 14% respectively. Future research in message retransmission in the context of hazard communicators like the National Weather Service should attempt to better understand other potential kinds of interest/saliency based on potential hobbies, interests, and cultural contexts.

Space & Space Weather is an interesting category, for instance many communications are about meteor showers, auroras, and other discussions which could be seen as "community building" – however, there are also communications regarding geomagnetic storms that could potentially influence radio and electrical systems. Understanding how much of these topics are due to underlying "hazards" associated with the topic versus "community building" would allow us to better understand how organizations talk about weather and other topics to garner interest and participation before the storm. Community building in times of non-threat can be important for organization's like the National Weather Service to illustrate to their audiences that they will always be there as an official source of quality information. By interacting periodically with followers that organization may be more immediately recalled by individuals in times of actual weather threat/hazard. It is important that these agencies put extra effort into these community-building messages since it seems like most off-topic communications are harder to get passed on overall.

Finally, research should be done to understand the interpretive difference users may be making between automated or "robotic" communications compared to handcrafted messages from a human. Our study points to a negative influence on message passing for messages posted through the NWSBot source. While there has been work done understanding how individuals interpret hazard warnings and alerts (Brotzge and Donner, 2013; Sutton et al., 2021), no current studies have investigated whether users are subconsciously filtering automated communications by these automated "robotic" processes. It would be interesting to know what the threshold for filtering these kinds of communications and whether the combination of emphasis like the use of hazard keywords or ALL CAPS would prove relevant to audiences.

## 2.8 Conclusion

It's been nearly 75 years since Allport and Postman's work on "The Psychology of Rumor" was published, and over 50 years since Shibutani's "Improvised News: A Sociological Study of Rumor," yet even on an Online Social Network like Twitter, we find that these social mechanisms are present and functioning in similar ways. Twitter, and particularly communications by the National Weather Service show that many of the classic influences of message passing, social amplification, and rumoring are present today, despite the context being new, the kinds of things that are likely to get passed on remain the same. A slight caveat to this similarity is "information salient to whom?" Allport and Postman discuss individual salience as a driving factor for message passing, yet, in the context of a the National Weather Service using a service to broadcast information is that public conversations with particular individuals on a one-to-one basis, results in a significant narrowing of the audience and leads to dramatic decreases in retransmission (1300% for replies).

This could perhaps be part of an issue in translation by the National Weather Service coming from more traditional forms of broadcast media (like Television and Radio), where they now have to present as a forward facing entity, answering questions and responding to the constituents puts them in a communicationally complicated place. Organizations that service collectives of individuals should refrain from publicly replying to or mentioning of single individuals if the goal is to provide generally useful information to their larger constituent base. For instance, if a user reaches out with a question and the answer may be salient to a general audience who may also benefit in knowing, this study informs us how to effectively proceed. First, a response should be made to that individual directly through private message or a reply, but in either case, the second step should be to make a general post aimed to a general audience, without mentioning others.

The results from this study clearly show that the audiences for National Weather Service accounts are mainly motivated to share information that is salient to them – which probably means relating to some ongoing or upcoming hazard or threat – and provides them sense-making information that can help them understand their risks. Individuals were more likely to pass on hazard keyword messages, nearly 40% compared to baseline, than quotidian weather terminology (decrease of 5%). Information about weather models (16%), who is going to be impacted (Demographics) (32%), and mention of named-weather hazards (198%), were all associated with positive influence on the potential for retransmission.

# Chapter 3

# Cutting Through the Noise: Predictors of Successful Online Message Retransmission in the First Eight Months of the COVID-19 Pandemic

## 3.1 Abstract

In this paper, we investigated how message construction, style, content, and the textual content of embedded images impact message retransmission over the course of the first 8

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months of the COVID-19 pandemic within the United States. We analyzed a set of tweets (n = 372,466) from 704 public health agencies, state and local emergency management agencies, and elected officials posted on Twitter between January 1 and August 31, 2020. We measured message retransmission via the count of retweets (ie, the number of times a message was passed on by others), an important indicator of engagement and reach. To assess content, we extended a lexicon developed from the early months of the pandemic to identify key concepts within messages, employing it to analyze both the textual content of messages themselves, as well as text included within all embedded images (n = 233,877) as extracted via optical character recognition. Finally, we modelled the message retransmission process with a negative binomial regression, allowing us to quantify the extent to which particular message features amplify or suppress retransmission, net of controls related to timing and properties of the sending account. In addition to identifying other predictors of retransmission, we show that the impact of images is strongly driven by content, and with textual information in messages and embedded images operating in similar ways. We provided a number of potential lessons for crafting and deploying social media messages that can "cut through the noise" of an infodemic.

## 3.2 Introduction

Content pushed by public-facing organizations to social media can be thought of as a proverbial "message in a bottle." The "bottle" is cast out into a "sea" of communication roiled by waves of vastly divergent content, all vying for user attention—some messages are borne to their destinations while most others sink. Like the bottle, not all content is created equal, either in terms of propensity to "float" or in terms of the importance of the enclosed message. Some especially important messages—like those relating to public health communications—can lead to lives lost if they fail to reach their intended recipients. The importance of such health messages is intensified during hazard events like an ongoing global pandemic. Public health communicators, emergency managers, and elected officials thus face the challenge of cutting through the noise of misinformation, disinformation, and competing background content to get these critical messages to the public. The complexity of this information environment has been described by the World Health Organization (WHO) as an "infodemic," encapsulating the combination of information overload, active dissemination of misinformation and unproven claims, and other messaging that compete with scientifically established facts and professional expertise. Operating within an infodemic makes the jobs of public health communicators, emergency managers, and elected officials all the more difficult(World Health Organization (WHO), September 23, 2020). For public communicators to cut through the noise, it is necessary to understand what leads a message to be actively retransmitted, increasing its penetration and exposure. Here we examine several dimensions of public officials' communication strategies on Twitter during the first 8 months of the coronavirus disease 2019 (COVID-19) pandemic, from message content and structural features to the textual content on images and infographics, relating these features to observed message retransmission rates. Our analysis identifies message construction tactics that can potentially enhance retransmission in a pandemic setting, helping agencies reach members of the public within an especially challenging communication environment.

## 3.3 Public Health Communication in the Pandemic Response

During times of uncertainty, individuals tend to look toward officials, local or otherwise, to help make sense of what is going on around them (Danzig et al., 1958a; Taylor et al., 2012). In the COVID-19 pandemic, public health and emergency management agencies and elected officials have served as the primary entities tasked with informing and educating the public about the state of scientific knowledge regarding virus transmission, prevention, and mitigation strategies (Vaughan and Tinker, 2009). By bypassing the intermediaries involved in traditional forms of media, social media allows for public entities to disseminate information more efficiently and to speak directly to their constituents. These organizations utilize social media to instantaneously deliver crucial information to their audiences, often including actionable items that, if seen and heeded, can reduce health risks. In addition to allowing for rapid information dissemination, social media also allows for active conversation with constituents, which can potentially help increase trust and credibility through open and transparent communication while correcting erroneous information that may be in circulation (Danzig et al., 1958b; Olson et al., 2019). At the same time, the factors that make social media attractive to public organizations also make it attractive to other actors, leading to an extremely crowded and ever-changing communication landscape. Navigating this shifting terrain continues to be a critical challenge.

## 3.4 Information (Re)Transmission and Social Media

Twitter is widely used by officials to communicate on topics ranging from natural hazards and emergencies to issues of public health. As with other crowded social media environments, public entities posting messages on Twitter can, at best, hope to reach a very small number of users by initial, direct exposure; only a fraction of those subscribed to receive messages will be attending when a post is posted. Instead, message penetration (number of persons reached) and exposure (total views, including multiple views of the same message) are driven in large part by retransmission, where users who initially receive or otherwise find the post, pass it on to others (a process called "retweeting" on Twitter). A highly viral message may be retransmitted tens of thousands of times (resulting in extremely large numbers of exposures), while less successful messages may not be retransmitted at all. Thus, understanding the predictors of message passing is vital to effectively reaching an online audience. Prior studies have identified several key message and sender attributes that influence message passing. These include message content and structural features, the time the message was sent, the characteristics of the sending account, and the number of followers associated with the account. Previous studies from a range of hazard contexts (including the initial weeks of the COVID-19 outbreak) have found that message content conveying the severity of threats, communicating actionable information, and including media (photos and videos) all amplify message retransmission (Vos et al., 2018; Sutton and Butts, 2014; Sutton et al., 2015a,0,0). Conversely, messages that facilitated user engagement, such as direct replies and mentions, and the inclusion of hyperlinks lead to an attenuation of retransmission (Sutton et al., 2015c,0). It was also found in the first 2 months of the COVID-19 pandemic that the use of question marks and exclamation points (both emotive but informal syntactic elements) were both associated with decreased retransmission (Sutton et al., 2020) As noted, the use of multimedia attachments, including videos and static images, can provide significant increases in retransmission. Infographics and videos have been found to be effective tools for disseminating health-related information and helping to reach a larger audience (Marin-Gonzalez et al., 2016). Infographics, formally a "visual image such as a chart or diagram used to represent information or data in an easily understandable form," (OED Online, Accessed 2020) are important tools for reaching users with limited attentional resources. Studies suggest that visual representations paired with textual information ease users' cognitive load, helping make the content easier to process and remember compared to textual representation alone (Bateman et al., 2010; Otten et al., 2015; Harrison et al., 2015; Dunlap and Lowenthal, 2016). With public health communicators trying to increase information retention and recall, engagement, and behavioral uptake, the use of infographics has become an important piece of the public health communicator's arsenal (Scott et al., 2017). To date, however, the effect of image content (beyond mere inclusion) on retransmission has not been studied. This study fills a gap in the literature on public health communication in 2 crucial ways. First, it updates our understanding of what messaging strategies are—and are not—proving effective in cutting through the noise of a pandemic, as this study considers a longer time span (8 months) than prior work in this area. Second, it establishes a quantitative evidence base for the impact of textual features embedded in images—an increasingly important tool in the COVID-19 context, and in social media messaging more generally.

## 3.5 Methods

### Data Collection

This study analyzes a list of 704 unique Twitter accounts, comprised of public health organizations (n = 383), state governors (n = 77), state emergency management organizations (n = 50), local mayors (n = 96), and local emergency management agencies (n = 98) for the 100 largest cities in the United States. Public health accounts were identified through publicly available lists18 and prior projects on social media risk messaging(Vos et al., 2018; Vos and Buckner, 2016). Our sampling design was purposefully constructed to ensure coverage of (1) major types of public entities involved in online COVID-19 communication, and (2) a large number of local municipalities representing a large fraction of the US population, while at the same time remaining within data collection limits. We provide a breakdown of the administration levels of these accounts as well as the complete list of sampled accounts and their associated account types in the supplemental materials in the published document.[2] We collected all 372,466 tweets produced by the 704 accounts between the dates of January 1 and August 31, 2020, using the Twitter representational state transfer (REST) application programming interface (API). This API allows for the collection of tweets by specific accounts and includes account and tweet metadata. On average, each account produced 529.1

[2](Supplemental Tables 1 and 2, www.liebertpub.com/doi/suppl/10.1089/hs.2020.0200)

messages during the study period, with 10 accounts producing only a single tweet and WHO producing the most (n = 6,005).

## Microstructural Features

By using regular expressions, we code for items present within the content of the message, including microstructural features, such as structure and style. These microstructural features are coded as either present or absent and include the following features: the inclusion of a video or an image, a hyperlink (URL), a mention (@username), a direct reply, a quoted tweet, a hashtag, or a COVID-19 specific hashtag (eg., #COVID, #Coronavirus)

Table 1: Tweet Microstructural Features

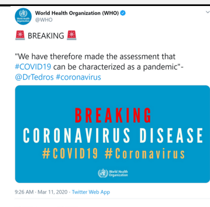
| Variable | Definition | Frequency | % of Tweets | Example |
|---|---|---|---|---|
| Image | Messages coded for the presence of an image or media. | 185,012 | 49.7% |  |
| Video | Messages coded for the presence of a video. | 16,848 | 4.5% |  |
| Hyperlink / URL | Message contains a hyperlink to external website. | 205,490 | 55% | All Hands on Deck! Geospatial mapping meets outbreak control. To learn more about the vital role geospatial science and technology can play in public health, go to **https://t.co/lIK3Iarc9o** #CDCEHblog **https://t.co/B2lEA98OHY** |
| Reply | Message is in response to a Tweet from another user. | 84,360 | 22.6% | **@Cindy_Lee_G @NCCommerce** Hi, please see this link: https://t.co/vX6KfvO5Og. It includes information as well as contact information for @NCCommerce. |
| Mention | Message includes the Twitter handle of an individual or organization. | 107,308 | 28.8% | Thank you **@TaosSkiValley**! #AllTogetherNM https://t.co/t0yFy9n3k8 |
| Hashtag | Message includes a #hashtag. | 163,595 | 44% | Our COVID-19 site has information for businesses about how to prepare and what to do if an employee becomes sick. https://t.co/iZI0IsUjWA **#COVID19 #AZTogether** |

Table 3.1: Tweet Microstructural Features

| | | | | |
|---|---|---|---|---|
| COVID-19 Hashtags | Message contained a #hashtag for #coronavirus #COVID19. | 74,845 | 20% (45% of all hashtag usage) | We all can be health leaders and practice physical distancing and also wear our face coverings. **#COVID19** |
| Quote | Message quotes another message in its entirety. | 32,042 | 8.6% | <br>Governor Gretchen Whitmer<br>@GovWhitmer<br>Hi, my name is Gretchen Whitmer, and that governor is me 👋<br>I've asked repeatedly and respectfully for help. We need it. No more political attacks, just PPEs, ventilators, N95 masks, test kits. You said you stand with Michigan — prove it.<br>Daniel Dale @ddale8 · Mar 26<br>Trump says he's having a big problem with "the young, a woman governor, you know who I'm talking about, from Michigan."<br>7:19 PM · Mar 26, 2020 · Twitter for iPhone |
| Exclamatory | Message includes an exclamation mark (!) | 55,851 | 14.9% | Stay Healthy Nevada**!** #StayHomeForNevada #COVID19 https://t.co/8CXK2sJcda |
| Interrogatory | Message includes a question mark (?) | 26,272 | 7% | Do you have questions about tenant rights and the current eviction moratorium**?** Register now for the A Way Home for Tulsa webinar on tenant rights during the COVID-19 pandemic. The webinar will be held Friday, April 3 at 9:30 a.m. #Tulsa<br><br>https://t.co/IPlYOhcGEk |

## Topic Lexicon Development

Lexicons are specialized keyword lists that assist in the process of identifying key topics of a specific corpus. Similar systems have been developed and leveraged in previous studies whereby researchers identify crisis-specific keywords that are relevant to an emerging disaster (Olteanu et al., 2014; Imran et al., 2014). We developed a lexicon that identifies keywords for our specific account set that (1) aligns with theoretical concepts, (2) draws upon prior studies of disaster communication on Twitter, and (3) accounts for observed COVID-19 event salient content, language, and terms that appear in our corpus. Lexical categories were constructed by manually reviewing 100 randomly sampled tweets per day over the course of a multimonth period (n = 21,300), from February 1 to August 31, 2020. We extend the lexicon of Sutton et al 2020 which was based on the first 2 months of the COVID-19 pandemic in the United States, and integrated the following identified content themes: closures and openings, information sharing, official information, resilience, surveillance, symptoms, and technical information. In addition to using those themes, we added the category of "location" and divided the lexical category of "efficacy" into "efficacy" and "action." Location messages contained mentions of international locations, usually in reference to places where major outbreaks of the virus had occurred, among them China, Japan, and Italy. Efficacy and action were separated based on observation of more distinct use of terms by health communicators in recent months; specifically, we found greater separation between the articulation of which protective actions to take (efficacy) and information on how to take those actions (action). It should be noted that category "action" is applicable to any action directives and is not necessarily COVID-19 specific. Further, our extension accounts for additional words or phrases that became commonplace after the month of April and are not retroactively coded. We provide the definitions of the aforementioned categories in Table 3.2. Additional background on the motivation for the original content categories and related coding considerations used in prior work can be found in Sutton et al. (2020).

Table 2: Lexicon Set: Definitions, Frequencies, and Examples

| Variable | Definition | Frequency In Tweets | % of Total Tweets | Frequency In Images | % of Images | Example *(extended lexicon in italics)* |
|---|---|---|---|---|---|---|
| Susceptibility | Keywords describing individuals or groups at risk of COVID-19 | 41,508 | 11% | 14,013 | 7.5% | Vulnerable, risk, unlikely, travel, veteran, older, kids, age-60, chronic, immune, dialysis, diabetes, homeless, jail, shelter, facilities, African American *Underserved, child, immigrant, senior, unhoused, essential worker, public servant,* |
| Surveillance | Keywords describing strategies to identify population impact | 88,380 | 23.7% | 33,375 | 18% | Test, result, case, presumptive, death, contact trace, hospitalize, dashboard, sadden, recover *Retrace, diagnostics, intensive care, antibody test, coronavirus vaccine* |
| Symptoms | Keywords describing symptoms of disease | 10,472 | 2.8% | 6,991 | 3.7% | Symptom, shortness of breath, fever |
| Actions | Keywords instructing people on protective actions to take | 92,143 | 24.7% | 14,466 | 7.8% | Donate, follow, get tested, contact a doctor, stock up *Isolate, care, reengage, avoid crowds* |
| Efficacy | Keywords on how individuals are to take protective measures to safeguard themselves from the threat | 59,735 | 16% | 22,688 | 12% | Stay home, self isolate, physical distance, social distance, quarantine, shelter in place, face, mask, hand wash, soap and water, 20 seconds, six feet, disinfect *Maskup, 6 feet, ppe, face covering, sanitize, cover* |

Table 3.2: COVID-19 Lexicon Set: Definitions, Frequencies, and Examples

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | | *your nose, bleach* |
| Collective efficacy | Keywords reflecting the capacity to achieve an intended effect | 48,173 | 12.9% | 12,320 | 6.6% | Neighbors, united, solidarity, together, community, mitigate the spread, flatten the curve, stay home save lives, shelter in place *Work together, crush the curve, beat the virus, move forward together* |
| Technical information | Keywords describing mechanism of how the virus spreads | 7,973 | 5.7% | 13,648 | 7% | Droplet, cough, sneeze, surface, transmission, infect, incubate, contagious *Talk, not showing symptoms* |
| Official information | Keywords about governmental responses to COVID-19 and how to access information. | 89,560 | 24% | 35,259 | 19% | Public health authority, official, task force, declaration, proclamation, executive order, activate, monitor, model, advisory *Test site, community based testing, testing locations, protection program, rent control* |
| Information Sharing | Keywords that relate to outlets or events for information sharing. | 57,842 | 15.5% | 20,254 | 10% | Helpline, briefing, livestream, broadcast, town hall, press conference, guidance *News release, roundtable, data-driven, based on science, public service announcement, misrepresented* |
| Resilience | Keywords that express thanks and appreciation. | 33,028 | 8.8% | 3,516 | 10% | Hero, salute, thank, recognize, grateful *Rockstars, lit bright blue* |
| Closures and openings | Keywords about suspension or reinstatement of | 61,307 | 16.5% | 21,436 | 11% | Suspend, close, mandatory, lockdown, |

| | | | | | | |
|---|---|---|---|---|---|---|
| | service, activities, and facilities. | | | | | visitation, cancel, large gatherings, non essential *In-person, new normal, grocery, sports leagues, gym, malls* |
| Location | Keywords about International Locales. | 1,151 | < 1% | 693 | < 1% | China, Wuhan, Japan, Italy, Iran |
| Primary threat | Keywords used to describe COVID-19. | 132,392 | 35.5% | 52,066 | 28% | Coronavirus, COVID-19, ncov, outbreak, pandemic |
| Secondary Impacts | Keywords used to describe additional threats that result from the pandemic. | 86,859 | 23% | 24,020 | 13% | Mental health, substance abuse, domestic violence, evict, food insecure, blood drive, scam, rumor, stigma, school, unemployment panic buy, PPE, compliance, grief |

### Period Effects and Account Properties

We also control for different types of period effects and account properties. For period effects, we control for the time a message was sent, the day of the week, the month it was sent, and whether it was sent after the Presidential Emergency Declaration on March 15, 2020. We also control for the type of organization that published the message (public health agency, state emergency management, local emergency management, governor, or mayor), the log of the number of followers they have, and the log of the number of friends they have on Twitter. Specific fixed effects were added for WHO- and US Centers for Disease Control and Prevention (CDC)-affiliated accounts, given their prominence and distinctive roles in the pandemic response.

| Table 3: Negative Binomial Regression Model | Estimate | Rate Multiplier | Std. Error | Sig. |
|---|---|---|---|---|
| Intercept | -4.962 | 141.88 | 0.039 | *** |
| *Account Properties* | | | | |
| Governor Account | 1.273 | 2.57 | 0.009 | *** |
| Log Follower Count | 0.768 | 1.16 | 0.002 | *** |
| Mayor Account | 0.532 | 0.70 | 0.008 | *** |
| Log(+1) Friends Count | -0.089 | 0.09 | 0.002 | *** |
| State EM Account | -0.005 | 0.01 | 0.012 | N.S. |
| Local EM Account | -0.442 | 0.56 | 0.009 | *** |
| CDC Affiliated Accounts | 0.027 | 0.03 | 0.015 | N.S. |
| World Health Organization | 0.158 | 0.17 | 0.023 | *** |
| *Microstructural Properties* | | | | |
| Incl. Video | 0.214 | 0.24 | 0.014 | *** |
| Incl. Hashtag | -0.034 | 0.03 | 0.007 | *** |
| Incl. Image | -0.13 | 0.14 | 0.011 | *** |
| Incl. Quote | 0.073 | 0.08 | 0.01 | *** |
| Incl. Question Mark(?) | -0.115 | 0.12 | 0.01 | *** |
| Incl. Mention | -0.227 | 0.25 | 0.006 | *** |
| Incl. Exclamation(!) | -0.19 | 0.21 | 0.008 | *** |
| Incl. URL | -0.381 | 0.46 | 0.006 | *** |
| Reply | -1.712 | 4.54 | 0.007 | *** |
| Incl. #COVID19 Hashtag | 0.044 | 0.04 | 0.01 | *** |
| *Lexical Categories* | | | | |
| Surveillance | 0.231 | 0.26 | 0.007 | *** |
| Technical Info. | 0.083 | 0.09 | 0.011 | *** |
| Actions | -0.077 | 0.08 | 0.006 | *** |
| Efficacy | 0.422 | 0.53 | 0.007 | *** |
| Symptoms | 0.127 | 0.14 | 0.016 | *** |
| Primary Threat | 0.174 | 0.19 | 0.008 | *** |
| Secondary Impacts | 0.121 | 0.13 | 0.006 | *** |
| Official Responses | 0.156 | 0.17 | 0.006 | *** |
| Location | 0.506 | 0.66 | 0.044 | *** |
| Collective Efficacy | 0.085 | 0.09 | 0.008 | *** |
| Closures/Openings | 0.066 | 0.07 | 0.007 | *** |
| Resilience | -0.084 | 0.09 | 0.009 | *** |
| Susceptibility | 0.001 | 0.00 | 0.008 | N.S. |
| Info. Sharing | -0.137 | 0.15 | 0.008 | *** |
| *Image Textual Content* | | | | |
| Image Has Text | 0.008 | 0.01 | 0.009 | N.S. |
| # of Images | -0.018 | 0.02 | 0.006 | ** |
| Surveillance | 0.224 | 0.25 | 0.012 | *** |
| Technical Info. | 0.054 | 0.06 | 0.016 | *** |
| Actions | 0.032 | 0.03 | 0.015 | * |
| Efficacy | 0.161 | 0.17 | 0.013 | *** |
| Symptoms | 0.122 | 0.13 | 0.021 | *** |
| Primary Threat | 0.057 | 0.06 | 0.01 | *** |
| Secondary Impacts | 0.052 | 0.05 | 0.012 | *** |
| Official Responses | 0.036 | 0.04 | 0.011 | *** |
| Location | 0.019 | 0.02 | 0.058 | N.S. |
| Collective Efficacy | -0.04 | 0.04 | 0.015 | ** |
| Closures/Openings | 0.121 | 0.13 | 0.013 | *** |
| Resilience | 0.143 | 0.15 | 0.026 | *** |
| Susceptibility | 0.184 | 0.20 | 0.015 | *** |
| Info. Sharing | -0.003 | 0.00 | 0.013 | N.S. |
| *Period Effects – National Emergency Declaration Period* | | | | |

Table 3.3: Negative Binomial Regression

| | | | | |
|---|---|---|---|---|
| Post-Declaration | 0.256 | 0.29 | 0.014 | *** |
| *Period Effects – Month* | | | | |
| February | -0.043 | 0.04 | 0.014 | ** |
| March | 0.842 | 1.32 | 0.016 | *** |
| April | 0.381 | 0.46 | 0.018 | *** |
| May | 0.214 | 0.24 | 0.018 | *** |
| June | 0.411 | 0.51 | 0.018 | *** |
| July | 0.41 | 0.51 | 0.018 | *** |
| August | 0.23 | 0.26 | 0.018 | *** |
| *Period Effects – Time of Day* | | | | |
| 12 am UTC | -0.612 | 0.84 | 0.033 | *** |
| 1 am UTC | -0.333 | 0.40 | 0.034 | *** |
| 2 am UTC | -0.131 | 0.14 | 0.035 | *** |
| 3 am UTC | -0.073 | 0.08 | 0.037 | N.S. |
| 5 am UTC | -0.295 | 0.34 | 0.051 | *** |
| 6 am UTC | -0.314 | 0.37 | 0.064 | *** |
| 7 am UTC | 0.01 | 0.01 | 0.077 | N.S. |
| 8 am UTC | -0.56 | 0.75 | 0.072 | *** |
| 9 am UTC | -0.561 | 0.75 | 0.065 | *** |
| 10 am UTC | -0.501 | 0.65 | 0.049 | *** |
| 11 am UTC | -0.668 | 0.95 | 0.039 | *** |
| 12 pm UTC | -0.569 | 0.77 | 0.034 | *** |
| 1 pm UTC | -0.583 | 0.79 | 0.032 | *** |
| 2 pm UTC | -0.597 | 0.82 | 0.032 | *** |
| 3 pm UTC | -0.656 | 0.93 | 0.031 | *** |
| 4 pm UTC | -0.613 | 0.85 | 0.031 | *** |
| 5 pm UTC | -0.617 | 0.85 | 0.031 | *** |
| 6 pm UTC | -0.694 | 1.00 | 0.031 | *** |
| 7 pm UTC | -0.567 | 0.76 | 0.031 | *** |
| 8 pm UTC | -0.631 | 0.88 | 0.031 | *** |
| 9 pm UTC | -0.597 | 0.82 | 0.032 | *** |
| 10 pm UTC | -0.534 | 0.71 | 0.032 | *** |
| 11 pm UTC | -0.379 | 0.46 | 0.032 | *** |
| *Period Effects – Day of Week* | | | | |
| Sunday | 0.318 | 0.37 | 0.011 | *** |
| Monday | 0.099 | 0.10 | 0.009 | *** |
| Tuesday | 0.079 | 0.08 | 0.009 | *** |
| Thursday | 0.112 | 0.12 | 0.009 | *** |
| Friday | 0.062 | 0.06 | 0.009 | *** |
| Saturday | 0.139 | 0.15 | 0.01 | *** |

Observations: 372,466; AIC: 2,271,754

Log-Likelihood: -1,1357,790; Dispersion Parameter: 0.514; Std. Error: 0.001

* P < 0.05, ** P < 0.01, *** P < 0.001.

*Note: The rate multiplier is the exponentiated absolute value of the beta coefficient – 1.*

### Optical Character Recognition

To analyze the textual content of images, we employed optical character recognition (OCR) through the use of the Image Magick and Tesseract packages for the R statistical programming language (Ooms, 2019,0; R Core Team, 2020). OCR can convert an image that contains alphanumeric characters into a computer-readable text format (Schantz, 1982). Of the 372,466 messages in our dataset, 185,012 (almost 50%) messages included an image attachment. As part of our content coding protocol, we coded for textual information contained in images embedded in or attached to messages. To collect the images for analysis we first constructed a web scraper in the R statistical programming language. This allowed us to download images for any tweets that contained an image attachment, as the link to the image is available in the tweet metadata. Since Twitter allows for the inclusion of up to 4 images in a single post (< 10% of all images contain more than 1 image), the resulting set of images to be analyzed was 233,877 images at nearly 37 gigabytes in storage size. This set was then processed by Image Magick and analyzed by Tesseract, which took over 37 hours (approximately an hour per gigabyte of images on a 6-core CPU). Taking all words extracted at high confidence from each image, we applied the same lexicon as used for message text to words contained within the image. The resulting content codes were then used as predictors for the message retweet rate; if multiple images were present for a given tweet, content types were merged. Our coding is limited to static images, as videos could not be coded for semantic content. Please refer to Table 3.2 for descriptive information about the application of the lexical categories to the images.

## 3.6 Data Analysis

Following prior literature, we defined retransmission as the total number of times a message was retweeted. Similar to prior work on modeling retransmission on Twitter (Sutton and

Butts, 2015), we found that the majority of messages do not get retransmitted, with 65% being retweeted only 6 times or less, but a small fraction of messages is retweeted many thousands of times. Therefore, to estimate the contribution of mechanisms that affect the message passing process while accounting for the heterogeneity of retransmission outcomes, we performed a negative binomial regression—using the R statistical programming language and the glmmADMB package (Fournier et al., 2011; Skaug et al., 2016)—on the retweet count using predictors that capture message content, style, and image textual content. The resulting model coefficients were interpreted as follows: for a given message feature, a positive coefficient indicates an increase in message retransmission (with other conditions remaining the same), while a negative coefficient indicates a decrease in retransmission. In particular, each unit increase in a covariate increases the log of the expected retweet count by the amount of the associated coefficient. A more in-depth discussion of the negative binomial model in application to message retransmission can be found in Sutton et al 2020.

## 3.7 Results

The reported model (Table 3.3) indicates the factors that influence the process of retweeting the communications of public health agencies, local and state management organizations, and elected officials during the first 8 months of the COVID-19 pandemic (see Table 3.1 and Table 3.2 for descriptions and frequencies of the factors).

## Message Retransmission

## Period and Account Effects

As seen in Figure 3.1, the month the message was posted affected expected retransmission, suggesting overall increases or decreases in attention by the public during the 8-month period. Compared to the baseline month of January, February had a slight decrease in retransmission by 4%, followed by March, the month with the greatest focus on the coronavirus pandemic in the United States, at 132% increase to retransmission. We also found that messages posted after the emergency declaration had a 29% increase in message passing. From April to August, retransmission remained fairly steady, with slight declines in May and August.

In terms of the individual or organization posting the message, we found that with public health accounts as our baseline (the largest percentage of accounts in this dataset) that governors (257%) and mayors (70%) had the greatest impact on retransmission. Accounts associated with the US CDC were not found to be significantly different than the retransmission of the public health accounts; however, the sole WHO Twitter account had a positive influence of retransmission, at 17%. Emergency management accounts at the local level had 36% lower retransmission rates, while state emergency management accounts were not significantly different from the baseline group of public health accounts. Finally, every 1 unit increase in the log follower count corresponds positively to a 116% increase in the expected retransmission rate.

## Message Structure and Sentence Style

As seen in Figure 3.2, we also found that message structural features can increase the potential for retransmission. Including a video in a tweet was found to increase retransmission

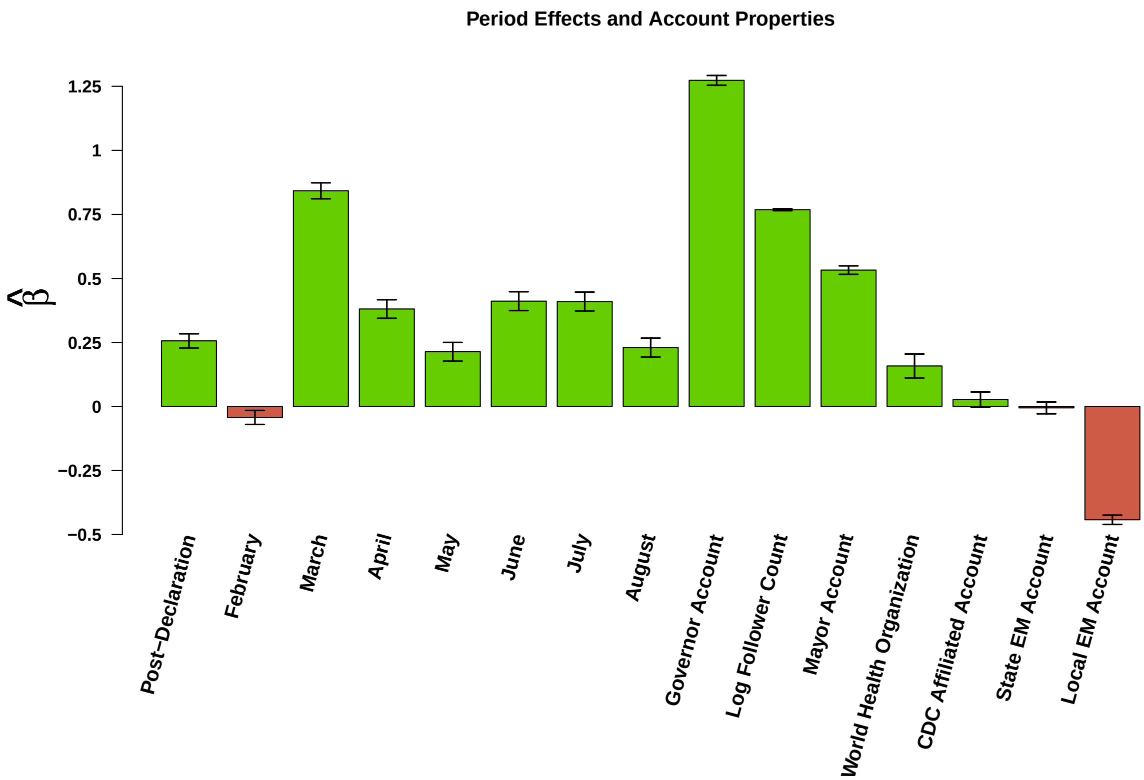



Figure 3.1: Effects of time period and account type on message retransmission. Bars indicate effects of content covariates (horizontal axis) on log expected retweet count (Table 3.3); whiskers indicate 95% confidence intervals.

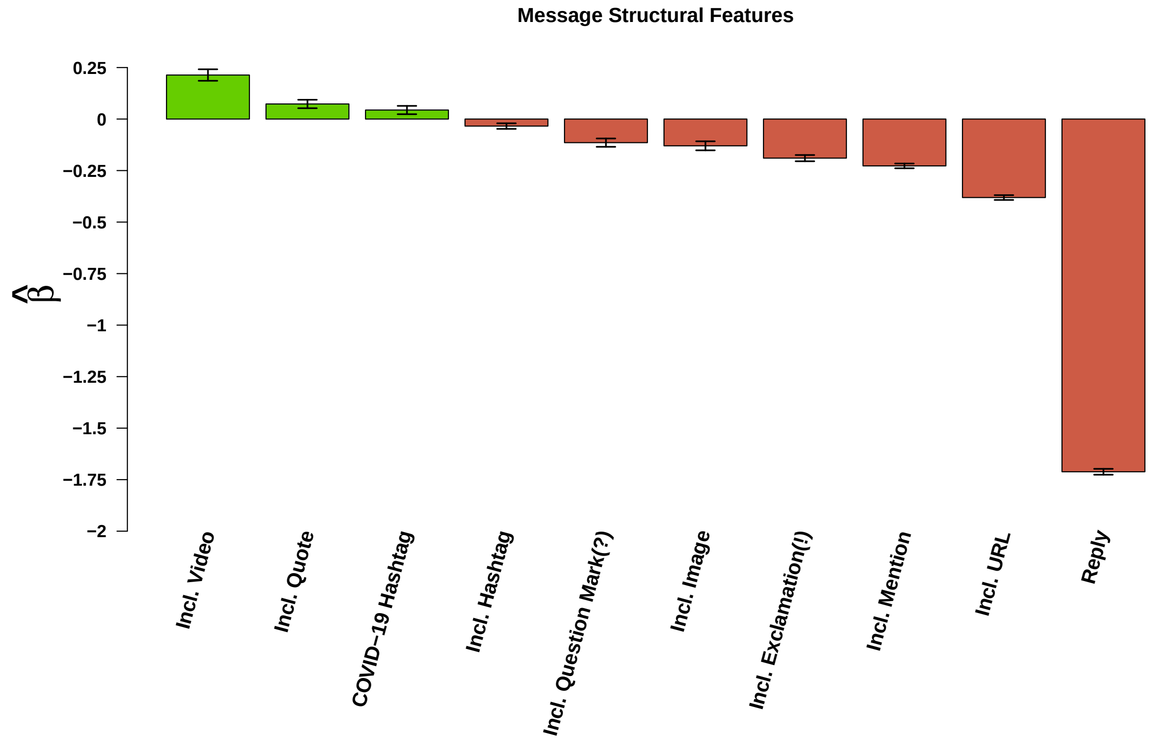



Figure 3.2: Effects of messages structural features on message retransmission. Bars indicate effects of content covariates (horizontal axis) on log expected retweet count (Table 3.3); whiskers indicate 95% confidence intervals.

of the associated message by 24%. Furthermore, "quote" tweets, by which a user quotes the message of another user while adding their own content, were found to increase message retransmission by 8%.

Often a large, positive influence on message retransmission, we found that the use of most hashtags negatively influenced retransmission in this context, decreasing its potential by 3%. We did, however, find that the use of #COVID19 or #Coronavirus hashtags increased retransmission by 4%, leading to a net 1% increase in retransmission overall. In contrast, inclusion of question marks and the use of exclamation marks decreased the rate of message retransmission by 12% and 21%, respectively. Mentioning other users, which narrows conversation, and the inclusion of hyperlinks or URLs decreased message retransmission by 25% and 46%, respectively. Finally, as has been found in multiple studies in other contexts (Vos et al., 2018; Sutton et al., 2020) the use of 1-to-1 responses (replies) on Twitter has a strongly negative impact on message passing, decreasing retransmission by 454%.

## Lexical Content

The largest impact on retransmission (Figure 3.3) by content features is the mention of international locales (location) associated with large COVID-19 outbreaks, corresponding to a 66% increase in retransmission, followed by efficacy (53%) and surveillance (26%) messaging. Messages that made reference to COVID-19 or coronavirus (primary threat) were found to increase retransmission by 19%. Official responses were found to increase retransmission by 17%. The mention of symptoms and secondary impacts like mental health and other side effects of the pandemic were each found to positively influence message retransmission by 13%. The other items that were found to positively influence message transmission were that of technical information (9%), collective efficacy (9%), and closures/openings (7%).

Lexical categories including actions, resilience, and information sharing were found to negatively influence the message retransmission process by 8%, 9%, and 15%, respectively. Furthermore, the model shows that messages that contained content relating to susceptibility were not found to significantly impact message retransmission in any meaningful way.

## Image Semantic Content

Our OCR analysis (Figure 3.4) provided us with insights on the impact of image semantic content on message retransmission. In general, when the semantic content of an image was held constant, we found that adding an image did not increase the potential for message

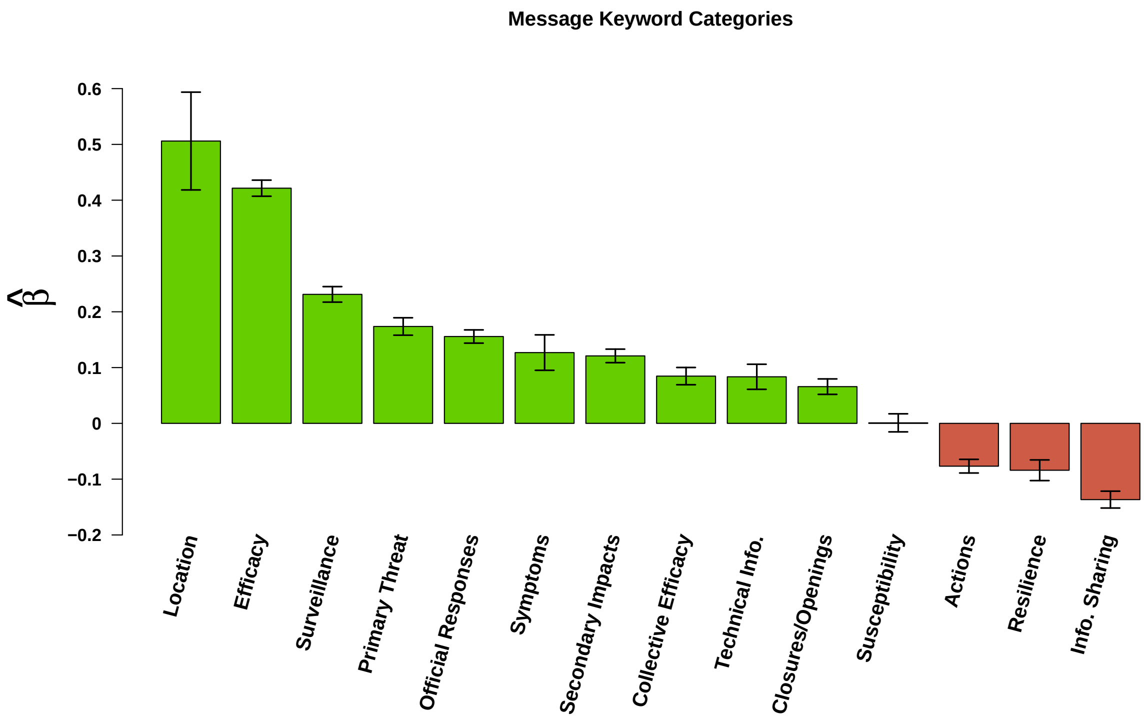



Figure 3.3: Effects of message keyword (lexical) categories on message retransmission. Bars indicate effects of content covariates (horizontal axis) on log expected retweet count (Table 3.3); whiskers indicate 95% confidence intervals.

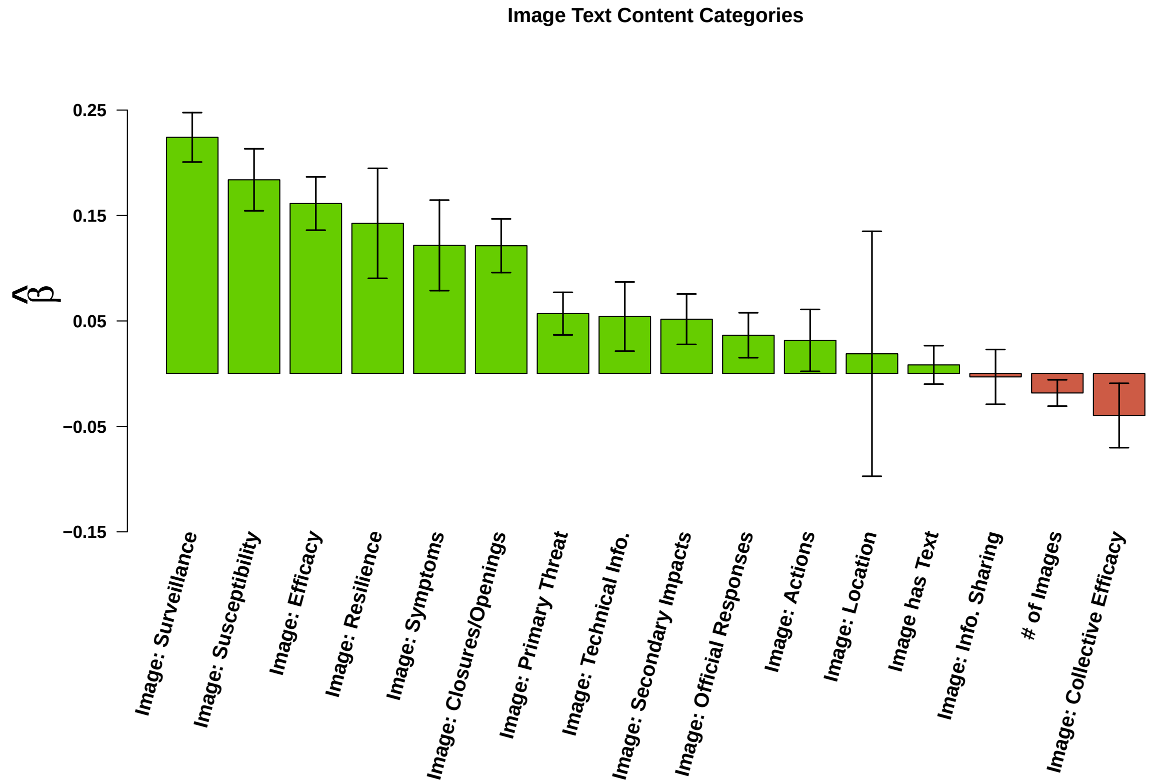



Figure 3.4: Effects of image textual content (lexical) categories on message retransmission. Bars indicate effects of content covariates (horizontal axis) on log expected retweet count (Table 3.3); whiskers indicate 95% confidence intervals.

retransmission—in fact, we found the opposite to be true: including an image decreased the expected retransmission rate by 14%. An image containing generic textual content (ie, content outside the coded lexical categories) was found to have no significant impact on message retransmission, and the number of images uploaded had a weakly negative effect on message passing, with a 2% decrease per each image attached after the first image.

We also analyzed images that contained text within them. Images containing text relating to surveillance keywords, information about susceptibility, and efficacy had the greatest positive impacts on retransmission (25%, 20%, and 17%, respectively). This is followed increased message retransmission of images with text that depict resilience (15%), discussed

COVID-19 related symptoms (13%), or referenced closures and openings(13%). If image text referenced the primary threat of COVID-19 or secondary impacts associated with COVID-19, the potential for retransmission is increased by 6% and 5%, respectively. Finally, image text that positively impacted retransmission had technical information (6%), discussed official responses (4%), or contained action keywords (3%). In contrast, images that conveyed information relating to collective efficacy were found to negatively impact message retransmission by 4%. The reference of international locations within an image, and keywords that convey information sharing on an image did not significantly impact message retransmission. Note that all of the above effects are cumulative with both each other and with the base (negative) effect of images; thus, images without appropriate content tend to decrease retransmission rates, but images containing the right mix of content types can end up being strongly conducive to retransmission.

## 3.8 Discussion

### Trends and Comparisons with Initial Outbreak Period

"COVID fatigue" or "quarantine fatigue" is clearly shown in the data. We found that March had the most retransmission, which was reduced by half in April and was nearly halved again in May. We did find that there was an uptick in retransmission that stayed steadily for June and July, only to be reduced again in August, but nowhere near the levels of retransmission in March. This trend showcases that there are real effects to the concept of COVID fatigue, in that we find communication from these accounts greatly reduced as the pandemic drags on.

## Comparisons with Effects from Prior Messaging Studies

An account's organizational type has been shown to influence the message passing process (Sutton et al., 2020). This study supports these findings. Both governor and mayor accounts were found to have higher likelihoods of retransmission, which we speculated in our previous work to potentially be a function of individuals' responsibility for decision making during the unfolding pandemic (Sutton et al., 2020). Also, consistent with other studies (Vos et al., 2018; Sutton et al., 2015c,0), the number of followers in the immediate audience of the message increases the potential for exposure and increases the potential that those exposed to the message are more likely to share it with their extended network of followers. One of the largest positive effects found in this and prior studies is the use of video media. It is apparent that within the context of information communication, the combination of video and audio leads to higher levels of message passing, compared with text-only messages, as evidenced in prior literature (Vos et al., 2018). We also find, in this context, that the use of quoting tweets does lead to a slight increase in retransmission, perhaps catching the coattails of a popular message and, thereby, expanding the initial audience for the message. However, this feature warrants further investigation to understand how the aspects of the account being quoted affect retransmission. In line with patterns seen in other hazard contexts, this analysis also shows that there are several structural features that lead to a weakening of the retransmission process. Mentions and replies are some of the largest attenuators and have been found to consistently affect the message retransmission process in conditions of imminent threat, emerging infectious disease (Sutton et al., 2020), and now over sustained durations of threat. The use of directed mentions and message replies is an important engagement strategy used by organizations, having been hypothesized to increase trust in organizations through increased levels of responsiveness. However, the same strategy also narrows the intended audience. If the content of that message could be useful to others, one should consider replying in a private message to the individual and additionally making a public post for a more general audience. In agreement with prior literature, we find that the inclusion of URLs remains one of the largest detractors of message passing. We hypothesize that this is due to the fact that clicking on a URL takes users away from Twitter's service, making retweeting an afterthought. Finally, the use of interrogatory language and exclamation points did not help the potential for message passing.

## Message Content and Retransmission

While style and context can matter, content is key to retransmission potential. Messages that discussed international locations with particularly famous outbreaks or responses (eg, Italy, South Korea, or Wuhan, China) were the most likely to be passed. This may be in part due to organizations such as WHO that discuss other countries' experiences with the coronavirus. Another positive factor for retransmission is efficacy or discussion of methods of protecting oneself by limiting exposure to the threat. Identified by keywords and phrases like "mask," "social distancing," and "handwash," this category has had a positive effect on retransmission (Vos et al., 2018; Sutton et al., 2015c). Collective efficacy was also found to help increase message passing but to a lesser extent than efficacy. We also found tweets containing content about surveillance (eg, hospitalizations, deaths, tracing, testing) were more likely to be retransmitted, aligning with prior studies on surveillance content (Sutton et al., 2020). Generally, messages containing information about hazards and their impact or severity also increased message passing (Vos et al., 2018; Sutton et al., 2015c). There are also a few lexical categories that decreased message passing—chief among them was information sharing. For instance, messaging about town halls, press conferences, and webinars did not seem to warrant retransmission since the content more likely to be passed was the video or stream itself, which had a positive retransmission effect. Finally, the categories of actions and resilience were found to attenuate message passing. One of the largest improvements to prior studies on retransmission on Twitter is our ability to analyze the semantic content of images included in a post. While past studies found that the baseline effect of merely including an image positively increased retransmission, we found that controlling for text within images unveiled that an image without text negatively influences retransmission. Therefore, for a message to be successfully retransmissible, the content, goal, approach, and strategy of the text and image or graphic used should be considered carefully and thoughtfully. If the intent of an image or infographic is to be retransmitted as widely as possible, many of the lexical categories identified here can help in that process. Besides keywords relating to surveillance content (one of the largest promoters of retransmission), we found that susceptibility, efficacy, and resilience were the next top 3 positive effects for text in images. This differs somewhat from our results for susceptibility-themed message content, which had no influence on message retransmission, and resilience, which was found to negatively influence retransmission for message content. This could suggest that information about who is at risk (susceptibility) and information about positive concepts/terms that recognize and honor those who are risking their lives on the frontline of the pandemic (resilience) are more evocative when expressed in visual form and are overlooked when they are in purely text format. On the whole, however, we see considerable consonance between the effects of message and image content, suggesting that they may be processed in similar ways.

## 3.9 Further Directions

As the pandemic evolves, it will be important to examine the impact of exogenous events that may influence retransmission rates outside the context of the communication medium of Twitter—this might include surges/spikes of deaths or cases associated with the virus, or even news associated with vaccines or other treatments. Likewise, the penetration of the virus into rural areas raises the question of whether there are distinct messaging strategies that work better (or worse) for local accounts in these regions than elsewhere. The current data do not suggest distinct effects for smaller communities, but a specialized rural sample would be required to draw more definitive conclusions. Finally, the slight increase in retransmission from quote tweets suggests value in further examining this phenomenon, in particular, whether attributes of the original poster influence the retransmission rate. Doing this type of analysis would require a specialized data collection design and could shed light on how this new platform feature could be effectively utilized.

## 3.10 Recommendations for Practice

We summarize the practical implications of our findings for public health communicators, emergency management agencies, and governmental officials as follows:

- Don't Be Cute About It: Our findings support the evidence that the public is responsive to passing on messages with practical information about the pandemic, its impacts, and ways to take action. Focusing on useful content rather than gimmicks to go "viral" will prove helpful in the long run.
- Use Media Critically: Videos and images can be powerful tools to amplify messages. For images, having meaningful content embedded is crucial for their success—simply adding images without relevant content can potentially reduce message retransmission.
- Not Everything Should Be an Image: Largely, information embedded in images has a qualitatively similar impact on retransmission to information in the message text itself. Therefore, when crafting messages, it may be more useful to focus on what information will be useful rather than through which medium it is delivered.
- #Hashtag or Not?: Like images, hashtags are not universally useful. We found little impact with the use of COVID-19-associated hashtags and a slight negative mean impact of hashtags overall on retransmission. Past studies suggest that hashtags can

be effective, but in the current pandemic they may need to be carefully targeted to have a useful effect.

- Capitalize on Weekend Attention: During our current pandemic, it appears that weekends are particularly active time for message retransmission, which can be used to maximize message impact.

- Don't Narrow Your Audience: Many of the findings from previous studies on retransmission during hazard events are also true here, including the impact of audience narrowing. While there are good reasons to use replies, mentions, and other techniques that target individuals, it is important to be aware that these were found to consistently and largely reduce retransmission.

- Cultivate Your Network (Especially Elected Officials): While having a large follower count undoubtedly helps with retransmission, other sources of prominence also matter. High-level elected officials can direct attention in ways that local officials, public health organizations, and even some prominent government or intergovernmental agencies cannot. Allying and cooperating with these individuals to strategically boost public health messaging may be an important tool for getting critical information to a wide audience.

## 3.11 Conclusion

During an infodemic, with misinformation and disinformation surging and swirling around us all, the need for evidence-based communication strategies is substantial. It is hoped that these results will aid health communicators, emergency managers, and elected officials in crafting messages that can cut through the noise surrounding the COVID-19 pandemic.

# Chapter 4

# Modeling Complex Interactions in a Disrupted Environment: Relational Events in the WTC Response

## 4.1 Abstract

When subjected to a sudden, unanticipated threat, human groups characteristically self-organize to identify the threat, determine potential responses, and act to reduce its impact. Central to this process is the challenge of coordinating information sharing and response activity within a disrupted environment. In this paper, we consider coordination in the context of responses to the 2001 World Trade Center disaster. Using records of communications among 17 organizational units, we examine the mechanisms driving communication dynamics, with an emphasis on the emergence of coordinating roles. We employ relational event models (REMs) to identify the mechanisms shaping communications in each unit, finding a consistent pattern of behavior across units with very different characteristics. Using a

simulation-based "knock-out" study, we also probe the importance of different mechanisms for hub formation. Our results suggest that, while preferential attachment and pre-disaster role structure generally contribute to the emergence of hub structure, temporally local conversational norms play a much larger role. We discuss broader implications for the role of microdynamics in driving macroscopic outcomes, and for the emergence of coordination in other settings.

## 4.2 Introduction

It is a common "disaster myth" that, when faced with a sudden threat, social groups lacking specific preparation will either passively wait for rescue, or fly into a state of uncontrolled panic (Tierney et al., 2006). In fact, it is far more common for those in harm's way to take immediate action to assess the threat, determine appropriate response measures, and take the initiative to carry them out (Auf der Heide, 2004). Such complex behavior under adverse and disrupted circumstances poses significant problems of *coordination*: to accomplish it, groups must compile information regarding the evolving situation (as well as relevant background knowledge), identify actions that need to be taken (and the resources needed for those actions), and direct behavior to ensure that requisite actions are performed with a minimum of task interference. Central to successful coordination is communication, the structure of which can either facilitate or inhibit performance (as has been known at least since the pioneering studies of Bavelas and colleagues (e.g. Bavelas and Barrett, 1951)). At a more microdynamic level, effective communication also depends upon shared interaction norms, whether embedded in formal protocols or in conventional cultural practices, without which information passing becomes extremely difficult.

While this emergence of coordination in response to threat is well-established, the exact mechanisms by which it is accomplished *in situ*, and the relative importance of those mechanisms for successful response in practice, remain the subject of inquiry. Among the challenges in studying this phenomenon have been the relative paucity of detailed data on communication dynamics in disrupted settings, and until recently a lack of principled modeling strategies for inferring the driving mechanisms behind interaction processes from observational data (particularly in naturalistic settings wherein many different types of mechanisms may be simultaneously at play). Progress within the Relational Event Modeling (REM) paradigm (Butts, 2008) has greatly lowered this latter barrier, making it practical to investigate complex microdynamics within a statistically principled framework. There remains, however, the empirical challenge of identifying and analyzing cases of emergent coordination in response to external threat.

In this paper, we contribute to this latter goal via an investigation of coordination in response to the 2001 World Trade Center disaster. Building on the work of Butts (2008), who studied six small communication networks from this event, we here analyze 17 relational event systems from both specialist and non-specialist responders. Considering a range of candidate mechanisms, we identify those present in each network and estimate their effects. Further, we employ simulation-based analysis of the estimated models to probe the relative importance of different mechanisms for the emergence of hub structure - a critical coordinative adaptation in these groups. As we show, beneath the diversity of these responding groups lies considerable consistency, with the vast majority of communication mechanisms operating in similar ways across networks when present (though not all mechanisms operate in all networks). While we find that well-known mechanisms such as preferential attachment and the prominence of pre-disaster coordinative roles do consistently contribute to the formation of hub structure, a much larger fraction in fact emerges from the action of temporally local communication norms, which have the side effect of creating conversational "inertia" that leads to large differences in communication activity. The macro-level structure of the WTC communication networks is thus seen to arise in large part from microdynamic mechanisms.

The remainder of the paper proceeds as follows. First, we give a brief overview of communication in disaster context, along with the use of interpersonal radio devices (on which the present case is based) as a medium for communication. Next, we provide some details on the differences between specialist and non-specialist networks and how network size may influence communication, followed by a discussion of the mechanisms potentially involved in hub formation. We then describe our dataset and the methods used for model selection, analysis, and the simulation knock-out experiment. This is followed by a presentation of the results for our relational event models, as well as our simulation study. Finally, we end the paper with a discussion of the implications of our findings for communication and coordination in disrupted settings more generally, and for future studies. Our paper is also accompanied by an R package (R Core Team, 2021) with the complete WTC radio data set, thereby facilitating further analysis of this rich historical case.

## 4.3 Background

Responses to disasters depend upon a complex interplay of formal (i.e., institutional) and informal factors (Quarantelli, 1966; Dynes, 1970; Stallings, 1978). This interplay is perhaps nowhere more evident than in the domain of responder communication, where technical constraints, formal roles, and standard operating procedures must cope with responders' shifting demands for information and the capacity to provide it. An important aspect of the total response process is the emergence of communication networks that promote information transmission and coordination. The structural characteristics of such networks, as well as the mechanisms that facilitate their formation, are of crucial importance to researchers and practitioners alike.

By definition, disasters are exceptional events, in which conventional social processes are subject to substantial disruption. While losses are perhaps the most salient characteristic of disasters, Drabek's (1986) classic synthesis of findings on disaster response emphasizes the "accidental or uncontrollable" nature of disaster events (p. 7), and the extent to which they exceed the capacity of conventional mechanisms for managing disruption. Indeed, a central feature of the US Federal Emergency Management Agency's definition of disaster is the requirement that the event "cannot be managed through the routine procedures and resources of government" (FEMA, 1984). Uncertainty and disruption of routines are therefore an important aspect of the social responses to disaster events. Organizationally, such disruptions of routine generate a high-uncertainty environment in which coordination demands escalate, while infrastructure (both human and technical) degrades. The problem of "many people trying to do quickly what they do not ordinarily do, in an environment with which they are not familiar" (Tierney, 1985, p77) generates the potential for confusion and task interference, particularly where tasks are time-critical and resources are limited. Negotiating such difficulties, acquiring information about losses and ongoing hazards, and other coordinative tasks require a high degree of interpersonal communication. Thus, actors responding to a disaster depend on the emergence (or retention, if pre-existing) of communication networks, which can convey information from those who have it to those who need it without placing excessive demand on the communicants (Drabek, 1986).

Also central to the nature of disaster communication is the time frame in which the communication takes place. Disaster researchers conventionally divide the "life cycle" of a disaster into several periods or phases (Fischer, 1998), distinguished by characteristic patterns of activities and events, e.g. a "pre-impact period" before the hazard manifests; an "impact period" during which the hazard is active; a "response period" in which damage is contained and survivors are attended to; and a "recovery period" in which attempts are made to restore conditions to a stable state. Although communication is critical in all periods, the impact and response periods constitute a crucial interval in which survivors attempt to respond to ongoing hazards, search and rescue operations begin, and emergency response organizations respond to the scene and attempt to coordinate their efforts. Within that interval, it is common in practice to refer to an "emergency phase" in which immediate, time-sensitive action is required to react to an active hazard. Communication in this period plays a vital role in facilitating situational awareness, and in coordinating response activities. At the same time, such communication is made more difficult by disruption of conventional resources, roles, and routines, the high opportunity cost of engaging in communication versus task performance, and the high cognitive load facing communicants in what is typically a confusing, fast-changing, and possibly threatening environment. Understanding the emergent dynamics of emergency phase communication thus has the potential to shed light on how groups organize in response to threats within a high-pressure setting that differs greatly from everyday conditions. To date, the lack of detailed data from real emergencies has been a major barrier to such understanding, and the methodology needed to make use of such data has only become available in recent years. In this paper, we capitalize on the unique assets of the World Trade Center dataset (described below). The 2001 World Trade Center (WTC) disaster stands as one of the largest communication-coordination "emergency phase" related events in recent history. With this data and the increasingly widely-used relational event framework, we intend to provide novel insights into communications during the emergency phase of disaster response.

## Interpersonal Radio Communications

From the mid-20th century onward, radio communication via portable devices has been a critical tool for coordination among responders (McElroy, 2005), despite numerous limitations (Auf der Heide, 1989). In the immediate post-impact period, when communications infrastructure may be degraded and alternate systems have not yet been deployed, handheld radio devices serve to connect responders in the field to one another. In addition, the relatively low cost of hand-held transceivers in the modern context makes this technology accessible to organizations which do not specialize in emergency response activities. Since the first responders to any disaster are those who happen to be at the impact site, interpersonal radio communication is an important "workhorse" tool for improving coordination in the emergency phase of a disaster. This raises the question, however, of how responders – especially those who are not specialized in emergency response – actually use radio communication during the emergency phase of a disaster. At the most basic label, radio communications require the use of fairly rigid communication protocols to avoid confusion due to cross-talk; these are typically codified into a set of practices or standard operating procedures (SOP) that involve systematic identification of the sending party and intended receiving party, formal acknowledgments of contact and receipt, etc. In prior work on a subset of the WTC radio networks, Butts (2008) found strong evidence for the prominence of radio SOP via pronounced and systematic participation shift effects. Organizations using radio communications may also delegate coordination tasks to specially designated individuals (e.g. dispatchers), potentially leading to a more centralized structure in which individuals largely interact with the institutionally designated coordinator rather than directly with each other. We discuss this further below.

## Specialized vs. Non-Specialized Responders

It is commonly posited that behavioral responses to disasters by "ordinary people" within the initial phase of a hazard event are deviant and chaotic, by contrast with the disciplined and efficient actions of emergency response organizations (Tierney et al., 2006). In practice, however, organizational responses are not necessarily better coordinated than those of others on the scene (Fischer, 1998), and the latter may indeed prove quite effective (Auf der Heide, 2004). As Fischer (1998) famously observed, variation in extent of prior planning, rehearsal of plans, and previous experience with similar events plays a large role in determining which organizational responses are successful and which fall short (a point also noted by e.g. Drabek (1986); Auf der Heide (1989)). That said, since the first individuals and organizations to respond to a disaster are those who happen to be present when the impact occurs, it is not necessarily the case that the true "first responders" will be trained for or equipped to deal with the event at hand. Much emergency-phase response activity is thus improvised, but it does not follow that such activity will be disorganized or ineffective (Wachtendorf, 2004; Mendonça et al., 2014). Repurposing of existing communication networks, together with the emergence of new ones, may result in highly structured interaction patterns. The question of how such networks develop, then, and their dependence upon pre-disaster organization, is of clear importance to understanding responder communication in the immediate post-impact period.

In the case of radio communications by teams of WTC responders, Butts et al. (2007) distinguish between groups of "specialist" responders - police, security, or other personnel who are specifically trained and organized to respond to emergencies (if not disasters) - and "non-specialist" responders (e.g., maintenance personnel) who are present and active at the scene, but whose conventional organizational structure and practices are not intended for emergency response. Specialist and non-specialist groups responding to a disaster share goals such as getting individuals to safety (Quarantelli, 1960; Mileti et al., 1975; Abe, 1976; Noji, 1997), but specialist groups may also be charged with other objectives (e.g., securing the area, taking actions to prevent or mitigate emerging or ongoing hazards, coordinating with other organizational units, etc.) that may pose different communicative or coordinative challenges. Butts et al. (2007) found that the time-aggregated networks of communication among specialist and non-specialist groups share structural features, with relatively minor quantitative differences but a high level of overall similarity. In a dynamic analysis of the six smallest WTC networks, Butts (2008) also found broad similarity in the communication patterns of specialist and non-specialist responders. However, some consistent differences have also been identified; for instance, an analysis of robustness of the WTC networks to attack (Fitzhugh and Butts, 2021) found that specialists were consistently more dependent upon individuals in institutionalized coordinative roles to maintain connectivity (and hence more vulnerable to their removal). This last suggests a potential difference between specialist and non-specialist networks in their hub organization, a matter that we revisit in our simulation study below.

## Emergent Coordination and Institutionalized Coordinative Roles

In cross-sectional analyses of the WTC data, Petrescu-Prahova and Butts (2008) show evidence that both specialist and non-specialist networks are held together by a relatively small number of highly central actors (*coordinators*). While some of these actors occupy *institutionalized coordinative roles* (e.g., manager, dispatcher) that formalize their status as a coordinator under nominal conditions, the relationship between such formal roles and actual coordination is imperfect. Although individuals occupying an institutionalized coordinator role (ICR) are more likely to become coordinators than those without such roles, the majority of coordinators were found to be *emergent* (i.e., to lack an ICR). This raises the question of what drives the emergence of coordination during the unfolding emergency, and the relationship of those drivers to ICR status. Using REMs, we can directly probe the effect of ICR occupancy on communication behavior patterns, as well as differences in these behaviors between specialist and non-specialist networks (an effect not examined in previous work). Using simulation, we can further analyze the impact of ICR effects on the formation of communication hubs at the network level, allowing us to investigate the extent to which behavioral differences involving ICRs do or do not ramify into differences in structural position (and to which this varies between specialist and non-specialist networks).

## Network Size

Another factor that may plausibly impact WTC radio communications is network size. The 17 networks vary over a large range, from 24 to 256 individuals (mean 127), reflecting substantial differences in the complexity of events within the group of actors and the cognitive load entailed in keeping track of events within the group. This may lead to differences in the relevant mechanisms driving communication between networks; for instance, egocentric "tracking" of distinct communication threads beyond the currently active conversation is likely to be of substantially greater importance in large networks with many different lines of activity, while adherence to local conversational norms may be greater in smaller groups with fewer risks of interruption. Likewise, some mechanisms may have greater impact in networks of larger or smaller size. For instance, preferential attachment may have a greater impact in larger networks, as there may be less *a priori* clarity in who is available to communicate in a large group and a correspondingly greater signal value of visibility. For ICRs, the task of coordinating activity becomes more difficult in larger networks, as they must coordinate a larger number of actors as well as relay information to more individuals, while presumably receiving information from more sources as well. This may plausibly reduce the gap between ICRs and other members of the network, as emergent coordinators step in to perform tasks that ICRs cannot. Below, we examine the question of whether these and other mechanisms operate differently in networks of different size.

## 4.4 Potential Hub-Forming Mechanisms

A consistent finding in prior descriptive analyses of the WTC networks (Butts et al., 2007; Petrescu-Prahova and Butts, 2008; Fitzhugh and Butts, 2021) is that specialist and non-specialist networks alike are held together by a relatively small number of individuals occupying hub-like coordinator roles. These positions are distinguished by high degree, betweenness, and total communication volume, and are reflective of individuals who played outsized roles in coordinating activity during the WTC event. As noted above, the majority of these positions are *emergent,* in that that do not correspond to ICR membership, although those in

ICRs are disproportionately likely to occupy coordinator/hub roles. This raises the question of whence these hubs come: what are the dynamic mechanisms that drive the hub-focused organization of the WTC networks, and are these mechanisms consistent across organizational units? Here, we consider three categories of mechanisms that could plausibly account - individually, or in tandem - for hub formation in the WTC radio networks.

## Preferential Attachment

One of the best known mechanisms driving the emergence of hubs in social networks is preferential attachment (Price, 1976). Early empirical studies of preferential attachment go back as far as the 1950s and 1960s (Merton, 1968; Simon, 1955), with the emphasis on "cumulative advantage" processes in settings such as citation networks, where new entrants tend to cite papers already cited by others; the derivation of power law degree distributions from such processes is due to Price (1976), with much later rediscoveries several decades later by researchers outside the social network community. In the context of a relational event process with fixed vertices, preferential attachment can be understood as an increasing propensity to direct events towards vertices with a larger share of prior communication (i.e., larger total communication volume), as implemented e.g. by Butts (2008); Gibson et al. (2019,0). In a radio communication setting, those who speak first are known to all persons attending to the channel to be active, thus making them a likely target for incoming communications. This may in turn lead to their receiving more calls, their responding and thus getting more air time. Over time, this process may produce a positive feedback loop in which those who are active early on (possibly for idiosyncratic reasons) end up becoming hubs. In the case of the WTC disaster, there are reasons why we might expect this pattern to appear. First, communication is occurring through the use of radio, meaning the first responders cannot see who they are communicating to, or identify who is available to communicate with. The simplest way to know who is available to respond is by noting who has already spoken, making the likelihood of their response high. Secondly, in the early stages of the disaster, individuals are cognitively overloaded and often disoriented; the cognitive load can be eased by choosing to communicate to those who are known to be already talking rather than trying to call individuals who may not be able to respond.

The social mechanism of preferential attachment may also be more likely to drive the formation of hubs in non-specialist networks when compared to their specialist counterparts. Specialist networks have protocols in place that often dictate a pre-planned chain of command for whom to contact in the case of a disaster, which may make them less likely to experience preferential attachment. Non-specialists lack these pre-existing norms and training, leading to a greater reliance on the "call whom you hear" heuristic that drives preferential attachment.

## Conversational Inertia

A second mechanism that could account for the emergence of coordination hubs is that of *conversational inertia*, which arises from the turn-taking structure of conversational norms (in this case, radio SOP). Parties engaged in conversation tend to remain in conversation, either because of the back-and-forth of call/response dynamics, or because of other normative actions such as sequential address (in which the same party continues to be the sender), baton-passing (in which the receiving party becomes the sender), "piling on" (in which the current receiving party becomes the subject of additional incoming communications), etc. tend to keep one or both currently communicating parties involved. This produces a form of autocorrelation that can potentially amplify other sources of variation (including random events) in communication volume: individuals who, for whatever reason, are drawn into conversation tend to stay there, accumulating substantially more communication volume than those who are not. While not normally thought of as a driver of hub formation, it is apparent that such micro-level processes could have this effect, and given the central importance of radio SOP to effective communication in events such as the WTC disaster we investigate its potential impact. As we shall show, this impact turns out to be substantially greater than might be supposed.

## Institutionalized Coordinator Roles (ICR)

The last hub forming mechanism we investigate here is differential behavior by and towards individuals occupying institutionalized coordinative roles. As discussed above, persons in ICRs (whom we simply refer to as "ICRs" where there is no danger of confusion) are expected, to receiver and relay information, direct action, and perform other duties requiring high levels of communication. ICRs have also been found to be more likely to occupy coordinator roles in practice (Petrescu-Prahova and Butts, 2008), though as noted above most hubs are not ICRs. Similar results have been seen in other contexts, with those individuals in superordinate roles or rank in conversational contexts tending to talk more (Fisek et al., 1991) and higher ranking individuals being more likely to send and receive e-mail communications (Gibson et al., 2019). It is thus highly plausible that ICRs are more attractive targets for interaction, and more active in initiating contact with others, thereby contributing to hub formation. This may be particularly important in specialist networks, where centralizing coordination activity on a small number of pre-assigned hub roles is often a deliberate strategy (albeit one that may fail in the context of a real disaster).

| | Actors | Events | % ICR | Specialization |
|---|---|---|---|---|
| Newark Maintenance | 27 | 77 | 3.70 | Non Spec. |
| PATH Radio Comm | 32 | 70 | 6.25 | Non Spec. |
| WTC Operations | 130 | 562 | 1.54 | Non Spec. |
| Newark Operations Terminals | 138 | 1012 | 4.35 | Non Spec. |
| PATH Control Desk | 229 | 1066 | 6.99 | Non Spec. |
| Newark Facility Management | 237 | 1100 | 2.95 | Non Spec. |
| WTC Vertical Trans | 246 | 780 | 1.22 | Non Spec. |
| WTC Maintenance Electric | 256 | 864 | 6.25 | Non Spec. |
| Newark Police | 24 | 83 | 8.33 | Specialist |
| NJSPEN 2 | 32 | 149 | 15.62 | Specialist |
| WTC Police | 37 | 481 | 8.11 | Specialist |
| Newark CPD | 50 | 271 | 16.00 | Specialist |
| PATH Police | 93 | 689 | 3.23 | Specialist |
| Newark Command | 111 | 320 | 2.70 | Specialist |
| WTC Security | 118 | 582 | 10.17 | Specialist |
| NJSPEN 1 | 166 | 575 | 9.04 | Specialist |
| Lincoln Tunnel Police | 229 | 1145 | 4.37 | Specialist |
| Mean | 127 | 578 | 6.52 | |

Table 4.1: Summary statistics for the WTC radio networks.

## 4.5 Data and Methods

### Data

The data we employ here are derived from transcripts of radio communications among responders to the WTC disaster on the morning of 9/11/2001, released by the Port Authority of New York and New Jersey and coded by Butts et al. (2007). We analyze the radio communication transcripts from seventeen groups of responders to the WTC disaster, each of whom was using one radio channel exclusively. All transcripts begin immediately after the first airplane crashed into the North Tower at 8:46 am, and extend for three hours and 33 minutes or until communication was terminated by structural collapse (as occurred for some units located within the WTC complex).

Based on information provided by the original transcriber and/or other transcript content, a unique identifier was assigned to the sender and named target(s) of each transmission (Butts et al., 2007). Where one-to-many communications were encountered, each was coded as a series of dyadic transmissions from the sender to each of the named recipients (in the order named). Transmissions with no clear target(s), and/or targets that were identified only as a group (e.g., “anyone,” “all units”) were not included. The resulting lists of ordered transmissions (one per transcript) comprised the relational event sets employed in subsequent analyses. Lengths range from 70 to 1,145 eligible transmissions, with the number of named communicants ranging from 24 to 256. Figure 4.1 illustrates the networks in question, while showcasing the coordinative hub structure we aim to investigate. In conjunction with the relational event data itself, we consider the formal coordinative status of individual responders as an illustrative covariate, and distinguish between specialist and non-specialist responder networks, using the classification criteria provided by (Butts et al., 2007). A package containing the full data set is included as a supplement to this paper.

Summary statistics for the 17 networks are shown in Table 4.1, including the number of individuals in the system (network size), the number of events, the fraction of individuals who are ICRs, and the specialist/non-specialist encoding. About 6.5% of responders occupy ICRs, with this fraction varying from 1.2-16%. Butts et al. (2007) previously found that these networks are highly centralized, as is evident in Figure 4.1.

## Methods

### Relational Event Models

As in the original work by Butts (2008), we use the relational event modeling framework to understand the effects of various conversational drivers involved in the formation of emergency communication networks. Because the 17 networks studied here vary greatly in size,

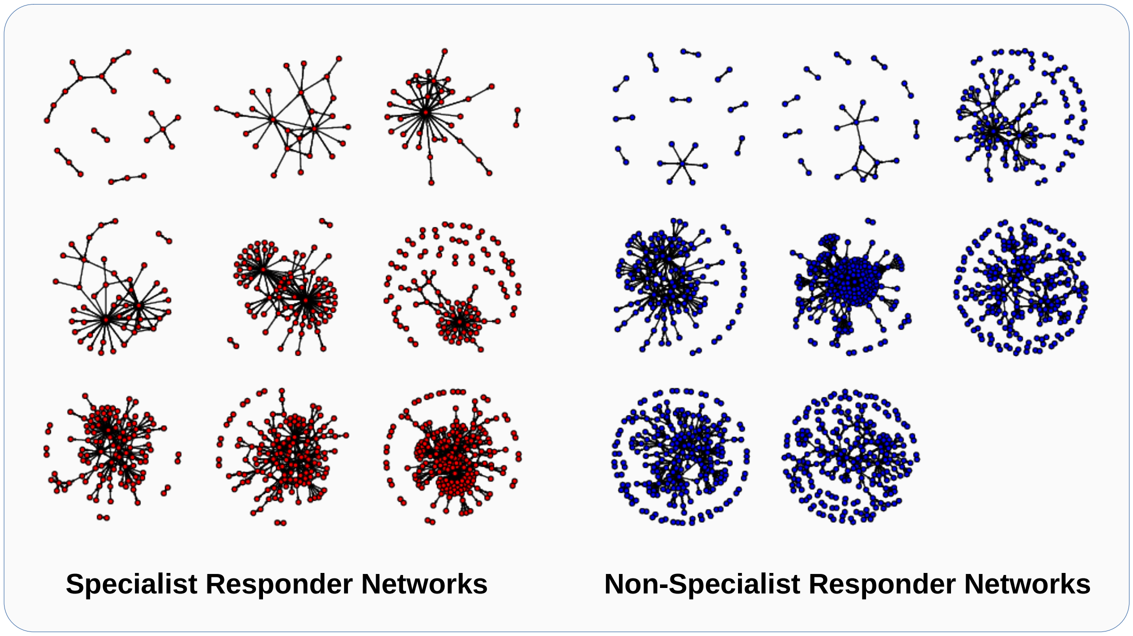



Figure 4.1: Visualization of the time-marginalized WTC networks, sorted by specialization. All networks show high levels of centralization, with a relatively small number of coordinators providing much of the connectivity in each case.

specialization, location, and types of task performance, it is entirely plausible that different mechanisms are active in different groups; rather than attempting to fit a pooled model (or a hierarchical model with common effects, as in DuBois et al. (2013)), we instead proceed by (1) identifying a space of substantively plausible models, and then (2) performing complexity-penalized model selection (AICc) to find the effects active in each network. We verify adequacy of the selected models using local prediction and recall. (All models were fit and simulations performed using the `relevent` package (Butts, 2013) v1.1 for the R statistical computing system (R Core Team, 2021).)

The space of plausible mechanisms includes those discussed by Butts (2008), as well as effects motivated by the background discussion above. The effects considered include the following. *Preferential attachment*, where ego tends to call those with more airtime, is parameterized as the effect of normalized total communication volume on call receipt (*NTDegRec*). This results in a single statistic whose parameter will be positive if preferential attachment is present and negative if a rotating turn effect is present. Next, we consider cognitive effects: *persistence* (previous out-alters are salient for ego's out-calls) is parameterized as the tendency for responders to direct calls to those that they have previously directed calls to, and *recency* (more recent in-alters are salient for ego's out-calls) is parameterized as the tendency for responders to direct calls to those that they have most recently received calls from. A positive value for these parameters would indicate the presence of these cognitive mechanisms, while negative values might indicate a search pattern for individuals or perhaps an attempt to disseminate information across a wide swath of the network.

Similar to triadic effects in the static networks, there are potential patterns of triadic closure in the REM framework. For the first two of these statistics, one is parameterized as the number of outbound two paths from ego to some alter and the other as the number of inbound two paths from some alter to ego (*OTPSnd* and *ITPSnd*). For the former, if the parameter is positive, this indicates a pattern of transitive closure. Substantively, this may come from responders choosing to share information with individuals directly, rather than through third parties. If this parameter is negative, it may indicate that responders are choosing to rely on intermediaries to spread information throughout the network. For the latter, a positive coefficient for this statistic would indicate a tendency toward cyclic closure. This would indicate that if individuals are relaying information through intermediaries, those on the receiving end have a tendency to reply directly. A negative coefficient would indicate a tendency away from cycles and imply that individuals more often respond to the intermediaries, rather than those two steps away. We also include out-bound and incoming shared partner effects *OSPSnd* and *ISPSnd* - analogous to the *sibling effects* of Fararo and Sunshine (1964) - to help understand other triadic communication patterns between communicants.

The next set of parameters are *conversational inertia terms* or *participation shifts* (tendencies reflecting "local" conversational norms (from  Gibson, 2003)). The ones included in the following analysis are *PSAB-BA* or call and response, *PSAB-AY* and *PSAB-XB* or persistence of source and target, respectively, *PSAB-XA* or source attraction, and finally *PSAB-BY* or "handing off" of communication. Lastly, the pre-disaster organizational role is parameterized as a covariate effect for ego occupying and institutional coordinative role (*ICR*) on in and out calls.

To estimate model parameters, we perform Bayesian inference using the Laplace approximation on all 17 WTC networks, using diffuse $t$-priors with prior location 0, scale 10, and 4 degrees of freedom; model selection is performed by AICc minimization, as described below. Comparison of parameters from fitted models is used to assess the differences between specialist and non-specialist responders, similar versus dissimilar mechanisms driving behavior across networks, and to evaluate the respective impact of ICR membership and endogenous factors in shaping the emergence of coordinator roles.

## Model Selection

We begin by noting that it is plausible that different mechanisms may be active in different networks, and that - recognizing that any model for a complex system is at best an approximation, rather than a "true" model - we focus on identifying collections of mechanisms likely to have good generalization performance (in terms of deviance under hypothetical replication). This motivates the use of model selection via the (sample-size corrected) Akaike's Information Criterion (AICc), which is a complexity-adjusted estimator of replicate deviance akaike:itac:1974,bozdogan:jmp:2000. Given the set of candidate terms, we attempt to select the model that minimizes the AICc (a procedure analogous to so-called "$L_0$" regularized model selection). This is a non-convex optimization problem, requiring exhaustive enumeration for an exact solution. We thus approximate the exact solution by a local optimization procedure (aka "hill-climbing") that seeks the AICc-optimal model by steepest descent. At each iteration, the procedure considers all single-term changes to the current model (addition or deletion of terms), taking the change that results in the greatest AICc reduction and terminating when no improvement can be made. We initialize the search procedure with the empty (null) model. As a check on the quality of the hill climbing optimization process, we generated a full factorial design using the smallest network, PATH Radio Communications, which was small enough for enumerative search; the hill-climbing procedure was indeed able to find the optimal model in this case. Manual inspection of paths followed by the search procedure likewise showed no evidence of pathological behavior. While - as with any heuristic optimization procedure - it is not possible to guarantee that the optimal model is identified in every case, this approach does guarantee that (1) the selected model is locally optimal (i.e., it cannot be improved by adding or removing effects), and (2) if not a null or one-term model, the selected model is better than the null or any one-term model.

## Knock-Out Simulation Experiment

To better understand how preferential attachment, ICR, and conversational inertia terms influence the hub-generation process in these radio communication networks, we perform a series of computational "knock-out" experiments for these effects. Specifically, we use the `simulate` function from the `relevent` package to take draws from the posterior predictive distribution of relational event trajectories from each network, drawing 50 trajectories of equal length to the observed data (and with identical covariates) with parameters simulated using the fitted posterior mean and variance-covariance matrix. (We employ the Laplace approximation, treating the posterior as multivariate Gaussian.) We then conduct 50 replicate simulations for each of four knock-out conditions: in the first we remove (set to 0) the preferential attachment term (NTDegRec); in the second we remove conversational inertia terms (e.g., PSAB-BA, PSAB-BY etc.); in the third we remove the ICR term; and the final condition all of the three hub-forming term sets are removed. All non-removed parameters in each condition take the same values as were used for the full model. This process results in a total of 5100 simulated trajectories across the 17 networks.

In order to examine the impact of mechanisms on the generalized tendency to form hubs, we need a way to characterize how concentrated the distribution of the communication volume is. We choose a widely used concentration index, the Theil index (Theil, 1967) for this purpose, which is has been used to study various phenomena: from income inequality (Silva and Leichenko, 2009), crime (Kang, 2016), to health disparities (Borrell and Talih, 2011; Kirsi M. Manz, 2021), just to name a few. It has a natural interpretation in terms of the entropic "cost" of going from an equal distribution to that of the observed system – we can think of the Theil index as expressing the extent to which social mechanisms are systematically organizing/biasing activity, versus letting it happen at random, making it a sensible measure of communication volume concentration in our networks.

Using the simulations in each condition, we then calculate the Theil index for each network using total communication volume per actor (taking the mean index value over all simulated replicates). We assess the contribution of each mechanism to the extent of hub formation by examining the reduction in the mean Theil index when the respective set of terms is removed (versus the full model). Larger reductions imply a greater role for the associated mechanism in hub formation in the respective network. (For cases in which a given mechanism was not in the best fitting model, its contribution is trivially 0.)

## 4.6 Results

### Model Adequacy

In order to check the adequacy of our models, we assess the ability of each model to accurately identify the next event in its respective event history. Table 4.2 shows the observed

| | Match to Next Event | | | | Recall (Coverage) | | |
|---|---|---|---|---|---|---|---|
| | Either Match | | Both Match | | Top | Top | Top |
| Network | Fitted | Null | Fitted | Null | 1% | 5% | 10% |
| PATH Radio Communications | 0.67 | 0.06 | 0.56 | 0.001 | 0.67 | 0.73 | 0.86 |
| Lincoln Tunnel Police | 0.23 | 0.01 | 0.08 | <0.001 | 0.70 | 0.81 | 0.86 |
| Newark Command | 0.72 | 0.02 | 0.64 | <0.001 | 0.76 | 0.83 | 0.90 |
| Newark Police | 0.81 | 0.08 | 0.75 | 0.002 | 0.82 | 0.83 | 0.88 |
| Newark CPD | 0.72 | 0.04 | 0.56 | <0.001 | 0.74 | 0.86 | 0.91 |
| Newark Operations Terminals | 0.75 | 0.01 | 0.65 | <0.001 | 0.80 | 0.90 | 0.93 |
| Newark Maintenance | 0.79 | 0.07 | 0.78 | 0.001 | 0.87 | 0.88 | 0.90 |
| PATH Control Desk | 0.75 | 0.01 | 0.62 | <0.001 | 0.83 | 0.91 | 0.94 |
| NJSPEN 1 | 0.61 | 0.01 | 0.49 | <0.001 | 0.67 | 0.80 | 0.83 |
| NJSPEN 2 | 0.65 | 0.06 | 0.50 | 0.001 | 0.65 | 0.79 | 0.89 |
| WTC Operations | 0.68 | 0.02 | 0.56 | <0.001 | 0.77 | 0.90 | 0.92 |
| WTC Police | 0.79 | 0.05 | 0.68 | <0.001 | 0.82 | 0.93 | 0.96 |
| WTC Vertical Transportation | 0.64 | 0.01 | 0.56 | <0.001 | 0.73 | 1.00 | 1.00 |
| Newark Facility Management | 0.72 | 0.01 | 0.67 | <0.001 | 0.78 | 0.87 | 0.89 |
| PATH Police | 0.78 | 0.02 | 0.62 | <0.001 | 0.83 | 0.96 | 0.97 |
| WTC Security | 0.71 | 0.02 | 0.59 | <0.001 | 0.74 | 0.87 | 0.92 |
| WTC Maintenance Electric | 0.57 | 0.01 | 0.53 | <0.001 | 0.76 | 0.82 | 0.85 |
| Mean | 0.68 | 0.03 | 0.58 | <0.001 | 0.76 | 0.86 | 0.91 |

Table 4.2: Model adequacy checks. Observed and null probabilities of matching features of the next event in each sequence ("Eiher" implies that sender or receiver match, while "All" implies that both sender and receiver match). All models correctly identify the next event with probability greatly exceeding the null model, on average doing so the majority of the time. Recall columns show the fraction of observed events covered by the respective fraction of probability-ordered predictions (higher is better).

probability that the model was able to accurately predict either sender or receiver for a given event, followed by the null random probability of predicting either sender or receiver, then the observed probability of the model correctly guessing both the sender *and* receiver of a given event, and finally, its corresponding null random choice probability. Despite the seemingly chaotic communication environment of the WTC, the models perform extremely well. On average across all models, our ability to predict either of the two individuals in a given communication event correctly is 68%, meaning that in approximately 68% of cases the model's top choice for the next event in the sequence specifies the sender or receiver correctly. The lowest prediction probability for a specific model is for the largest network of the set, Lincoln Tunnel, and even in this case the model is able to predict either the sender or receiver from the set of 229 individuals 23% of the time. This is substantially larger than the probability of correct prediction under the null model. We also examine the probability of correctly predicting both sender *and* receiver, an extremely difficult task. On average, we find that our models can accurately predict both sender and receiver for the next event 58% of the time, with for some models as high as 78% and for the Lincoln Tunnel model, 8% of the time. While the latter seems low in absolute terms, we observe that the likelihood of randomly guessing the sender and receiver combination for Lincoln Tunnel is 0.000002%, with 10 other networks also having random predictions correct at a similarly low probability. While getting the next event right is a very strong test of adequacy, we also consider more general recall rates, i.e., the fraction of observed events that are "covered" by the top $k$% of predictions (the events judged most likely to occur). We examine recall rates for the top 1%, 5%, and 10% of predictions, providing a sense of the ability of the model to focus attention on events that are relatively likely to occur. As Table 4.2 shows, the vast majority of events are covered by the top few percent of predictions, with 76% on average contained within the top 1%, and over 90% within the top 10%. These results suggest that the selected models are able to capture the dynamics of the WTC system with sufficient fidelity to advance to the next stage of analysis.

## Relational Event Model Analysis

The coefficients for the selected models (posterior mean estimates) are shown in Tables 4.3–4.4; 95% posterior intervals can also be seen in Figure 4.2. For convenience in identifying effects whose signs are well-determined by the data, Tables 4.3 and 4.4 identify posterior mean estimates for which the central 95%, 99%, and 99.9% posterior intervals (sometimes called "credible intervals") exclude 0.

To summarize the mechanisms active in each network, Table 4.5 provides a schematic view of effects across networks, with their estimated signs. One of the more striking results is that all network final models contain the turn taking P-shift term, PSAB-BA, meaning that in all sizes of networks and regardless of specialization, turn taking is an important feature in driving the local patterns interaction. Additionally, the PSAB-BA term is the only one present in all final models. Some other commonly occurring terms that do not relate to the hub formation process, but that modulate the overall communication process and control for communicational differences between networks include: recency in receiving (RRecSnd), present in 88.2% of all networks, recency in sending (RSndSnd) occurring in 88.2% of all networks, persistence (FrPSndSnd), which is in 70.6% of all networks, and the outbound two path term (OTPSnd), present in 58.8% of all final networks. Other effects, like OSPSnd (present in 47% of all networks), ITPnd (present in 35.3% of all networks), and ISPnd (present in 29.4% of all networks), are less common and have little effect.

RRecSnd is a term for recency of receiving a communication from an alter affecting the actor's current rate of sending to that particular alter, while RSndSnd is the recency of sending a communication to an alter affecting the actor's rate of sending to that same alter. For the networks in which they are present, the mean value is 1.82 for RRecSnd and 2.63 for RSndSnd. Both effects are always positive when they appear in a final model. This would suggest that these cognitive mechanisms do govern some of the observed conversational

| | Lincoln Tunnel | Newark Command | Newark Police | Newark CPD | NJSPEN 1 | NJSPEN 2 | WTC Police | PATH Police | WTC Security |
|---|---|---|---|---|---|---|---|---|---|
| PA | $-0.56$ | | $-3.77^{*}$ | $3.60^{**}$ | $3.91^{**}$ | $4.61^{***}$ | $3.83^{***}$ | $1.46^{**}$ | $6.17^{***}$ |
| | (0.37) | | (1.89) | (1.11) | (1.29) | (1.22) | (0.76) | (0.49) | (1.31) |
| P | $-1.68^{***}$ | $-1.48^{**}$ | | $-1.69^{***}$ | | $-2.14^{***}$ | $-1.35^{***}$ | $-0.72^{**}$ | $-1.24^{***}$ |
| | (0.12) | (0.50) | | (0.43) | | (0.62) | (0.35) | (0.27) | (0.27) |
| Rr | $0.29^{*}$ | $1.77^{***}$ | $2.50^{***}$ | | $1.17^{***}$ | $1.16^{**}$ | $1.87^{***}$ | $1.59^{***}$ | $1.72^{***}$ |
| | (0.14) | (0.39) | (0.72) | | (0.27) | (0.40) | (0.29) | (0.23) | (0.26) |
| Rs | $6.36^{***}$ | $1.98^{***}$ | | $2.75^{***}$ | $2.66^{***}$ | $3.52^{***}$ | $1.26^{***}$ | $1.44^{***}$ | $2.62^{***}$ |
| | (0.14) | (0.50) | | (0.31) | (0.18) | (0.42) | (0.27) | (0.21) | (0.24) |
| ICR | $1.21^{***}$ | $1.42^{***}$ | | $1.17^{***}$ | $0.39^{***}$ | | $0.69^{***}$ | $1.66^{***}$ | $-0.30$ |
| | (0.06) | (0.19) | | (0.14) | (0.11) | | (0.18) | (0.13) | (0.17) |
| T-OTP | $-0.05$ | | | $0.12$ | $0.33^{***}$ | $0.35^{**}$ | $-0.09$ | | $0.14^{**}$ |
| | (0.03) | | | (0.08) | (0.06) | (0.11) | (0.05) | | (0.04) |
| T-ITP | $-0.07^{**}$ | | | $-0.29^{**}$ | | $-0.35$ | $0.15^{***}$ | | |
| | (0.03) | | | (0.09) | | (0.22) | (0.04) | | |
| T-OSP | | | | $0.16^{***}$ | | $-0.38$ | $0.04^{*}$ | | $-0.05$ |
| | | | | (0.04) | | (0.23) | (0.02) | | (0.03) |
| T-ISP | $0.20^{***}$ | | | | | $0.22^{*}$ | | $0.05^{***}$ | |
| | (0.05) | | | | | (0.10) | | (0.01) | |
| PS-ABBA | $2.93^{***}$ | $7.85^{***}$ | $6.11^{***}$ | $6.72^{***}$ | $7.81^{***}$ | $4.47^{***}$ | $5.75^{***}$ | $7.42^{***}$ | $7.30^{***}$ |
| | (0.11) | (0.34) | (0.68) | (0.20) | (0.24) | (0.34) | (0.24) | (0.22) | (0.21) |
| PS-ABBY | $2.18^{***}$ | $1.63^{**}$ | $2.08^{**}$ | $1.70^{***}$ | $2.83^{***}$ | $2.02^{***}$ | $2.13^{***}$ | $3.46^{***}$ | $3.04^{***}$ |
| | (0.15) | (0.52) | (0.67) | (0.31) | (0.24) | (0.35) | (0.28) | (0.21) | (0.22) |
| PS-ABXA | $0.31^{*}$ | $3.06^{***}$ | $1.87^{*}$ | $2.16^{***}$ | $3.35^{***}$ | $0.79^{*}$ | $1.67^{***}$ | $2.87^{***}$ | $2.98^{***}$ |
| | (0.14) | (0.26) | (0.81) | (0.26) | (0.17) | (0.39) | (0.26) | (0.21) | (0.19) |
| PS-ABXB | | $2.31^{***}$ | $1.88^{*}$ | | $2.31^{***}$ | | $1.31^{***}$ | $2.01^{***}$ | $1.71^{***}$ |
| | | (0.35) | (0.80) | | (0.26) | | (0.28) | (0.27) | (0.29) |
| PS-ABAY | $3.11^{***}$ | $2.52^{***}$ | $2.35^{***}$ | $1.86^{***}$ | $3.01^{***}$ | $2.20^{***}$ | $1.87^{***}$ | $3.90^{***}$ | $2.62^{***}$ |
| | (0.13) | (0.34) | (0.61) | (0.33) | (0.22) | (0.34) | (0.33) | (0.20) | (0.27) |
| AICc | 16,368.72 | 2,295.98 | 344.67 | 1,791.26 | 5,943.17 | 979.30 | 2,176.21 | 4,137.43 | 4,562.27 |

Stars indicate 0 excluded from posterior intervals: 95%: *, 99%: **, 99.9%: ***

Table 4.3: Posterior means and standard deviations for AICc-selected models for the specialist networks.

| | PATH Radio Comm | Newark Operations Terminals | Newark Maintenance | PATH Control Desk | WTC Operations | WTC Vertical Transport | Newark Facility Management | WTC Maintenance Electric |
|---|---|---|---|---|---|---|---|---|
| PA | | $8.88^{***}$ | $3.37^{**}$ | $2.56^{***}$ | $1.56^{*}$ | | $9.92^{***}$ | $11.41^{***}$ |
| | | (1.28) | (1.25) | (0.50) | (0.68) | | (1.99) | (2.15) |
| P | $-2.88^{**}$ | $-0.76^{***}$ | | $-0.50^{*}$ | $-1.13^{***}$ | | | $-0.80^{***}$ |
| | (1.06) | (0.21) | | (0.20) | (0.28) | | | (0.21) |
| Rr | 1.27 | $2.19^{***}$ | | $0.93^{***}$ | $1.51^{***}$ | $3.26^{***}$ | $3.07^{***}$ | $3.00^{***}$ |
| | (0.67) | (0.20) | | (0.21) | (0.27) | (0.20) | (0.20) | (0.19) |
| Rs | $4.23^{***}$ | $1.96^{***}$ | | $1.26^{***}$ | $3.51^{***}$ | $1.86^{***}$ | $1.06^{***}$ | $3.03^{***}$ |
| | (0.95) | (0.17) | | (0.17) | (0.27) | (0.16) | (0.14) | (0.22) |
| ICR | | | $1.36^{***}$ | $1.23^{***}$ | | $-0.66$ | $0.67^{***}$ | |
| | | | (0.41) | (0.09) | | (0.48) | (0.13) | |
| T-OTP | | $-0.12^{**}$ | | | $0.11^{***}$ | | $0.52^{***}$ | 0.18 |
| | | (0.04) | | | (0.03) | | (0.12) | (0.11) |
| T-ITP | | $0.16^{***}$ | | | | $0.60^{***}$ | | |
| | | (0.03) | | | | (0.13) | | |
| T-OSP | | $0.04^{***}$ | | | $0.06^{*}$ | $-0.17$ | | $0.21^{***}$ |
| | | (0.01) | | | (0.03) | (0.11) | | (0.06) |
| T-ISP | | | | $-0.09$ | | | $-0.30^{**}$ | |
| | | | | (0.06) | | | (0.12) | |
| PS-ABBA | $5.35^{***}$ | $7.35^{***}$ | $7.15^{***}$ | $9.86^{***}$ | $7.07^{***}$ | $7.25^{***}$ | $7.97^{***}$ | $6.74^{***}$ |
| | (0.57) | (0.16) | (0.30) | (0.19) | (0.22) | (0.15) | (0.16) | (0.13) |
| PS-ABBY | $1.80^{**}$ | $3.15^{***}$ | | $3.91^{***}$ | $3.05^{***}$ | $3.08^{***}$ | $2.96^{***}$ | $1.57^{***}$ |
| | (0.55) | (0.18) | | (0.16) | (0.23) | (0.23) | (0.23) | (0.41) |
| PS-ABXA | $1.63^{**}$ | $2.99^{***}$ | | $3.63^{***}$ | $2.47^{***}$ | $3.38^{***}$ | $3.01^{***}$ | $2.26^{***}$ |
| | (0.55) | (0.16) | | (0.16) | (0.22) | (0.18) | (0.18) | (0.22) |
| PS-ABXB | | $1.85^{***}$ | | $2.85^{***}$ | $1.76^{***}$ | $2.28^{***}$ | $2.29^{***}$ | $1.81^{***}$ |
| | | (0.23) | | (0.21) | (0.30) | (0.29) | (0.23) | (0.27) |
| PS-ABAY | | $3.00^{***}$ | | $3.99^{***}$ | $3.45^{***}$ | $2.47^{***}$ | $2.92^{***}$ | $2.26^{***}$ |
| | | (0.20) | | (0.16) | (0.20) | (0.31) | (0.23) | (0.30) |
| AICc | 483.66 | 6,862.60 | 289.70 | 8,336.29 | 4,545.03 | 7,584.97 | 8,382.05 | 8,807.99 |

Stars indicate 0 Excluded from posterior intervals: 95%: *, 99%: **, 99.9%: ***

Table 4.4: Posterior means and standard deviations for AICc-selected models for the non-specialist networks.

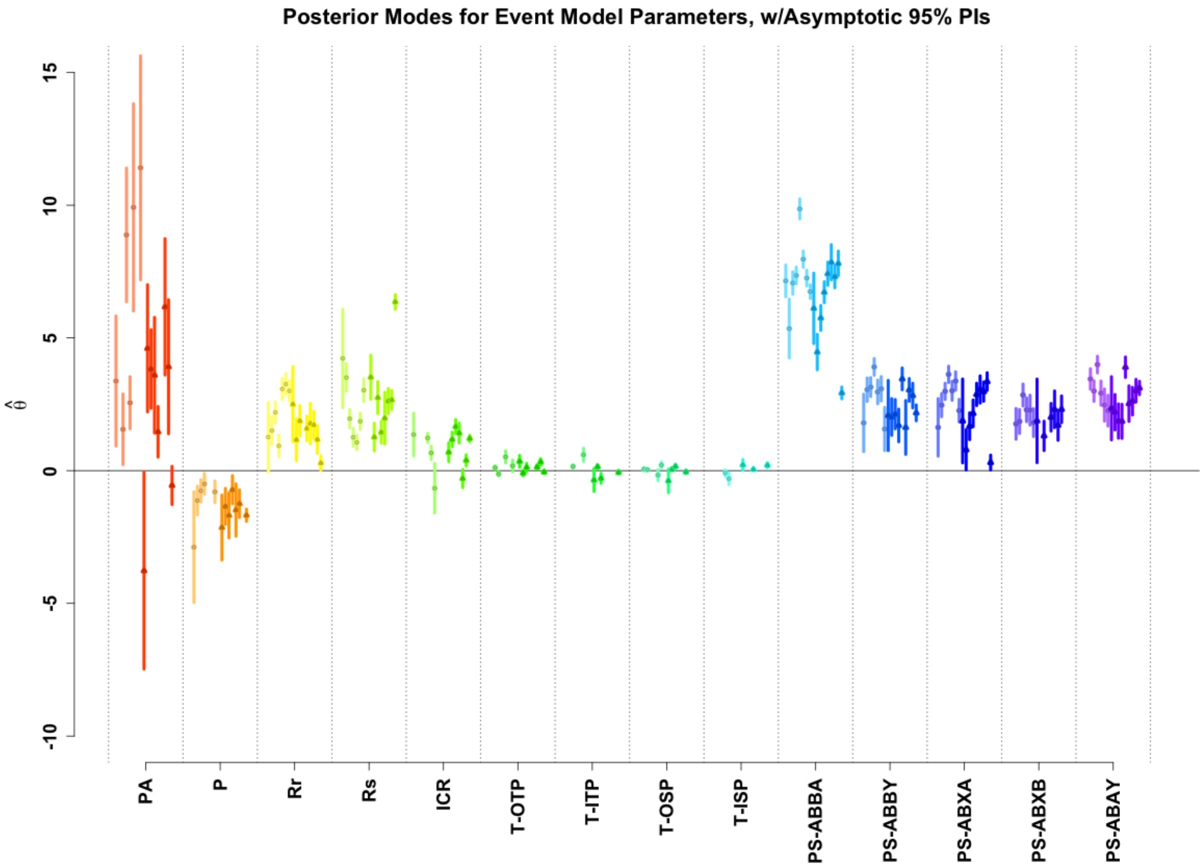



Figure 4.2: Posterior modes and their asymptotic 95% posterior intervals for the event model parameters for all 17 WTC radio communication networks. Darker colored line segments represent specialist networks, while lightly colored line segments represent non-specialist networks. Term codes are as follows: PA, preferential attachment; P, persistence; Rr, recency of receipt; Rs, recency of sending; ICR, role effect; T-OTP, outgoing two-path; I-ITP, incoming two-path; T-ISP, incoming shared partners; T-OSP, outgoing shared partners; PS-$*$, P-shift effects.

| | P | Rr | Rs | T-OTP | T-ITP | T-OSP | T-ISP | PS-ABBA | PS-ABAY | PS-ABXB | PS-ABXA | PS-ABBY | PA | ICR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PATH Radio Comm | - | + | + | | | | | + | | | + | + | | |
| Lincoln Tunnel Police | - | + | + | - | - | | + | + | + | | + | + | - | + |
| Newark Command | - | + | + | | | | | + | + | + | + | + | | + |
| Newark Police | | + | | | | | | + | + | + | + | + | - | |
| Newark CPD | - | | + | + | - | + | | + | + | | + | + | + | + |
| Newark Operations Terminals | - | + | + | - | + | + | | + | + | + | + | + | + | |
| Newark Maintenance | | | | | | | | + | | | | | + | + |
| PATH Control Desk | - | + | + | | | | - | + | + | + | + | + | + | + |
| NJSPEN 1 | | + | + | + | | | | + | + | + | + | + | + | + |
| NJSPEN 2 | - | + | + | + | - | - | + | + | + | | + | + | + | |
| WTC Operations | - | + | + | + | | + | | + | + | + | + | + | + | |
| WTC Police | - | + | + | - | + | + | | + | + | + | + | + | + | + |
| WTC Vertical Trans | | + | + | | + | - | | + | + | + | + | + | | - |
| Newark Facility Management | | + | + | + | | | - | + | + | + | + | + | + | + |
| PATH Police | - | + | + | | | | + | + | + | + | + | + | + | + |
| WTC Security | - | + | + | + | | - | | + | + | + | + | + | + | - |
| WTC Maintenance Electric | - | + | + | + | | + | | + | + | + | + | + | + | |

patterns, with individuals relying on recall when taking an action to address individuals in the network.

FrPSndSnd is a general effect for persistence, which is the fraction of an actor's past sending actions to a particular alter affecting their future rate of sending to that alter; this effect is always negative when present, with a maximum value of -0.50, a minimum value of -2.88, and a mean value of -1.36. This term being negative suggests an overall movement of conversation, rather than individuals continuously addressing only a small proportion of the network.

OTPSnd and ITPSnd are both triadic two-path effects, measuring the effect of the number of out-bound or incoming two-paths from actor to alter or alter to actor on the rate of actors sending to that alter. OTPSnd ranges from -0.12 to 0.52, with a mean of 0.15, while ITPSnd ranges from -0.35 to 0.60, with a mean value of 0.03. This suggests that networks vary in their three-way communication styles, with some likely to observe triadic closure, while others trend away from these patterns. OSPSnd and ISPSnd are triadic terms for out-bound and incoming shared partner effects, where the number of shared partners between actor and alter affect the future rate of sending to that alter. OSPSnd ranges from -0.38 to 0.21, with a mean of -0.01. ISPSnd has a range between -0.30 and 0.22, with a mean at 0.01, which again suggests wide variation in triadic communication structure.

## Hub-Forming Mechanisms

Figure 4.2 provides a visual representation of the posterior modes and their asymptotic 95% posterior intervals for the event model parameters for each of the 17 networks. Line segments that are darkly colored represent the specialist networks, while the lightly colored lines represent their non-specialist counterparts. Despite some small differences between specialists and non-specialists, in particular their slight difference in magnitude for preferential attachment, the effects are overwhelmingly similar between the two groups. Effects are especially similar in regards to direction, and in the majority of cases the magnitude of the effects are also strikingly similar. This can also be seen in Table 4.5, which clearly shows strong similarities in patterns across networks. Indeed, figure 4.2 suggests that some effects may be even more consistent than Table 4.5 would indicate, since some apparently reverse-signed terms have relatively uncertain signs (as evidenced by 95% posterior intervals that include 0).

Overall it appears that, when the respective mechanism is active in a given network, recency on receiving, recency on sending, and all of five conversational inertia terms (PSAB-BA, PSAB-BY, PSAB-XA, PSAB-XB, PSAB-AY) enhance event probability. Likewise, persistence always has a negative influence. ICR and preferential attachment effects are nearly always positive (with the former having fairly similar size), but some networks show negative modal estimates (though the 95% PIs are wide and cross zero, suggesting that the direction of effect is somewhat uncertain). We observe that preferential attachment effects tend to be hard to estimate, with large posterior uncertainties, making quantitative comparisons across cases difficult. However, the overwhelming majority of preferential attachment effects are positive, with two networks as possible exceptions (though their 95% posterior intervals include positive values). The triadic structure terms (OTP, ITP, OSP, ISP) seem to have small magnitude effects of varying direction, and in some cases are of uncertain sign. Their persistent inclusion and predominantly positive effects indicate systematic tendencies towards triadic closure, but it is possible that these reflect relatively general pressure for cohesive interaction that is not greatly sensitive to the type of triadic structure involved.

Considering these effects in more detail, we find that for the conversational inertia terms have the following positive effects on event probability: PSAB-BA, call and response, the most ubiquitous term found in every optimized final model, on average has an effect of 6.8, a minimum of 2.9 and a maximum effect of 9.9. PSAB-XA, source attraction, found in all but one model, has an effect mean of 3, a min of 0, and a max of 3.63. The PSAB-BY, "handing off" term, is also found in all but one model, with a mean effect of 2.4, a min of 0, and a maximum value of 3.9. The fourth participation shift effect, found in 88% of all models, is the PSAB-AY, sequential address term. Sequential address has a mean effect of 2.4, a min effect of 0, and a maximum value of 4. Finally, PSAB-XB, the effect of turn usurping, is found in 70% of the models and accounts for a mean effect of 1.4, a min of 0, and a maximum of 2.9.

The effect of preferential attachment was found to be in 82% of the optimized final models. The mean effect for preferential attachment, where present, has a mean effect of 3.5, with a maximum effect of 11.4.

The covariate effect for receiving and sending by ICRs appears in 65% of all networks, with a minimum effect of -0.67, a mean effect of 0.52, and maximum effect of 1.7. Because of the way this term is specified, if two individuals of ICR status in the network communicate to one another the event probability effect is doubled: for instance, in the case of PATH police which has the greatest effect for ICR, the effect for two ICRs communicating would be $1.7 \times 2 = 3.4$. Those networks with high-certainty coefficients have positive effects, but we see two cases with small negative posterior means and posterior intervals that place considerable mass in the positive direction.

Finally, our analyses showed no systematic differences between the average coefficient of specialized and non-specialized networks. Therefore, at least in terms of effect magnitude and direction, specialized and non-specialized networks during a disaster event are more similar than they are different, despite what we might otherwise expect.

| | Full Model | PA Removed | PS Removed | ICR Removed | All Removed |
|---|---|---|---|---|---|
| PATH Radio Comm | 0.68 | | 0.23 | | 0.23 |
| Lincoln Tunnel Police | 0.37 | 0.40 | 0.35 | 0.14 | 0.14 |
| Newark Command | 0.99 | | 0.19 | 0.51 | 0.10 |
| Newark Police | 0.25 | 0.29 | 0.09 | | 0.11 |
| Newark CPD | 1.25 | 0.98 | 0.41 | 0.49 | 0.07 |
| Newark Operations Terminals | 1.72 | 0.27 | 0.05 | | 0.04 |
| Newark Maintenance | 0.55 | 0.44 | 0.20 | 0.35 | 0.08 |
| PATH Control Desk | 0.80 | 0.74 | 0.16 | 0.25 | 0.06 |
| NJSPEN 1 | 0.54 | 0.37 | 0.09 | 0.39 | 0.08 |
| NJSPEN 2 | 1.11 | 0.58 | 0.26 | | 0.14 |
| WTC Operations | 0.64 | 0.57 | 0.08 | | 0.08 |
| WTC Police | 0.95 | 0.57 | 0.13 | 0.61 | 0.04 |
| WTC Vertical Trans | 0.51 | | 0.10 | 0.46 | 0.10 |
| Newark Facility Management | 1.95 | 0.38 | 0.08 | 1.82 | 0.06 |
| PATH Police | 1.86 | 1.66 | 0.26 | 0.20 | 0.04 |
| WTC Security | 1.27 | 0.48 | 0.07 | 1.32 | 0.07 |
| WTC Maintenance Electric | 1.97 | 0.77 | 0.16 | | 0.11 |
| Mean | 0.97 | 0.57 | 0.16 | 0.54 | 0.09 |

Table 4.6: Mean Theil index before and after mechanism knock-out. Full model includes all AICc-selected terms; for removed terms, PA=preferential attachment, PS=P-shifts, ICR=ICR covariate, all=all hub-forming mechanisms.

| | PA Removed | P-Shifts Removed | ICR Removed |
|---|---|---|---|
| PATH Radio Comm | | -65.37*** | |
| Lincoln Tunnel Police | 7.47 | -3.99 | -60.90*** |
| Newark Command | | -80.96*** | -48.71*** |
| Newark Police | 13.36 | -63.29*** | |
| Newark CPD | -21.61*** | -67.52*** | -61.15*** |
| Newark Operations Terminals | -84.19*** | -97.24*** | |
| Newark Maintenance | -19.86* | -63.97*** | -36.11*** |
| PATH Control Desk | -7.90* | -80.18*** | -69.11*** |
| NJSPEN 1 | -31.81* | -82.69*** | -28.66* |
| NJSPEN 2 | -48.08*** | -76.62*** | |
| WTC Operations | -10.23 | -86.91*** | |
| WTC Police | -39.94*** | -86.25*** | -36.30*** |
| WTC Vertical Trans | | -80.26*** | -9.71 |
| Newark Facility Management | -80.69*** | -95.67*** | -6.81 |
| PATH Police | -10.68** | -85.81*** | -89.47*** |
| WTC Security | -62.06*** | -94.14*** | 4.12 |
| WTC Maintenance Electric | -60.64*** | -91.66*** | |
| Mean | -30.46 | -72.36 | -36.90 |

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 4.7: Percentage change in Theil index of communication volume mechanism knock-out. Full model includes all AICc-selected terms; for removed terms, PA=preferential attachment, PS=P-shifts, ICR=ICR covariate, all=all hub-forming mechanisms. $p$-values reflect two-sample $t$-tests (knock-out vs. full model).

## Knock-Out Experiment Results

Our initial analysis suggests that the three hub-forming covariates of preferential attachment, ICR, and conversational inertia can all matter in terms of predicting the local conversational patterns, but does not directly address how these mechanisms contribute to hub formation (an emergent, macroscopic outcome of social microdynamics). Here we employ simulation to investigate this latter question.

Figure 4.3 provides an intuitive visual representation of the results from simulations of each network (the corresponding Theil index values can be found in Table 4.6). Here, we define the "baseline" concentration level when no hub effects are included as 0 (no "excess" concentration), normalizing all concentration values by affine transformation so that the level of concentration when all hub effects are included is set equal to 1 (100% of the "excess" concentration produced by all effects in tandem). Given this scale, we can now compare across networks the relative amount of excess concentration that remains when we suppress each class of hub effect (vertical bars). Note that while the fraction of concentration observed after knocking out an effect is usually in the [0,1] interval, it does not have to be: values higher than the "all hub effects" level, or lower than the "no hub effects" level, can occur when either (1) a nominally hub-promoting mechanism actually inhibits hub formation in a specific network, or (2) nonlinear interactions between dynamic mechanisms lead to nonmonotonic outcomes. The most obvious cases here involve the two networks (Lincoln Tunnel Police and Newark Police) with negative preferential attachment effects; since the PA mechanism is on average hub *suppressive* for these two cases, knocking it out actually enhances hub formation. For convenience in interpretation, networks in Figure 4.3 are ordered using a 1-dimensional non-metric multidimensional scaling of the Euclidean distance between their respective concentration levels; this highlights both similarities and differences across networks. Percentage change in values following knock-out can be found in Table 4.7.

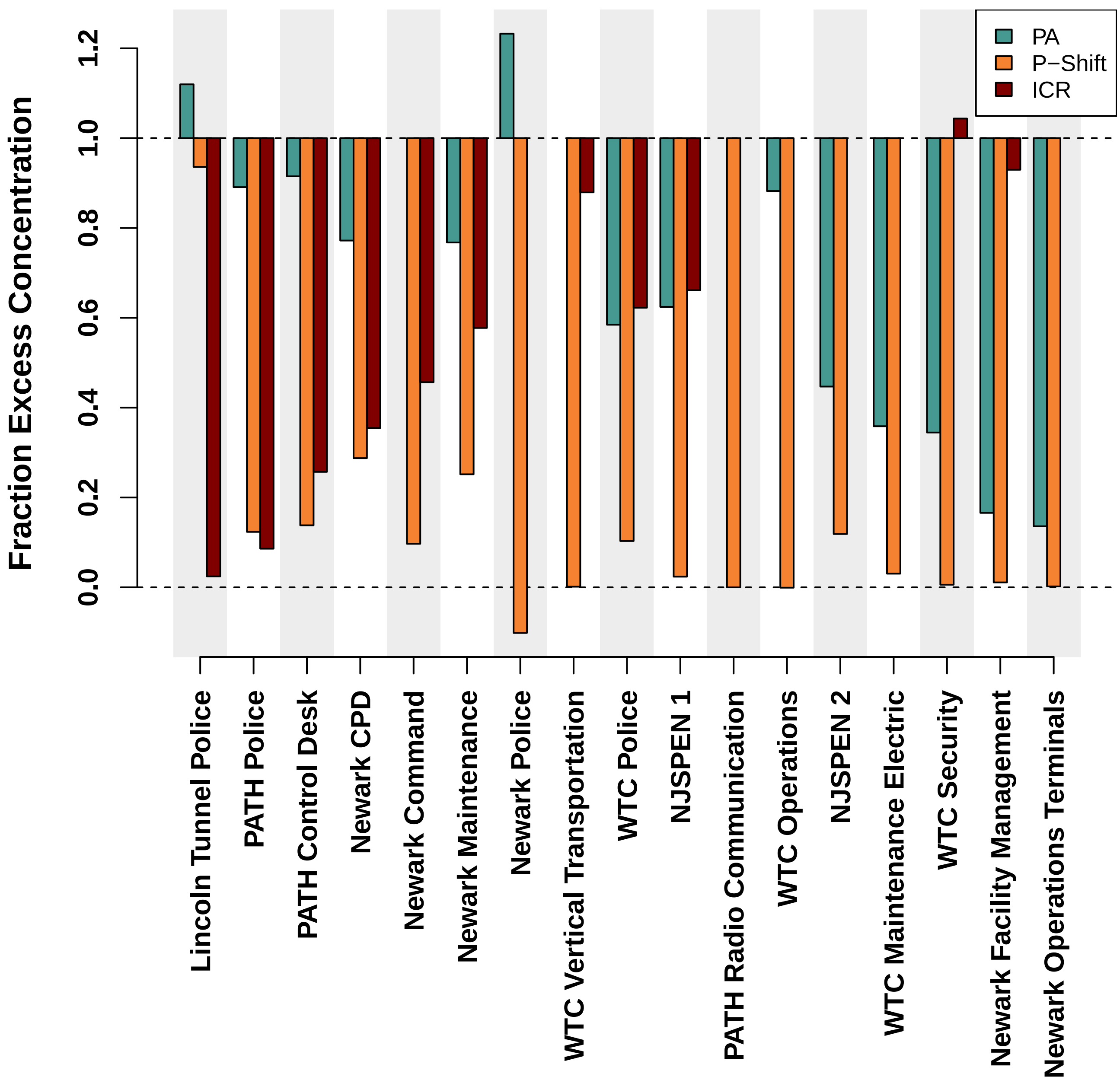



Figure 4.3: Excess concentration in communication volume (above no-hub mechanism baseline) as a function of knock-out condition; values of 1.0 correspond to full model. Networks differ in importance of ICR and PA effects for hub formation, while removing P-shift effects nearly always greatly reduces concentration. (Note: concentration outside the 0-1 interval is possible.)

Overall, conversational inertia terms account for the largest individual factor reducing the Theil index when they are systematically removed from the models, with these terms comprising the strongest hub-forming mechanism in 88% of the networks, and knocking them out reduces hub formation in all of the networks we analyzed. The mean reduction for participation shifts removal was an 88% reduction, with a median reduction of 97%. For one network, Newark Police, we find that by removing the conversational inertia p-shifts terms while keeping preferential attachment, that the network has a 110% reduction in the theil index – thus we are seeing a 10% greater reduction for just removing p-shifts than a model with none of the hub-forming terms. (This appears to be driven, as noted, by the presence of a hub-suppressive PA effect.)

Knocking out ICR effects in these networks tends also to reliably reduce hub-formation, with this effect seen in 91% of the networks the effect appears in. Across all networks, where the ICR term was eligible to be removed, we found a mean reduction of 30% in the Theil index. For PATH Police and Lincoln Tunnel Police, we find that ICR removal provides a larger reduction in hub-formation than conversational inertia term's effect, at 91% and 97% respectively. We also find that in the WTC Maintenance Electric network removing ICR has a slight 4% increase in the Theil index for inequality of total communication volume.

Preferential attachment (PA) follows suit with conversational inertia and ICR effects, where 85% of the models where preferential attachment was removed caused a reduction in the Theil index of inequality of total communication volume. The average effect of removing PA, in the networks it is present in, is a 28% reduction in the Theil index for communication volume, with the largest reduction in the Newark Operations Terminals at 86%. However, as noted above, for Lincoln Tunnel Police and Newark Police, we find that by removing the PA term the resulting models have increases in the Theil index, of 12% and 23%. Therefore, it appears that on average conversational inertia terms (participation shifts) have the largest impact on system level hub formation (88%), followed by ICRs (30%), and preferential

| | PA Removed | PS Removed | ICR Removed | All Removed |
|---|---|---|---|---|
| Specialist | -24.17 | -71.25 | -45.87 | -84.97 |
| Non-Specialist | -43.92 | -82.66 | -30.43 | -87.47 |
| Small | -21.14 | -72.69 | -55.76 | -83.44 |
| Medium | -47.08 | -88.39 | -24.42 | -90.67 |
| Large | -35.44 | -70.35 | -36.63 | -85.42 |

Table 4.8: Mean percentage change in Theil index by group, under mechanism knock-out. For removed terms, PA=preferential attachment, PS=P-shifts, ICR=ICR covariate, all=all hub-forming mechanisms.

attachment (23%).

Looking across the effects in Figure 4.3, we observe that the impact of p-shifts is consistent, but that there is a general trend in which ICR effects trade off against PA effects: networks that see large reductions in hub formation when ICR effects are knocked out show smaller effects for knocking out PA effects, and vice versa. This suggests a mechanism for the contrast between ICRs and emergent coordinators discussed by Petrescu-Prahova and Butts (2008), with preferential attachment arising as a heuristic for filling coordinator roles when ICRs are unable to carry the requisite load. It should be noted in this regard that for many of these networks, positive effects for both ICR interaction and preferential attachment are present; clearly, however, the mechanisms are not equally critical to hub formation in all networks.

Though we do see some patterns of difference, they do not necessarily fall out along lines that are *a priori* obvious. In order to determine whether there were differences in system level hub formation between our specialized and non-specialized networks, we compared the mean reduction in Theil indices for each knock-out simulation across the two groups, in Table 4.8. In order to determine whether these differences were significant between groups, we performed a two-sample $t$-test. We find that none of the changes in the Theil indices between specialized and non-specialized networks within our simulation results were significantly different, suggesting that each mechanism has the same impact, on average, in both categories.

We also compare the differences in the mean reduction in Theil indices for each knock-out simulation between differently sized networks, in Table 4.8. To test whether these size differences were significantly different we conducted a Kruskal-Wallis one-way analysis of variance for three differently sized groups. As with the differences among specialist and non-specialist categories, we find no significant differences between the size of the networks and the mean reduction in Theil indices.

## 4.7 Discussion

In this study we focused on understanding the process of emergent coordination within the context of an unfolding disaster. We did so by investigating networks from the 2001 World Trade Center disaster, providing empirical evidence for the role of conversational norms, preferential attachment, and institutional status in shaping both the local and system level structure and dynamics. From prior studies, it was known that the WTC radio networks had hub-like structures that emerged during the communication process. It was also known that while an individual in an institutionalized coordinator role would have a greater likelihood of inhabiting a hub position, it was more often the case that these hubs were emergent, meaning they were occupied by individuals without institutional coordinator status. Our analysis takes this prior work one step further by modeling and simulating these networks, allowing us to understand which factors tend to guide communication, and how these same factors affect the overall structure. We did this by determining which mechanisms from the space of plausible effects were active in each network, and by estimating the strength and direction of effects that were present. We then conducted a knock-out simulation experiment to understand how the three classes of potential hub formation mechanisms impact emergent structure, comparing network Theil indices of communication volume with and without each of the respective effects. Lastly, we compared our results from both analyses across various groups to search for systematic differences by specialization and size. Overall, we find that despite the differing contexts, environments, roles, specializations, and even sizes, the results across all networks are far more similar than different. When mechanisms appear, they generally have the same sign (and usually are of comparable magnitude). Deviations from these central tendencies seem idiosyncratic, and do not suggest a clear pattern of differences by size or specialization. In terms of local effects on conversation, there is a dominance of p-shift effects being present in all networks, while ICR and preferential attachment only appear in particular cases; this showcases the significance of radio SOP and conversational norms. Again, it is striking that regardless of whether individuals are communicating at ground zero, or responding to an event happening in the next state over, the communication patterns we observe are surprisingly robust.

In terms of the simulation knock-out experiment results, the first general observation is that almost all of the findings are significant, meaning that when you systematically take out any of the hypothesized hub-forming mechanisms, networks on average show large reductions in the Theil index of communication volume from their baseline state. Further, we find that the largest influencing factor is conversational inertia, which represents an 88% decrease on average in the Theil index of communication volume when the effect is knocked out. This was followed by the ICR effect and the preferential attachment effect, with reductions of 30%, and 28% respectively. In particular, these findings suggest that conversational norms are strong drivers of emergent coordination

0 [

]gibson.et.al:po:2019, even during an unfolding disaster – findings that also accord with participation shift usage of pilots during the unfolding Air France 447 incident (David and Schraagen, 2018). While both ICR and preferential attachment do seem to affect the formation of coordination hubs, they do not seem to be the dominant force. The low impact from our ICR term tells us that individuals are likely to form hubs and coordinate organically in situations of disaster and that ICRs are not a necessary requirement for emergency coordination to take place. Preferential attachment's lower level of impact on our index tells us that while preferential attachment has an important role to play in disaster communication, it is not the sole driver in every context. Our results lead us to believe that more consideration should be given to alternative forms of coordination in future literature.

By comparing REM coefficients as well as simulated behavior, we show that coordination arises in these communication networks through surprisingly similar means; what we are seeing is an emergent macro sociological phenomenon of human communication during a hazard event. It seems that by and large the most important factor driving the emergent coordination is conversational inertia. In particular, the AB-BA call and response participation shift was found in every single network after model optimization, while the AB-XA source attraction, and AB-BY "handing off" terms were present in all but one of the networks - compare that to the preferential attachment term appearing in 14 networks, and the ICR term appearing in only 11. Because of the robustness of our findings across various categorizations, we believe these results would likely reappear in other hazard or disaster contexts. Further, we believe that this might even transfer in part to non-disaster contexts that are particularly influenced by conversational norms. Researchers going back to the late 1960's and 1970's have documented the importance of conversational norms in governing social interactions (Schegloff, 1968; Schank, 1977) ; these results show that these humble aspects of micro-interaction have important macroscopic consequences, and that those hold even in the midst of an unfolding disaster.

## 4.8 Future Studies

An obvious question for future work is whether the patterns seen here generalize to other hazard communication contexts. While these results appear to be quite robust - with regular patterns across networks of different size, composition, and task orientation - all networks reflect groups responding at the same time to the same event using the same technology, and some aspects may differ in other settings. For instance, in our study's context, individuals were restricted to a single channel of voice communication, greatly amplifying the importance of conversational norms for communication. It is possible that other media with less dependence upon such norms might yield a correspondingly reduced impact of conversational norms on hub formation, or simply less hub formation overall. In this vein, it would be natural to probe the emergence of coordination in other single channel communication media, like singular chat rooms (NWSChat), and in multi-channel communication media, like slack or discord. Do these newer forms of communication media create new kinds of norms, or hinder certain kinds of interactions?

In our study we found that preferential attachment, despite being a popularly studied mechanism for social network hub-formation, was not the dominant contributing factor for these communication networks. This leads us to believe that in future studies, where hub-formation in networks is of interest, more careful theoretical consideration should be paid to alternative mechanisms. In this case, conversational inertia played the largest role in coordination across multiple communication contexts, a novel finding for disaster communication networks. It is plausible that concentration in other networks may also stem from similar microdynamics. Since such behavior is "invisible" in conventional network studies, caution is needed when interpreting macroscopic patterns; formal development that links unobserved micro-processes with network structure (e.g., Butts (2020) in an ERGM setting, or Snijders (2001) for panel dynamics) is helpful in this regard, but gaining data on microdynamics when possible is certainly advisable.

Finally, researchers may want to more broadly consider the implications of "how" an organization communicates, and what norms are set by and exist in certain media channels, as they could greatly shape the potential for organizations to deal with ongoing and future threats. This may involve taking an inventory of the various communication media an organization uses officially or unofficially, assessing how robust they are to infrastructure failure, and assessing whether secondary forms of communication may serve as primary forms in an active hazard or disaster event. Lastly, it should be considered how the alternative or secondary communication forms might hinder the effectiveness of their potential communication process.

## 4.9 Conclusion

Even at this temporal remove, the WTC case remains unique in the lens it provides on the detailed dynamics of the emergency phase of a disaster, and it continues to offer lessons in the drivers of coordinative behavior. In this special issue recognizing progress in REMs since their introduction, it seems apposite to provide a complete analysis of the data that motivated the initial work. The accompanying data release will likewise be a useful resource for others who wish to investigate this important historical case. Our findings point to an emergent macro sociological phenomenon, finding that even in chaotic disaster events, and diverse contexts, actors in these networks by and large utilized the conversational norms we use in everyday life.

# Chapter 5

# Conclusion

The aim of this thesis was to investigate several aspects of communication, namely message retransmission and communication dynamics, across a spectrum of hazard frequency & familiarity.

The first chapter provides an examination of a census of communication for the entire National Weather Service organization across a single medium from 2009 to 2021 in the context of information retransmission. Due to the duration of the communications studied, we have communications that occur in more quotidian & non-threat times as well as communications occurring during unfolding atypical hazards (hurricanes, tornadoes, etc.). This chapter investigates several micro-structural, content, and style related covariates to understand the properties that make messages more likely to be retransmitted by the audience of the National Weather Service.

The second chapter analyzes public-health and emergency management communications during the first 8 months of the COVID-19 outbreak, while providing the first large-scale image content analysis using optical character recognition (OCR) and analyzing nearly a quarter of a million images for textual content. In this chapter, we identify effective communication strategies that health communicators can use to get their important life saving information out.

Finally, chapter 4 focused on the exotic end of the hazard frequency spectrum by investigating 17 communication radio networks during the 2001 World Trade Center Disaster. We model 17 networks to understand the mechanisms at play for individuals communicating in a disrupted environment. The chapter then goes a step further by providing the first of its kind Relational Event Model simulation study of these dynamics, allowing for the identification of communication norms and mechanisms that tend to lead to the hub-structures found in these communication networks.

This dissertation has several contributions, including:

- Using TF-IDF as a method of cutting through large text datasets to efficiently get out key information. Without this applied innovation to NWS communication, we would not have identified nearly 50 named event hazards that occurred between 2009 and 2021.

- chapter 3 is the first large scale implementation of Optical Character Recognition to study image textual content on Twitter. This provides a framework for future studies to import the approach to other communication domains.

- chapter 3 also provides 7 recommendations for practice that can immediately be implemented by public health, emergency management, and elected officials to communicate on ongoing public health threats/hazards.

- chapter 4 provides the first general purpose REM simulation, showing that humble aspects of the micro-interaction process (conversational norms & RADIO SOP) have important macroscopic consequences, that hold true even in the midst of an unfolding disaster.

While we believe the findings in this thesis are robust and generalizable to the contexts they are studying, there are a few limitations to the work:

- Random effect or lasso regression may have been a more ideal option for the negative binomial models in Chapter's 1 and 2. However, due to the size of these datasets (the NWS dataset is 10 gbs in RAM, the average computer comes with 8 gbs) and that (at this time) random effect models are poorly optimized for large datasets, it was not a feasible choice. Further, R packages with lasso negative binomial regression implementations have only recently been released, whereas the negative binomial implementation in the MASS R package & "glm.nb" function has been in use since 2002, is well documented, and has been used in many contexts. Without those considerations, it is likely that an alternative approach could have found a better fitting AIC or BIC model in both cases.

- For Chapters 1 and 2, the use of Lexicons is pragmatic as it provides the user to better understand the kinds of words and phrases that constitute a lexical category, however, it is not without its flaws. It requires using sampling methods like TF-IDF to cut through the space, where other machine learning methods would be able to make use of the entire corpus. The downside to the machine learning approach is that it can be harder to interpret what's going on "under the hood" so to speak. Sociologists need to find ways to bridge the gap within our field between "shallow" and "deep" machine learning approaches.

- The knock-out experiment for chapter 4 could be strengthened a bit more by increasing the number of simulation draws (currently 50 per experiment). Also, in the simulations we test participation shifts as a ensemble instead of each effect individually, we may want to break these effects out individually to better understand which of the conversational norms are most impactful[1]. It may also be interesting to understand how the

[1]Thanks to an anonymous reviewer for this idea.

effects interact with one another (e.g., ICR & P-Shifts) in terms of Hub-formation[2].

The findings from the 3 studies in this thesis, suggest practical steps forward for future research:

- Future work studying message retransmission on social media should attempt to tackle non-threat periods and lead up periods to see whether community engagement before a storm leads to increase retransmission and interaction in emergency phases. Early work has begun to look into this, but only in a 6 month period (Olson et al., 2019), we should expand this kind of work.

- Analyzing image content for it's impact on communication and message passing is still in its infancy; future work should construct additional measures outside of pure textual content. This includes quantifying the use of color in images, and comparing the effects of differently generated images, specifically looking at whether computer generated images or photography are more likely to grab peoples attention.

- We should apply the REM framework and the findings of chapter 4 to non-hazard contexts, including single channel communication media like chat rooms or Team Speak, or multi-channel chat rooms like Slack/Discord. It would help us establish the generality of the findings, if they are Hazard specific or a more general social phenomena of communication and organization between humans.

- Barriers to applying Relational Event Models for data during unfolding disasters is difficult to collect retroactively and only a handful of these datasets exist – for the unique modeling and simulation approach taken in chapter 4 to gain traction and be applied in other areas we need to collect more conversation/transcript data within spaces facing hazards (NWSChat is a good example of a rich target, but the data is not publicly available).

[2]Thanks to Sean Fitzhugh for pointing this out at our 2022 Sunbelt Conference talk.

From the literature on rumoring in Shibutani 1966, to how people respond and organize in the face of disaster in Tierney (2003) and Auf der Heide (2004), it is evident that humans undergo collective sense-making during unfolding hazards and disasters. This dissertation hopes to add to this rich literature by showcasing various aspects of this sense-making process across the spectrum of hazards and disasters, from pandemics to meteorological disasters. The authors hope that it can inspire future researchers to take the aforementioned next steps toward answering these important and interesting open questions in this area.

# References


Abe, Kitao. 1976. “The Behavior of Survivors and Victims in a Japanese Nightclub Fire: A Descriptive Research Note.” *Mass Emergencies* 1:119–124.

Allport, Gordon and Leo Postman. 1947. *The Psychology of Rumor*. Henry Holt: Oxford, England.

Anthony, Susan. 1972. “Anxiety and Rumor.” *The Journal of Social Psychology* 89:91–98.

Arabshahi, Furough, Furong Huang, Anima Anandkumar, Carter T. Butts, and Sean M. Fitzhugh. 2015. ““Are you going to the party: depends, who else is coming?” Learning hidden group dynamics via conditional latent tree models.” In *IEEE International Conference on Data Mining (ICDM)*.

Auf der Heide, Erik. 1989. *Disaster Response: Principles of Preparation and Coordination*. St. Louis, MO: Mosby.

Auf der Heide, Erik. 2004. “Common Misconceptions about Disasters: Panic, the “Disaster Syndrome,” and Looting.” In *The First 72 Hours: A Community Approach to Disaster Preparedness*, edited by M. O’Leary, chapter 27, pp. 340–380. Lincoln, Nebraska: iUniverse.

Barrie, Christopher Chun-Ting Ho, Justin. 2021. “academictwitteR: an R package to access the Twitter Academic Research Product Track v2 API endpoint.” *Journal of Open Source Software* 6:3272.

Bateman, Scott, Regan L. Mandryk, Carl Gutwin, Aaron Genest, David McDine, and Christopher Brooks. 2010. “Useful junk?: the effects of visual embellishments on comprehension and memorability of charts.” In *CHI ’10: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*.

Bavelas, A. and D. Barrett. 1951. “An Experimental Approach to Organizational Communication.” *Personnel* 27:366–371.

Bongwon, Suh and Peter wand Chi Ed H. Hong, Lichan wand Pirolli. 2010. “Want to be retweeted? Large Scale analytics on factors impacting retweet in Twitter Network.” In *Second IEEE International Conference on Social Computing (SocialCom)*, pp. 177–184.

Borrell, Luisa N and Makram Talih. 2011. "A Symmetrized Theil Index Measure of Health Disparities: An Example Using Dental Caries in U.S. Children and Adolescents." *Statistics in Medicine* 30:277–90.

Brotzge, Jerald and William Donner. 2013. "The Tornado Warning Process: A Review of Current Research, Challenges, and Opportunities." *Bulletin of the American Meteorological Society* 94.

Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38:155–200.

Butts, Carter T. 2013. "relevent: Relational Event Models." Electronic Data File.

Butts, Carter T. 2020. "A Dynamic Process Reference Model for Sparse Networks with Reciprocity." *Journal of Mathematical Sociology* .

Butts, Carter T., Miruna Petrescu-Prahova, and B. Remy Cross. 2007. "Responder Communication Networks in the World Trade Center Disaster: Implications for Modeling of Communication within Emergency Settings." *Journal of Mathematical Sociology* 31:121–147.

Caplow, Theodore. 1947. "Rumors of War." *Social Forces* 25:298–302.

Centola, Damon. 2010. "The spread of behavior in an online social network experiment." *Science* 329:1194–1197.

Chong, Mark and Murphy Choy. 2018. "The Social Amplification of Haze-Related Risks on the Internet." *Health Communication* 31.

Danzig, Elliot R., Paul W. Thayer, and Lyla R. Galanter. 1958a. *The Effects of a Threatening Rumor on a Disaster-Stricken Community*. National Academies Press (US).

Danzig, E. R., P. W. Thayer, and L. R. Glanter. 1958b. "The Effects of a Threatening Rumor on a Disaster-Stricken Community." Technical Report 517, Washington, DC.

David, Lida Z. and Jan Maarten Schraagen. 2018. "Analysing communication dynamics at the transaction level: the case of Air France Flight 447." *Cognition, Technology and Work* 20:637–649.

Drabek, Thomas E. 1986. *Human System Responses to Disaster: An Inventory of Sociological Findings*. New York: Springer-Verlag.

DuBois, Christopher, Carter T. Butts, Daniel McFarland, and Padhraic Smyth. 2013. "Hierarchical Models for Relational Event Sequences." *Journal of Mathematical Psychology* 57:297–309.

Dunlap, Joanna C. and Patrick R. Lowenthal. 2016. "Getting graphic about infographics: design lessons learned from popular infographics." *Journal of Visual Literacy* 25:42–59.

Dynes, R. R. 1970. *Organized Behavior in Disaster*. Lexington, MA: Heath Lexington.

Erikson, Bonnie H., T.A. Nosanchuk, Liviana Mostacci, and Christina Ford. 1978. "The Flow of Crisis Information as a Probe of Work Relations." *The Canadian Journal of Sociology* 3:71–87.

Fararo, Thomas J. and M. H. Sunshine. 1964. *A Study of a Biased Friendship Net*. Syracuse, NY: Youth Development Center.

FEMA. 1984. *Federal Emergency Management Agency: Objectives for Local Emergency Management, CPG 1-5*. Washington, DC.

Fischer, H. W. I. I. I. 1998. *Response to Disaster: Fact Versus Fiction and Its Perpetuation: the Sociology of Disaster*. New York: University Press of America.

Fisek, H. Hamit, Joseph Berger, and Robert Z. Norman. 1991. "Participation in Heterogeneous and Homogeneous Groups: A Theoretical Investigation." *American Journal of Sociology* 97:114–142.

Fitzhugh, Sean M. and Carter T. Butts. 2021. "Staying Connected Under Fire: Effects of Individual Roles and Organizational Specialization on the Robustness of Emergency-Phase Communication Networks." *Social Networks* 64.

Fournier, David A., Hans J. Skaug, Johnoel Ancheta, James Ianelli, Arni Magnusson, Mark N. Maunder, Anders Nielsen, and John Sibert. 2011. "AD Model Builder: using automatic differentiation for statistical inference of highly parameterized complex nonlinear models." *Optimization Methods and Software* 27:233–249.

Genes, Nicholas and Kevin Chary, Michael Chason. 2014. "Analysis of Twitter Users' Sharing of Official New York Storm Response Messages." *Med 2.0* 3.

Gibson, Ben, Blaine Hoffman, Claire-Genevieve La Fleur, and Norbou Buchler. 2021. "Endogeneity and Permeation in an Organizational Communication Network." *Social Networks* 66:65–71.

Gibson, C. Ben, Norbou Buchler, Blaine Hoffman, and Claire-Genevieve La Fleur. 2019. "Participation Shifts Explain Degree Distributions in a Human Communications Network." *PLoS ONE* 14.

Gibson, David R. 2003. "Participation Shifts: Order and Differentiation in Group Conversation." *Social Forces* 81:1335–1381.

Greenberg, Bradley S. 1964. "Person-to-Person Communication in the Diffusion of News Events." *Journalism & Mass Communication Quarterly* 41:489–494.

Harrison, Lane, Katharina Reinecke, and Remco Chang. 2015. "Infographic Aesthetics: Designing the First Impression." In *CHI '15: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*.

IFRC. n.d. "What is a disaster)." `https://www.ifrc.org/what-disaster`. Accessed August 30, 2022.

Imran, Muhammad, Shady Elbassuoni, Carlos Castillo, Fernando Diaz, and Patrick Meier. 2014. “Practical extraction of disaster-relevent information from social media.” In *WWW '13 Companion: Proceedings of the 22nd International Conference on World Wide Web*.

Kang, Songman. 2016. “Inequality and Crime Revisited: Effects of Local Inequality and Economic Segregation on Crime.” *Journal of Population Economics* 29.

Kasperson, Jeanne, Roger E. Kasperson, Nick Pidgeon, and Paul Slovic. 2010. *The social amplification of risk: assessing fifteen years of research and theory*. Cambridge University Press.

Kasperson, Roger E., Ortwin Renn, Paul Slovic, Halina S. Brown, Jacque Emel, Robert Goble, Jeanne X. Kasperson, and Samual Ratick. 1988. “The Social Amplification of Risk: A Conceptual Framework.” *Risk Analysis* 8:177–187.

Kirsi M. Manz, Ulrich Mansmann. 2021. “Inequality Indices to Monitor Geographic Differences in Incidence, Mortality and Fatality Rates Over Time During the COVID-19 Pandemic.” *PLoS One* 16.

Kouloumpis, Efthymios wand Wilson, Theresa and Joanna Moore. 2010. “Twitter Sentiment: The Good the Bad and the OMG.” In *ICWSM 2011 Conference Proceedings Association for the Advancement of Artificial Intelligence*, pp. 538–541.

Kwak, Haewoon, Changhyun Lee, Housing Park, and Sue Moon. 2010. “What is Twitter, a social network or a news media?” In *WWW '10 Companion: Proceedings of the 19th International Conference on World Wide Web*.

Lerman, Kristina and Rumi Ghosh. 2010. “Information Contagion: An Empriical Study of the Spread of News on Digg and Twitter Social Networks.” In *Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media*, pp. 90–97.

Marin-Gonzalez, Esther, Davide Malmusi, Lluis Camprubi, and Carme Borrell. 2016. “The Role of Dissemination as a Fundamental Part of a Research Project: Lessons Learned from SOPHIE.” *International Journal of Health Services* 47.

McElroy, Gil. 2005. “A Short History of the Handheld Transceiver.” *QST* 89:47–50.

Mendonça, David, Gary Webb, Carter T. Butts, and James Brooks. 2014. “Cognitive Correlates of Improvised Behaviour in Disaster Response: the Cases of the Murrah Building and the World Trade Center.” *Journal of Contingencies and Crisis Management* 22:185–195.

Merton, Robert K. 1968. “The Matthew Effect in Science: The reward and communication systems of science are considered.” *Science* 159:56–63.

Mileti, Dennis. 1999. *Disasters by Design: A Reassessment of Natural Hazards in the United States*. Joseph Henry Press, Washington D.C.

Mileti, Dennis S., Thomas E. Drabek, and J. Eugene Haas. 1975. *Human Systems in Extreme Environments*. Boulder, CO: Institute of Behavioral Science, University of Colorado.

National Weather Service, Glossary. n.d.a. "National Weather Service Glossary." https://w1.weather.gov/glossary/. Accessed August 30, 2022.

National Weather Service, Mission. n.d.b. "National Weather Service (NWS)." https://www.weather.gov/about/. Accessed August 30, 2022.

Noji, E. K. 1997. "Earthquakes." In *The Public Health Consequences of Disasters*, edited by E. K. Noji, pp. 135–178. Oxford University Press.

OED Online. Accessed 2020. "Oxford Dictionary Online: Infographic." "https://www.oed.com/view/Entry/242309". "Accessed October 29, 2020".

Olson, Michele K., Jeanette Sutton, Sarah C. Vos, Robert Prestley, Scott L. Renshaw, and C Carter T. Butts. 2019. "Building community before the storm: The National Weather Service's social media engagement." *Journal of Contingencies and Crisis Management* 27:359–373.

Olteanu, Alexandra, Carlos Castillo, Fernando Diaz, and Sarah Vieweg. 2014. "CrisisLex: A Lexicon for Collecting and Filtering Microblogged Communication in Crises." In *Eighth International AAAI Conference on Weblogs and Social Media*.

Ooms, Jeroen. 2019. "tesseract: Open Source OCR Engine. R package version 4.1."

Ooms, Jeroen. 2020. "magick: Advanced Graphics and Image-Processing in R. R package version 2.5.0."

"Organization" NOAA, National Oceanic Atmospheric Administration. n.d. "Organization." https://www.weather.gov/organization/. Accessed August 30, 2022.

Otten, Jennifer J., Karen Cheng, and Adam Drewnowski. 2015. "Infographics and Public Policy: Using Data Visualization to Convey Complex Information." *Health Affairs* 34:1901–1907.

Panagiotopoulos, Panos Barnett, Julie Bigdeli Alinaghi Ziaee Sams Steven. 2016. "Social media in emergency management: Twitter as a tool for communicating risks to the public." *Technological Forecasting and Social Change* 111.

Perrow, Charles. 1999. *Normal Accidents: Living with High-Risk Technologies*. Belmont, CA: Princeton University Press.

Petrescu-Prahova, Miruna and Carter T. Butts. 2008. "Emergent Coordinators in the World Trade Center Disaster." *International Journal of Mass Emergencies and Disasters* 28:133–168.

Price, Derek J. de Sola. 1976. "A General Theory of Bibliometric and Other Cumulative Advantage Processes." *Journal of the American Society for Information Science* 27:292–306.

Quarantelli, E. L. 1960. "Images of Withdrawal Behavior in Disasters: Some Basic Misconceptions." *Social Problems* 8:68–79.

Quarantelli, E. L. 1966. "Organizations Under Stress." In *Symposium on Emergency Operations*, edited by Robert Brictson, pp. 3–19. Santa Monica, CA: Systems Development Corporation.

R Core Team. 2020. "R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria."

R Core Team. 2021. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Renn, Ortwin. 1992. *The social arena concept of risk debates. In: Sheldon Krimsky and Dominic Golding (eds) Social Theories of Risk*. Praeger.

Renshaw, Scott L., Sabrina Mai, Elizabeth Dubois, Jeannette Sutton, and Carter T. Butts. 2021. "Cutting Through the Noise: Predictors of Successful Online Message Retransmission in the First 8 Months of the COVID-19 Pandemic." *Health Security* 19.

Rosnow, Ralph L. 1980. "Psychology of Rumor Reconsidered." *Australian Journal of Emergency Management* 87:578–591.

Scanlon, Joseph T. 1971. "News flow about release of kidnaped diplomat researched by J-students." *Journalism & Mass Communication Education* 26:35–38.

Scanlon, Joseph T. 2007. "Sampling an Unknown Universe Problems of Researching Mass Casualty Incidents." *Statistics in Medicine* 26:1812–1823.

Schank, Roger C. 1977. "Rules and Topics in Conversation." *Cognitive Science* 1:421–441.

Schantz, Herbert F. 1982. *The history of OCR, optical character recognition*. Recognition Technologies Users Association.

Schegloff, Emanuel A. 1968. "Sequencing in Conversational Openings." *American Anthropologist* 70:1075–1095.

Scott, Hilary, Samantha Fawkner, Christopher W. Oliver, and Andrew Murray. 2017. "How to make an engaging infographic?" *British Journal of Sports Medicine* 51:1183–1184.

Shibutani, Tamotsu. 1966. *Improvised News: A Sociological Study of Rumor*. Indianapolis, IN: Bobbs-Merrill.

Silva, Julie and Robin Leichenko. 2009. "Regional Income Ineqaulity and International Trade." *Economic Geography* 80.

Simon, Herbert A. 1955. "On a Class of Skew Distribution Functions." *Biometrika* 42:425–440.

Skaug, Hans J., David A. Fournier, Ben Bolker, Arni Magnusson, and Anders Nielsen. 2016. "Generalized Linear Mixed Models using 'AD Model Builder' R package version 0.8.3.3."

Snijders, Tom A. B. 2001. "The Statistical Evaluation of Social Network Dynamics." *Sociological Methodology* 31:361–395.

Stallings, Robert A. 1978. "The Structural Patterns of Four Types of Organizations in Disaster." In *Disasters: Theory and Research*, edited by E. L. Quarentelli. Beverly Hills, CA: Sage.

Starbird, Kate, Emma Spiro, Isabelle Edwards, Kaitlyn Zhou, Jim Maddock, and Sindu Narasimhan. 2016. "Could This Be True?: I Think So! Expressed Uncertainty in Online Rumoring." In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pp. 360–371.

Sutton, Jeanette, C. Ben Gibson Nolan Edward Phillips Cedar League Britta Johnson Sean M. Fitzhugh and Carter T. Butts. 2015. "A Cross-hazard analysis of terse message retransmission on Twitter." *Proceedings of the National Academy of Sciences (PNAS)* 112:14793–14798.

Sutton, Jeannette, Emma S. Spiro Sean Fitzhugh Britta Johnson C. Ben Gibson and Carter T. Butts. 2014. "Terse Message Amplification in the Boston Bombing Response." In *International Conference of Information Systems for Crisis Response and Management (ISCRAM)*.

Sutton, Jeannette, Laura Fischer, and Michael M. Wood. 2021. "Tornado Warning Guidance and Graphics: Implications of the Inclusion of Protective Action Information on Perceptions and Efficacy." *Weather Climate and Society* 14.

Sutton, Jeannette, C. Ben Gibson, Nolan E. Phillips, Emma S. Spiro, Cedar League, Britta Johnson, Sean M. Fitzhugh, and Carter T. Butts. 2015a. "A Cross-hazard Analysis of Terse Message Retransmission on Twitter." *Proceeedings of the National Academy of Sciences* .

Sutton, Jeannette, C. Ben Gibson, Emma S. Spiro, Cedar League, Sean M. Fitzhugh, and Carter T. Butts. 2015b. "What it Takes to Get Passed On: Message Content, Style, and Structure as Predictors of Retransmission in the Boston Marathon Bombing Response." *PLoS ONE* 10:e0134452.

Sutton, Jeannette, C. Ben Gibson, Emma S. Spiro, Cedar League, Sean M. Fitzhugh, and Carter T. Butts. 2015c. "What it Takes to Get Passed On: Message Content, Style, and Structure as Predictors of Retransmission in the Boston Marathon Bombing Response." *PLoS ONE* .

Sutton, Jeannette, Scott L. Renshaw, and Carter T. Butts. 2020. "COVID-19: Retransmission of official communications in an emerging pandemic." *PLoS One* 15.

Taylor, Mel, Garrett Wells, and Beverley Howell, Gwynethand Raphael. 2012. "The role of social media as psychological first aid as a support to community resilience building. A Facebook study from 'Cyclone Yasi Update'." *Australian Journal of Emergency Management* 27:20–26.

Theil, Henri. 1967. *Economics and Information Theory*. Studies in Mathematical and Mangerial Economics, 7. North-Holland.

Tierney, Kathleen J. 1985. "Emergency Medical Preparedness and Response in Disasters: the Need for Interorganizational Coordination." *Public Administrative Review* 45.

Tierney, Kathleen J. 2003. "Disaster Beliefs and Institutional Interests: Recycling Disaster Myths in The Aftermath of 9-11." In *Research in Social Problems and Public Policy*, edited by Lee Clarke, volume 11, pp. 33–52. Oxford: Elsevier.

Tierney, Kathleen J., Christine Bevc, and Erica Kuligowski. 2006. "Metaphors Matter: Disaster Myths, Media Frames, and their Consequences in Hurricane Katrina." *Annals of the American Academy of Political and Social Science* 604:57–81.

"Timeline" NOAA, National Oceanic Atmospheric Administration. n.d. "History of the National Weather Service." `https://www.weather.gov/timeline`. Accessed August 30, 2022.

Vaughan, Elaine and Timothy Tinker. 2009. "Effective Health Risk Communication about Pandemic Influenza for Vulnerable Populations." *American Journal of Public Health* Suppl 2:S324–332.

Venables, William N. and Brian D. Ripley. 2000. *S Programming*. New York: Springer. ISBN 0-387-98966-8.

Vos, Sarah C. and Marjorie M. Buckner. 2016. "Social Media Messages in an Emerging Health Crisis: Tweeting Bird Flu." *Journal of Health Communication* 21:301–308.

Vos, Sarah C., Jeannette Sutton, Yue Yu, Scott Leo Renshaw, Michele K. Olson, C. Ben Gibson, and Carter T. Butts. 2018. "Retweeting Risk Communication: The Role of Threat and Efficacy." *Risk Analysis* 38:2580–2598.

Wachtendorf, Tricia. 2004. *Improvising 9/11: Organizational Improvisation Following the World Trade Center Disaster*. Ph.D. thesis, University of Delaware.

Walker, Charles J. and Carole A. Beckerle. 1987. "The effect of state anxiety on rumor transmission." *Journal of Social Behavior & Personality* 2:353–360.

World Health Organization (WHO). September 23, 2020. "Managing the COVID-19 Infodemic: Promoting behaviors and mitigating the harm of misinformation and disinformation." `https://www.who.int/news/item/23-09-2020-managing-the-covid-19-infodemic-promoting-healthy-behaviours-and-mitigating-the-harm-from-misinformation-and-disinformation`. Accessed October 29, 2020.