WHAT DO THE PEOPLE SAY? TWEETING AS A TOOL FOR ESTABLISHING THE SOCIAL FACTS OF RISK DURING COVID-19

by

HEATHER SUE M. ROSEN

(Under the Direction of James E. Coverdill)

ABSTRACT

Since the discovery of the SARS-CoV-2 virus in late 2019, there has been widespread debate about the severity and mitigation of COVID-19 risk. While many have alleged that both the scientific facts and public perceptions of COVID-19 risk have changed, there has been no comprehensive investigation of the “social facts” of COVID-19 risk, which encompass both scientific findings and ideological views, prior to their alleged shift in mid-June 2021. For this exploratory study I developed a new approach to structural topic modeling, the seeded structural topic model, to identify nuances in the social facts of COVID-19 risk and mitigation accounting for emotional undertones alongside sentence structure using tweets about “risk” by U.S. Twitter users from December 2019 through June 2021. The findings reveal that risk mitigating behavior in the United States does not always reflect perceptions of COVID-19 risk, and that risk perceptions maligned with scientific findings do not always reflect a rejection of scientific facts. I identify three major factors linking perceptions of COVID-19 risk with risk mitigating behavior in the United States: confusion about the science of COVID-19 risk and prevention, ease of access to tools needed to mitigate COVID-19 risk effectively, and “fear” that preventions themselves were harmful. For example, many attributed resisting masks to a (mis)understanding that COVID-19 transmission occurs primarily via droplet exposure. Others who accepted the predominant mode of transmission as airborne refuted the notion that an airborne pathogen could be mitigated with surgical masks, pointing to fit-tested N95 respirators as the appropriate alternative. Like masks, many believed vaccination and social [physical] distancing were futile, but many also feared they could cause worse illness and injury than COVID-19 infection. Access to masks was wealth-based, as was quarantining, making extreme inequality in the United States crucial for engagement with risk mitigation. Despite speculation that COVID-19 risk mitigating behavior in the United States reflects a "pro" or "anti" science ideology, the importance of "social facts" opposing scientific facts has not been taken seriously. Future studies examining the link between health beliefs and risky behavior should account for social, not just scientific, facts of risk.

INDEX WORDS: Risk, COVID-19, Health Belief Model, Toxic Agent, Emotion, Structural Topic Model

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A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2023

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May 2023

DEDICATION

This dissertation is dedicated to the disabled community, with a special thanks to the community of disabled folks on Twitter known as #DisabilityTwitter, the first people to encourage me to embrace my identity as a disabled person. While the study's focus ultimately expanded to include social facts of COVID-19 risk and prevention that were not directly related to chronic illness and disability, my pursuit of the project was initially related to the unique social isolation experienced by the "medically vulnerable" when public health recommendations for COVID-19 risk and prevention focused on protecting the least, not the most, vulnerable. I could not have accomplished this research, and might not have pursued graduate school, without the support and encouragement of our amazing community, which began long before COVID-19 when I was still a teenager trying to find my way. Thank you for refusing to let me quit when things were tough, somehow doing so without toxic positivity, for showing me what true love and friendship are and teaching me how to practice the radical acceptance they require, and for reminding me every day of the reasons I decided to pursue research related to health beliefs and behavior. Nothing about us without us.

ACKNOWLEDGEMENTS

I would like to thank my committee chair, Dr. James E. Coverdill, for his patience and unwavering support on this project and throughout my time in graduate school. I had big dreams for my research, and it takes a special kind of mentor to keep a highly independent and strong-willed student like me grounded without discouraging their growth. I am so incredibly lucky to have one of those mentors. Thank you for refusing to give up on me, and for teaching me most of what I know about successful navigation of life, teaching, and research in medical sociology.

I would also like to acknowledge the support of several mentors whose guidance was invaluable while pursuing this research. To my mentor, friend, and biggest cheerleader since my recruitment visit on campus, Dr. Lydia Aletraris, thank you for everything, from answering my worried texts, even in the middle of the night, to spending hours staring at data with me so I understood what to do with a codebook. To my mentor in all things related to research methods, Dr. Dawn T. Robinson, thank you for encouraging me to pursue my interests in mathematical sociology, social networks, and social media, for reminding me that failure is often progress, and for giving me the tools I needed to truly understand quantitative research methods. To my first mentor and lifelong friend, Dr. L. Allen Furr, thank you for initiating my interest in sociology as an undergraduate at Auburn University, and for helping me start my career.

Finally, to my partner in life, love, and the one who agreed to let me share his last name, Jake. Thank you for sticking with me through it all. We made it!

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CHAPTER 1

INTRODUCTION TO THE DISSERTATION

One of the central concepts in sociology is the idea that knowledge is socially constructed and therefore highly subject to social context. The social construction of knowledge involves the presentation of ideas to form a consensus about their meaning, or the creation of "social facts" (Durkheim 1982). Social facts include the knowledge and conceptualizations we accept as true (James and Burkhardt 1975; Mannheim 1936, 1952).

Sometimes social facts align with scientific findings, but often, they do not. Just as people may accept science as "true," they may also believe ideas deemed inaccurate, false, contrarian, and mis/disinformation. The wealth of research investigating the mechanisms underlying seemingly irrational behavior, or deviant behavior, is premised on the understanding that the general public's behavior may convey a misunderstanding or ignorance of scientific research findings. Moreover, scientific findings are not objective or permanent, instead, they are fluid and constantly changing with new applications of the scientific method (Black 1993). Understanding social facts is vital to explaining the varied behaviors used to accomplish some goal, especially behaviors that directly oppose science-based recommendations.

The novel coronavirus brought an onslaught of new social facts. Relatedly, the COVID-19 pandemic presented a new opportunity for contesting previously established social facts, including those rooted in science. This allowed for renewed efforts to question expert authority at a time of extreme political polarization in the United States, when it was becoming increasingly popular to label the research findings of credentialed experts as “fake news” (Albright 2017; Allcott and Gentzkow 2017; Tandoc 2019; Tandoc, Lim, and Ling 2018).

Facts about “risk” were central to the management of the COVID-19 pandemic (Becher et al. 2021; Daher-Nashif 2022; Park, Chung, and Kim 2022; Safford, Whitmore, and Hamilton 2021). The COVID-19 pandemic prompted widespread scientific debate about the concept of “risk” (Altheide 2020; Bröer et al. 2021; Pulido et al. 2020; Rock, Degeling, and Adams 2020). Many of these debates have involved the necessity and effectiveness of behaviors used to mitigate the risk of COVID-19 (Au, Fu, and Liu 2022; Dustin et al. 2021; Rock et al. 2020).The downside of scientific debate regarding COVID-19 risk and its mitigation is much of the focus has remained on findings from randomized controlled trials, many of which cannot account for the nuances of risk and its mitigation outside of the controlled lab environment. One such nuance is emotion, which can shape risk-related behavior independent of one’s conscious belief about risk. For example, “anger” has been linked with engagement in activities considered risky or dangerous, while “fear” is often associated with risk-avoidance (Lerner and Keltner 2001). These nuances could be key to resistance versus willingness to adopt behaviors to mitigate COVID-19 risk.

Although some research on risk mitigation during COVID-19 has investigated ideology as an important factor underlying one’s willingness to adopt risk mitigating health behaviors, it has characterized ideology as distinct from science, with some insinuating that ideological views about health behavior and COVID-19 represent a resistance to, disinterest in, misunderstanding, or ignorance, of the scientific understanding of COVID-19 risk (Morelock and Narita 2022).

Resistance to risk-mitigating behaviors has hindered worldwide efforts to eradicate SARS-CoV-2, constituting an unresolved problem of interest for scientists. However, it is not entirely clear that ideology's role in this resistance is exclusive to politically driven anti-science opinions. Furthermore, the adjusting of "science-backed" policy recommendations to account for political opposition to science suggests that political motivations may similarly underlie the interpretation, if not also the construction, of scientific findings about COVID-19 risk. For example, an increasingly popular trend during the COVID-19 pandemic involves policy experts presenting, as fact, ideas like the public believes the pandemic is over (Berghs 2022; Carr 2021; Drezner 2022; Fitzgerald 2021; Hancock and Garner 2021; Kantrowitz-Gordon 2021; Krzyzanowski and Krzyzanowska 2022; Walther 2021; Wu 2022), or that most people believe masks are unnecessary (Dynel 2021).

The existing evidence that there is consensus about these "facts" about the public's perception of COVID-19 risk and risk mitigation remains largely anecdotal, being published primarily in news media opinion pieces (Carr 2021; Drezner 2022; Sherman 2021; Walther 2021; Wu 2022). In the absence of more concrete evidence that the public rejects COVID-19 risk mitigation and per some belief that the risk has been eradicated, sociology may hold the key to addressing resistance to mitigating COVID-19 (Dingwall, Hoffman, and Staniland 2013; Monaghan 2020; Zinn 2021a, 2021b), as doing so requires understanding what ideologies exist (Ho 2020), how they vary (Beyerlein, Nirenberg, and Zubrzycki 2021; Bröer et al. 2021), and how they are shaped by social forces (Botting 2021). Relatedly, there is still a considerable amount of disagreement regarding the importance of scientific findings about of risk for determining the public's participation in COVID-19 risk mitigation. Bearing in mind that the growing body of scientific evidence suggesting the risk of COVID-19 infection remains high and widespread coincides with the nullification of policies aimed at increasing participation in risk mitigation efforts in the United States, research into risk mitigating behavior during COVID-19 cannot provide a true understanding of why behavior to mitigate risk varies without accounting for the wider scope of social facts beyond the scientifically grounded.

Contending with resistance to risk mitigating behavior during COVID-19 in the United States requires an understanding of the "social facts," not just the scientific findings, of the risks posed by COVID-19. While it is tempting to look only at the most current perceptions of COVID-19 risk and mitigation, the allegation that the public's disbelief in COVID-19 risk and disinterest in its mitigation constitutes a shift from their response earlier in the pandemic remains unfounded in absence of a comprehensive study of the social facts of COVID-19 risk and mitigation during this "earlier" phase of the pandemic. This study aimed to contribute to the sociological understanding of health beliefs and health behavior related to the COVID-19 pandemic by identifying the "social facts" of COVID-19 risk and risk-mitigation in the United States in the first 19 months of the pandemic, asking:

What do people living in the United States believe about COVID-19 risk?

SOCIAL FACTS, THE SOCIOLOGY OF KNOWLEDGE, AND IDEOLOGICAL BELIEFS ABOUT HEALTH AND RISK

Sociologists have theorized about and investigated why, and how/whether the "accepted" truth, the social facts, change per context and over time. They have suggested that social facts are tied to ideology (Mannheim 1936) and are shaped by epistemology reflecting one's position in existing social structure (Mead 1934; Merton 1972). Other sociologists have suggested there are different *types* of social facts, some of which are specific to institutions (Berger and Luckmann 1966). For instance, legal facts are social facts established in the court of law (Black 1983, 1993, 1995), while clinical facts are social facts established during the medical diagnostic process (Davis 2011, 2015; Jenkins and Short 2017; Jutel 2011; Jutel and Nettleton 2011). Scientific facts based on research may also be considered social facts, as they are sensitive to change over time with the emergence of updated research, and they may vary per scientific paradigm. For example, sociological facts may differ from the facts of other academic fields, like psychology (Berger and Luckmann 1966).

To this end, the understanding that a social fact exists does not mean agreement about its conceptualization is inevitable (Berger and Luckmann 1966; Mead 1934; Merton 1972). For example, actors may agree on the "fact" that disability is a characteristic that exists in the population while disagreeing about the parameters for determining whether something should be counted as a disability (Grue 2016; Thomas 2004). The lacking consensus surrounding disability is not unique or new to medical practice, just as it is not new to medical science, making disability a useful example for examining scientific facts as social in context of a pandemic. The imprecision and fluctuation of scientific facts is often ignored, but it is no coincidence that neither social nor scientific facts are predestined to elicit widespread agreement about a fact's meaning and existence. The recognition of scientific facts as social facts, including those upon which medical practice operates and from which clinical facts are established, is key to grasping the role scientists and medical professionals may have played in fostering confusion and widespread disagreement about COVID-19 risk and its mitigation.

Importantly, while social facts are subjective and sensitive to context, this subjectivity does not mean they are inconsequential (Goffman 1963; McHugh 1968; Merton 1972). Social facts shape human behavior—humans act based on what they believe to be true for a given context and role (Durkheim 1982). Humans form an understanding of the truth and how to act, or what sociologists refer to as "social norms," through processes of social interaction, making social interaction a key mechanism through which social facts are established (Castells 2000;

Mead 1934). Social interactions are not neutral or random, and thus, the establishment of social facts is impacted by selection effects, institutions, and power status, among other things (Merton 1972). Beliefs, or ideologies, may accordingly be understood as the set of social facts which an individual accepts to be true, and they are shaped by a process of interaction leading to consensus with others (Castells 2000).

The subjectiveness of social facts remains particularly relevant to sociology, as it remains consequential for society and social structure (Bourdieu 1986; De Vries and de Graaf 2008; DiMaggio 1982). This includes the areas of health disparities (Cockerham 2013; Gengler and Jarrell 2015; Mollborn, Rigles, and Pace 2021; Shim 2010) and risk assessment/exposure (Brown 2016; Van de Werfhorst and Hofstede 2007). The subjectiveness of facts about biology continues to be especially consequential, exacerbated in an era of increased "lay" authority and contestation of credentialed medical expertise (Arguedas 2022; Epstein and Timmermans 2021; Gengler 2014; Timmermans 2020). This is highlighted in the long history of efforts by medical actors arguing for a specific definition of sex, gender, and the "normal" body, such as the forced suppression of intersex traits (Davis 2011, 2015). These consequences have come to the forefront at the institutional level recently in renewed efforts to criminalize trans people and gender-affirming healthcare in the United States (Abreu et al. 2022).

Net of institutional consequences, the subjectiveness of social facts about biology, the body, illness, and disability has further consequences for population health and systemic inequality considering ongoing conflict about the COVID-19 pandemic (Arias-Maldonado 2020; Hameleers et al. 2021; Lupton and Willis 2021; Mollborn, Mercer, and Edwards-Capen 2021). One of the more substantial of the consequences for population health and systemic inequality relates to the growing body of scientifically grounded evidence that even COVID-19 infections with seemingly mild symptoms can have chronic and disabling consequences like microclots, autoimmunity, and increased susceptibility to complications from future infections, COVID-19 or otherwise (Christensen 2022; Davis et al. 2023; Goodman 2022; Werlein et al. 2022; Xu, Ilyas and Weng 2022). These consequences are even more severe when taken in context of additional findings that the risk of long-term disability from COVID-19 infection grows substantially with each infection, with about 80% of those infected three times experiencing chronic symptoms of illness that are severe enough to interfere with everyday activities like work, school, and household chores (Davis et al. 2023; Smith 2022).

Even if it is the case that COVID-19 infection was initially more severe for the elderly and people with chronic illnesses, the proportion of the population with heightened susceptibility to complications and death from future COVID-19 and other infections will only increase as the number of people infected and suffering long-term consequences of COVID-19 grows. Considering other ongoing global crises like climate change and the long history of gain-of-function research involving dangerous pathogens, COVID-19 is unlikely to be the last novel and dangerous pathogen to threaten humans. Understanding the reasons people resisted risk mitigation during COVID-19 is crucial to mitigation efforts for future pathogens, given they may have a more severe impact on a larger portion of the population than COVID-19 did in the first 19 months since it's discovery.

SOCIOLOGICAL THEORIES RELEVANT TO THE SOCIAL FACTS OF COVID-19 RISK

While the eradication of COVID-19 is primarily a problem of Public Health, the difficulties authority figures in the United States have faced when implementing solutions informed by Public Health science to mitigate the risk of SARS-CoV-2 infection indicate a need for further investigation into the factors influencing the risk-mitigating behaviors required for

Public Health solutions to succeed in this context. Not only does Sociology provide several useful frameworks for explaining human behavior, but sociologists have also previously provided insight as to why individuals and groups may reject behaviors recommended by Public Health that are aimed at mitigating risks to health and safety (Becker 1974; Cockerham 2005).

Public Health science has pinpointed the need for collective action to address problems with a population-wide impact (Muñoz 2018; Wiltshire, Fullagar, and Stevinson 2018). This is especially true for problems of global health, but facilitating collective action internationally is highly challenging (Breznau 2021; Fitzgerald 2021). The global spread of COVID-19 was challenging to address, in part, because of resistance among some social groups against collective risk-mitigating action (Bhasin et al. 2020; Gonzalez et al. 2021).

It is not entirely clear that theories of collective action capture the most relevant reasons behind engagement in/resistance to risk mitigation during COVID-19. Additionally, much of the pushback against collective action to mitigate the risk of COVID-19 emphasized individual agency (Nygren and Olofsson 2020; Rooke 2021). Sociological theories of behavior, particularly those focused on health behavior, can help explain the limits of individual agency as a replacement for collective action to address non-individual issues like the spread of a novel pathogen. So, while this study is exploratory, there are several sociological theories that are useful for understanding the social facts of risk during COVID-19.

Theories Related to Networked Social Interaction

Of the major sociological paradigms, the symbolic interactionist paradigm is useful for understanding the findings of this study because it emphasizes the importance of individuals in the creation, maintenance, and evolution, of social structure (Carter and Fuller 2016). By situating individual actions in context of larger societal phenomena, like collective action, symbolic interactionism provides some clarity on the implied connection between the two in public health policy recommendations related to COVID-19. Furthermore, symbolic interactionist frameworks are often used to understand how and why cultural norms change in periods of social turmoil, uncertainty, and unpredictable or extreme changes to the navigability of physical space (Carter and Fuller 2016). The COVID-19 pandemic brought all three, extreme uncertainty, social turmoil, and changes to the navigability of physical space.

Somewhat related to symbolic interactionism, postmodernist theories also center uncertainty, though the precariousness is framed as pervasive in society instead of being understood as specific to interactions themselves (Baumann 1992; Goffman 1963). Postmodern societies, which emerged with the rise of globalization and have persisted through the Digital Age, are characterized by volatility (Giddens 1981; Habermas and Ben-Habib 1981; Shalin 1993). That the uncertainty is characteristic of postmodern society rather than interactions themselves means there are parameters to the subjectivity of social facts such that social norms may be established and maintained via a group consensus (Long and Hadden 1985). Postmodernism does not discount culture, nor does it ignore that networked social structure is embedded in cultural values about power and therefore also hierarchical (Castells 1996, 2000a, 2000b; Emirbayer and Goodwin 1994; Giddens 1981). These attributes render postmodern theories important beyond interactionism.

The postmodern theories differ in how they conceptualize the importance of culture versus structure for social interaction and behavior. For example, Bourdieu's theory of capital (1986) focuses on the importance of socialization for social interaction with people of different cultural backgrounds. It argues that one's prior socialization is obvious because it is embodied, terming the culturally embodied self the "habitus" (Bourdieu 1986). From this perspective, social structure is external to the individual, and one's position in the social structure is allegedly obvious because different cultural expectations exist for people of different backgrounds, and in different institutional roles and settings (Bourdieu 1986). In contrast, Giddens' theory of structuration posits structure internally, within the individual actor (1991). Structuration theory assumes actors have much more agency than the theory of capital (Bourdieu 1986; Giddens 1991).

Other perspectives, like relational sociology, have extended the connection between culture and social interaction to include the importance of historical time and the cumulative effects one interaction on subsequent interactions with the same actor (Emirbayer 1997; Mützel 2009). Another, actor-network theory, places more emphasis on social structure, conceptualizing the social network as a site of cultural production and socialization (Breiger 1974; Callon and Latour 1981; Latour 1996). Another distinction between relational sociology and actor-network theory is the understanding of the actors as exclusively human (relational sociology) versus the idea that actors include human and non-human living beings, institutions, and objects (actor-network theory) (Breiger 1974; Callon and Latour 1981; Emirbayer 1997). Extensions of actor-network theory include the idea that the networked cultural structure is a site of identity formation and social bonding (White 1992, 2008; White, Boorman and Breiger 1976).

Middle-Range Theories of Risk, Behavior, and Emotion

Sociological theories of risk, behavior, and emotion are also highly relevant, as the social facts of COVID-19 risk include risk perceptions for engagement in "preventive" versus "risky" behaviors related to COVID-19 transmission and exposure, but also additional factors. For example, [emotional] sentiments have been identified as influential for behavior in a variety of contexts (Shelly 2016) and language is understood as an important source of information about sentiments and their variation across cultures (MacKinnon and Heise 2010). Considering the relevance of emotions/sentiments for behavior, and the possibility that language used to express the social facts of COVID-19 risk may include emotional undertones that provide cultural context about their meaning, the theoretical links between risk perceptions, risky versus preventive health behavior, and emotions, are important for interpreting the social facts of COVID-19 risk.

Theories of Risk

Postmodern sociological theories of risk situate the concept within the context of capitalism or “modern” society. From this perspective, the meaning of risk is somewhat fluid, but the importance of preventing risk is not. For instance, the theory of the Risk Society suggests that, in modern societies that have become reliant upon some technology, mitigating a risk is only important to the extent that its mitigation would not interfere with the use of vital technology (Beck 1992; 1996). The meaning of risk varies with the introduction and adoption of new technologies, but it is always important to mitigate the effects of risk when they threaten the use of important technology, and the mitigation is always left to the individual (Beck 1992; Giddens 2002). Constructionist theories of risk similarly argue that definitions of risk are not stable, but instead of framing risk as related to technology, the meaning of risk and understanding of how to respond to a risk are situated in social structure and understood to be shaped by power and authority (Zinn 2020).

Other theories situate the importance of risk as related to the relationship between people and place. One such theory, the Relational Theory of Risk, argues that there are risk objects, or things that have potential to cause harm to valued objects, and objects of risk, the valued objects subject to potential harm (Boholm and Corvellec 2010). Another explains the importance of the relationship between people and place in terms of identity and the self, arguing that there are "rites of risk" and "rituals of symbolic safety" involved in urban adventurists' formations of the self. In this case, seeking out risks, especially those which have been reduced in urban environments by land development, is a means of affirming one's self-identification as a "thrill-seeker" when living in the city (Kidder 2013).

Thrill-seeking outside of the urban environment has been referred to as "edgework," with some drawing on postmodern theorists like Bourdieu (1977) to suggest that there is a habitus specific to people with this "edgeworker" identity, meaning there are particular ways of embodying the "adventurer" self when compared to other identities (Bunn 2022). Edgework highlights the positive and affirming aspects of encountering risk, which is distinct from most other sociological theories of risk (Lupton 1999, 2013; Lyng 2008). Sociological theories of risk have tended to focus on the negative consequences of risky behavior, framing risk as something which, if encountered, may threaten one's identity rather than affirm it (Lyng 2008).

These include the cultural theories of risk. Cultural theories of risk have characterized risk-taking as a uniquely individual phenomenon, arguing that "risk" at the group level is better understood in terms of "taboo," and that both risk and taboo are forms of boundary work (Douglas 1966). From this perspective, risk and danger are framed as threats to the individual self/identity and community boundaries, meaning risk is synonymous with deviance (Becker 1963; Erickson 1966). In similar fashion, dramaturgy examines risk in terms of boundary work and as a violation of social, identity, or cultural boundaries (Goffman 1963). However, boundaries are more fluid from the dramaturgical perspective, and risk is linked to social interactions and the concept of "stigma" (Goffman 1963). In social interactions, there is always a "risk" of being stigmatized, but the level of risk varies depending on other factors, such as having a stigmatized identity, and whether that stigmatized identity is obvious (Goffman 1963). Some have argued that, when a stigmatized identity is obvious and leads to social exclusion, there is no longer a risk of stigma because the chance of being "othered" is almost certain (Anzaldúa 1987). Other theories of deviant behavior have also been applied to the idea of risk, but they are focused specifically on the behaviors considered "risky," and thus, are more appropriately discussed as theories of behavior.

Theories of Behavior

Many theories of behavior are focused on deviant behavior, or behavior that violates social or situational norms (Becker 1963; Erickson 1966; Goffman 1963). Deviant behavior is often framed as risky, dangerous, or unsafe, and the understanding of these behaviors as risky relates to their potential negative impact on health leading to injury, illness, disability, or death. Some theories assume engagement in behaviors that may result in physical harm to oneself, or others, is related to knowledge about the potential outcomes and their likelihood. Rational choice theory frames behavior as the result of an individual's cost-versus-benefit assessment of the potential outcomes of that behavior (Goldthorpe 1998). The decision to engage in a behavior with significant costs to one's health is often discussed as irrational, assuming individuals had complete knowledge of the risks prior to engaging in some behavior.

Theories of health behavior have heavily criticized this tendency to assume people are rational actors, with many emphasizing the importance of the individual's understanding of risk, arguing many people are not aware of the risks prior to engaging in a deviant and/or dangerous behavior (Becker 1974). Some, like the theory of the life course, have linked behavior and understanding of risk with age to suggest younger people are less experienced and therefore less knowledgeable about risks, which makes them more likely to engage in behaviors considered deviant or dangerous (Elder 1994).

Others have agreed with the rational choice theorists on the notion of expert versus "lay" knowledge, sharing the understanding that formal education may indeed be necessary prerequisites for accurately identifying and assessing risk (Becker 1974; Cockerham 2005; Goldthorpe 1998). They diverge from rational choice theory in their understanding of "choice," framing knowledge as related to access, not just agency/motivation (Becker 1974; Cockerham 2005; Shim 2010). For instance, Cockerham's health lifestyle theory suggests that many people do not have access to the material assets needed to access knowledge about what behaviors are "healthy" (and relatedly, "risky" or "unhealthy") (2005, 2013). Cockerham argues that there are limits to agency that are out of the individual's control, pointing to structural factors like poverty (2005). These factors limit the availability of choice, meaning the ability to choose "healthy" or "safe" behaviors is not equally distributed throughout the population (Cockerham 2005, 2013).

Similarly, Becker's health belief model highlights barriers to accessing the goods and/or social circumstances necessary to avoid or mitigate a risk as one of four major factors influencing health behavior (1974). The other four barriers include the belief that oneself is at risk, the belief a risk is serious, and the belief that the benefit of engaging in prevention and/or avoiding the risk is worth the cost (Becker 1974).

Shim's theory of cultural health capital (2010) builds on Bourdieu's theory of capital (1986), arguing that there is a unique form of cultural capital involved in clinical encounters between patients and physicians. Having high cultural health capital increases the likelihood that a patient will understand that a risk to their health exists or has already been encountered (Shim 2010). Independently of this, cultural health capital can determine whether someone is able to effectively advocate their needs to obtain things like prescriptions that may be necessary to avoid risk or alleviate future effects of an encounter with risk that has already resulted in harm to health (Gengler 2014).

Constructionist theories also touch on the understanding of personal risk as important for behavior. In contrast to structural and cultural theories of health behavior, constructionist theories do not heavily emphasize access to healthcare and other vital resources to maintain health, like food (Becker 1974; Cockerham 2005, 2013; Gengler 2014; Shim 2010). Instead, they draw on the dramaturgical concept of "defining the situation," extending it to the definition of self as chronically ill and/or disabled, and the definition of certain biological, psychological, or phenotypical, characteristics as pathological (Barker 1998; Charmaz 1991; Conrad 1975, 2007; Conrad and Schneider 1980; Davis 2015; Goffman 1963). Most of the research in this area uses a medical social control framework, which argues that powerful actors like doctors, politicians, and other influential social elites, have the power to define whether something is illness or disability, if someone is at risk of illness or disability, and whether some deviant condition is pathological and concerning enough to warrant treatment or steps towards prevention (Conrad 1975; Zola 1972). In this case, behavior is something seen as warranting social control by actors in medicine because it is not simply deviance, it is pathological, and thus, illness (Conrad and Schneider 1980; Zola 1972).

Charmaz's theory of the self in chronic illness and time is one exception to the constructionist medical sociologists working within the medical social control framework (1991). This approach examines the social construction of illness in a way that is reminiscent of symbolic interactionism, focusing on the importance of interactions with others and with oneself over time for accepting the chronically ill identity (Charmaz 1991; Charmaz and Belgrave 2013).

This acceptance is an alleged necessary precursor to coping, which is measured by behavior aimed at mitigating existing and future risks to health given one's illness (Charmaz 1991).

The interactionist theories frame behavior as a social phenomenon constituting a form of exchange (Homans 1958). Social exchange occurs between actors in a social network, and these actors could be individuals, but they can also be groups of individuals (Homans 1958). As such, the size and composition of the network of actors has additional importance related to the formation of social norms (via the exchange of ideas), namely, that some actors and groups have more power to influence which ideas are exchanged most often and thus become social norms (Emirbayer and Goodwin 1994). From this perspective, behavior is both collective, via interaction, and individual, via agency (Emirbayer and Goodwin 1994). Agency, the means for an individual to act of their own free will, is a key reason for examining behavior as interaction between actors in a network reflecting their relative positions in social structure and their prior experiences/interactions rather than as something entirely predictable by some objective and permanent position in the structure of society (Emirbayer and Mische 1998; Ridgeway and Erickson 2000).

Theories of Emotion

Research applications based in symbolic interactionist theory have examined emotions and sentiments as important to perceptions of risk and participation in risk-related behavior. For example, research examining social exchange and meaning making when uncertainty is high has found the presence of "trust" to be an important predictor of consensus and/or acceptance of influence (Kollock 1994). Some theories of emotion have drawn on the importance of emotion for risky versus preventive behavior, like the theory of responsible sociality (DeSoucey and Waggoner 2022). The theory of responsible sociality argues that a multidimensional proximity to risk impacts how people make sense of fear versus trust regarding risk (DeSoucey and Waggoner 2022). When proximity to risk is unequally distributed in an intentional way through human actions, such as funneling pollution to a predominantly Black residential area and away from a predominantly white one, it can be understood as environmental racism, which reinforces existing feelings of mistrust among Black residents (Benz 2017). The connection between place, social status, proximity to risk, and emotion has also been examined with applications of social disorganization theory (Sampson 1993; Sampson and Wilson 1995; Shaw and McKay 1942). These applications suggest that disorganization at the neighborhood level, which increases the chances of engaging in deviant behavior, is tied to experiencing feelings of anger and mistrust (Ross and Mirowsky 2009).

Other studies of emotion and risk have employed theories of health behavior like the health belief model to explain risk prevention (Becker 1974). They focus on components 1 and 2 of the health belief model, which include the belief that a risk is personally impactful and the belief that the risk is serious, demonstrating that fear is an important emotion underlying the belief that risk is serious, but also that this fear does not tend to arise until one has already come to the conclusion that they are personally at risk, at least in context of HIV/AIDS (Prohaska et al. 1990). Another popular conceptualization of emotion in research on health risk focuses on the concept of "feeling rules," drawing on Hochschild's theory of emotion work (1977) and Goffman's assertion that deviance in an interaction can produce emotions like embarrassment (1956, 1963). The stress process model positions violation of feeling rules, or what some refer to as emotional deviance, as one of several intervening mechanisms in the relationship between stress and illness, discussing them in terms of coping with stress (Pearlin et al. 1981). Those expressing feelings that violate feeling rules for coping with stress are evidence of mal-coping, or a lack of ability to cope with stress (Pearlin et al. 1981; Thoits 1985). However, violation of feeling rules is not the only evidence of mal-coping; deviant behavior can also be evidence that someone has failed to appropriately cope with stress, independent of emotion (Thoits 1985, 2010). Strain theory provides a similar framework, but the behavior is the end-point of the model whereas it is a precursor to physical and mental illness in the stress process model (Agnew 1992; Merton 1938). Strain is also conceptualized differently than stress with a narrower scope (Merton 1938; Pearlin et al. 1981; Thoits 2010). When someone is unable to adhere to social norms and/or rejects those norms, they experience strain (Merton 1938). This strain can lead to a variety of coping behaviors, which Merton groups into four categories of deviance based on ability to adhere to and endorsement of social norms (1938). Extensions of strain theory like General Strain Theory connect strain to emotions like anger and frustration, which increase the chance that someone will respond to strain with deviant behavior (Agnew 1992). Deviant behaviors studied with general strain theory have often overlapped with behaviors considered risky because of their potential to harm health, like drug use or attempts to die by suicide (Agnew 1992, 2001; Zhang 2019).

Theories of emotion themselves are often linked to sociological social psychology, an experimental approach to testing theories of identity, emotion, and interaction, with roots in symbolic interactionism (Blumer 1969; Stryker 1980). Proper theories of emotion have a different focus than theories of risk and behavior that have been used to examine emotion as part of a larger model. These theories focus on the importance of emotion for the outcome of social interactions, and the impact of social interactions on emotion (Smith-Lovin 1989). Identity theory, affect control theory, and identity control theory, each propose cyclical models connecting interaction with emotional expressions, and emotional expressions with interaction

(Burke 1997; Burke and Stets 2009; Heise 1977; Smith-Lovin and Heise 1988; Stryker and Burke 2000; Stryker and Serpe 1982).

INFORMATION AND MISINFORMATION ON THE INTERNET: CONSEQUENCES FOR GLOBAL CRISES AND HEALTH BELIEFS ABOUT RISK

The Information Age, sometimes called the “digital era,” introduced the internet, bringing with it the capacity for quicker interactions with a wider audience and variety of ideas (Castells 1997, 2000a, 2000b, 2002; Mitchell 2000). With these characteristics, the internet constituted a powerful new force for establishing social facts while also providing an avenue for grassroots and other non-expert participation in the social construction of knowledge (Castells 2000a). Some research suggests that access to a wider variety of social facts via the internet is useful for increasing expert influence, providing the uneducated members of the public with information they would not otherwise have available (Murthy 2011, 2012, 2018; Timmermans 2020).

While it is often the case that those with higher power status hold heightened authority to establish social facts (Blau 1964; Lenski 1984), studies of deviant behavior indicate that the public, as well as other authority figures, may just as well reject facts established by credentialed experts and other powerful members of society (Becker 1963; Berger and Luckmann 1966). Furthermore, sociologists studying symbolic interaction through the transition from the Industrial Age to the Information Age observed that a new, networked, social structure seemed to be emerging with the introduction of non-expert voices to realms of knowledge previously controlled almost exclusively by credentialed experts and other powerful entities (Castells 2000).

The importance of online interactions for the social construction of knowledge has only grown with the budding popularity of online social networking platforms (Gerbaudo 2016; Hunt, Koteyko, and Gunter 2015; Shao et al. 2018; Silver and Matthews 2017). Social networking sites like Twitter have also become popular spaces for discourse on public issues (Beraldo 2022; Earl et al. 2013; Graham and Smith 2016; Murthy 2011; Pearce and Rodgers 2020), communication during crises (Sutton et al. 2014; Trezza, Punziano, and De Falco 2021), and for disseminating information from experts to the public (Chew and Eysenbach 2010; Kauk, Kreysa, and Schweinberger 2021; Park, Rodgers, and Stemmle 2013).

Medical sociologists and other health care researchers have previously highlighted the ways social media use can benefit health practitioners if they embrace that the technology is not going away (De Las Heras-Pedrosa et al. 2020; Timmermans 2020). This includes endorsing the possibility that it provides an avenue for presenting accurate information and combatting misinformation, and its potential as a tool for disseminating information from experts to the public quickly in the event of a crisis (Bode and Vraga 2018; Grajales III et al. 2014; Hameleers et al. 2021; Thorson 2016).

Ideology and Discourse: The Social Construction of "Risk" Online

Quantitative approaches to text analysis, also known as natural language processing (NLP), have become popular with the increased access to publicly available information via the internet. Discourse analysis and corpus linguistics are particularly useful for developing an understanding of how people conceptualize risk, focusing on framing of semantics in addition to dictionary-based definitions of words used in discourse about risk, and thus, providing context about the cognitive schemas shaping beliefs in various contexts (Fillmore and Atkins 1992). This is important because the sociology of risk is informed by the understanding that seemingly "rational" actors may not behave in a way that is considered "rational" given the end goal for the action, but instead, may behave according to affect and prior experiences (Beck 1992; Giddens

1990; Robinson 2014). We cannot truly understand ideological views through discourse analysis focusing on different dictionary definitions alone.

Patterns of word usage called “lexico-syntactic patterns” are comprised of relationships between lexicon (dictionary) and semantics (usage). Corpus linguistics is a method of examining lexico-syntactic patterns in discourse using a “corpus,” which is an object containing the text of a set of documents, like tweets, that has been converted to a machine-readable format (Fillmore and Atkins 1992; Hamilton, Adolphs, and Nerlich 2007). The corpus can be analyzed in a way that allows for lexical and grammatical framing while also accounting for information about neighboring words and phrases, and therefore word usage, not just word definition (Atkins 1994).

Word usage is critical to the understanding of risk via discourse from a sociological perspective because the way people use words reflects their prior experience. Previous studies employing discourse analysis and corpus linguistics to the sociological study of risk ideology have established that media discourse about risk both reflects and shapes ideological views about risk among the public (Zinn and McDonald 2016). Fillmore and Atkins (1992) assert that word usage, specifically, is critical to the understanding of ideological views about risk, proposing that at least two distinct semantic framings for “risk” exist among common semantic framings and lexical definitions: those employing “risk” as a noun, and those using “risk” as a verb. “Risk,” as a noun, can indicate uncertainty or chance, as there is some assessment to be mase about whether a “risk” exists in some context. As a verb, “risk” may indicate harm posed to a person, object, or environment, for example, willingly entering a circumstance understood as dangerous is an action during which the actor risks being victimized. The framing semantics approach provides a means of distinguishing the usage of “risk” in both contexts.

Risk discourse is also found in discussions of health, illness, and injury more often than discussions about other dangers that do not necessarily impact the body, like financial loss (Hamilton et al. 2007; Lupton 1999). Given the importance of health and illness in context of COVID-19, examining discourse about risk during the pandemic could provide great insight about the existing ideological views about risks related to COVID-19 and the health behaviors used to mitigate these risks.

Dictionary-based approaches are an emerging set of techniques for identifying emotion and sentiment in text accounts by linking sentiments with words (Heise 2007; Munezero et al. 2014). Dictionary-based sentiment analysis of text is highlighted by scientists as a useful tool for predicting behavior in response to social stimuli, because emotions can predict behavior in response to social stimuli (Heise 2007; Thomas and Heise 1995). Market research has produced compelling evidence supporting this assertion (Jaffe 1999; Mostafa 2013). Research on health beliefs and health behavior has turned to dictionary-based sentiment analysis to understand varying responses to health risks, given the link between sentiments and behavior and increasing availability of public "accounts" about matters of health, illness, disability, and health care (Jones and Salathé 2009; Salathé and Khandelwal 2011).

Twitter: The Microblog Advantage in Social Media Research on Ideology During Crises

The weblog (blog) emerged in the late 1990s as a new type of website, social media, allowing for the simple creation and distribution of user-generated content (Garden 2011). The act of distributing user-generated content on blogs is known as "blogging" (Garden 2011). This content is often delivered in the form of personal testimony, like a journalistic "think-piece" or a diary entry. The social media platform Twitter, founded in 2006, used a new "microblogging" technique implementing a per-post character limit of 140 characters (later expanded to 280 characters) (Murthy 2012).

While emotions and sentiments are often understood as cognitive manifestations of some individual characteristic, sociologists have instead pointed to socialization as an important influence on how and when emotions and sentiments are expressed (Stets 2003; Thoits 1989; Turner and Stets 2006). As is consistent with the symbolic interactionist framework, I conceptualize emotions and sentiments as reflecting socialization by culturally similar others through interaction (Cooley 1909). From this perspective, the emotions and sentiments expressed in public "accounts," can provide additional context to differentiate one fact from another. "Accounts" are narrative testimony about one's experiences and interpretations of life (Orbuch 1997). Blogging techniques, including microblogging with tweets, are tools for people to express their "accounts." Examining emotional and sentiment expression in tweets can provide a more thorough overview of the variation in the understanding of the social facts about many phenomena than examining the accounts without this context.

Twitter posts, or "tweets," come in a few forms. At the most basic level, tweets contain personal testimony by a Twitter user who represents either an individual or institution. Tweeting at this basic level is not interactive, but the content of Tweets can be analyzed to gauge users' ideological views. Interactions on Twitter include "retweets," simple reposting of pre-existing tweet, "reply tweets," used to provide input on an existing tweet without posting to one's own profile, "quote tweets," a heightened form of reply tweet that includes commentary alongside a re-posting of the original tweet, and cold calls of another user initiated through the use of "@" and the other user's screen name. When one user sends a "reply tweet" to their own posting as a follow-up, the set of tweets by the original poster is called a "thread."

There are several advantageous aspects to the type of communication used on Twitter that separate it from other social media platforms, even seemingly similar, platforms like the long form blog site Tumblr. Like long form blogging sites, Twitter can be used as a means of posting personal accounts, social interaction, and the dissemination of information throughout a network. However, the short form of the microblog meant more efficient interaction with a wider audience, allowing for more dynamic and efficient interaction with other users than traditional blogs warranted (Murthy 2018; Panchenko 2018). The efficiency of microblogging for disseminating important information to a vast and diverse network of individuals and institutions has allowed Twitter to establish its dominance as a tool for communication and research about crises and ideology (Adamczyk, LaFree, and Barrera-Vilert 2019; Hou and Park 2019; Murthy 2012, 2018; Pöppel, Dreiskämper and Strauss 2021; Tomaszewski et al. 2021).

Despite its popularity, there can be drawbacks to using a microblogging platform like Twitter to communicate important information from experts during a crisis. One such drawback is related to the vast and unrestricted access to information via the internet. There has been a rising interest in false and intentionally misleading information available via the internet, information which is increasingly referred to as “misinformation” and “disinformation” (Bode and Vraga 2018; Ecker et al. 2014; Holme and Rocha 2019; Osman et al. 2022; Thorson 2016).

The increasing focus on mis/disinformation in research involving the internet hints at an ongoing academic interest in the subjectivity of knowledge, the notion that different social groups may endorse different social facts as true. For example, recent research has argued that groups like “Qanon” are constructed to provide people with a strong mistrust of experts an alternative set of social facts to consider as real, inflaming their mistrust of experts by suggesting that experts conspired to hide the truth (Bleakly 2021; DiMaggio 2022; Morelock and Narita

2022). Meanwhile, medicine, public health, and medical sociology have pointed to the popularization of complementary and alternative medicine (CAM) in the United States, arguing that it exploits public mistrust of medical experts by providing alternative scientific facts about risk, the body, illness and injury, and, medical treatment and recovery (Dew and Clark-Grill 2022; Epstein and Timmermans 2021; Fries 2013; Islam 2012; Pedersen, Hansen, and Grünenberg 2016; Schneirov and Geczik 1996).

Existing research has found evidence of misinformation about matters of health, illness, disability, and medical treatment is readily available online (Wang et al. 2019). Others have demonstrated that misinformation about health and illness is consequential to the extent that people engage with it (Shao et al. 2018) and are susceptible to endorsing conspiracy theories (Hagen 2019; Kauk et al. 2021; Smith and Graham 2019). It is also consequential that this misinformation is mixed in with other online information about health, illness, disability, and health care because the internet is one of the major ways the public accesses information about health, illness, disability, and medicine (Nettleton, Burrows, and O'Malley 2005). Medical practitioners have cautioned the use of the internet for obtaining information about health and illness, in part, because there is so much scientifically inaccurate information posted online about these topics (Bode and Vraga 2018; Ecker et al. 2014; Peng, Lim, and Meng 2022; Timmermans 2020).

The spread of misinformation about health, illness, disability, and medical treatment online is a pressing concern for risk-mitigation efforts in the fields of Medicine and Public Health. In context of the ongoing COVID-19 pandemic and resistance to risk-mitigation in afflicted western Capitalist countries like the United States, the influence of misinformation about health, illness, disability, and medical treatment on ideological views of health and risk constitutes a social problem of greater public and scientific interest (Kim and Tandoc 2022). Given online social media/networking platforms exist and have remained central modes of communication about health and safety for much of the American public since their popularization in the early 2000s (Nettleton et al. 2005), the elimination of scientifically inaccurate information available to the public via the internet is unlikely. Considering this reality, misinformation spread can at least prove useful for social scientific research into ideology and beliefs. This research may then be used to inform public policy and advocacy efforts aimed at minimizing the influence of online misinformation on individual health beliefs.

The Additional Advantages of Twitter for the Unique Context of COVID-19

Prior research has demonstrated that Twitter is useful for "infodemiology," a practice of obtaining an overview of the scope of established social facts about some phenomenon that accounts for the endorsement, not just the presentation, of misinformation. This includes investigations of matters related to COVID-19 misinformation but also related to other disease outbreaks, like the H1N1 influenza outbreak in the United States in 2009 (Chew and Eysenbach 2010; Choi and Park 2021). There is evidence from infodemiological and other studies that some members of the public, including the American public, have previously endorsed misinformation related to viruses discovered well before SARS-CoV-2 like the H1N1 strain of influenza (Chew and Eysenbach 2010), the Ebola virus (Broom and Broom 2017; Dalrymple, Young, and Tully 2016; Morin et al. 2019), and the Zika Virus (Chan et al. 2018; Laurent-Simpson and Lo 2019; Seltzer et al. 2017; Wirz et al. 2018; Wirz, Mayorga, and Johnson 2021). The prior susceptibility of the American public to misinformation about infectious disease outbreaks gives weight to the idea that some of the American public remained susceptible to misinformation about the SARS-CoV-2 novel coronavirus, too.

Prior studies on crisis communication using Twitter have focused on a variety of crisis types impacting health and safety (Panagiotopoulos et al. 2016). These have included crises impacting health and safety indirectly, such as financial crises (Beraldo 2022; Ems 2014; Redek and Godnov 2018), crises of social justice like protests and riots (Earl et al. 2013; Pearce and Rodgers 2020; Procter, Crump, et al. 2013; Procter, Vis, and Voss 2013; Ramluckan et al. 2017), diplomatic crises like those involving war and terrorism/extremism (Altahmazi 2022; He and Lin 2017; Krzyzanowski 2018; Lee and Colautti 2022; Lin and Margolin 2014), and political crises including unrest surrounding national elections (Lee et al. 2022; Nonnecke et al. 2022).

Previous studies on Twitter crisis communication have also investigated crises that directly impact health and safety. This includes research into natural disasters like hurricanes (Chen et al. 2022; Jacques and Knox 2016; Murthy and Gross 2017), floods (Yap, Keling, and Abdullah 2022; Yeo, Knox, and Hu 2022), wildfires (Helsloot and Groenendaal 2013; Sutton et al. 2014; Weber et al. 2020), and earthquakes (Gurman and Ellenberger 2015). Also highlighted are public health crises like substance use and dependency (Dwyer and Fraser 2016; Martinez et al. 2019; Pöppel et al.2021), sexual assault and domestic violence (Bogen et al. 2018, 2021; Chowdhury et al. 2019; Guidry et al. 2021; PettyJohn, Anderson, and McCauley 2022; Schwab-Reese et al. 2018; Storer, Rodriguez, and Franklin 2021; Wekerle et al. 2018), preventable chronic/acute disease in the population and access to health care (Greaves et al. 2013; Haeder and Chattopadhyay 2022; Martinez et al. 2019; Monaghan, Rich, and Bombak 2019; Tomaszewski et al. 2021; Yuan and Crooks 2018; Zou et al. 2016), malnutrition and disordered eating (Declercq, Tulkens, and Van Leuven 2019; Koren, Bagozzi, and Benson 2021; Szto and Gray 2015), exposure to toxins (Getchell and Sellnow 2016; Gurajala and Matthews 2018; Moors 2019; Zhang, Veijalainen, and Kotkov 2016), and epidemics/pandemics predating SARS-

CoV-2 (Chew and Eysenbach 2010; Morin, Mercier, and Atlani-Duault 2019; Vraga and Bode 2018; Wirz et al. 2018; Young, Tully, and Dalrymple 2018). Studies of prior pandemics using Twitter, notably, include studies of other coronavirus outbreaks like the Middle East Respiratory Syndrome (MERS) outbreak in 2015 (Song et al. 2017).

Twitter is especially useful for crises of public safety and public health, like pandemics and natural disasters, because the necessary communication during these crises happens to involve the dissemination of information from experts to the public (Eriksson and Olsson 2016; Medina and Diaz 2016; Murthy and Gross 2017; Panagiotopoulos et al. 2016). The COVID-19 pandemic constituted a global crisis, and similarly to other crises, Twitter was a popular space for communication and information dissemination (BelAnger and Lavenex 2021; Haman, Skolnik, and Copik 2022; Hodson, Veletsianos, and Houlden 2022).

Twitter has also provided a space for people to express their sentiments about health risk and risk mitigating health behavior, in addition to providing a means to engage in discussion with others about shared or diverging sentiments about risk and risk-mitigating health behavior. Tweets posted during the earlier phases of the pandemic provided a unique opportunity to investigate health beliefs about the novel virus as they were developing. It was important that so many people were using the platform to testify regarding their health beliefs about COVID-19 risk at the onset of the pandemic.

The expressions of “Anger,” “Fear,” and “Trust,” have been identified in tweets about vaccination well before vaccines were available as a tool to mitigate COVID-19 risk (Majid and Ahmad 2020; Manca 2018; Peretti-Watel et al. 2019). Each of these three emotions/sentiments has been identified in sentiment analyses of textual accounts about risk during COVID-19, although most have examined data from sources other than Twitter (BelAnger and Lavenex

2021; Eiguren et al. 2021; Figueiredo and Massano-Cardoso 2021; Leap, Stalp, and Kelly 2022; Idoiaga Mondragon et al. 2022; Roccato et al. 2021; Xu et al. 2022). Given the importance of "Anger," "Fear," and "Trust," for variation in health beliefs, and the possibility that these emotions/sentiments underlying health beliefs are determinants of health behavior, any investigation of social facts about risk and mitigation during COVID-19 should include an assessment of emotions and sentiments in analyzed text accounts.

There is some evidence that Americans have been susceptible to misinformation about COVID-19 risk and its mitigation, but it is unclear how widespread these beliefs were or whether there were contextual nuances to the public's endorsement of them. This is, in part, because of the lacking consensus among scientists as to what information should be considered scientifically inaccurate. It is unclear whether Americans unilaterally endorsed or rejected all misinformation, or whether there were patterns of endorsement/rejection of misinformation among people with shared characteristics, but part of the lacking clarity is rooted in the casual but public dismissal of peer-reviewed scientific findings about COVID-19 risk and its mitigation by some scientists who had already gained public notoriety through appearances on major news networks and large social media followings.

It is possible that the public endorsed some misinformation while rejecting other misinformation related to risk and risk mitigation and COVID-19, for example, harboring anti-vaccination sentiments but believing masks are useful risk mitigation tools. Similarly, someone may endorse vaccination for adults but resist the idea that vaccination for children is safe, complicating the understanding of vaccine ideology as "pro-vaxx" or "anti-vaxx." However, it is also possible that members of the public were unaware that they were endorsing misinformation, instead, interpreting this information as empirically grounded per their exposure to the social and mass media presence of scientists questioning the validity of scientific findings that COVID-19 was harmful to human immune and vascular systems.

There are also signs that susceptibility and spread of misinformation about COVID-19 risk online differs from outbreaks of other viruses, indicating a need to verify that research examining social media use, misinformation, and perceptions of risk during previous disease outbreaks are applicable to the context of COVID-19. For example, much of the misinformation posted online during COVID-19 seems to have come from scientific experts. There is no evidence that scientific experts were a widespread source of misinformation on social media during prior epidemic/pandemics.

Complicating things further are contrarians who reject the definition of misinformation as information that is scientifically inaccurate. While this segment of American society is often characterized as a radical minority, the reality remains that to be contrarian is to be fundamentally American. Historically, the American public has not unilaterally and passively accepted information from scientists, or any other entity for that matter, as "fact," with many members of the public pushing back against scientists, politicians, and others who they accuse of spreading misinformation. This was only exacerbated by the public disagreement about COVID-19 risk and risk mitigation among scientists and medical professionals, which gave the public legitimate reasons to doubt the accuracy of testimony by credentialed experts. SARS-CoV-2 was a novel pathogen at the start of the pandemic, meaning all variation in understandings of health risk and behaviors to mitigate risks to health developed organically across groups with near-uniform baseline knowledge of the risk at hand (no prior knowledge).

The timing of the COVID-19 pandemic was another important factor distinguishing it from prior pandemics, occurring at a time when the internet was well-established and becoming central to the lives of many people living in industrialized nations. The internet allowed for officials to recommend that people work from home during the pandemic if their job could be accomplished virtually, providing an early means of facilitating near population-wide participation in "social distancing," a risk-mitigating health behavior of maintaining a physical distance of at least 6 ft. from non-household members. Historical record confirms that this was not something that took place during outbreaks of other viruses like Ebola virus and Zika virus, nor was it something that occurred with the previous coronavirus outbreaks of SARS in 2003 and MERS in 2013.

It was not simply the existence of and widespread access to home internet allowing for the recommendation and widespread shift to working from home in March 2020 that made internet use during COVID-19 unique, though. The popularization of a specific use of the internet also played a key role. Social media already played a central role in the personal and professional lives of Americans by the start of the pandemic. Not only did social media platforms allow for the quick and simple dissemination of information by experts to the public, but they also provided a seemingly natural go-to outlet for many to cope with the isolation from other people when practicing social distancing and other risk mitigating health behaviors. Social distancing and work from home orders during the initial months of the COVID-19 pandemic led many people to turn to social media and other online spaces to discuss risks related to the virus. COVID-19 emerged amidst booming popularity of social media sites like Twitter, Facebook, Instagram, LinkedIn, and Tik Tok for everyday communication and information, not just communication and information about matters of health and illness.

Previous studies of health beliefs on Twitter point to the online expression of health beliefs about specific health behaviors intended to mitigate risk. Twitter has already proven useful for gathering ideological views about health behavior related to the human papilloma virus (HPV), for example. Research on HPV has also examined Twitter discourse about vaccination against the disease with the "Guardasil," vaccine, with a specific focus on vaccine hesitancy (Tomaszewski et al. 2021). This is useful considering vaccination against COVID-19 has become a hot point of contest for the American public. Given Twitter has already proven an important resource for exploring vaccine hesitancy and anti-vaccine sentiment specific to the mitigation of other viruses, it may also be useful for exploring health beliefs about risk mitigation during COVID-19.

Health beliefs about risk mitigation during COVID-19 have included beliefs about the COVID-19 vaccines (Jiang et al. 2021; Kumar et al. 2022; Liew and Lee 2021; Luo et al. 2021; Roberts et al. 2021; Viskupic, Wiltse, and Meyer 2022; de Vries et al. 2022). Vaccines were one of several risk mitigating health behaviors recommended to mitigate COVID-19, though, and they were not immediately available (Bhasin et al. 2020; Dynel 2021; Gonzalez et al. 2021; Kumar et al. 2022; Mollborn, Mercer, et al. 2021). Additionally, there is evidence that vaccination was not the sole health behavior of focus in discussions of risk mitigation during COVID-19 (Becher et al. 2021). Discussions of risk mitigation on social media during COVID-19 are also alleged to include additional risk mitigating behaviors like wearing masks (Dynel 2021), social distancing (Ho et al. 2021; Nerlich and Jaspal 2021), and quarantining (Feng and Tong 2022).

It would suffice to say that it is unclear what beliefs about COVID-19 risk and risk-mitigation have existed over the course of the pandemic, expert or otherwise. Before we can say with certainty what Americans believed about COVID-19 risk, it is crucial to collect and analyze "infodemiological" data that is comprehensive in scope (Chew and Eysenbach 2010), which can be accomplished using tweet testimony about risk and risk mitigation during COVID-19 from experts and the public, alike. Given it is not clear expert beliefs were truly influential in shaping the American public's beliefs about COVID-19 risk and risk mitigation, establishing "the facts" about risk and risk mitigation during COVID-19 must begin with an examination of beliefs independent of the social characteristics of the person testifying to them.

With this study, I aim to provide a broad overview of Americans' health beliefs about COVID-19 risk and risk-mitigation in the early stages of the COVID-19 pandemic that may also be used as a guide for future research examining beliefs about COVID-19 risk and its mitigation. This dissertation expands the focus on discourse about health behaviors to mitigate risk of infection to include discussion of vaccination but also other health behaviors to mitigate risk by not limiting the focus to any one behavior. I demonstrate the use of a sociological approach to the exploration of health beliefs about COVID-19 risk and risk-mitigation that builds on the growing interdisciplinary literature using dictionary-based sentiment analysis techniques to analyze health beliefs and health behavior in testimonial accounts and discourse on Twitter, focusing on the presence of emotions and sentiments identified as important indicators of health beliefs about risk and health behaviors to mitigate risk.

CHAPTER 2

DATA AND METHODS

Identifying beliefs surrounding health behaviors and risk contexts during COVID-19 is a necessary first step towards evaluating the applicability of existing sociological theory to explain the connection between health disparities, health beliefs, health behavior, and health risk, in the new social context of the ongoing COVID-19 pandemic. This study also contributes to the growing popularity of network and mixed-methods for sociological research by providing a mixed-methods approach for analyzing data from social media websites that combines social network analysis with quantitative text analysis. I propose that natural language processing (NLP) and machine learning techniques are useful for exploring more readily accessible alternatives to traditional data sources like interviews and surveys.

DATA COLLECTION AND SELECTION

The Initial Sample

The data were drawn from tweets about the COVID-19 pandemic posted between December 2019—June 2021. The initial query pulled tweets mentioning general risk, one or more of several risk mitigating behaviors used to mitigate the spread of COVID-19, and social groups identified as "high-risk" with respect to COVID-19 infection and exposure (Table 1).

I operationalize "high-risk" as referring to two distinct circumstances of heightened risk: those at "high-risk" of exposure to COVID-19 because of their job requirements and/or designation as a "frontline" worker, and two social groups identified as being at "high-risk" for severe disease, hospitalization, and death from COVID-19, the elderly and people with immunocompromising disability and chronic illness (Table 1). The four risk-mitigating health behaviors of interest were wearing masks, social distancing, isolation/quarantine, and vaccination (Table 1). There was a possibility that tweets about vaccination could also include tweets mentioning the pharmaceutical manufacturers of the COVID-19 vaccines without mention of the words “vaccine,” “vaxx,” “jab,” or “shot,” so I executed two separate queries for tweets about vaccines, one about vaccines generally, and one into mentions of the manufacturers of vaccines for COVID-19 that were approved for use in the United States: Moderna, Pfizer-BioNTech, and Johnson & Johnson. (Table 1).

I collected the tweets through the Twitter API, accessed using the “academictwitteR” package in R (Barrie and Ho 2021). I excluded “retweets” from the queries to preserve independence among cases in the data. When a tweet appeared several times with the same text, it was an indication that the text was posted on several separate occasions, possibly by different users, not something posted by a single user and reposted by the same user at a later date or shared by other users.

The academictwitteR package stores the tweet-level data collected from the queried tweets in a series of JSON files alongside user-level data for the authors of the queried tweets. The user-level data are stored in a separate set of JSON files from the tweet-level data. To ensure all metadata were preserved in the conversion process, I parsed the raw data into two separate data frames in R, one for “users” data and another for the “tweets” data. While “users” were not relevant to this study, the user-level metadata was important for ensuring the tweets analyzed accurately reflected the views of real people in the United States who use Twitter.

Table 1. Query Criteria by Health Behavior and Risk Category

Query	N	Criteria
Query 1 – High Risk General	32,513	"risk" OR "danger" OR "emergency" OR "concern" OR "threat"
Queried Behavior	N	Criteria
Query 2 – Masks	279,835	"mask" OR "masked" OR "masking"
Query 3 – Social Distancing	33,791	"home" OR "distance" OR "distancing" OR "social" OR "socially"
Query 4 – Isolation/Quarantine	21,808	"isolation" OR "isolated" OR "isolating" OR "quarantine" OR "quarantined" OR "quarantining"
Query 5 – General Vaccines + Query 6 – Pharmaceutical Co.	53,013	"vaccine" OR "vaccinated" OR "vaccination" OR "vaxx" OR "anti-vaxxer" OR "pro-vaxxer" OR "vaxxed" OR "jab"
Queried Risk Category	N	Criteria
Query 7 – High Risk Age	19,517	"old" OR "elderly" OR "elder" OR "older" OR "sixty-five"
Query 8 – High Risk Disability	37,886	"disabled" OR "disabilities" OR "comorbid" OR "comorbidities" OR "underlying" OR "fragile" OR "pre-existing" OR "condition" OR "immunocompromised" OR "chronic" OR "chronically" OR "mental" OR "ill" OR "illness" OR "vulnerable" OR "diagnosed" OR "DX" OR "special" OR "developmental" OR "defect" OR "disease" OR "syndrome"
Query 9 – High Risk Frontline	39,186	"worker" OR" frontline" OR "healthcare" OR "doctor" OR "physician" OR "ED" OR "ER" OR "emergencymed" OR "ICU" OR "staff" OR "nurse" OR "hospital" OR "caregive" OR "nursing" OR "medical" OR "employee" OR "industry" OR "service"
Total Tweets	517,549	

I used the “dplyr” package in R to join the data about users with the tweets and related metadata prior to executing the analyses (Wickham et al. 2022). The “dplyr” package is part of the “tidyverse,” a coherent system of packages for data manipulation in R that is ideal for parsimonious workflows and large data frames, making it useful for a sample of several thousand tweets (Wickham et al. 2019). Both the tweet- and user-level data included an author identification number, and the data were merged using this identifier to ensure the correct author information for each tweet was accurate. I eliminated all identifying information about the tweet authors prior to executing the analyses, deleting user-level metadata with the name, username, biography, and url information from each account with tweets included in the study. I retained the minimum amount of information necessary to group tweets by user, preserving only the randomly generated, unique, numeric user id.

I preserved mentions of other users in tweet text because they could be meaningful to the interpretation of the results. For instance, it could be meaningful if tweets about risk repeatedly mention the same organization or powerful actor, demonstrating the importance of the individual or institution for the social facts of risk during COVID-19. Alternatively, even in instances where the mentioned user is a non-public figure and merely an “average” member of the American public, retaining information demonstrating that a user was mentioned without specifying their identity is useful for distinguishing confrontational interactions from general “accounts.” When usernames appeared in example text later generated as representations of the actual text of tweets, with the exception of verified accounts for political actors in the federal government like the President of the United States, I redacted the username replacing it with a marker, “@[user]”.

Table 2.1. Total Tweets, Initial Query and Full Sample after Bot Removal

Query		n	N
1	General Risk	70,844	32,513
2	Wearing Masks	769,086	279,835
3	Social Distancing	450,087	33,791
4	Isolation & Quarantine	856,866	21,808
5	General Vaccines	509,784	53,013
6	Pharmaceutical Co.	144,559	
7	High Risk Elderly	2,303,641	19,517
8	High Risk Disability	110,702	37,886
9	High Risk Frontline Workers	943,751	39,186
Total Tweets (n = initial; N = after eliminating bots)		6,159,360	517,549

I executed 9 queries per month across a period of 19 months, for a total of 157 queries (Table 2.2). I queried tweets for each month of the 19-month period separately to maximize the number of tweets collected for each query, as preliminary testing revealed that the Twitter API rate limits capped the data prior to collecting tweets from the entire time period. The total initial sample included 6,159,360 tweets (Table 2.1). Of the initial sample, the "elderly" query pulled the most tweets, collecting a total of 2,303,641 tweets about the elderly posted between December 2019—June 2021 by Twitter accounts originating in the US (Table 2.1).

Eliminating the "Bots" from the Sample

One of the dangers of data collected from social media sites is the limited ability to verify that the posts are made by a human (Savela et al. 2021). With Twitter data specifically, there is a verifiable presence of "non-human" accounts called "bots," which are virtual robots that use artificial intelligence (AI) to mimic human-like tweeting behavior, akin to how a physical robotics machine might behave (Clark et al. 2016; Nonnecke et al. 2022; Stukal et al. 2022). Hence why AI processes are sometimes called "machine learning" (ML), reflecting the idea that the virtual robot learns over time and adapts to be more human-like. The exact number of bots on Twitter is unknown, in part, because it is always in flux. Nonetheless, recent studies have suggested bots may account for up to 10% of tweets about social problems (Duan et al. 2022; Shi et al. 2020; Stukal et al. 2022).

Some have warned that bot activity could have serious consequences for researchers, particularly those interested in using tweets to understand variation in ideological beliefs and/or emotional sentiments about a societal phenomenon (Bail et al. 2018). There is a demonstrable bias towards extreme ideology and sentiments like "Anger" and "Fear" in tweets by bot accounts (Duan et al 2022; Shi et al. 2020). Studies of conflicts between Twitter users have also found a sizable presence of Tweets from bots "participating" in online conflicts (Nonnecke et al. 2022; Stukal et al. 2022). Failing to account for the presence of bots in research on ideology and emotional sentiments could lead to the misunderstanding that public opinion about a phenomenon is more extreme or negative than it is.

Even in studies where bots accounted for fewer than 1% of the total tweets in a sample, tweets from bot accounts were among the top 10 most influential (Rauchfleisch and Kaiser 2020). In any case, researchers who have examined the relevance of Twitter during and after the 2016 presidential election in the United States have argued that the mere existence, not just overwhelming presence, of bot activity can be consequential for public opinion and behavior, making the elimination of bots from any sample of tweets paramount to the provision of accurate results (Bail 2018; Nonnecke et al. 2022).

To address the potential issue of bias due to bots, I eliminated tweets from the sample that were posted by accounts with missing information from key variables in the user-level meta data and therefore not verifiably human (Li et al. 2022.; Rauchfleisch and Kaiser 2020; Zeng et al. 2022). Bots are often identifiable because they were created after the onset of the conflict about which they are tweeting. In this case, the conflict was marked by the start of the COVID-19 pandemic, therefore, I eliminated tweets from accounts created during the time frame in question (December 2019—June 2021), keeping only tweets from accounts created in November 2019 or earlier.

I also eliminated tweets from accounts without a user "biography," accounts with the word "bot" in the biography, account handle, or as part of their listed name, and accounts with the words "satire" or "parody" in the biography. The biography us a user-generated section on the Twitter profile in which the user identifies themselves, typically by one or more salient identities. While it is possible that some of the accounts without biography information were not bots, most human-backed accounts will include a biography.

Other bots are identifiable because they identify themselves as bots. Many of this type are not malicious, but instead are created as satirical memes, which are humorous, not entirely realistic, depictions of cultural phenomena (Makhortykh et al. 2022). Satire bots fall among those that tend to identify themselves. Satire/parody bots will often identify themselves as such by including the word "bot" in their name, username or biography, or with the words "satire" and "parody" in the biography. For example, the popular bot that generates satirical newspaper headlines, @DougJBalloon, includes the word "bot" as part of its listed name, "New York Times Pitchbot," and the word "Parody" in the account biography.

The final precaution I took to minimize the presence of bot tweets in the final sample was eliminating tweets from accounts without location information available. I drew from two types of location information. The first, the geolocation, verifies that a tweet was posted from a physical location on Earth. I excluded tweets that did not have geolocation information with the queries by limiting the queried tweets to those posted from a geolocation within the United States.

The other type includes information that users have input manually to identify their own location. The user-generated location is typically posted to the profile and visible beneath the biography. Many users include information other than their geographic location in this section, for example, users in the United States will often list their location as "stolen land" from their local Indigenous community. The presence of the information was my main interest with the user-generated location, though, as the presence of false information listed for the location did not threaten my ability to ensure the sample of tweets came from users in the United States. Additionally, given that the listing of false information in the location area of the Twitter profile biography often serves as a political statement (i.e. "land back"), it's presence was additional verification that human was responsible for posts on the account. Eliminating profiles without a user-generated location listed, when used alongside other precautionary measures for bots, served to maximize the reduction of tweets from bots while also minimizing the number of tweets from humans that were dropped from the final sample (Rauchfleisch and Kaiser 2020).

The initial reduced sample after the elimination of potential bots consisted of 517,549 tweets across the 9 queries. The final sample from the first query of tweets about risk, generally, included 32,513 tweets mentioning "risk" that were also related to the COVID-19 pandemic. From the remaining 8 queries, I initially retained 279,835 tweets about masks, 33,791 tweets about social distancing, 21,808 tweets about isolation/quarantine, 19,517 tweets about the heightened risk COVID-19 posed to the elderly, 37,886 tweets about the medically vulnerable, who included people with disabilities and chronic illnesses, and 39,186 tweets about frontline workers facing increased risk of exposure to COVID-19.

I combined the tweets from the two vaccine-related queries, including an additional 53,013 tweets about vaccines and/or pharmaceutical companies manufacturing COVID-19 vaccines approved by the United States Food and Drug Administration (FDA). (Table 2.2)

The Final Sample

Preliminary analyses indicated that the tweets from the general risk query (Query1, Table 1) included several tweets also included in the health behavior and risk category queries, and the additional queries revealed no substantial new information to that from the general risk tweets. Given the large sample size and easier interpretation of structural topic models with fewer than 100,000 documents and my use of structural topic modeling as a primary method for analysis, I chose to retain only the tweets from the general risk query for this study, effectively reducing the total final sample from 517,549 to just over 30,000 tweets (N = 32,513) (Table 1).

Table 2.2. Initial Sample by Query and Month, December 2019—June 2021

Query	Dec. 2019	Jan. 2020	Feb. 2020	Mar. 2020	Apr. 2020	May 2020	Jun. 2020	Jul. 2020	Aug. 2020	Sep. 2020	Oct. 2020	Nov. 2020	Dec. 2020	Jan. 2021	Feb. 2021	Mar. 2021	Apr. 2021	May 2021	Jun. 2021
General Risk	348	795	1,637	14,633	7,930	5,351	4,822	6,205	3,738	3,102	4,828	3,823	3,563	2,344	1,540	1,865	1,570	1,596	1,194
Masks	6,009	6,005	7,677	22,636	54,890	74,621	27,530	121,219	64,046	52,899	65,387	55,665	43,767	34,680	25,042	34,237	24,507	32,469	15,800
Social Distancing	5,162	5,071	5,455	120,766	90,182	48,720	27,530	29,060	19,360	12,967	14,789	18,798	15,002	9,885	7,458	6,608	5,095	4,713	3,466
Isolation & Quarantine	2,190	2,920	4,489	234,462	201,067	83,537	26,489	28,896	20,525	13,509	19,325	15,598	13,787	10,075	6,979	6,398	4,494	3,580	3,144
General Vaccines	2,137	2,580	3,627	12,566	14,646	13,079	6,640	11,855	10,516	12,702	9,543	24,108	63,486	47,142	38,538	73,177	72,155	57,895	33,392
Pharma Co.	8,267	8,009	5,713	6,335	6,243	5,651	5,133	5,547	5,311	5,672	6,170	12,277	13,965	8,941	10,016	15,767	19,631	9,964	5,633
Elderly	142,808	142,586	134,190	162,505	138,464	133,487	130,233	128,886	130,359	119,725	121,995	116,952	106,408	103,636	87,766	162,505	82,963	80,834	77,339
Disability	5,789	4,548	4,528	7,806	4,698	4,590	4,616	5,194	6,626	6,466	7,211	6,556	6,651	6,109	4,528	6,583	5,990	6,034	6,179
Frontline	27,543	29,019	34,587	124,882	110,656	63,771	44,855	48,266	110,656	36,695	47,373	41,518	41,432	32,561	24,776	63,771	20,189	21,797	19,404

METHODOLOGY

I combined several quantitative text analysis techniques to build a structural topic model (stm) using seeded keywords as training measures for modeling the document-topic classification, which I selected per the results of an automated sentiment analysis using Latent Dirichlet Allocation (LDA) models of the same documents. The incorporation of automated LDA into the structural topic models allowed me to account for emotional undertones of a document (tweet) alongside context of words by their meaning and location relative to other words in a single document (tweet).

Traditionally, topic modeling techniques have allowed for sentiment analysis as a postestimation technique. Few techniques exist for including emotion as a predictor in a topic model. The techniques that do exist are highly constrained, with most requiring hand designation of seed words to model a pre-defined structure on an existing set of documents. This leaves the model highly vulnerable to researcher bias, as there is no way to account for the context of the text being modeled.

For example, Targeted Topic Modeling (TTM) uses pre-identified key words to impose a structure on modeled documents (Kirsch et al. 2018), and Supervised LDA (sLDA) predicts a structure using information from a labeled dataset (Ashktorab et al. 2014), and there is evidence that both the TTM and sLDA are outperformed by other methods like Seeded Latent Dirichlet Allocation (seeded LDA) that use automation via the variational Bayes algorithm to generate key words to use as seeds (Ferner et. al 2020). However, the Gibbs sampling technique (a Monte Carlo Markov chain technique) used for all LDA, including automation-based techniques like seeded LDA, assumes that the text data are unstructured. The assumption that text data are unstructured is a big model limitation given the importance of syntax and grammar for conveying the meaning of one's words.

Advocates of structural topic modeling for quantitative text analysis, which can account for the structure of word use, point out that word use is structured in real life (Lee 2022; Neal 1995). The structure is important because it denotes context of words in the sentence, indicating slang, dialect, jargon, and other important nuances of language like metaphor and irony. Inferring context without accounting for structure has numerous consequences, including the possibility of mis-identifying the focus of emotional sentiment in topical discussions. While the structural topic model provides more context than other models, it remains far less popular for sentiment analysis of text data than more complex LASSO models employing the variational Bayes algorithm, despite the substantial difference in computing power needed for the structural topic models versus the LASSO models. When used together with other techniques, the structural topic model can accomplish similar goals with more efficiency, which is important for timeliness of research.

Pre-Processing the Text Corpus

All forms of quantitative text analysis require pre-processing the text data to remove non-text objects like punctuation and emoticons from the raw text. I used the "corpustools" and "Quanteda" packages to create text corpuses for each queried set of tweets (Benoit et al. 2022; Welbers and van Atteveldt 2022). The text corpus contains tweet raw text, storing all other information about the tweets as metadata.

Dictionary-lexicon Sentiment Analysis

Once the corpus for each set of queried tweets was constructed, I obtained the list of most frequent terms present in the text of tweets about each behavior and risk category, obtaining the terms occurring in 99% of the tweets in the sample. I used the information about the most frequent terms to construct a "document-term matrix" (dtm) from the text corpus, identifying the presence of each "most frequent" term present in each document (tweet). Next, I obtained collocations (pairs and sets of words), and key-words-in-context (kwic) identifying collocations preceding and following key words of interest at the sentence level. I then constructed a "document-feature matrix" (dfm) retaining metadata from the corpus, including the collocations, key words in context, and terms in the dtm as features in the metadata for the dfm. Analyses were based on the dfm to account for important metadata like the complete text of each tweet in conjunction with the most frequent terms captured in the dtm, ensuring the text analyses focusing on words remained grounded in sentence and multi-sentence context.

I began with a simple, dictionary-based, sentiment analysis, obtaining the overall emotional sentiments present across topical discussions of each risk behavior and category. I used the "corpustools," "Quanteda," and "syhuzet" packages in R to perform a dictionary search on the initial dfm for each behavior and risk category (Benoit et al. 2022; Jockers 2015; Welbers and van Atteveldt 2022). I initially referenced the NRC emotional sentiments dictionary and the LSD2015 sentiments dictionary, which contain lists of sentiments attached to the use of common English words. The NRC emotional sentiments include Anger, Anticipation, Disgust, Fear, Joy, negative, positive, Sadness, Surprise, and Trust, and the LSD2015 sentiments include positive, negative, negative-positive, and positive-negative.

The LSD2015 dictionary is preferable to the general "polar" dictionary because, in addition to containing positive and negative sentiment, the LSD2015 dictionary contains positive-negative and negative-positive information to provide context accounting for things like the use of a double negative to indicate something positive (e.g. "never not present" indicating presence, not absence). The LSD2015 sentiment analysis revealed that the majority of tweets taking a “positive” tone were indicating “positive” sentiment and not sarcasm or something bad, while most of the “negative” sentiments were truly negative, with few negative-positives. Given these preliminary findings, and because the NRC emotional sentiments include “positive” and “negative,” I did not include the LSD2015 sentiments in the final topic models.

Topic Modeling with Seeded Latent Dirichlet Allocation (Seeded LDA)

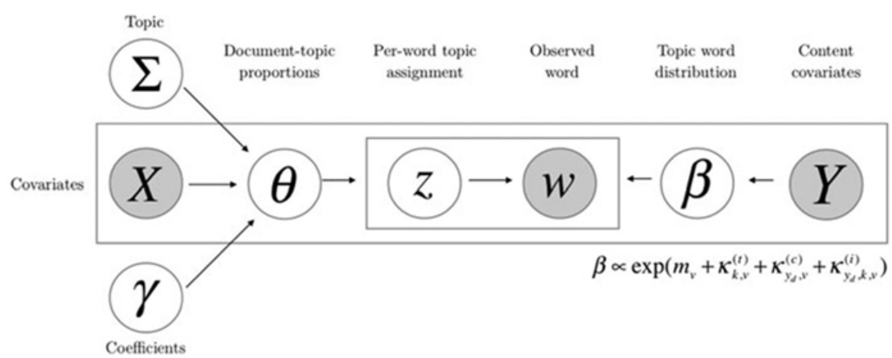
To obtain the training measures used to fit the structural topic models using type and valence, or strength, of the 10 NRC emotional sentiments in each document, I used the “seededlda” package in R (Watanabe and Xuan-Hieu 2022) to run a seeded LDA model with 10 topics embedded in the 10 emotions of the NRC dictionary (Lu et al. 2010). I bound the results of the seeded LDA model to the dfm as metadata to use as training measures for the structural topic models. The NRC emotion feature categorizes documents by NRC emotional sentiment, selecting the strongest emotion per document as the document category.

Next, I set the valence scores for the NRC emotions to range from -2.5 to 2.5. This allowed me to weight the measures for NRC emotional sentiment to include information about the presence of an emotion but also its strength relative to other emotions. I calculated the valence scores for NRC emotions per topic in the seeded LDA model, binding them to the dfm as metadata. I included the b-splined valence scores as a weighted measure for emotional sentiments in the prevalence equation for the structural topic models.

Structural Topic Modeling

I used the “stm,” “tm,” “topic models,” and “Quanteda” packages in R to build and analyze the structural topic models (Benoit et al. 2022; Feinerer 2020; Grün et al. 2021; Roberts et al. 2020). The conceptual overview of the structural topic model, as proposed by Roberts, Stewart, and Airoldi (2016), is shown in Figure 1. I employed the spectral initialization technique for the stm because it accounts for the sentence structure underlying word use and performs well for models with many documents (Roberts, Stewart, and Tingley 2016). Spectral initialization calculates semantic coherence, exclusivity, upper and lower bounds, holdout likelihood, and residual effects, meaning it also provides a more robust model of topical clusters than the Latent Dirichlet Allocation model. The structural topic model gamma likelihood score is not as easy to interpret as the widely used Gibbs Latent Dirichlet Allocation model, but the "stm" package for structural topic modeling in R obtains the Gibbs beta coefficient measuring the expected topic proportion, or the expected proportion of documents fitting into each topic, for ease of interpretation for other test statistics (Roberts et al. 2020).

Figure 1. Components of the Structural Topic Model (Roberts, Stewart and Airoldi 2016)



Topic models rely on K-means, using similar methods to those used in latent class analysis (LCA). The number of topics (K) is unknown and must be set by the researcher for the analysis. I used t-distributed stochastic neighbor embedding models (t-SNE) to project estimates for the number of discussion topics among the queried tweets prior to deciding which number of topics (K) to model.

The t-SNE modeling approach computes a randomized projection of the dfm based on an initial Principal Component Analysis (PCA) projection. The number of topics projected in the t-SNE model should not be taken as an object assessment of the number of topics across text documents, but it is useful as a baseline when deciding which measures of K to test for model selection.

I tested several structural topic models with different K number of topics based on the t-SNE projections prior to selecting the best fitting models. I included the NRC emotional sentiment categorization and b-splined valence measures constructed from the seeded Latent Dirichlet Allocation model output as prevalence covariates in the structural topic models, estimating the prevalence as a function of the NRC emotional sentiment category while controlling for the interaction between the standardized (log) valence measures (f(P)). Because the data in question cover a 19-month period, I also included "date" as a prevalence covariate, measured in cumulative days to identify day-to-day changes over a multi-month, multi-year, timeframe (Table 2.2).

f(P) ~ (factor(NRC emotional sentiment) + s(valence)) + factor(day*month*year))

Emotion can impact the prevalence of a topic, but it can also influence how a topic is discussed. I included an additional equation to include "NRC Emotional Sentiment" as a content covariate with 10 levels (f(cov)):

f(cov) ~ (factor(NRC Emotional Sentiments))

Categorization of Topics

Prior to estimating the effects of prevalence and content covariates, I obtained the most frequent and exclusive words for each topic. I then obtained a plot of the topic proportions, using the most frequent and exclusive words as annotation to demonstrate the focus of topics with context on their popularity among Twitter users discussing risk during COVID-19.

Given the large size of the model, after obtaining the expected topical proportions for all 180-topics (APPENDIX B), I obtained the expected proportions for topics represented in over 1% of the tweets modeled (n = 32,513). I looked for patterns in the top words for these topics before re-examining the top words for all 180-topics. I was able to identify patterns of similarity between top words in different topics, and I used these observations to hand-code topics into broad categories by common theme/focus.

Grouping topics by similar theme is one recommendation for focusing discussion of the results for moderate to large topic models (> 60 topics). The 180-topic model was a good candidate for analysis by broader topical theme given its size and the presence of obvious patterns of similarity between topics based on theme/focus of top words.

After the categorization, I plotted the relative topic proportions by category for each of the 11 categories identified, including the top words for each topic as annotation on the plots (Figure 3.3a-k). Next, I obtained the point estimations for each emotion in a topic, grouping topics by category to check for preliminary patterns of shared dominant emotions among topics within a hand-coded category. I used the 11 categories as information in several, later, network analyses.

Effect Estimations

I began by obtaining the effect estimates for emotional sentiment on topical prevalence. To estimate the effect of a categorical variable, you must identify a reference category to serve as the intercept in the model. Prior research has shown that "Fear" and "Anger" are both important correlates of risk perception, suggesting that they have opposite effects on risk-taking behavior and perceptions of risk (Lerner and Keltner 2001). My main interest being risk mitigation versus lack of risk mitigation, not risk-aversive versus risky behavior, but also the importance of risk-aversion as a risk mitigation technique during COVID-19, both pointed to the use of "Fear" as the base emotion. Emotional expressions of "Fear" are associated with increased risk aversion (Lerner and Keltner 2001). Considering this information, I used the "forcats" package in R to assign "Fear" as the reference level for the emotion measure prior to estimating the effect of emotion on topical prevalence.

The significant effect estimates for emotions other than "Fear" indicated that an emotion's effect on topical prevalence was significantly different from the effect of "Fear." I used the effect estimates for emotion create a second, estimation-based, categorization of topics into groups. I identified the topics for which the effect of an emotion on topical prevalence was significantly different than Fear for each of the 9 other NRC emotions, using the list to identify topic-emotion ties in later network analyses assessing the correlation of topics within emotion-based groups and within each hand-coded topical category.

Network Analysis.

I performed basic network analyses to assess the hand-coded categories before moving to more complex estimation-based analyses. To accomplish this, I constructed an artificial network with 11 nodes, each representing one of the 11 topical categories. I incorporated information about the topics in each node, identifying and assessing the strength of ties between topical categories by shared topic, with ties representing that the categories have a topic in common. I created a new layout for the network positioning nodes according to degree centrality, using the layout to provide a visual representation of the most central topical categories when accounting only for the size and similarity of topical categories based on number of topics and shared topics.

For the higher order network analyses, I began by obtaining the topic correlation network using the "stm" and "igraph" packages in R. I also constructed a smaller network with 9 nodes representing each of the emotions being evaluated in reference to "Fear," with no edge information linking the nodes representing "Anger," "Anticipation," "Disgust," "Joy," "negative," "positive," "Sad," "Surprised" and "Trust" to each other. Using the list of topic-emotion ties from the effect estimates for emotion on topical prevalence as edgelists, I combined the topic correlation network containing all 180 topics with the network containing the 9 nodes representing emotions with significantly different effects on topical prevalence compared to "Fear" into one bi-partite (two-mode) network. The effect estimates were used as edge weights to demonstrate the strength of ties between topic and emotion by effect-size.

Next, I obtained the network subgraphs for each of the emotion nodes. The topics within the "negative" and "positive" subgraphs were not highly correlated enough to extract network subgraphs for those two sentiments. I focused the remaining network analyses, including Hierarchical Random Graph modeling, on the 7 remaining non-Fear emotions, analyzing the subgraphs for "Anger," "Anticipation," "Disgust," "Joy," "Sadness," "Surprise," and "Trust" to gain a deeper understanding of the topic correlation network as it relates to the categorizations by (1) emotion and (2) theme similarity.

Time Series Analysis.

I estimated the effect for time in cumulative days on topical prevalence both independently and, in a final estimation, when controlling for emotion as a content covariate. I evaluated the effect of time without possible moderating effects first, plotting the linear estimates for change in topic proportion from December 1, 2019—June 30, 2021 for all 180 topics. To make the graphs more interpretable, I plotted the linear estimates for time again for all topics where the effect of time was a significant predictor of topical prevalence, and twice more to highlight the topics with significant increases over time, and separately, the topics with significant decreases in prevalence over time.

I also obtained the b-splined estimates for day on topical prevalence, both with and without the content moderator, smoothing the linear estimates to get a better visualization of how topical prevalence fluctuated on a day-to-day, month-to-month basis. I discuss the effect of time using the smoothed graphs to provide a more complete understanding of the mean increases and decreases captured by the linear estimates.

Assessing Differences in Topical Prevalence over Time Depending on Emotional Sentiments of Tweet Content.

After obtaining the effect estimates for day on topical prevalence when controlling for emotional content of the tweets in a topic, I compared the estimates for "day," noting any changes. I identified the topics for which the effect of time on topical prevalence was newly significant upon controlling for emotion, for which time was no longer significant after controlling for emotional content, and topics for which the effect of time was not significant in any model. Next, I compared the effect estimates for emotion as a content moderator to the effect estimates for emotion on topical prevalence, focusing on the topics selected for being most strongly tied to the emotion in a subgraph in the network analyses. For each of the selected topics, I identified the emotions with significant effects on topical content, plotting their prevalence over time for each of the selected topics.

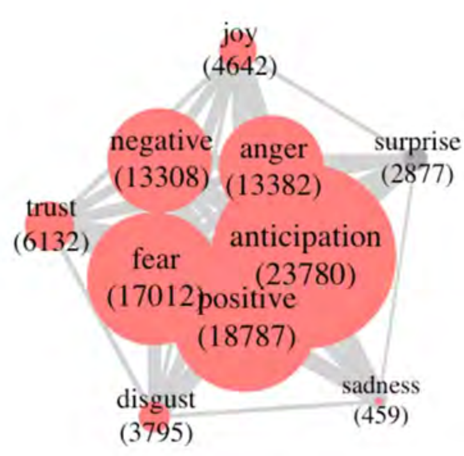
I also identified the emotional context accounting for the largest proportion of tweet content in the topics. I generated example tweets representing all emotional contexts where the content is significantly shaped by emotion, plotting the examples separately by (1) dominant emotion and (2) all other emotions with a significant effect on topical content. I concluded my explanation of the results with a discussion of each topic by emotional sentiment, explaining the example text for each emotional context regarding the effect of “time” on topical prevalence.

CHAPTER 3

RESULTS PART I: DESCRIPTIVE STATISTICS, NETWORK ANALYSIS, AND TIME SERIES ANALYSIS

The best fitting structural topic model for the tweets about general risk, when accounting for the effect of emotional sentiment and valence on topical prevalence and the effect of emotional sentiment on topical content, consisted of 180 topics (N = 180). I constructed several models between 30-240 topics, modeling each number of topics with and without accounting for date. The 180-topic model remained the best-fitting model when accounting for the additional effect of date, which indicated the year, month, and day a tweet was posted, on topical prevalence.

Figure 2. NRC Emotional Sentiment Dictionary Hits for General Risk Tweets



Note: Hits represent the total number of documents with at least one word with an emotional undertone

The dictionary search operates as a two-step process which first counts the number of "dictionary hits," or words matching each sentiment for the entire sample, then calculates a "feature co-occurrence matrix" (fcm) indicating the number of times sentiments co-occur in each sample of tweets (Figure 2). I converted the fcm resulting from each dictionary search to adjacency matrix format for network visualization with the "igraph" package in R (Nepusz 2022).

The NRC dictionary hits provided preliminary evidence that the largest quantity of tweets in the sample contained words expressing "Anticipation" (Figure 2). The NRC dictionary hits for the final sample of general risk tweets also indicated that, in addition to "Anticipation," words expressing "Positive" sentiment, "Fear," "Anger," and "Negative" sentiment were present in a larger number of tweets than the other NRC emotions, with words expressing "Trust," "Joy," "Surprise," "Sadness," and "Disgust" appearing in far fewer documents (Figure 2).

MODEL FIT

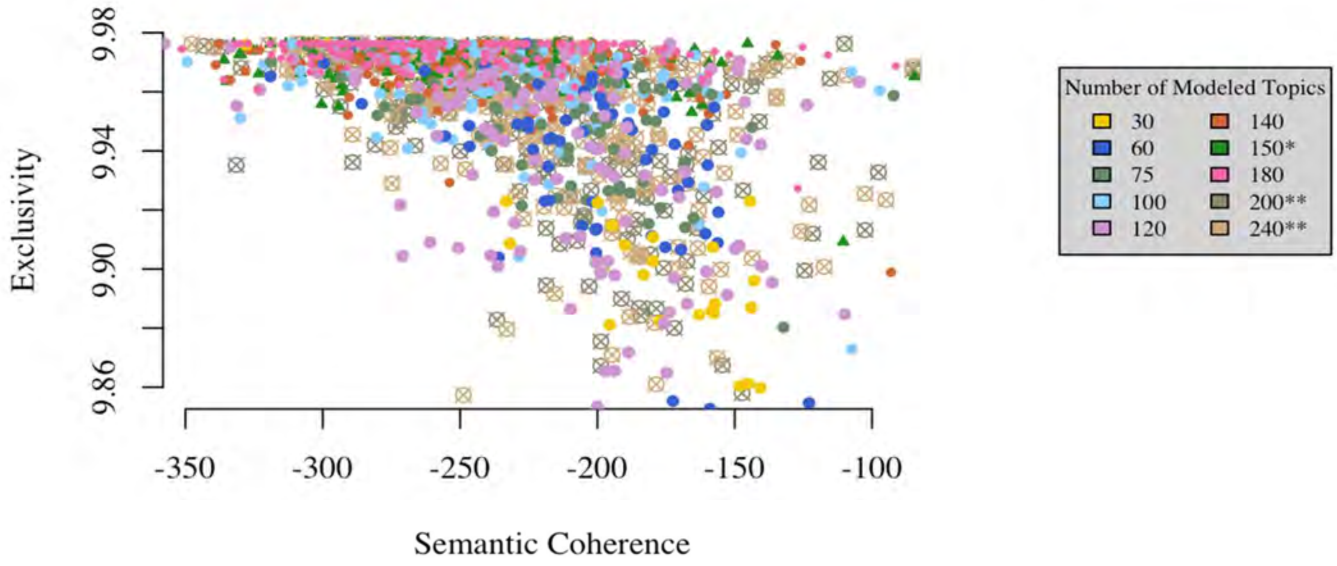
The sample size falling between 10,000 and 100,000 documents (e.g., tweets) was an indication that a an STM with a moderate to large number of topics (60-100+ topics) would be the best fit (Table 2.). I assessed model fit by obtaining measures of semantic coherence, exclusivity, and residual dispersion, and by plotting the distribution of MAP estimates of document-topic proportions for each model (APPENDIX A) (Taddy 2012). I avoided selecting models that converged quickly, looking for a model with high semantic coherence and exclusivity, and non-significant residual effects with a dispersion score approaching zero. Exclusivity cannot be calculated on models with content covariates, so I ran each model without content covariates to obtain all three measures of model fit before checking semantic coherence and residual dispersion for the models that included "emotion" as a content covariate.

Semantic coherence scores ranged from -400 to -50, while exclusivity scores ranged from 8—10. Models with exclusivity closer to 10 and semantic coherence closer to 0 were considered better fitting than those with exclusivity further away from 10 and semantic coherence further away from 0. When plotted together, the better fitting models hover near the top right/center of the plot. The plot in Figure 3.1 depicts semantic coherence and exclusivity, by topic, for models with 30, 60, 75, 100, 120, 140, 160, 180, 200, and 240 topics. The 180-topic model, represented by the color pink, is clustered near the top right/center of the plot (Figure 3.1).

The residual dispersion tests the null hypothesis that dispersion = 1 versus the alternative, dispersion > 1. If dispersion is negative, the residuals are undefined. A dispersion score of greater than 1 (rejection of the null) is strong evidence in favor of more topics, as it indicates that the latent topics cannot account for overdispersion (Taddy 2012). However, in the case that many (> 200) topics are unable to account for overdispersion, it is possible that additional factors are at play. In this case, the other measures of model fit should be used as the primary assessment for model fit (Taddy 2012). I was not able to reject the null for any of the tested models, an indication that something outside of the prevalence and content covariates in the model was influencing dispersion.

Larger points in Figure 3.1 indicate models with residual dispersion closer to 1. The models in which dispersion < 1 and therefore undefined are depicted by open encircled "x" symbols, while the PCA suggested 50-topic model is represented by triangles (Figure 3.1). The 120-topic model, represented by the lavender points, had the dispersion score closest to 1 (4.70). However, I selected the 180-topic model (pink) based on better semantic coherence and exclusivity, the distribution of MAP estimates (APPENDIX A), and its proximity to the residuals switching from > 1 to < 1 (Figure 3.1).

Figure 3.1. Topic Quality of Tested General Risk Models, 30-240 Topics



Note: Larger point sizes reflect residual dispersion scores closer to 1.
**PCR Model Suggested Number of Topics.*
***Residual Dispersion Undefined.*

I selected the final model from those that included date as a measure impacting topical prevalence, given the similarity between these and the models that only included emotion and valence as prevalence covariates and because I failed to reject the null for all models. I determined the 180-topic models provided the most information, despite being unable to account for overdispersion. After deciding that the 180-topic model would be the best fit for the sample of general risk tweets, I reran the models to include the NRC emotional sentiments as content covariates. This allowed me to investigate the additional context of emotion impacting *how* something was discussed while still accounting for emotion's impact on topical prevalence, or *how often* something was discussed. I retained the best-fitting model after controlling for a content covariate, estimating all effects for the selected, 180-topic, model of 32,513 tweets about risk posted by Twitter users in the United States between December 1, 2019, and June 30, 2021.

DESCRIPTIVE STATISTICS

The topics with an expected proportion > 0.01 included topics 65, 19, 45, 149, 104, 136, 24, 41, 137, 66, 129, 46, 76, and 160 (Table 3; Figure 3.2). Top words found across several of the topics included "COVID," "coronavirus," "time," and "emergency" (Figure 3.2). Topics 46, 66, 137, 41, 104, and 45 included mentions of life, death, sickness, and protection, during COVID-19, including the specific risk mitigating behavior of wearing masks highlighted in topic 66 (Figure 3.2). The expected topical proportions for all 180-topics are in APPENDIX B.

The topic accounting for the highest proportion of tweets (approx. 0.04) was topic 160, which at first glance, seemed to address something with respect to "Facebook," "risk," and "time" (Figure 3.2). Facebook was one of two social media platforms whose name was represented among the top words for topics in the 180-topic model. The other was Twitter, mentioned directly in topic 128 and indirectly in topic 170 with the mention of "tweet" (Figure

3.3b). The next highest proportion (approx. 0.025) was topic 76, which touched on the expected duration of the pandemic (Figure 3.2).

Six of the topics with proportion > 0.01 were represented by words indicating they were related to politics: topics 129, 24, 149, 136, 19, and 65. Of these, topics 24, 136, 19, and 65, had specific political entities among the top words for each topic. For example, topic 24 mentioned former President Donald Trump, by name, Twitter handle (@realdonaldtrump), and title "president," while topic 65 mentioned the now former governor of New York by Twitter handle (@nygovcuomo) (Figure 3.2). Topics 136 and 19 mentioned specific organizational entities involved in pandemic politics, the World Health Organization (WHO) in topic 19 and Brown University ("brown") in topic 136 (Figure 3.2). Topics 129 and 149 were less obviously political, alluding to things that became central to political discussions during the COVID-19 pandemic like the declarations of emergency (topic 129) and re-opening (topic 149), pointing to discussions of lockdown and the crisis response to an emerging threat (Figure 3.2).

Table 3. Description of Topics Expected to Account for >1% of Total Tweets

Topic Number	Topic Label	Topic Category
160	The time spent by members of the Baby Boomer generation on Facebook	Social Media
76	Discussing uncertainty about the expected duration of the pandemic	Other
46	Ignoring the pandemic will increase the total number of pandemic deaths	Life/Death
129	The duration of the federal declaration of emergency for COVID-19	Political
66	Mask mandates in the state of Texas	Political; Risk-Mitigating Health Behavior
137	Freedom of choice versus social responsibility	Other
41	Just pointing out/saying that literally nobody is fine [during the pandemic]	Other
24	President Trump says COVID-19 is a hoax.	Political
136	Checking for updates from the government on the status of COVID-19	Political
104	Discussion about the idea of eradicating COVID-19 in a matter of weeks	Other
149	Fear about the impact of re-opening versus remaining locked down	Risk-mitigating behavior
45	Humans transmit COVID-19 to other humans	Sickness/Symptoms
19	The World Health Organization is the official international public health organization.	Political
65	The COVID-19 emergency is taking a toll on New Yorkers	Political

In summary, the most topics with the highest expected proportions included topics about Facebook, the duration of the pandemic, the impact of the pandemic on people and businesses, political actors, and the idea that people did not feel okay as the pandemic emerged. Topic 160, the topic with the highest expected prevalence, concerned the amount of time members of the Baby Boomer generation spent on the social media platform Facebook. Topic 76 included tweets noting that there was great uncertainty about the expected duration of the pandemic in 2020 and 2021. Like topic 76, topic 129 related to the duration of the pandemic, but instead of the pandemic broadly, topic 129 focused on the duration of the federal declaration of a public health emergency. Topic 104 quantified the duration, with many expecting the pandemic would be resolved in a matter of weeks, not months or years. (Table 3; Figure 3.2)

Topic 46 discussed the possibility that ignoring COVID-19 would result in many deaths. Topic 66 was about mask mandates, specifically those in [or absent from policy in] the state of Texas. Another topic also involved a particular state—topic 65 concerned the emotional toll of the pandemic on people living in New York. The other mentions of specific political entities included an organization, the World Health Organization, and a powerful political actor. Topic 19 provided information about the World Health Organization, framing the organization as the official international public health authority. Topic 24 focused on President Donald Trump's accusation that the COVID-19 pandemic was a hoax. It was also clear that the United States government was understood as having some degree of authority regarding the assessment of COVID-19 risk in topic 136, which included reports from the public about obtaining information about COVID-19 risk through government updates. It may also have been the case that these authority figures did not effectively clarify information about the risk of COVID-19, including the crucial information that COVID-19 transmission is person-to-person via aerosols, as human to human transmission was the focus of topic 45. (Table 3; Figure 3.2)

Topic 137 tweets captured debate over freedom of choice versus personal responsibility regarding risk mitigating behavior. Topic 149 highlighted emotion, specifically fear over the negative impact of reopening versus remaining locked down during 2020. The final highly prevalent topic, topic 41, included discussions indicating people were emotionally unwell and/or having difficulty coping with the new circumstances brought about by the pandemic. (Table 3; Figure 3.2)

Political discussion was not sequestered among the topics with the highest expected proportions. Other topics also addressed specific political entities. For example, the top words for topic 89 included “state,” “governor,” “Florida,” and “California,” (Figure 3.3a), and the top words for topic 86 included “Fauci” (i.e., Dr. Anthony Fauci, head of White House Coronavirus Task Force) (Figure 3.3a). Topic 1 referred exclusively to political parties and positions, with top words including “gop[1],” “republicans,” “senate,” and “democrats” (Figure 3.3a). Other topics mentioning specific political entities that were also mentioned in more than one of the high-proportion topics, such as topic 44 mentioning both Governor Cuomo of New York and the White House[2]. Political topics also included discussion of voting and elections (topic 75).

Several topics addressed risk mitigation, including but also beyond wearing masks. Discussion of masks in the high proportion topic 66 was possibly exclusive to debate over mask mandates in the state of Texas (Figure 3.2, 3.3d). Other topics mentioned non-location-specific mask mandates using slightly different terminology, like in topic 29 where top words included

[1] The United States Republican Party is nicknamed the “Grand Old Party,” often shortened to “GOP”
[2] The official residence of the President of the United States is the “White House” located at 1600 Pennsylvania Ave. in Washington, D.C. The term is often used to refer to the entire executive branch of government.

“requirement” and “require” instead of “mandate”, or the similar topics 49 mentioning “restrictions” and 43 mentioning “order” (Figure 3.3c). Some discussed masks without mention of mandates or requirements, focusing on potential usefulness for risk mitigation (topic 5) or the existence of mandates generally (topic 157) (Figure 3.3c). Another set of topics discussed “guidelines,” “recommendations,” and “advice,” in lieu of mandates (topics 27, 131, 28) (Figure 3.3c). There were also topics alluding to isolation and quarantine by mentioning “lockdown” (topic 40), reopening (topics 59, 165), things being “shut” or “closed” (topics 175, 90) staying at home (topic 164), virtual events (topic 103), and online learning (topic 12) (Figure 3.3d). There were also some topics mentioning isolation or quarantine specifically (topics 133, 176) (Figure 3.3d).

Social distancing may have been mentioned explicitly, given the presence of the words “social” and “distance” together in topic 156. There were definitely topics alluding to social distancing by mentioning things important to the practice (or lack thereof), like being outdoors (distanced) (topic 84) versus indoors (not distanced) (topics 84, 125), or large versus intimate social gatherings (topics 170, 144) (Figure 3.3d).

Figure 3.2. Topics with Expected Topical Prevalence > 0.01

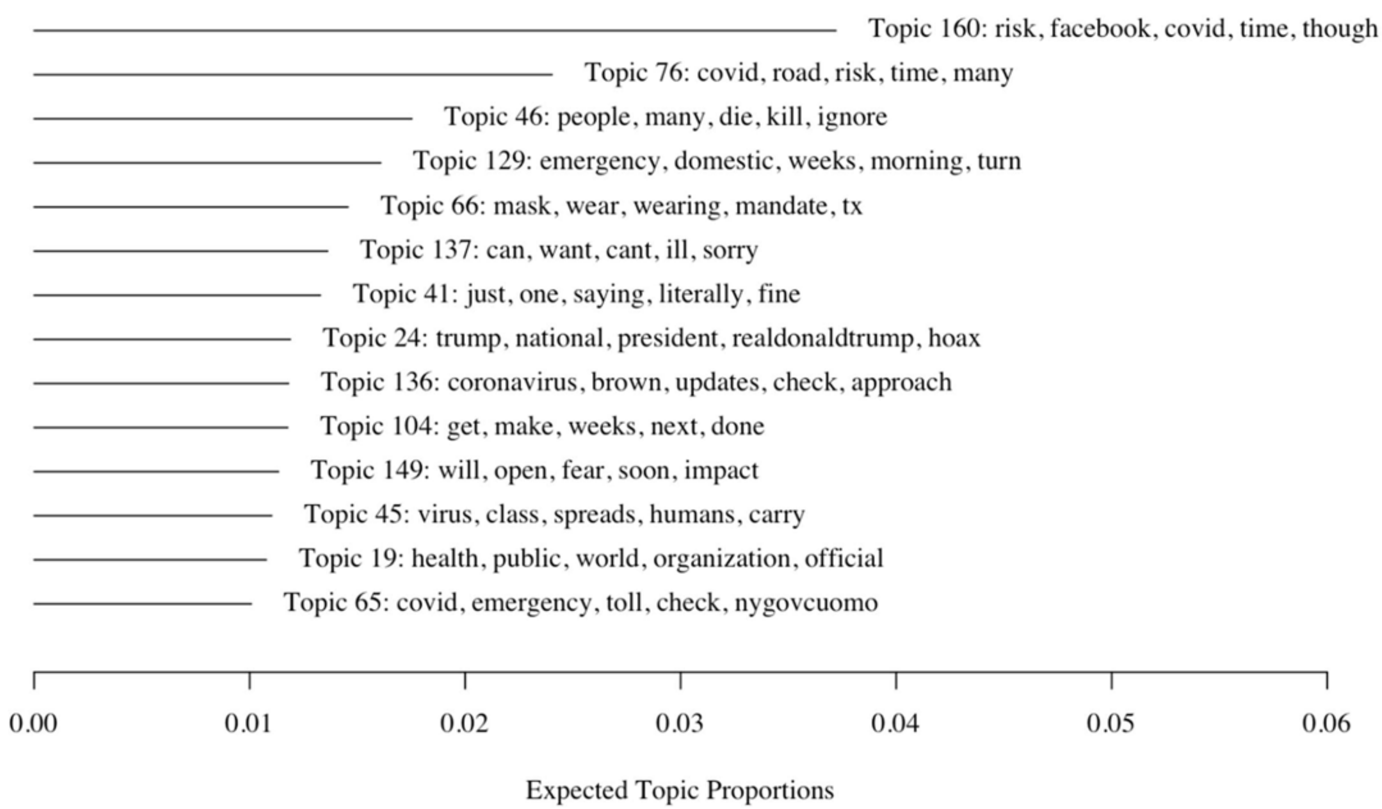


Figure 3.3a. Political Topics in a 180 Topic Model of 32,513 General Risk Tweets

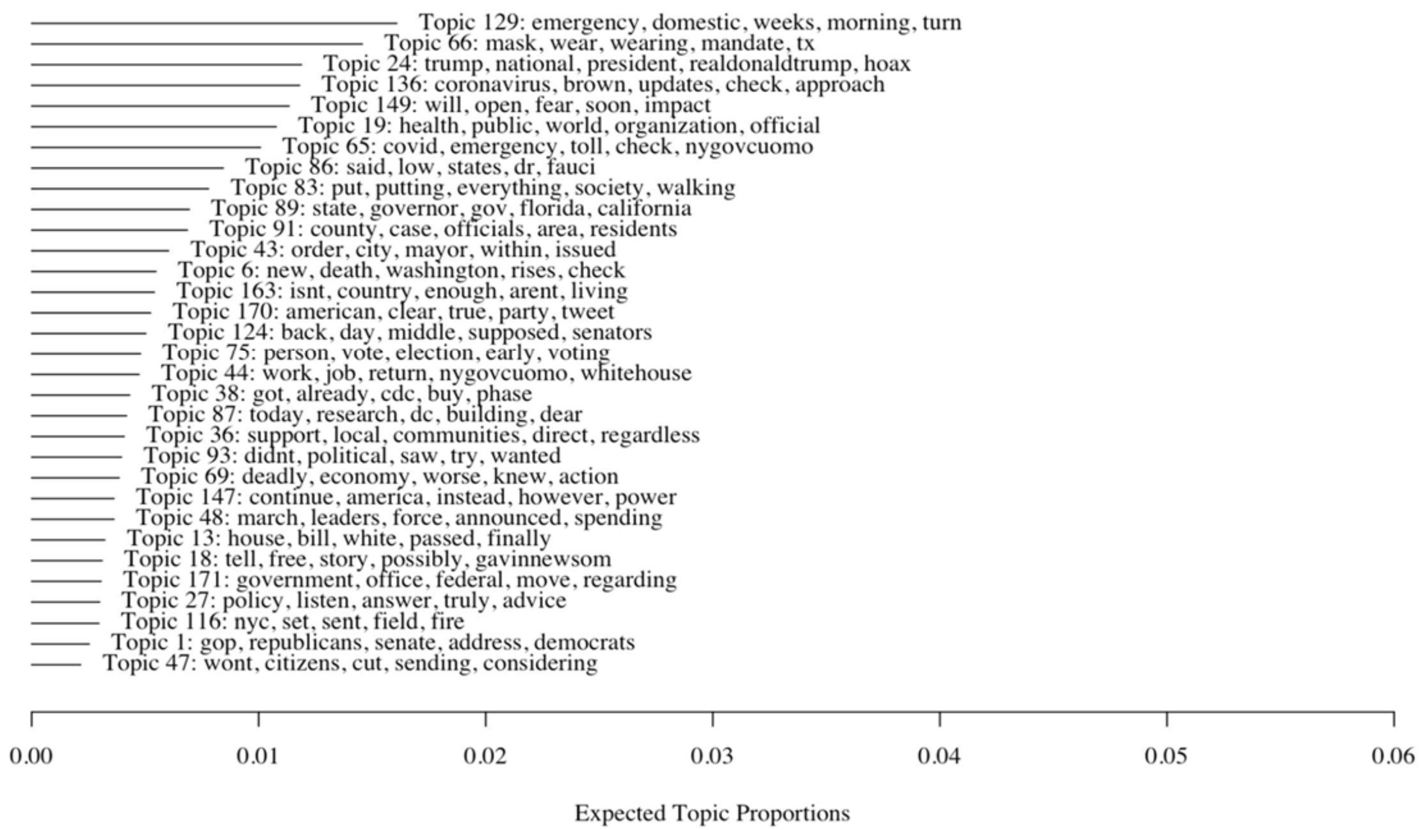


Figure 3.3b. Topics Related to Social Media in a 180 Topic Model of 32,513 General Risk Tweets

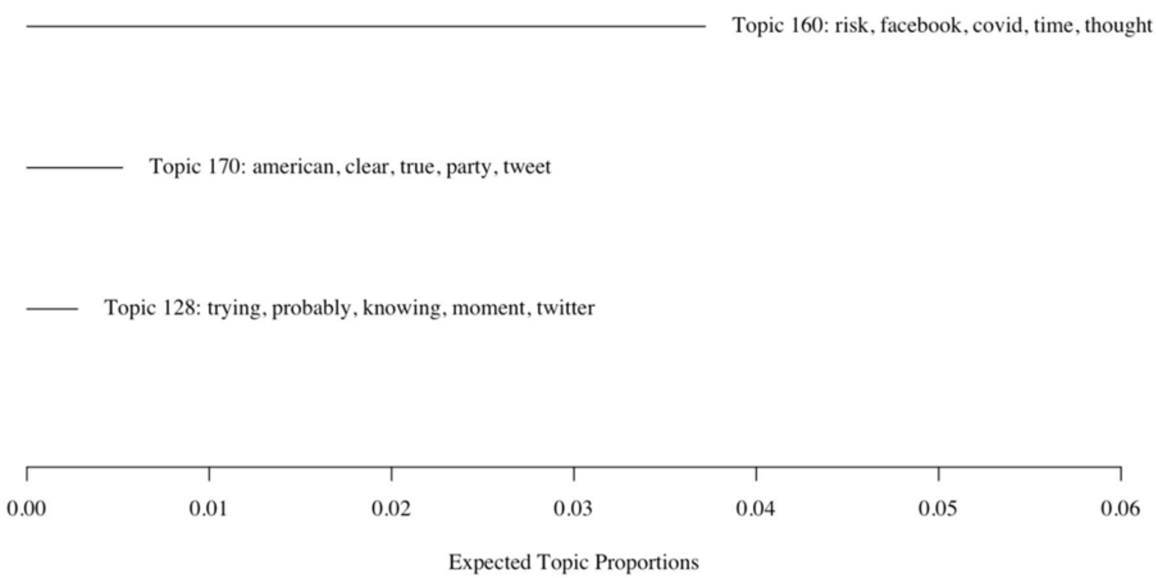


Figure 3.3c. Topics Related to Mandates/Recommendations in a 180 Topic Model of 32,513 General Risk Tweets

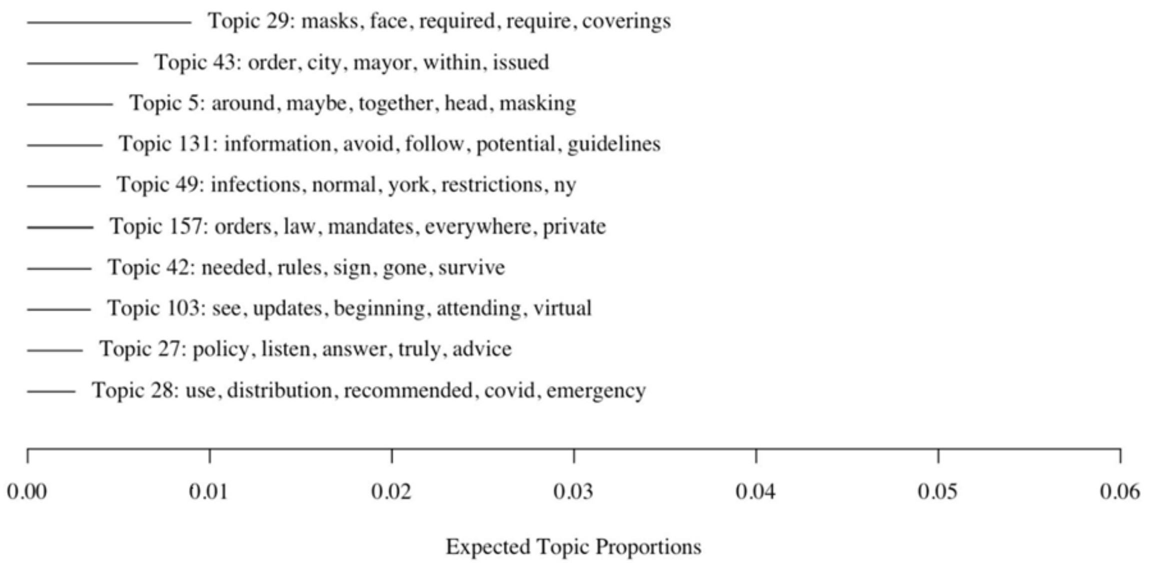


Figure 3.3d. Topics Related to Risk Mitigating Behavior in a 180 Topic Model of 32,513 General Risk Tweets

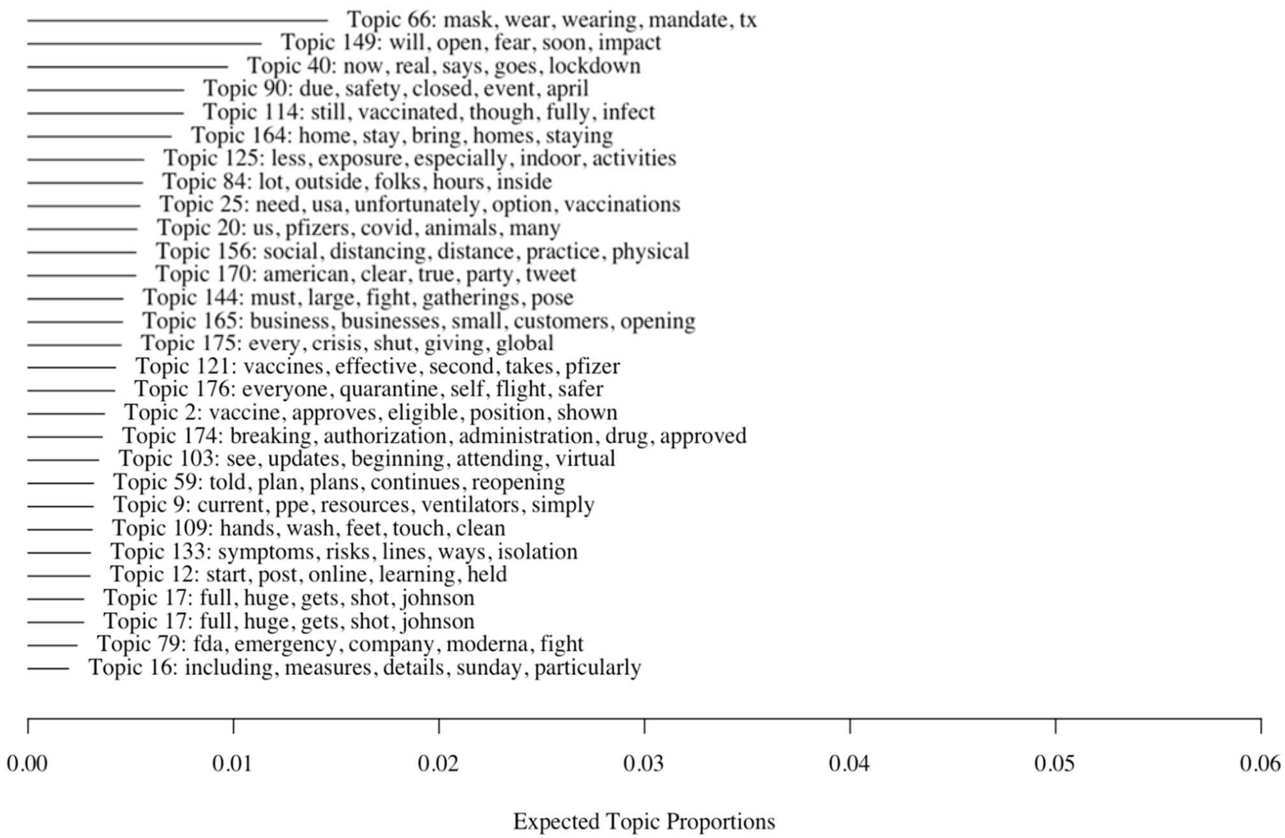


Figure 3.3e. Topics Related to Medically Vulnerable Social Groups in a 180 Topic Model of 32,513 General Risk Tweets

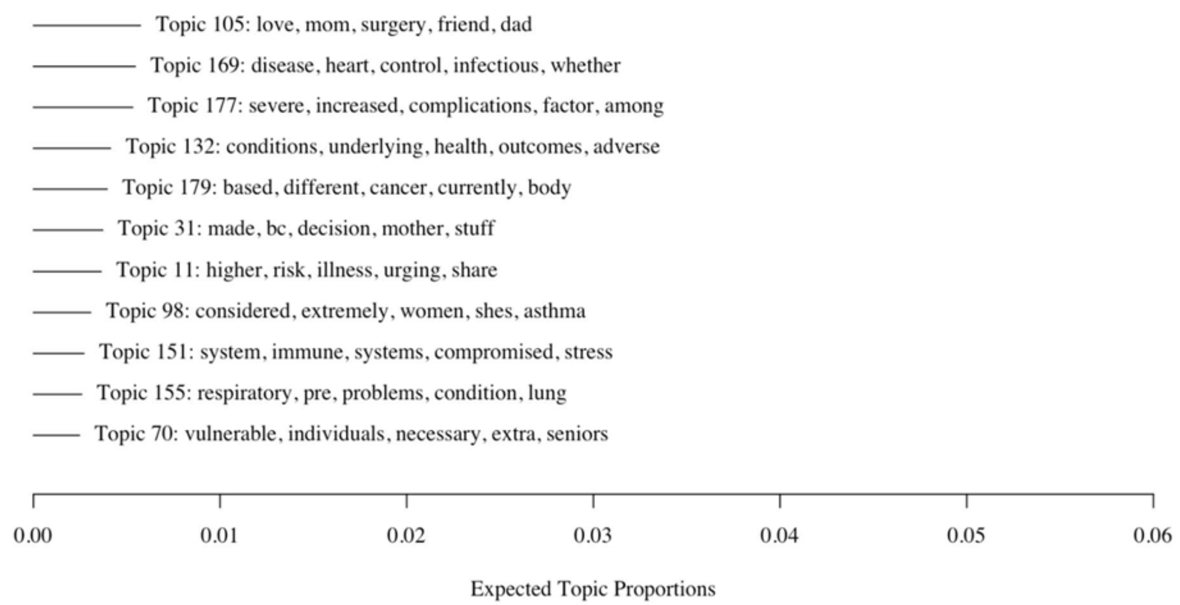


Figure 3.3f. Topics Related to Frontline Workers in a 180 Topic Model of 32,513 General Risk Tweets

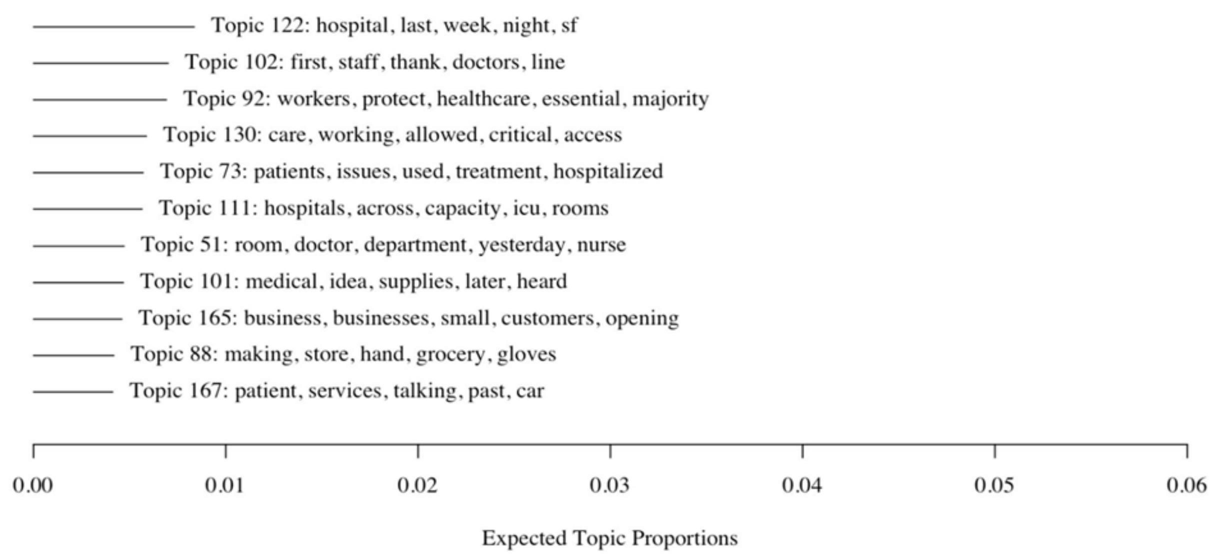


Figure 3.3g. Topics Related to Other Potentially Vulnerable Groups in a 180 Topic Model of 32,513 General Risk Tweets

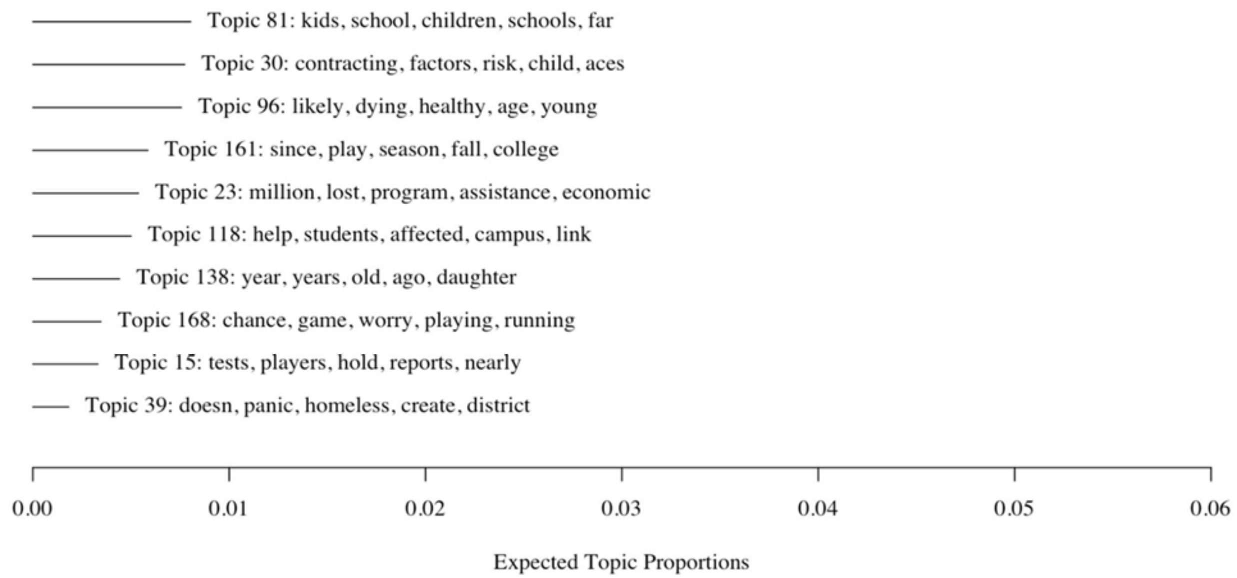


Figure 3.3h. Topics with Profanity in a 180 Topic Model of 32,513 General Risk Tweets

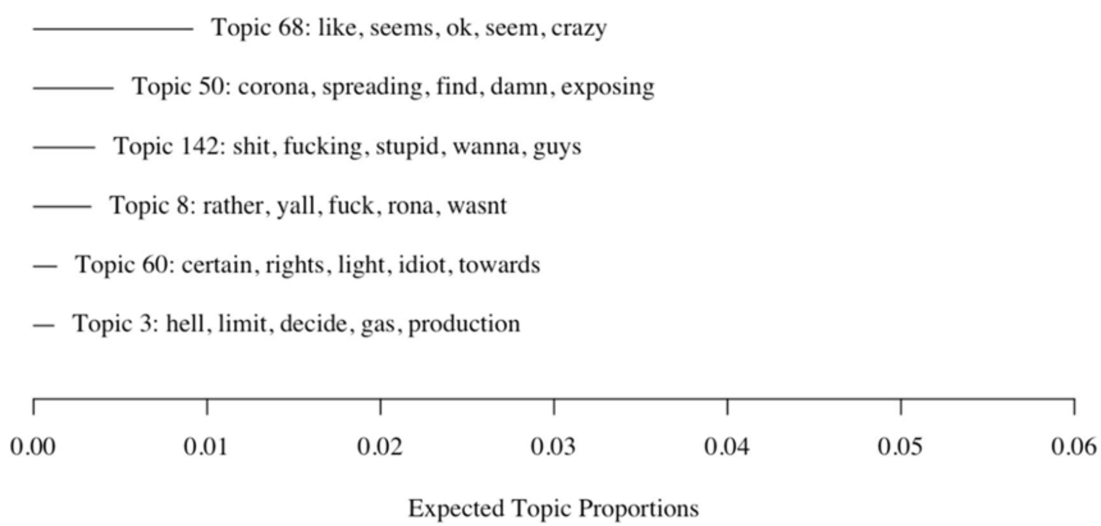


Figure 3.3i. Topics mentioning Life/Death in a 180 Topic Model of 32,513 General Risk Tweets

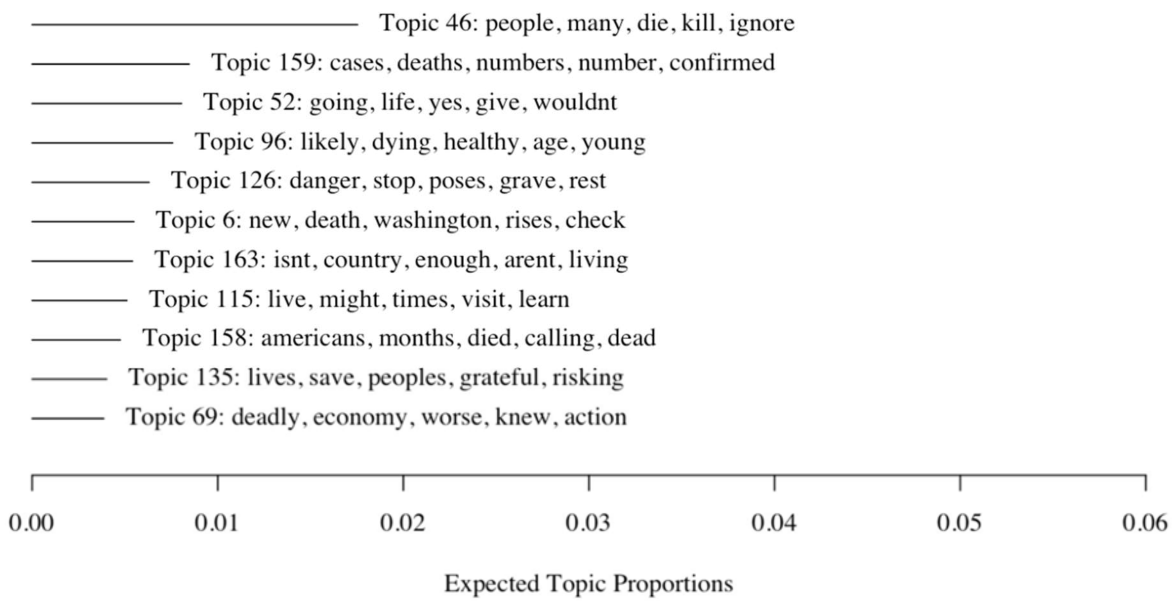


Figure 3.3j. Topics mentioning Sickness/Symptoms in a 180 Topic Model of 32,513 General Risk Tweets

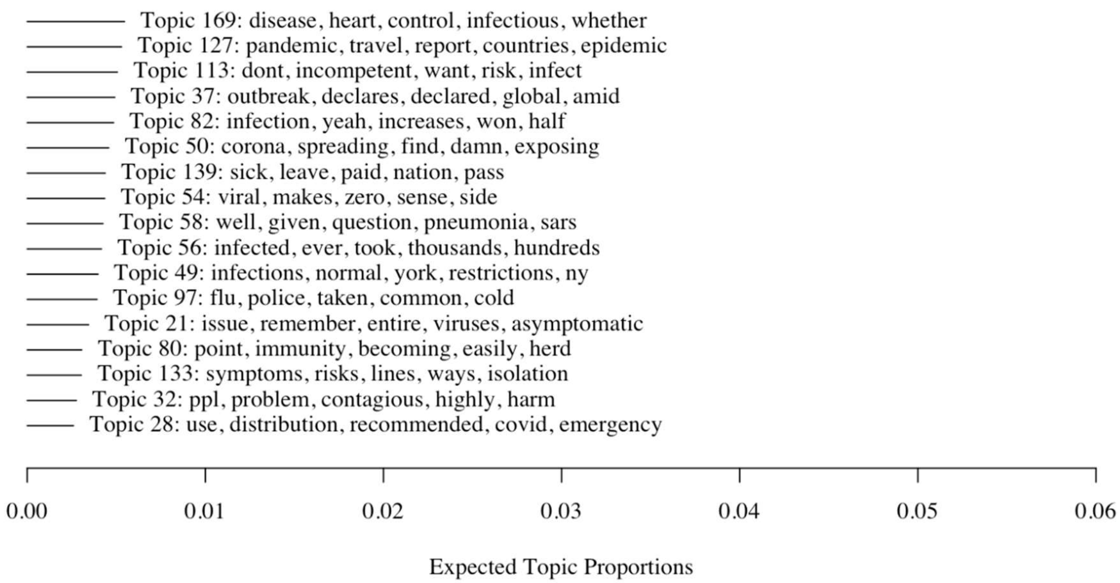
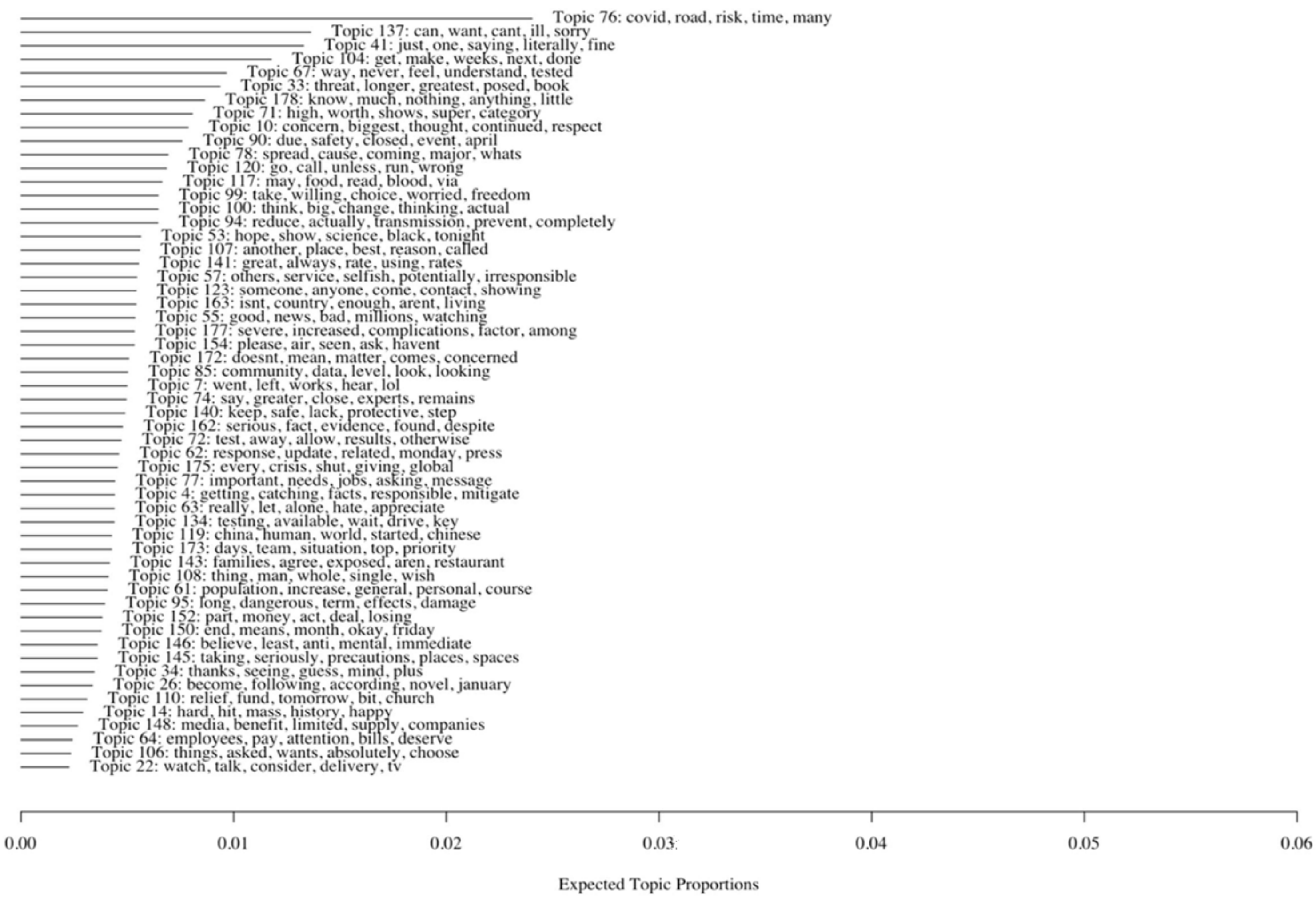


Figure 3.3k. Non-classified Topics in a 180 Topic Model of 32,513 General Risk Tweets



There were also several topics related to vaccination, though none had an expected proportion > 0.01 (3.3d). Some mentioned vaccines or vaccination generally (topics 114, 25, 121, 2, 17), while others mentioned pharmaceutical manufacturers who produced the vaccines approved for use in the United States: Pfizer (topics 20, 121), Moderna (topic 79) and Johnson & Johnson (topic 17) (Figure 3.3d). Other topics referred to pharmaceuticals/drugs, but it was unclear whether they were specific to vaccines (preventives) or therapeutics (treatments) (topic 174) (Figure 3.3d).

Groups considered "vulnerable" or "high-risk" due to their age (elder) (topics 31, 70) (Figure 3.3e), disability/health (topics 155, 151, 98, 11, 179, 132, 177, 169) (Figure 3.3e), or employment as a frontline worker (topic 167, 88, 165, 101, 51, 111, 73, 130, 92, 102, 122) (Figure 3.3f), were also highlighted among the top words for several topics in the 180-topic model (APPENDIX B). These included groups for whom their vulnerability remains up for debate among scientists, most notably, children (topics 81, 138, 30), athletes (topics 168, 15, 161), and young adults (topics 96, 118, 161) (Figure 3.3g). The 180-topic model also included mentions of groups considered vulnerable for environmental exposures of many types, including exposure to COVID-19 but also exposure to other diseases, malnutrition, and climate effects, for example, the unhoused (topic 39) (Figure 3.3g).

The remaining topics were more general, tending to highlight discussions about family, perceived risk, perception of new information, the idea of choice, general expressions of profanity, and other thoughts on life during the pandemic. The 180 topics about risk in the model are best summarized into 11 general categories: social media, politics, mandates and recommendations about behavior to mitigate risk, risk mitigating behaviors, medically vulnerable people, frontline workers, other potentially vulnerable social groups, profane expressions, and “other,” which is best described as including general non-profane expressions and thoughts about life during the pandemic (APPENDIX B). Besides the other/general category of topics, the categories with the greatest number of topics (T) were politics (T = 32) and behaviors (T = 28), while the fewest topics were general expressions of profanity (T = 5) (Figure 3.4).

Some topics did not feat neatly into one category. Topics 170, 69, 66, 43, 96, 6, 133, 169, and 50 could be classified as either of two categories (Figure 3.5). Topic 66 could be classified under politics or risk mitigating behaviors, mentioning both masks and “tx,” the abbreviation for the state of Texas (Figure 3.3a, 3.3d). Topic 170 highlighted social media with the top word “tweet,” but also highlighted “America” and “party” and thus could also fall into the political topics (Figure 3.3a, 3.3b). Topic 69 highlighted both “economy,” important to politics, and “deadly,” referring to matters of life and death (Figure 3.3a, 3.3i). Topic 43 was likely best classified under both (not either) topics about mandates and topics about politics, given “order” and “issue” were top words alongside “city” and “mayor” (Figure 3.3a, 3.3c).

Topic 6 mentioned “Washington,” and thus, could have been classified as political (Figure 3.3a). However, topic 6 also highlighted “death,” and this alongside the other top words “new” and “rises” suggests that rising death tolls were likely the focus of this topic (Figure 3.3i). Also highlighting matters of life and death was topic 96, which mentioned “dying” alongside “healthy,” “age,” and “young” (Figure 3.3i). I took this as an indication that topic 96 may involve the debate over vulnerability for young and “healthy” people (Figure 3.3g). Topics 133, 169, and 50, touched on sickness and/or symptoms of illness (Figure 3.3j) alongside risk mitigating measures (isolation) (Figure 3.3d), disability and health (Figure 3.3e), and profanity, respectively (Figure 3.3h).

Figure 3.4. Number of Topics per Topical Category

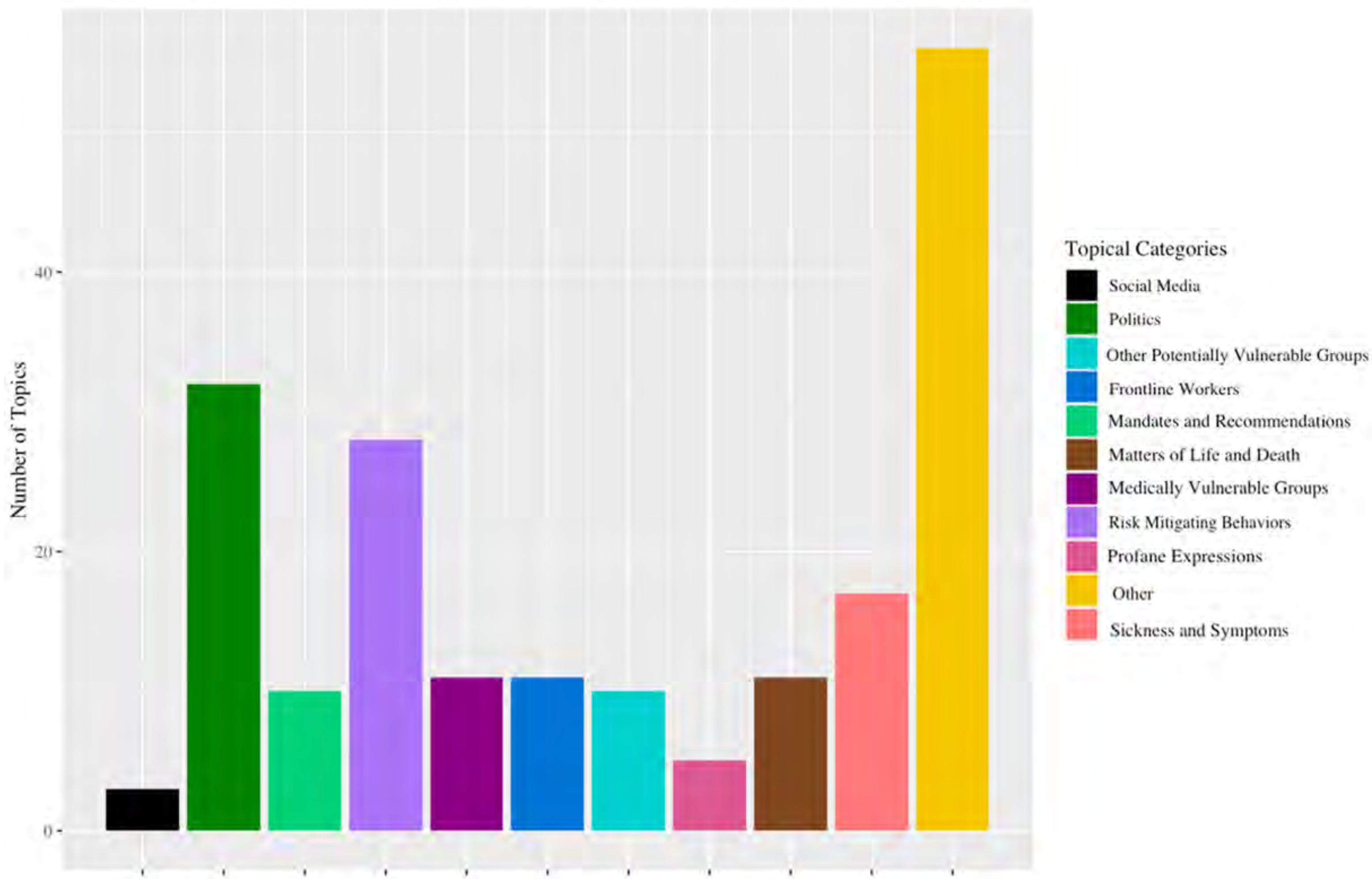
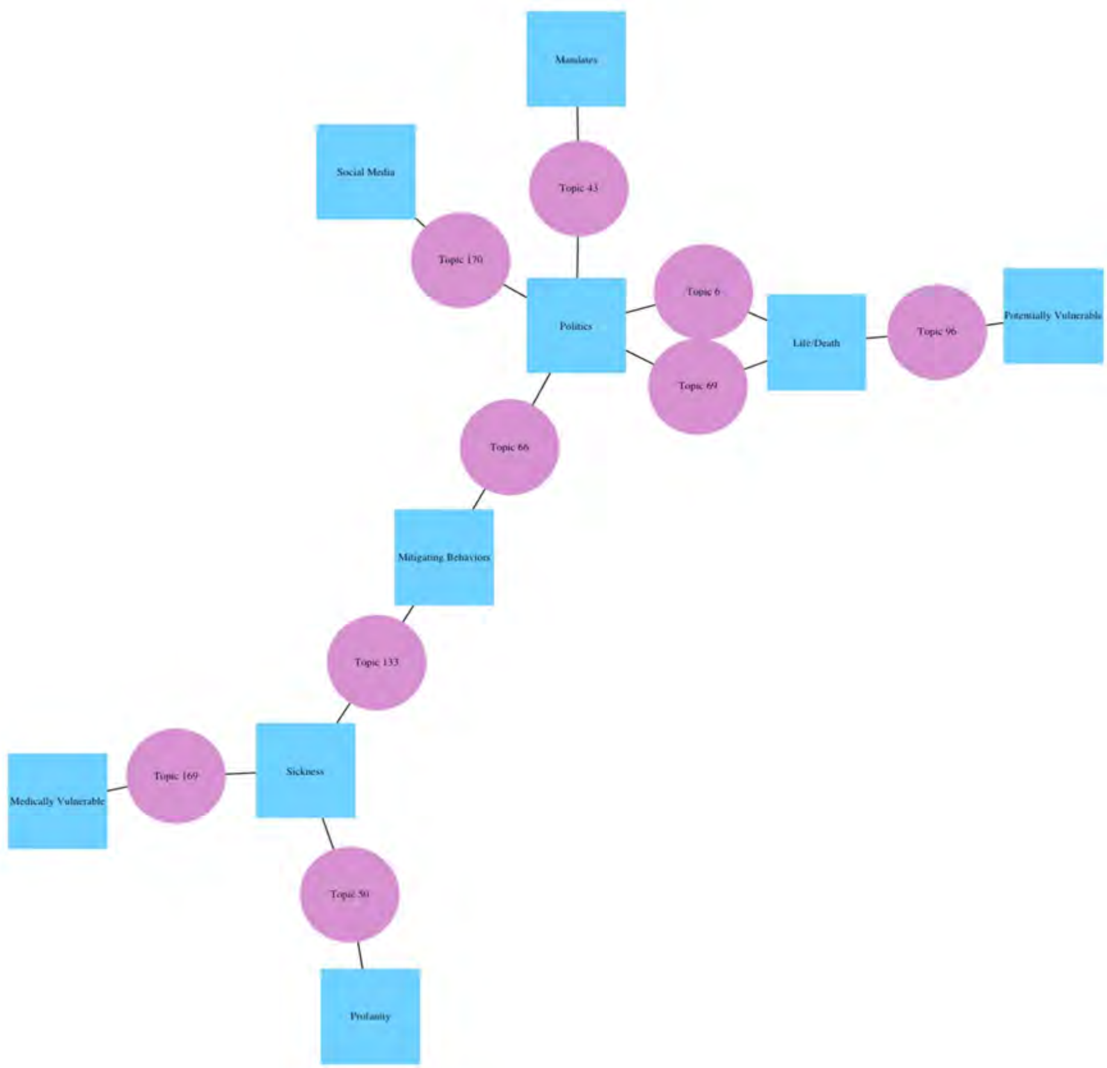


Figure 3.5. Ties Between Topic Number and Topic Category for Topics in >1 Category



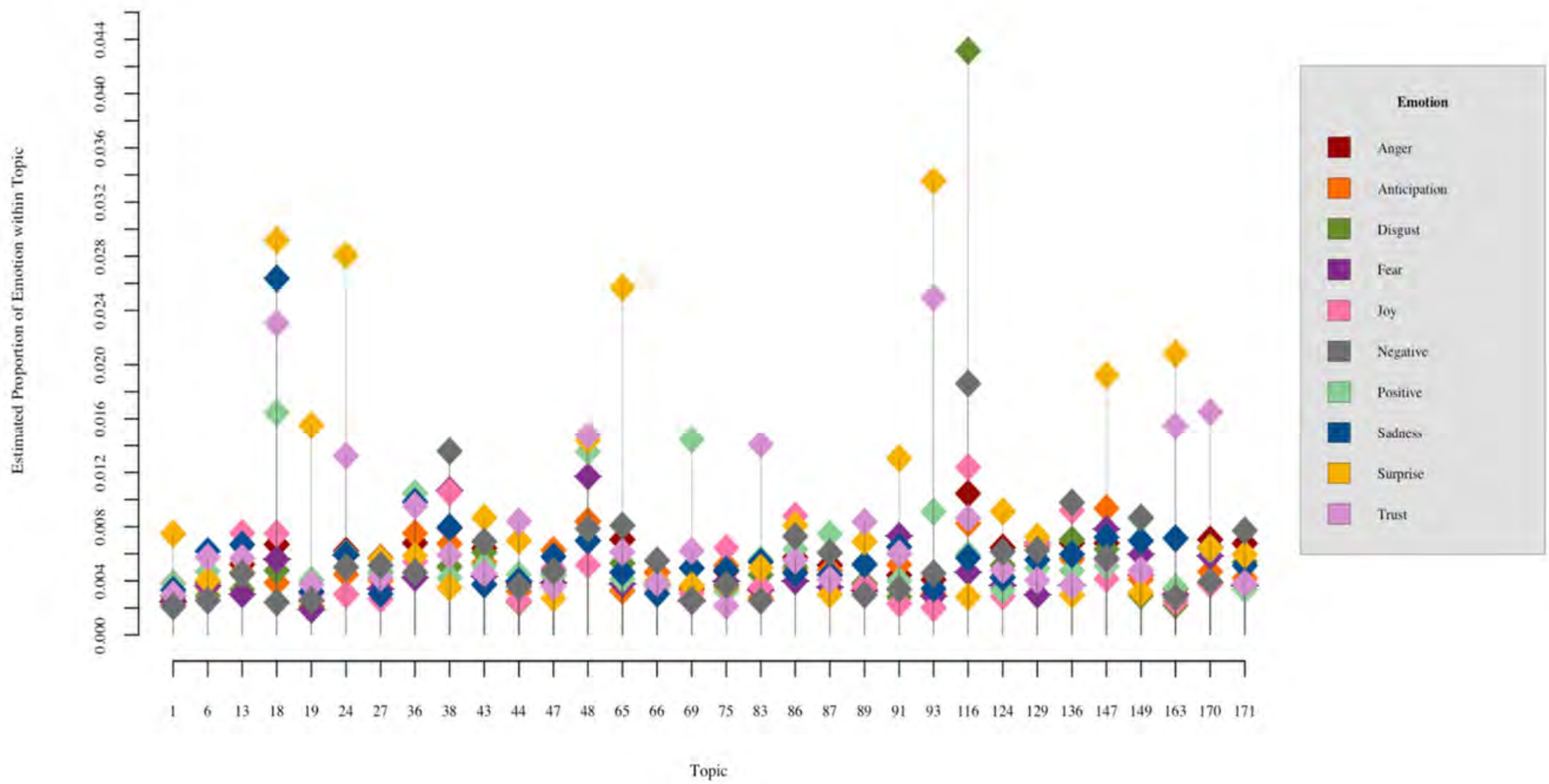
Politics was the most central topical category among the topics falling into more than one topical category (Figure 3.5). Five of the nine topics falling into more than one topical category were classified as “political” alongside another category (Figure 3.5).

ESTIMATED PROPORTIONS OF EMOTIONS WITHIN TOPICS OF THE SAME CATEGORY

When grouped by topical category, the point estimates for emotions in each topic reveal some interesting nuances about emotion across topics and topic categories (Figure 3.6a-k). The distribution of effect estimates for each emotion did not reveal any obvious patterns of dominant emotion across similar topics, instead revealing that emotions varied across similar topics. However, the point estimates for emotions per topic suggest that there are patterns of dominant emotions across similar tweets of the same topic for at least one topic per topical category, but not for all 180 topics total (Figure 3.6a-k). For example, "Trust" accounted for the highest proportion of tweets in three topics mentioning mandates/guidelines, topics 28, 49, and 103 (Figure 3.6c). In this same category, two other topics, 43 and 157, shared a pattern where "Disgust" followed by "Trust" had higher proportions than other emotions (Figure 3.6c).

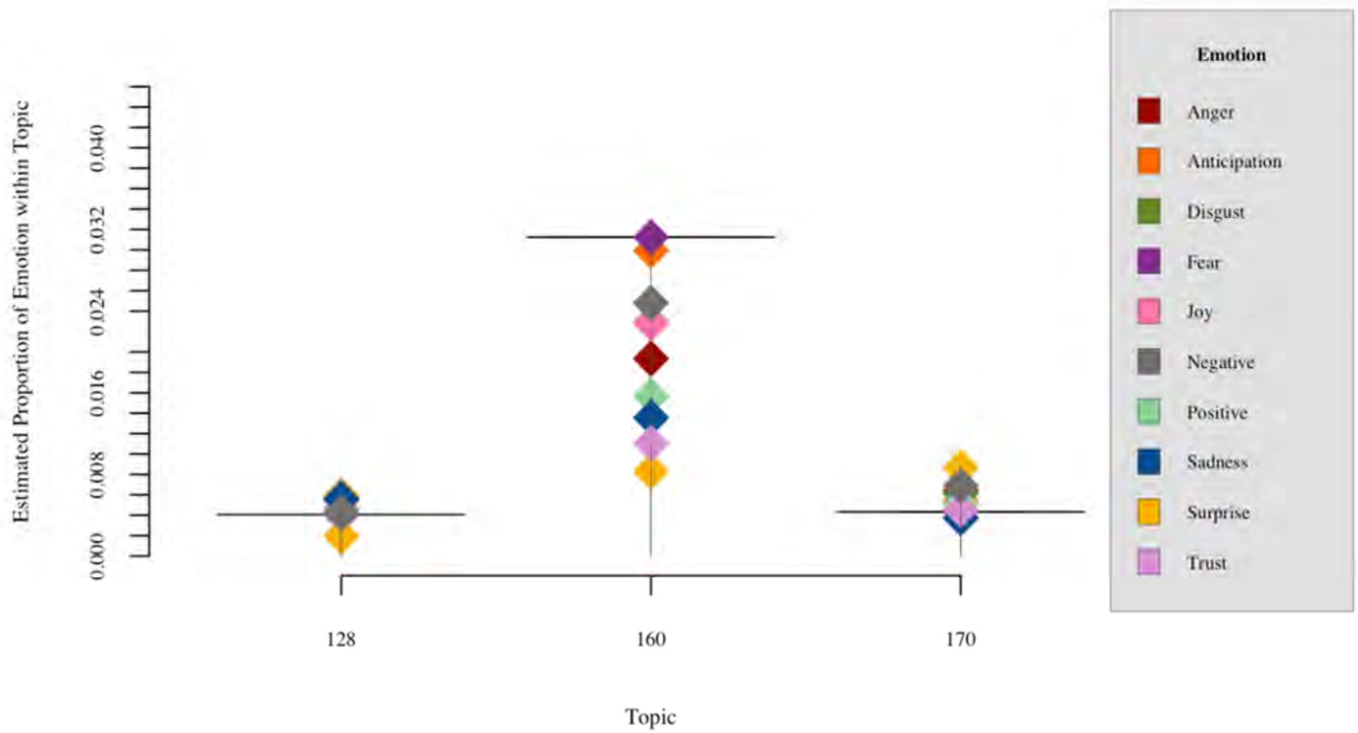
No topical category consisted only of topics with clear patterns for dominant emotions. Instead, one or more topics stood out for having one or a few dominant emotions for which the estimates were much higher than others, both within the topic and across topics in the category (Figure 3.6a-k). For example, topic 116 was a political topic in which the effect of Disgust was particularly pronounced, both compared with other emotions within the topic, and when compared to estimates of Disgust for other topics in the political category (Figure 3.6a).

Figure 3.6a. Point Estimates for Emotions in Topics about Politics



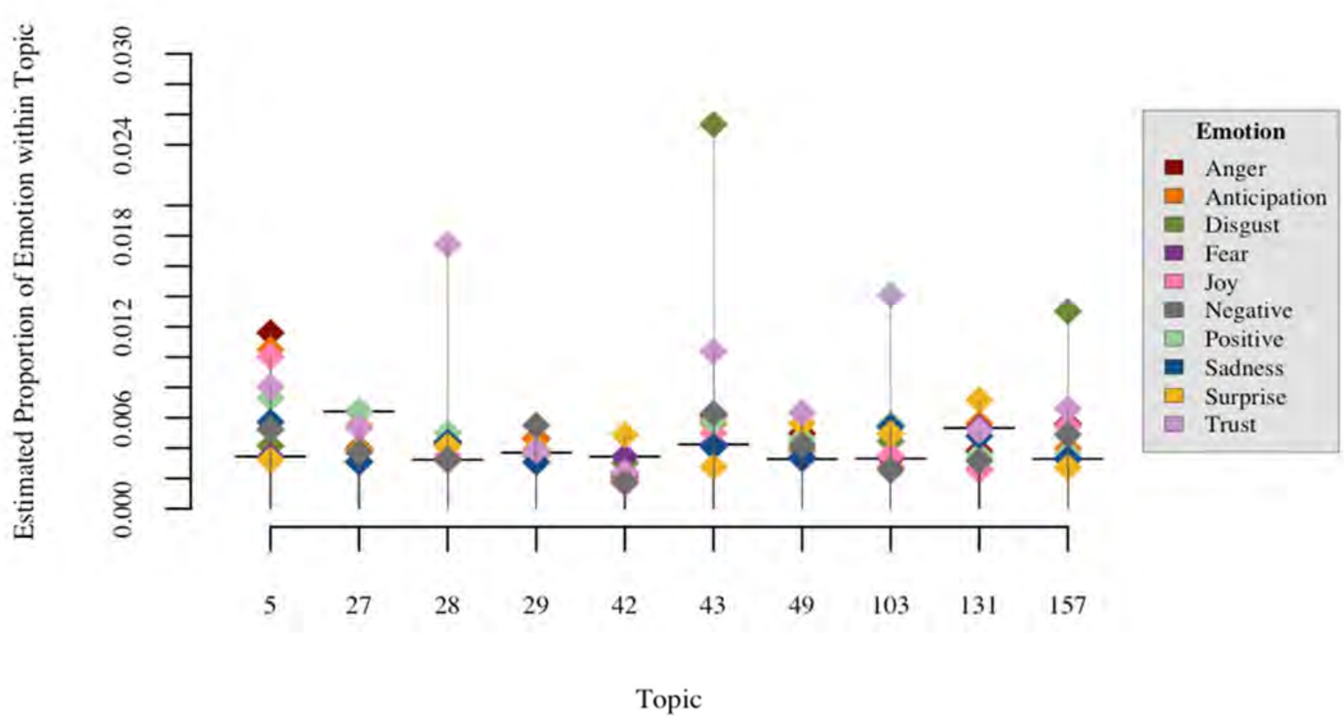
Note: Confidence intervals are shown for the intercept, 'fear'.

Figure 3.6b. Point Estimates for Emotions in Topics about Social Media



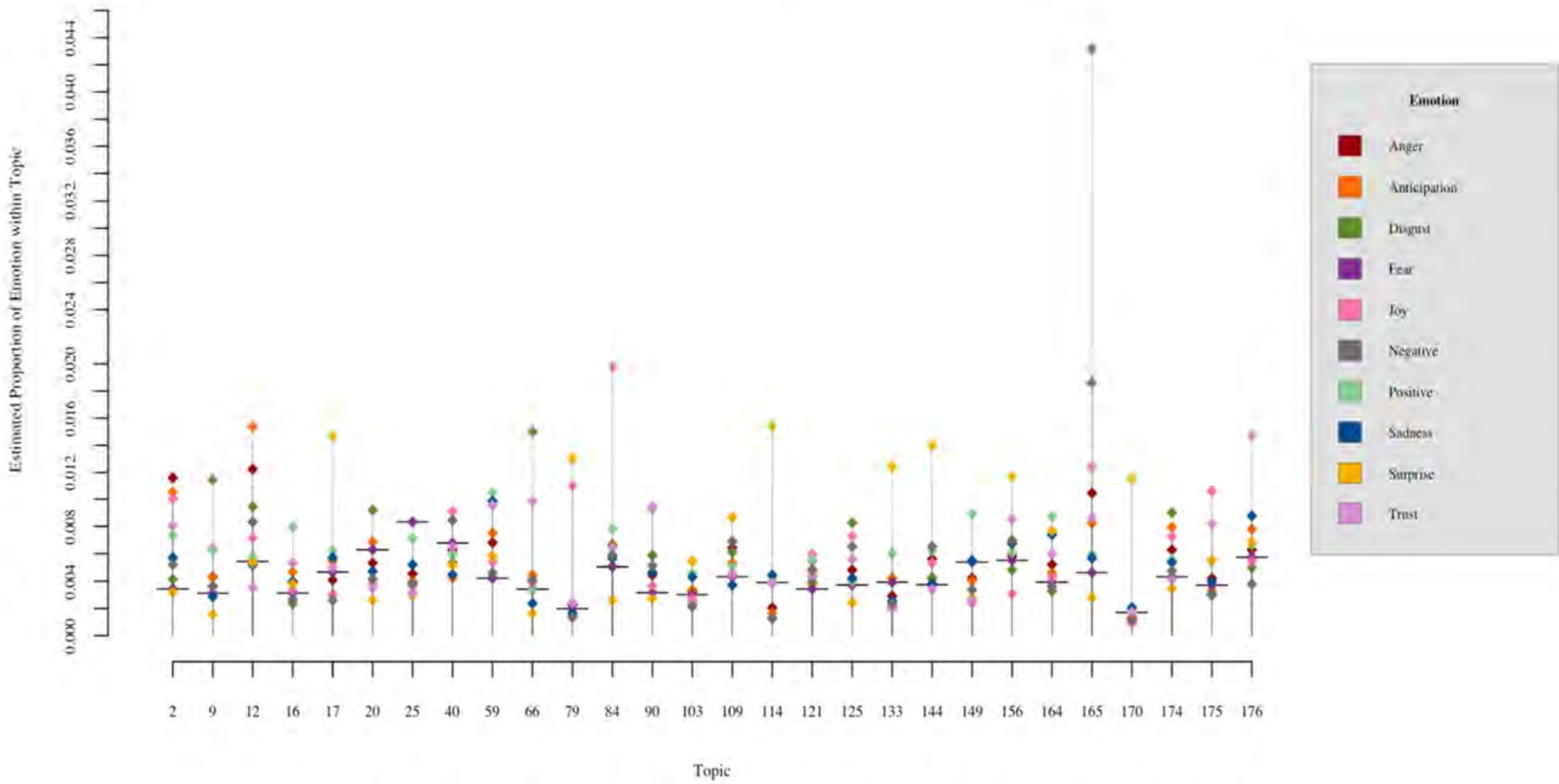
Note: Confidence intervals are shown for the intercept, 'fear'.

Figure 3.6c. Point Estimates for Emotions in Topics about Mandates/Guidelines



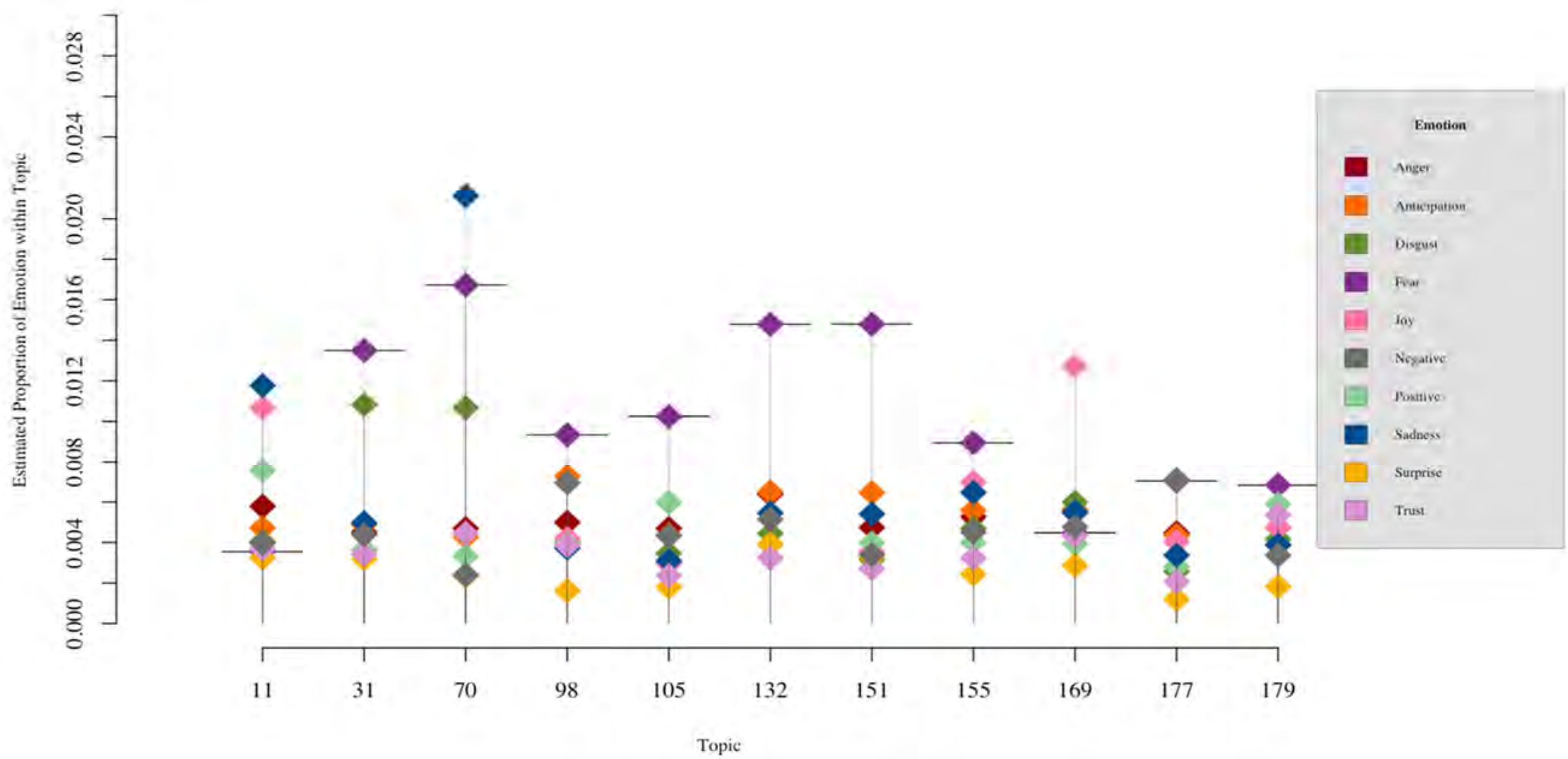
Note: Confidence intervals are shown for the intercept, 'fear'.

Figure 3.6d. Point estimates for Emotions in Topics about Risk Mitigating Behavior



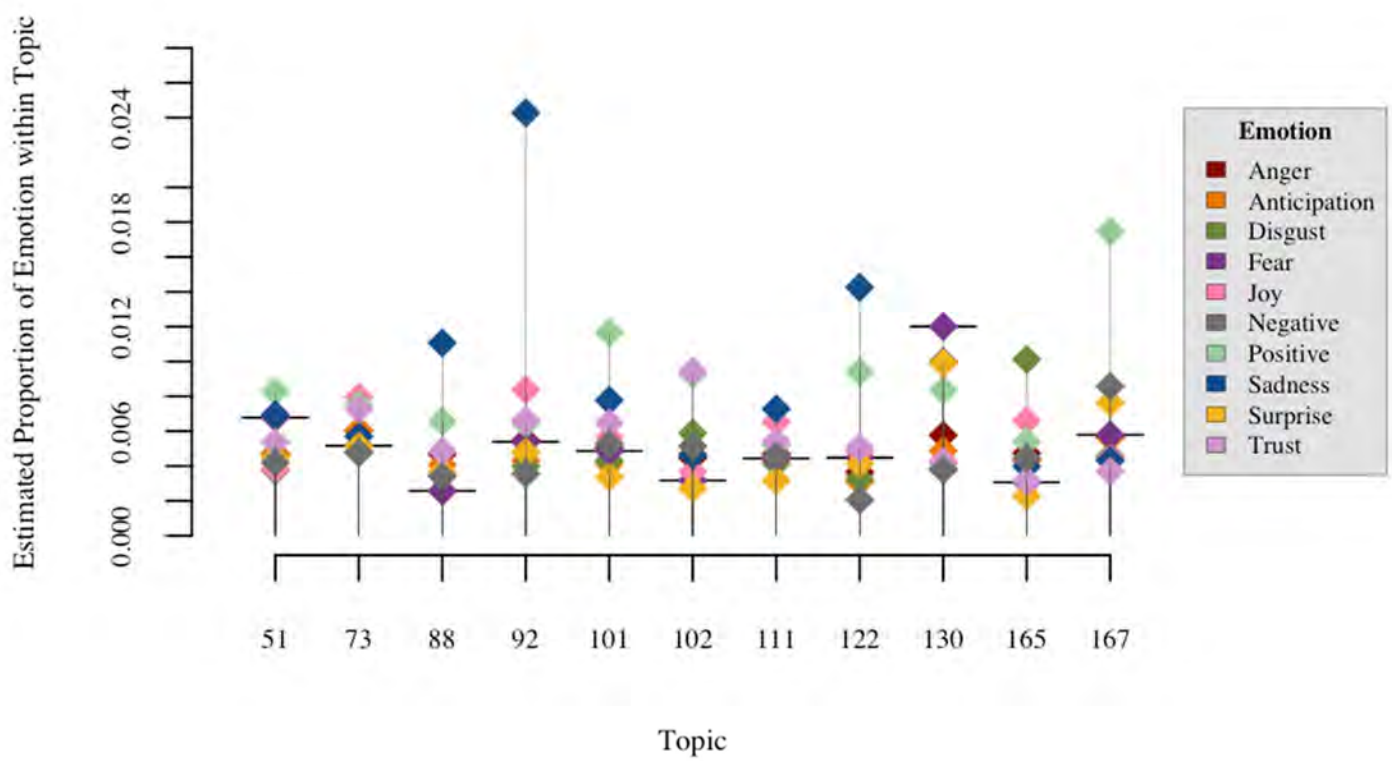
Note: Confidence intervals are shown for the intercept, 'fear'.

Figure 3.6e. Point estimates for Emotions in Topics about Disabled and Elderly People (The Medically Vulnerable)



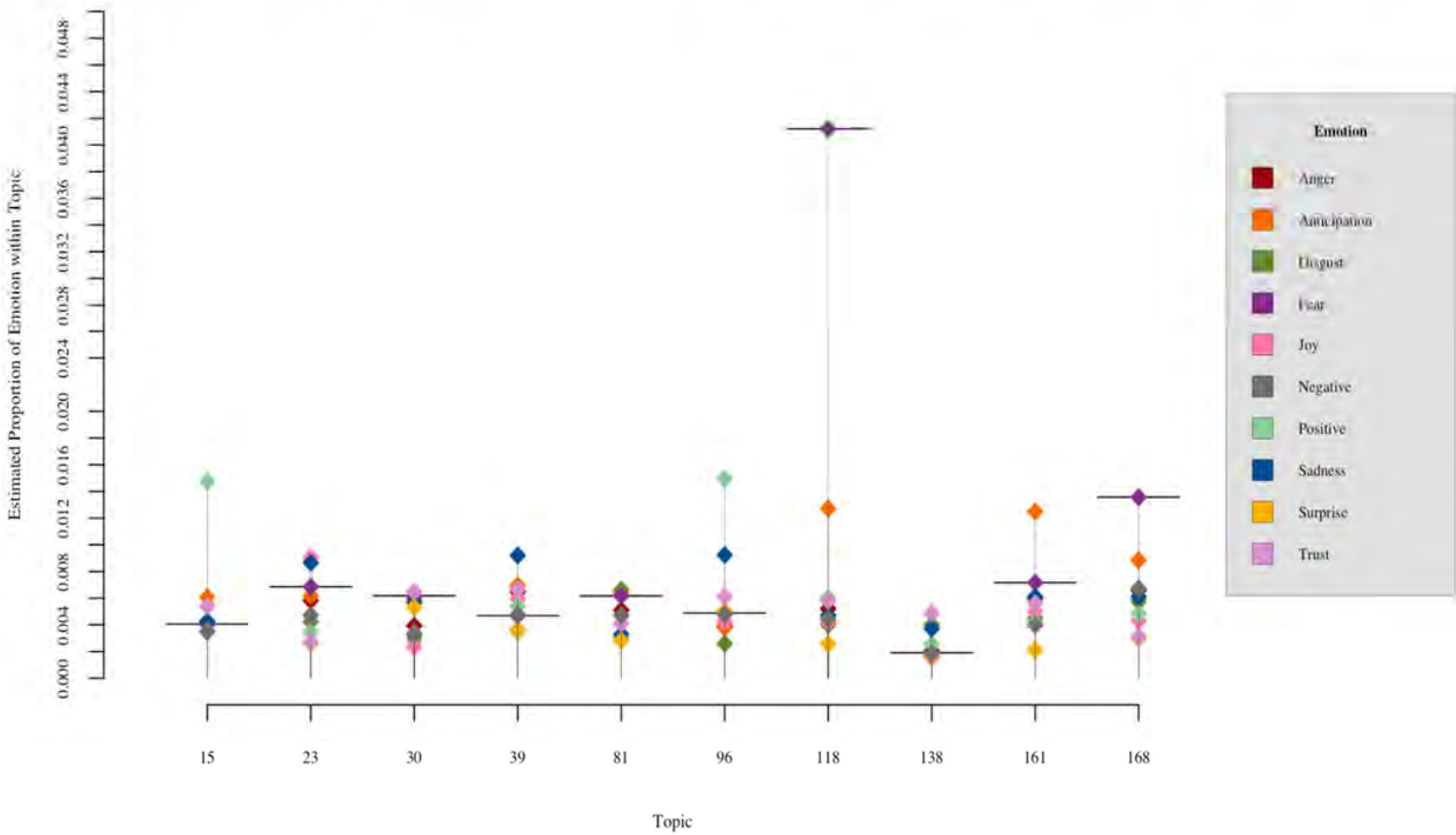
Note: Confidence intervals are shown for the intercept, 'fear'.

Figure 3.6f. Point Estimates for Emotions in Topics about Frontline Workers



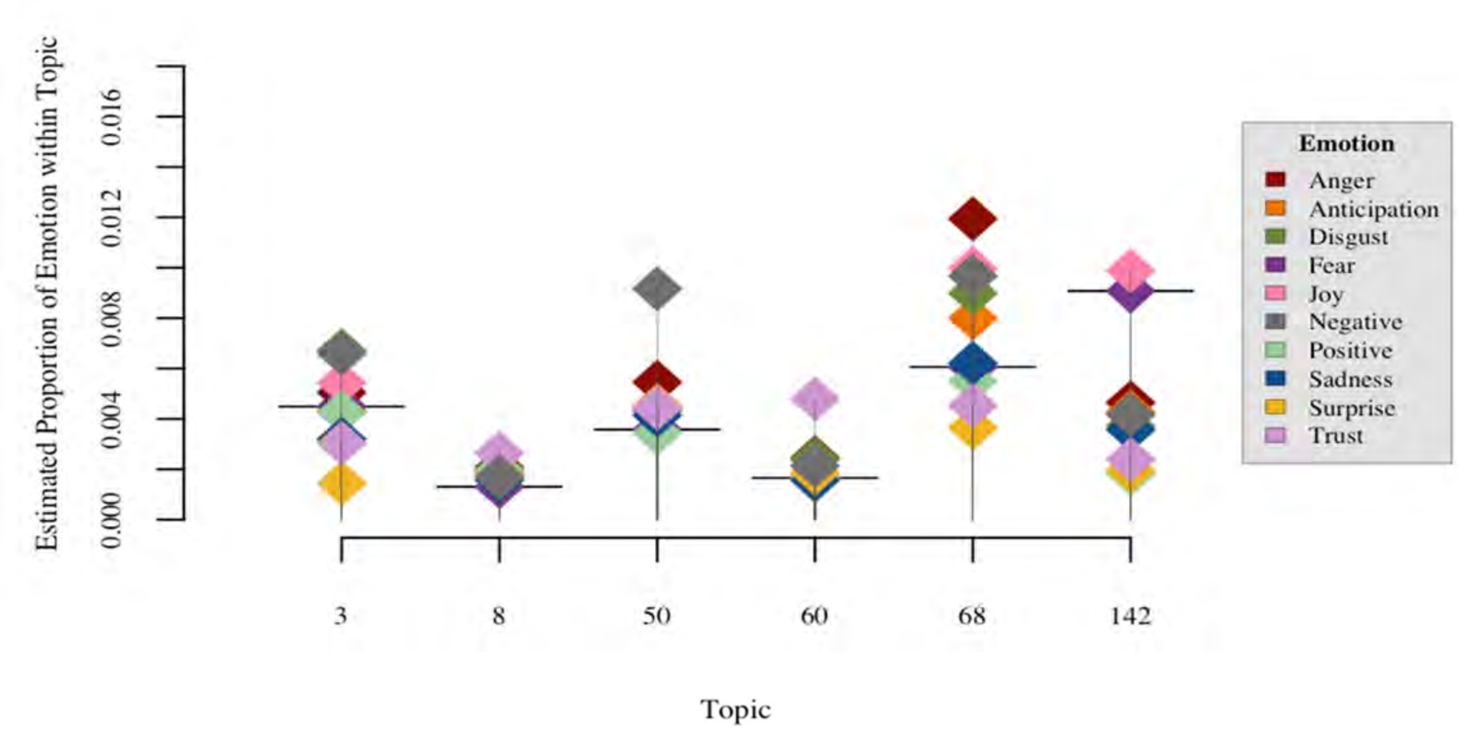
Note: Confidence intervals are shown for the intercept, 'fear'.

Figure 3.6g. Point estimates for Emotions in Topics Mentioning Other Potentially Vulnerable Groups (Young Adults, Children, Athletes)



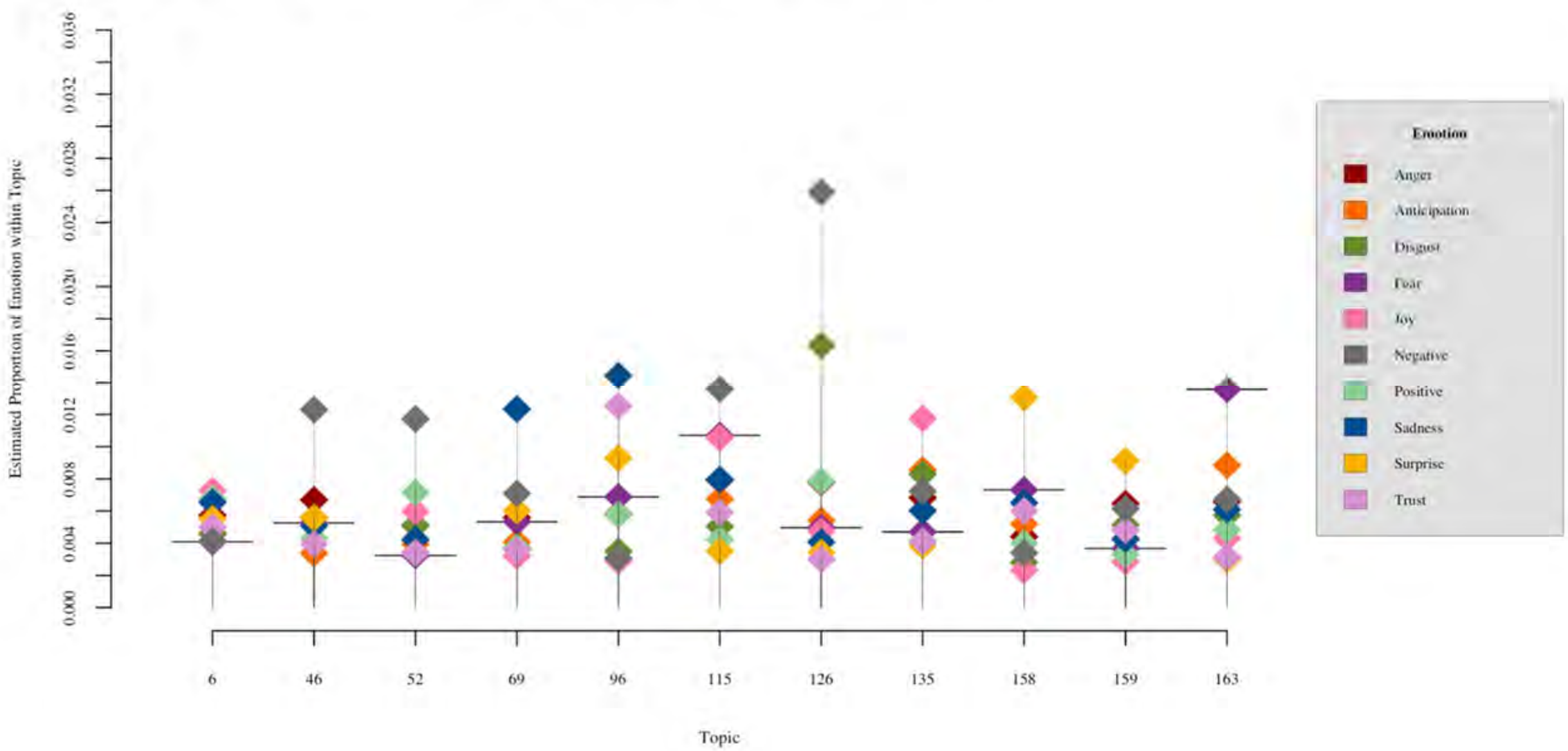
Note: Confidence intervals are shown for the intercept, 'fear'.

Figure 3.6h. Point Estimates for Emotions in Profane Topics



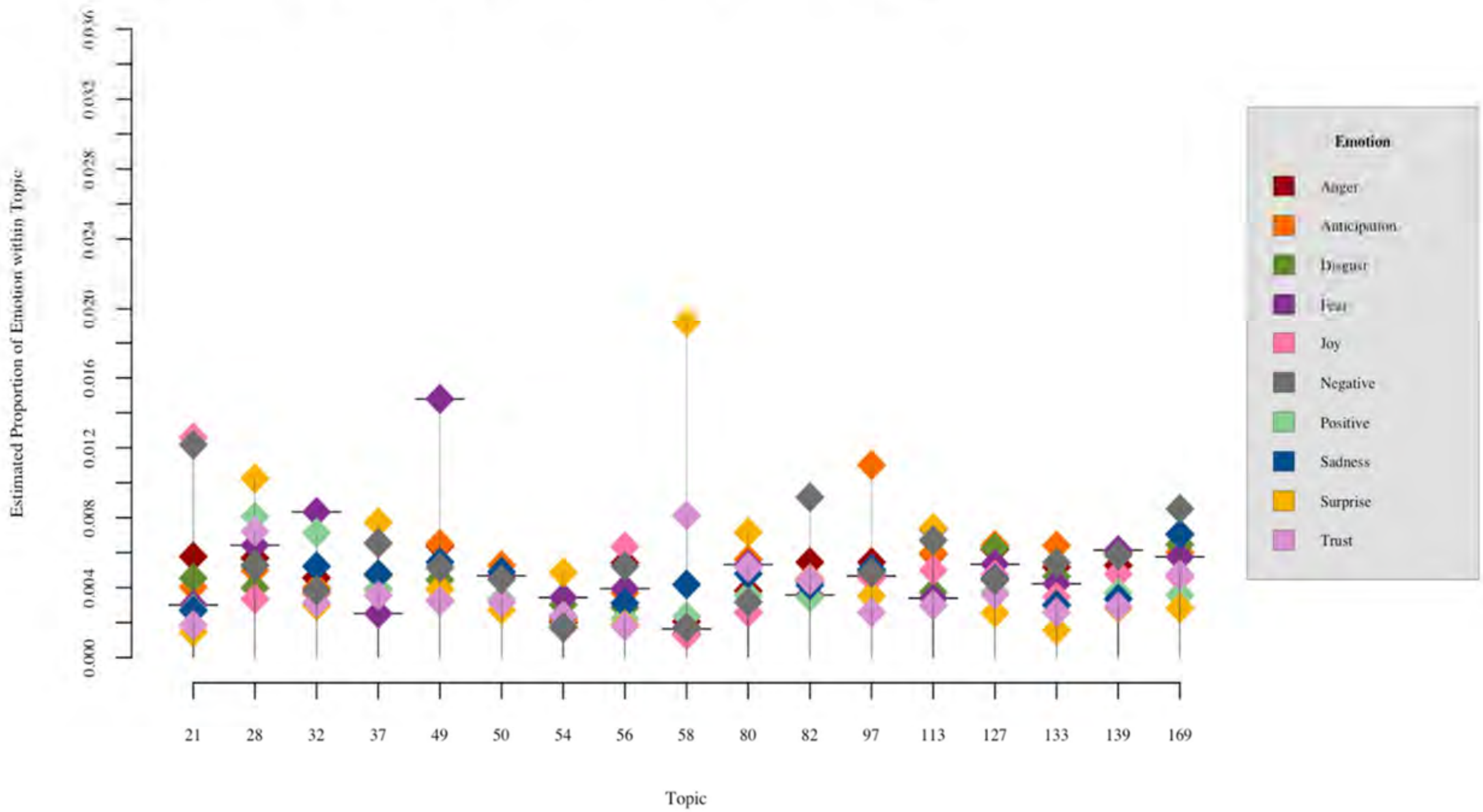
Note: Confidence intervals are shown for the intercept, 'fear'.

Figure 3.6i. Point estimates for Emotions in Topics about Matters of Life/Death



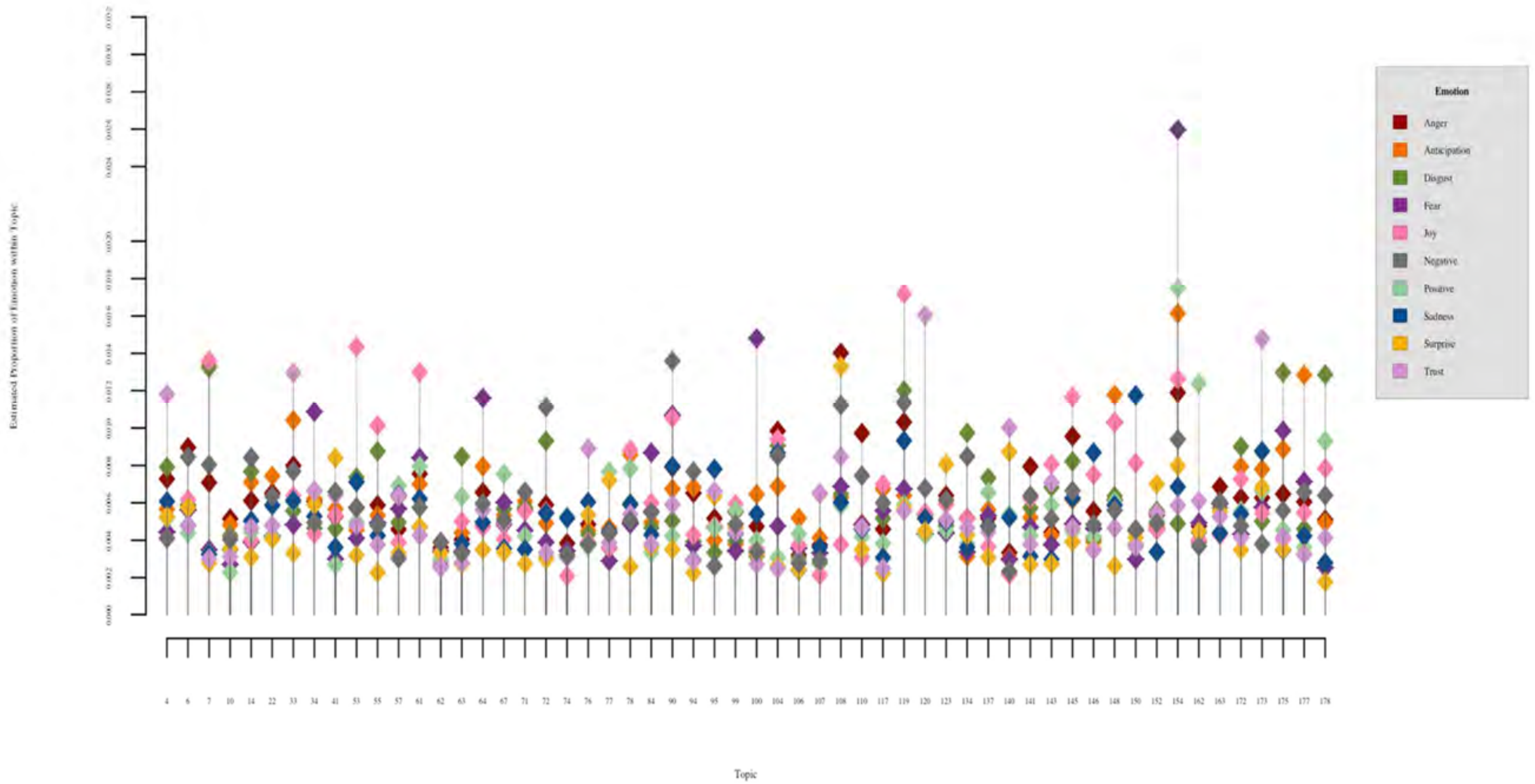
Note: Confidence intervals are shown for the intercept, 'fear'.

Figure 3.6j. Point estimates for Emotions in Topics Mentioning Sickness/Symptoms



Note: Confidence intervals are shown for the intercept, 'fear'.

Figure 3.6k. Point Estimates for Emotions in Other/Non-Classified Topics



Note: Confidence intervals are shown for the intercept, 'fear'.

NETWORK ANALYSIS: ESTIMATED EFFECT OF EMOTIONS ON TOPIC PREVALENCE

For each subgraph, I began with a simple layout with edge density reflecting the size of the effect estimate and the color of the edge identifying the effect direction by applying the “graph opt” layout in “igraph” optimized for large networks (Nepusz 2022). Next, I obtained the degree centrality scores for each node, incorporating information about how many times topics appear together in the other subgraphs for use for measures of edge density. I then applied the Kamada-Kawai layout algorithm (Kamada and Kawai 1989), which is a force-directed algorithm that increases the distance between nodes with increased tie strength so that longer edges represent stronger ties. I selected several topics in each subgraph for closer examination, identifying the topics furthest away from the emotion node as those whose prevalence is most strongly impacted by the subgraph emotion compared to Fear.

For each of the topics selected from an emotion subgraph for closer examination, I plot the top words for the emotion in question versus the top words for Fear within the topic. To visualize the comparison between word usage by emotion, I set the word size to reflect word prevalence in topic documents (tweets) and shaded the words on a red-blue gradient so that words used in predominantly “Fearful” contexts fell on the left of the plot shaded in red while the words used primarily in context of the subgraph emotion fell on the right of the plot shaded in blue. If a word was used in context of both “Fear” and the subgraph emotion within a single topic, the words fell closer to the center of the plot laying closer to the dominant context and taking on a purple shade indicating a mix of Fear (red) and the subgraph emotion (blue).

I then expanded the subgraphs, adding 11 nodes representing the 11 topical categories based on similar theme among topic top words, adding ties between the category nodes and topical nodes representing a topic’s inclusion in the topical category. I recalculated degree centrality, this time, for all nodes in the expanded subgraphs, setting node size so that larger nodes are more central.

After visually examining the expanded subgraphs, I used hierarchical random graph modeling (HRG/HRGM) to estimate the distance between nodes by fitting the nodes into several nested subgroups. To interpret the hierarchical random graph model, I obtained the predicted probability of ties to reveal possible missing ties from the fitted hierarchical random graph model. Finally, I compared the fitted versus predicted hierarchical random graph models for each subgraph.

While every emotion had a significant effect on the prevalence of several topics when compared with Fear, not every emotion had a significantly greater effect on all topics for which the effect was significantly different from Fear. Instead, there were also topics in which the effect of other emotions was significantly less than the effect of Fear, at least one per emotion (Figure 4.1). In a bipartite network where ties indicate the significant effect of the emotion (mode 1, pink) on the prevalence of the topic (mode 2, blue), there were 130 ties representing that an emotion’s effect was significantly less than the effect of Fear (Figure 4.2), and 157 ties representing that an emotion’s effect was significantly larger than the effect of Fear on a given topic (Figure 4.3).

Figure 4.1. Bipartite Network of Emotions and Topics

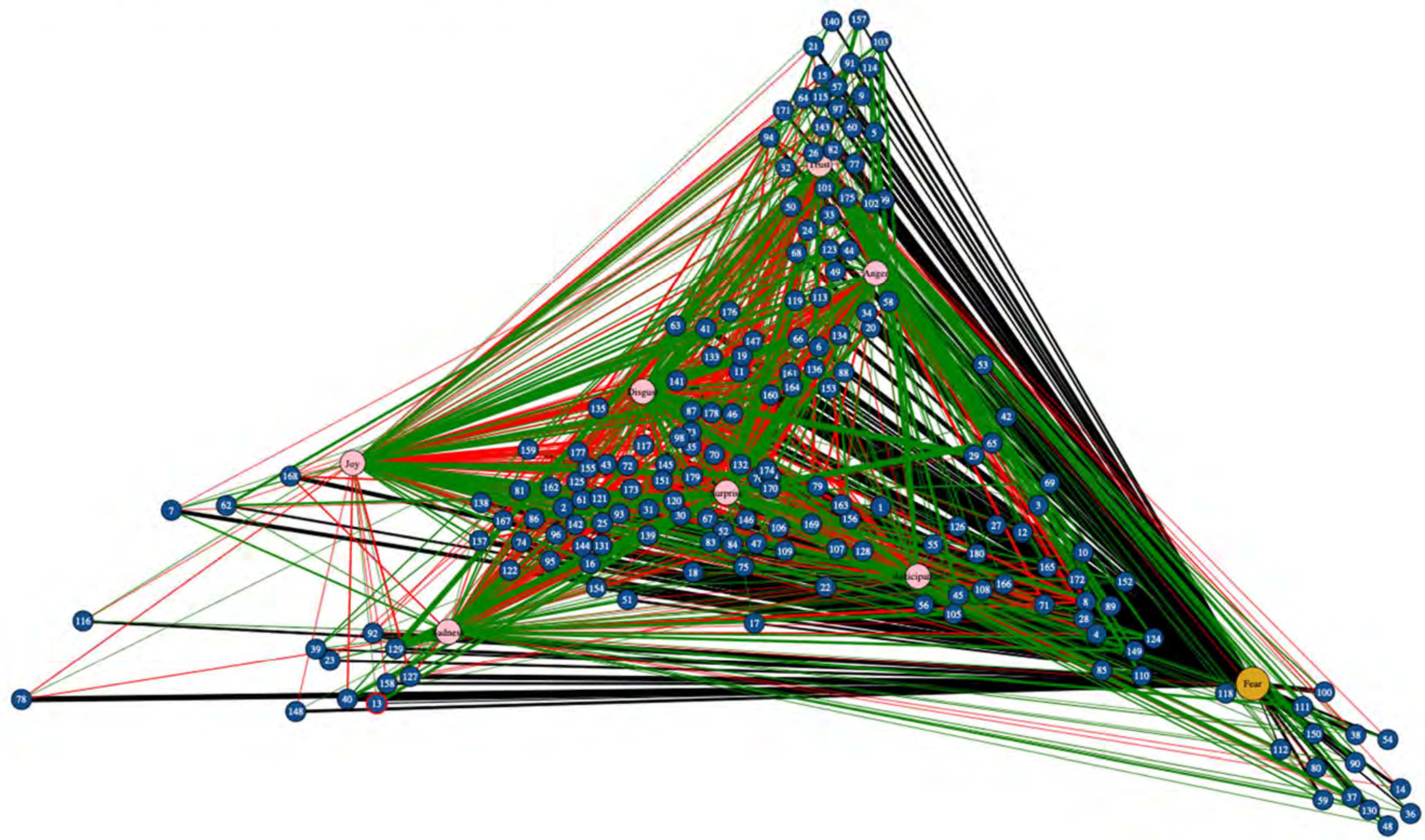


Figure 4.2. Bipartite Network Subgraph of Emotions with Significantly Weaker Effects on Topical Prevalence than Fear

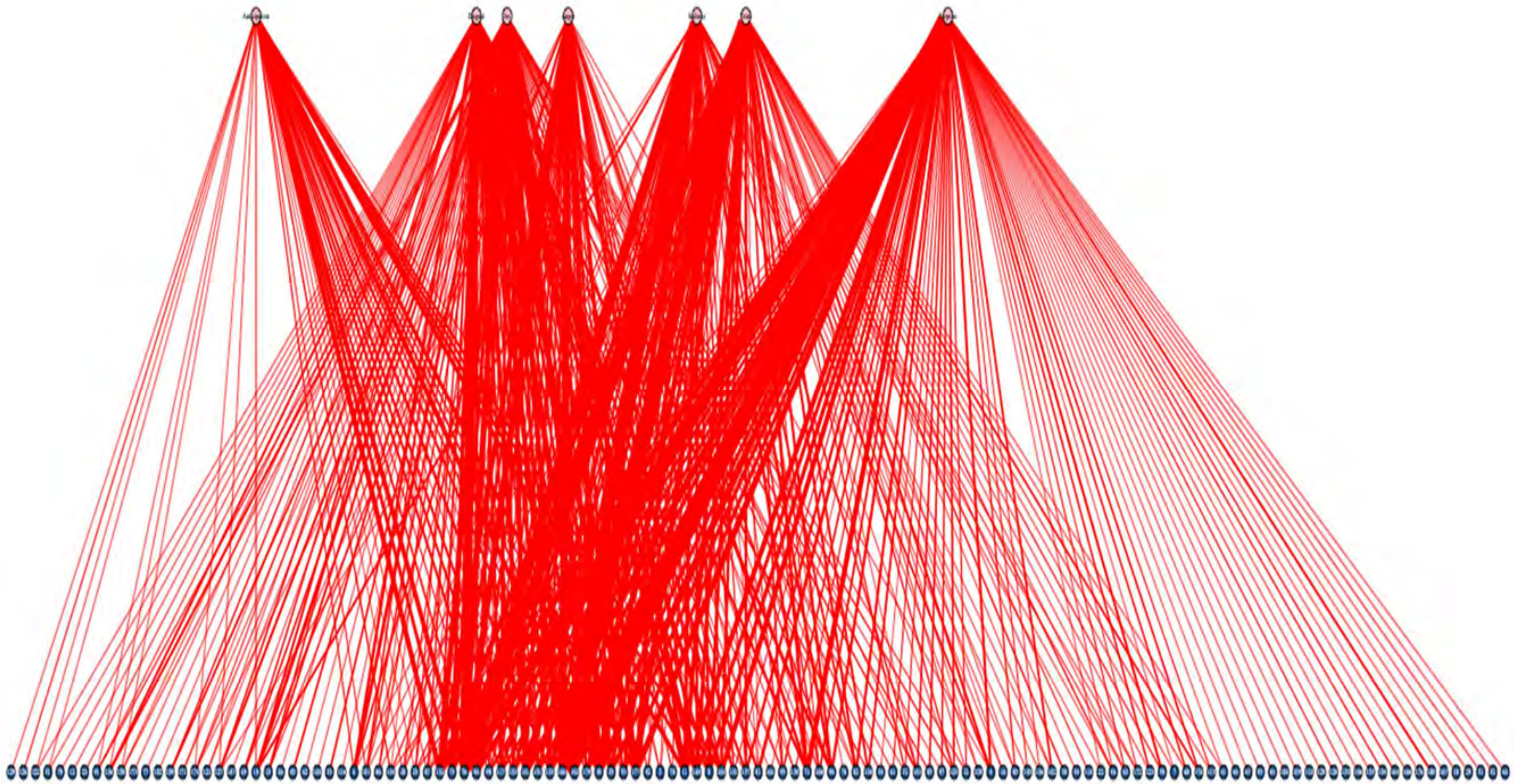
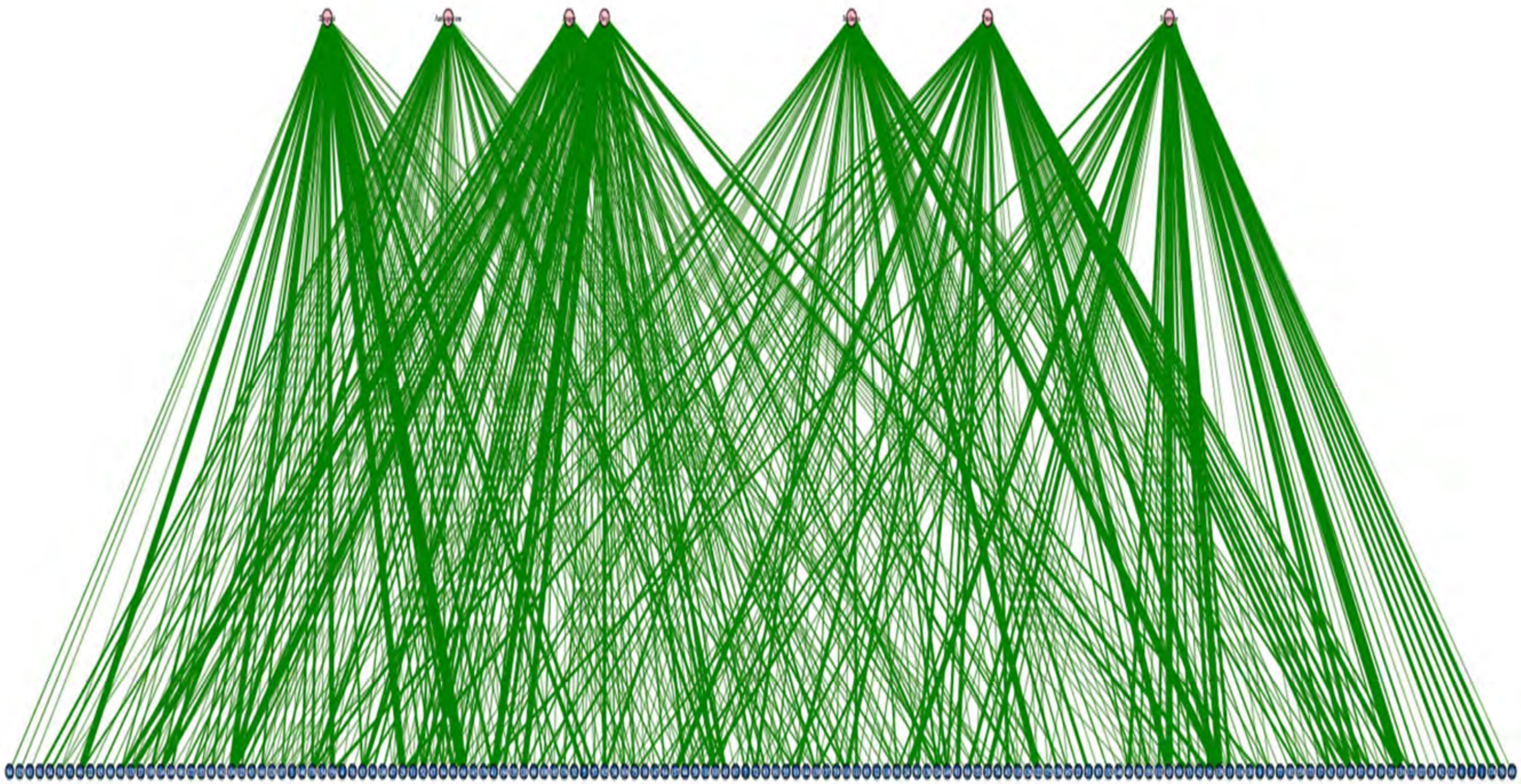


Figure 4.3. Bipartite Network Subgraph of Emotions with Significantly Stronger Effects on Topical Prevalence than Fear



Anger

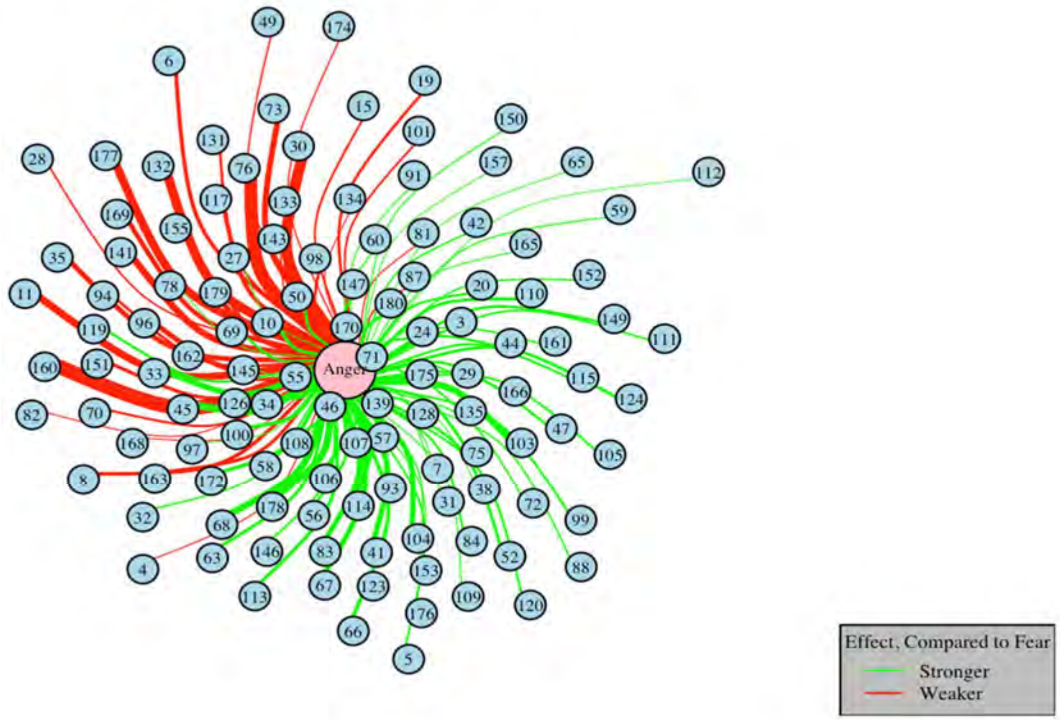
Anger had a significant effect on the prevalence of 120 of the 180 topics when compared with the effect of Fear, only 34 of which were significantly less than the effect of Fear (Figure 5.1). Most of the topics for which the effect of Anger was significantly different than Fear indicated that Anger had a significantly larger effect on the topic than Fear (Figure 5.1). However, the topics for which Anger was significantly less impactful than Fear tended to have larger effect sizes than for those where Anger's effect was significantly stronger than Fear (Figure 5.1, 5.2).

Figure 5.2 provides a different view of the network in Figure 5.1, with longer edges indicating stronger ties, or in this case, stronger effects of Anger compared to Fear (red and green edges) and stronger correlation between topics (grey edges). The effect of Anger was strongest compared to Fear for topics 8, 35, 76, 96, 112, 113, and 160 (Figure 5.2).

Among the topics for which the effect of Anger was strongest, those where Anger was significantly weaker than Fear were also significantly correlated with each other (Figure 5.2). Anger had a significantly stronger effect on the prevalence at which a topic was discussed than Fear for topics 112 and 113, which were not strongly correlated with each other (Figure 5.2).

At closer look, the strong effect of Anger compared to Fear may have been driven by the absence of "Angry" words combined with a single, highly prevalent, "Fearful" word that was also common across topics for topic 113. The word "don't" was a highly prevalent and highly "Fearful" word in topic 113, which had no pattern of prevalent "Angry" words (Figure 5.3f).

Figure 5.1. Network of Topics for Which the Effect of Anger was Significant



Less common “Fearful” words characterized other topics where there were no patterns of “Angry” words alongside a single, highly “Fearful” word (Figure 5.3c, Figure 5.3g). These also happened to be topics for which the effect of Anger on topical prevalence was significantly weaker than Fear (Figure 5.2, Figure 5.3c, Figure 5.3g). For example, the effect of Anger was significantly weaker than Fear in topic 160 (Figure 5.2), where the highly “Fearful” term “risk” was more exclusive to topic 160 (Figure 5.3g) than “don’t” was to topic 113 (Figure 5.3f). In topic 76, the “Fearful” term “COVID” was the lone highly prevalent term.

When there were patterns of “Angry” words alongside a single highly prevalent “Fearful” term, the effect of Anger was significantly weaker than the effect of Fear (Figure 5.2, Figure 5.3a). The “Fearful” term was also much more prevalent than the other, “Angry,” terms, an indication that the presence of the “Fearful” term “infection” may have been an important driver of the prevalence of tweets in topic 8 (Figure 5.3a).

In contrast to topic 113, the other topic for which the effect of Anger on topical prevalence was significantly stronger than Fear, topic 112, had few exclusively “Fearful” words, demonstrated by the words towards the center of the graph in Figure 5.3e shaded to indicate overlap between “Fearful” (red) and “Angry” (blue). The most prevalent among the “Angry” and “Fearful” terms from topic 112 was the “Angry” term “global,” a term also shown to be uncommon among other topics (Figure 5.3e). Other highly prevalent terms like “funding,” “cut,” and “congress” from topic 112 were “Fearful,” but also somewhat “Angry” (Figure 5.3e).

Figure 5.2. Strongest Effects and Correlation Between Topics in a Network of Topics for Which the Effect of Anger was Significant

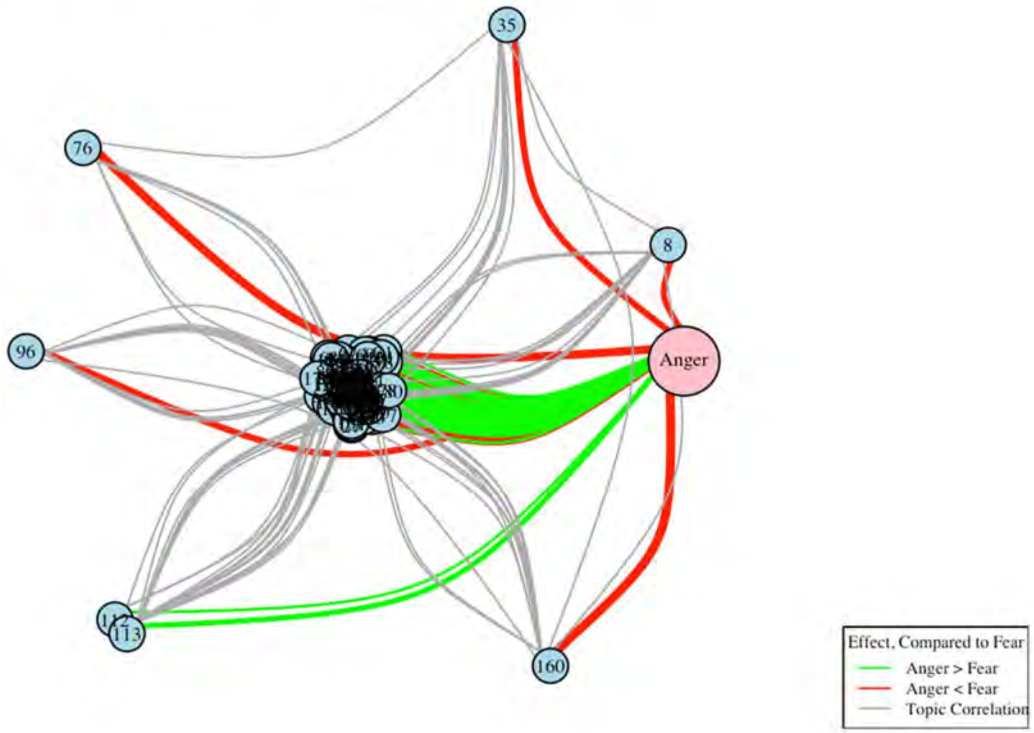


Figure 5.3a. Prevalence of "Angry" and "Fearful" Words in Topic 8

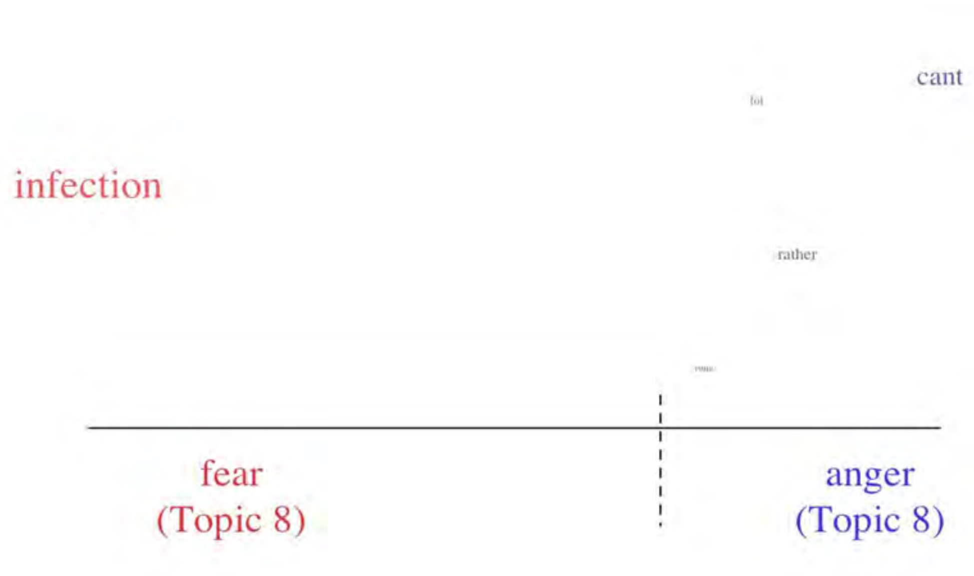


Figure 5.3b. Prevalence of “Angry” and “Fearful” Words in Topic 35

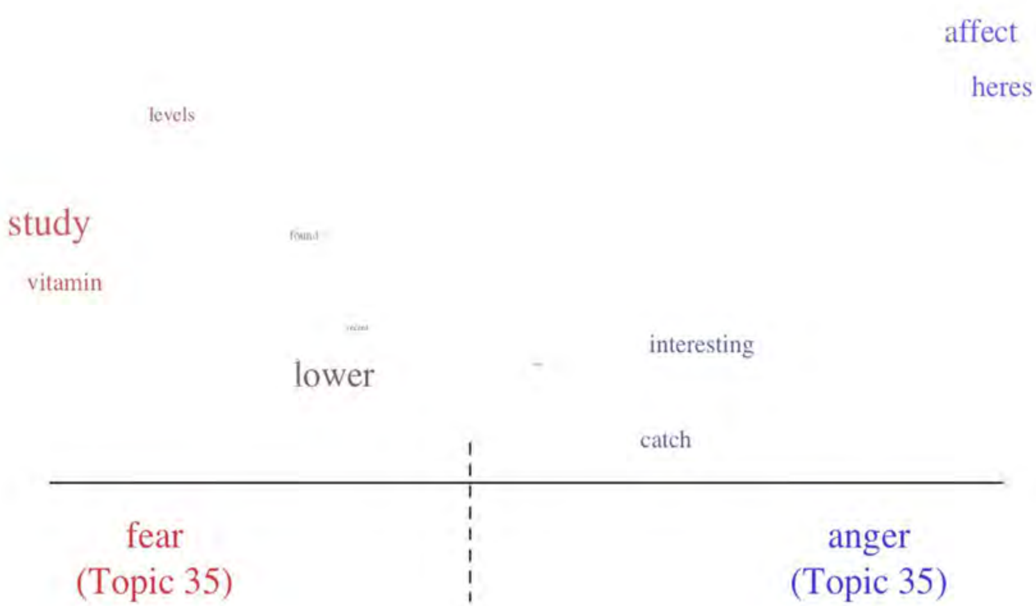


Figure 5.3c. Prevalence of “Angry” and “Fearful” Words in Topic 76

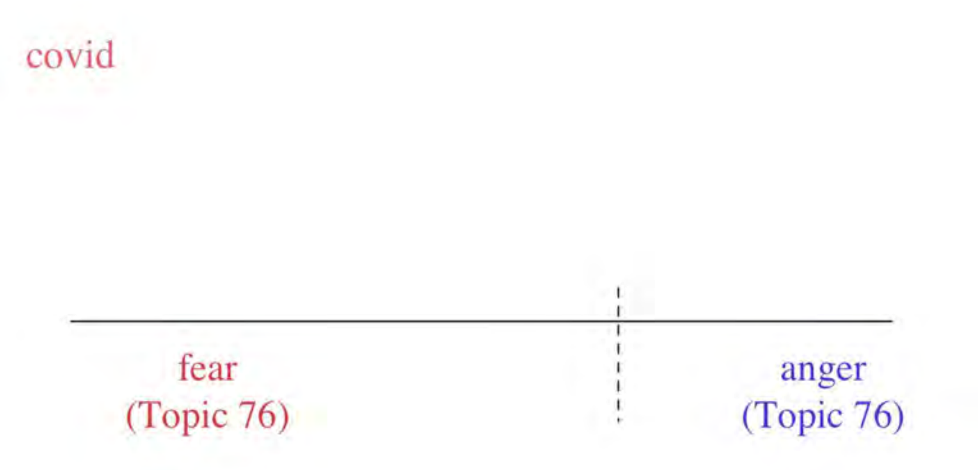


Figure 5.3d. Prevalence of "Angry" and "Fearful" Words in Topic 96

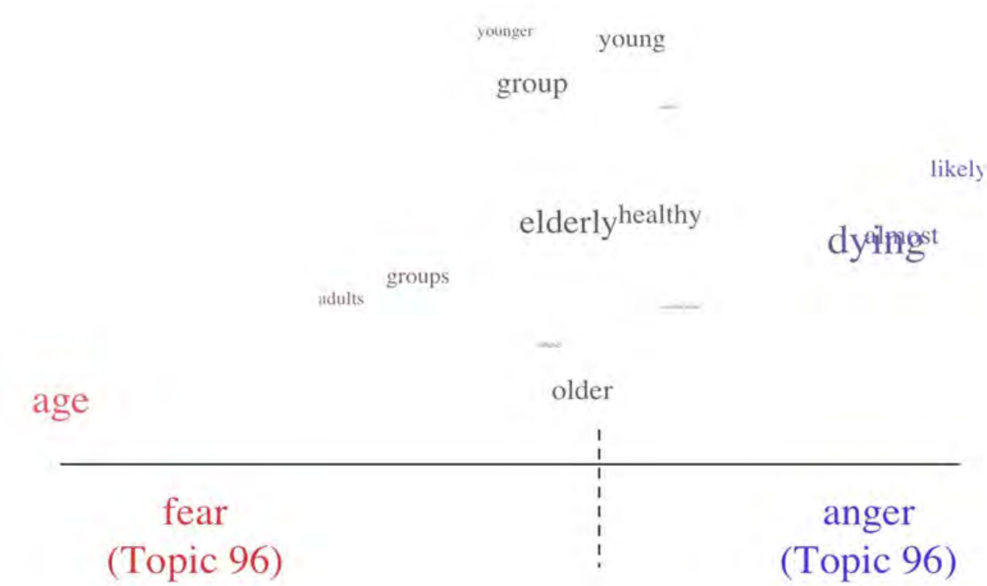


Figure 5.3e. Prevalence of "Angry" and "Fearful" Words in Topic 112

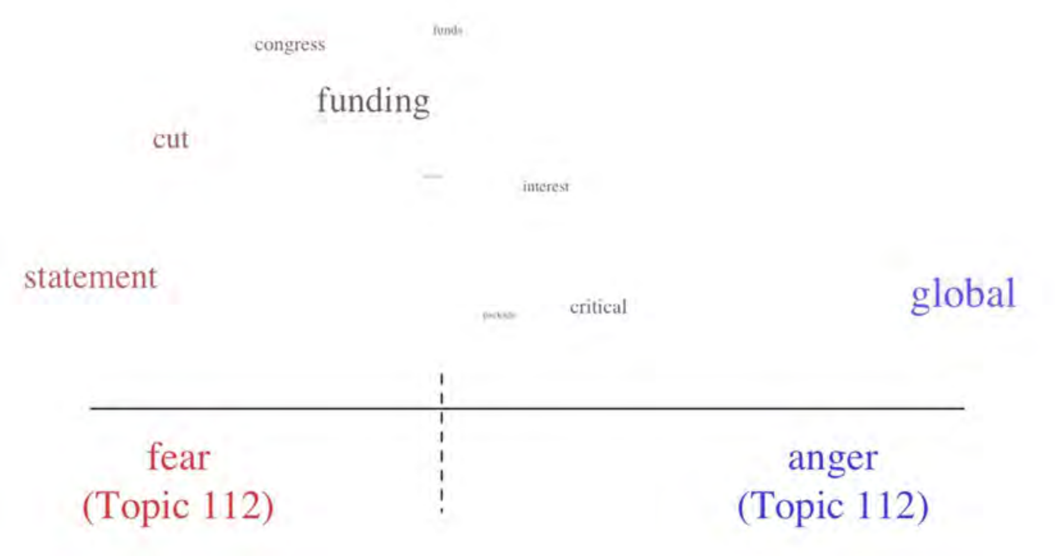


Figure 5.3f. Prevalence of "Angry" and "Fearful" Words in Topic 113

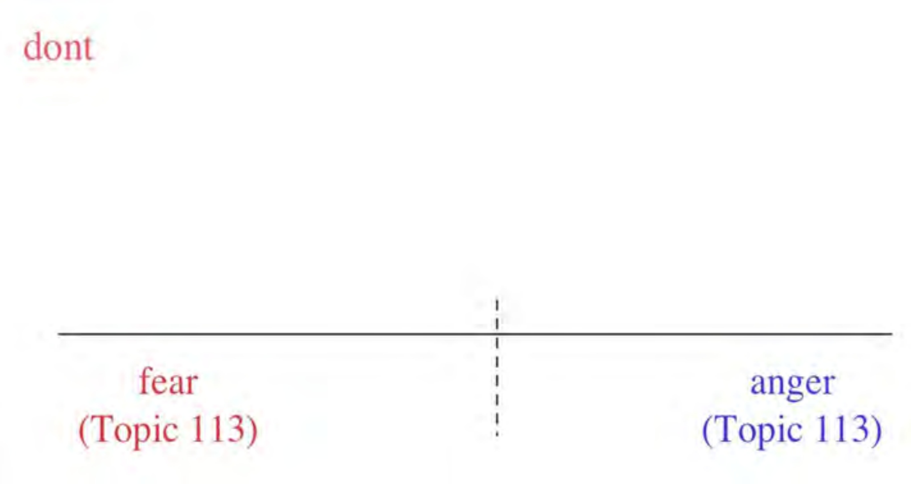
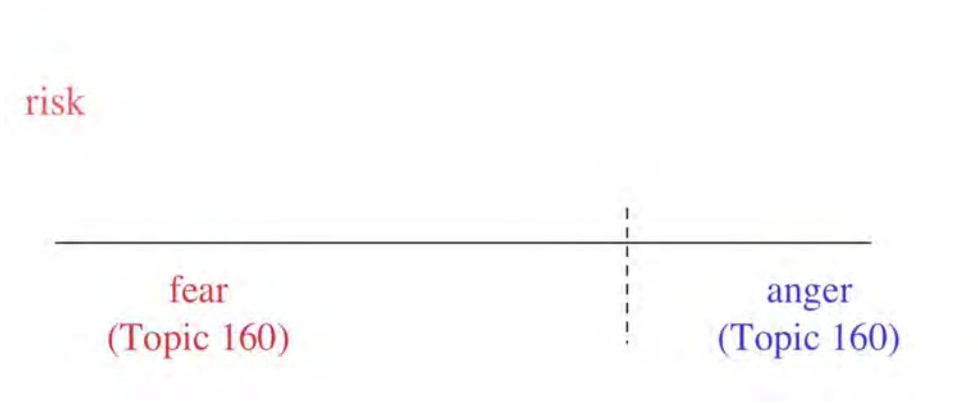


Figure 5.3g. Prevalence of "Angry" and "Fearful" Words in Topic 160



Some topics where the effect of Anger on topical prevalence was significantly weaker than Fear also included several terms that were both "Fearful" and "Angry." In some topics, the effect of Anger may have been reduced in part because, in addition to there being few exclusively "Angry" words, the only exclusively "Angry" words, while highly prevalent, were also highly common in other topics, such as the "Angry" word "dying" in topic 96 (Figure 5.3d).

The lone topic for which the effect of Anger was significantly weaker than the effect of Fear despite there being an apparently greater number of "Angry" words in the topic was topic 35 (Figure 5.3b). For this topic, the terms that were both highly prevalent and highly exclusive to topic 35 were either entirely "Fearful," or much more "Fearful" than "Angry" (Figure 5.3b).

Figure 5.4 includes additional ties linking topical categories to topics shown in Figure 5.1 to demonstrate whether the effect of Anger was significant compared to Fear in topics grouped under the same topical category. Notably, Figure 5.4 depicts the node representing the "Frontline Workers" topical category as an isolate. The absence of ties between "Frontline Workers" and all other nodes in the network indicates that the effect of Anger was not significant in any of the topics pertaining to frontline workers. There is also some evidence of a strong correlation between some, but not all, topics within the same categories for all categories containing topics for which the effect of Anger was significant (Figure 5.4).

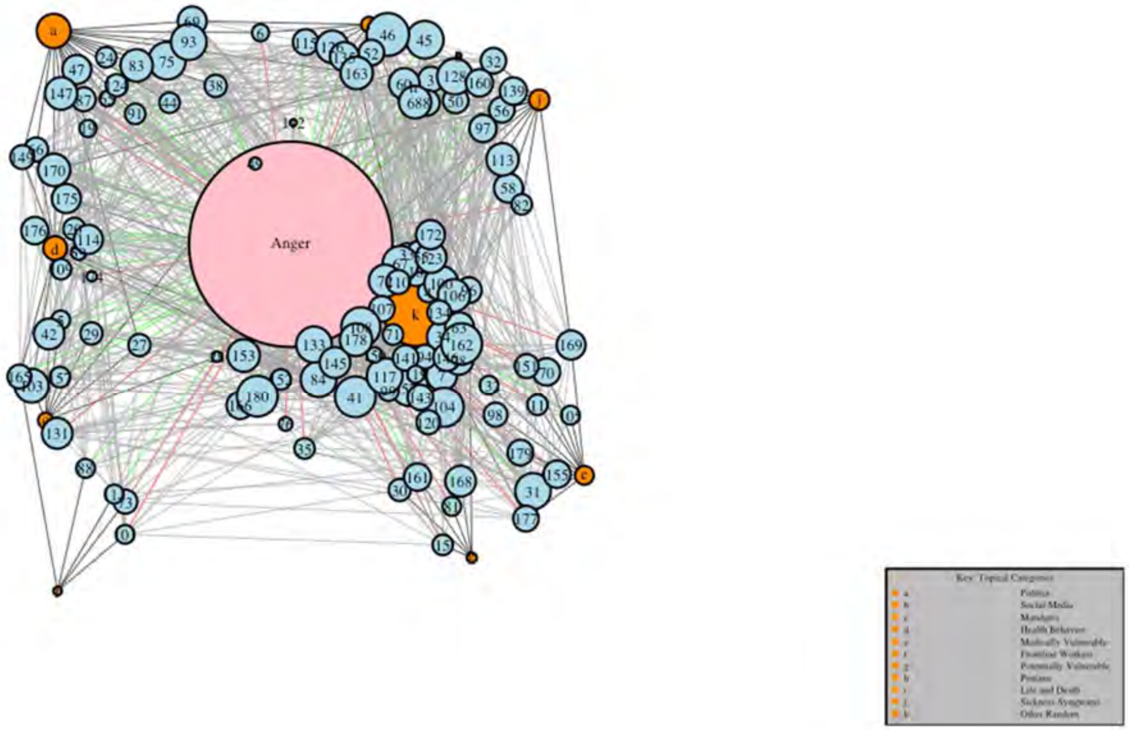
There was evidence of several strong correlations between topics of different categories, most of which indicated correlations between "Political" topics and topics related to risk mitigating "Health Behavior" (Figure 5.4). Anger tended to be either significantly stronger or significantly weaker for all topics under the same category, with one topical category, "Mandates," standing out for containing topics for which Anger was both significantly stronger and topics for which Anger was significantly weaker than Fear (Figure 5.4).

Among the topics for which the effect of Anger was the strongest (Figure 5.2), several of those for which Anger had a significantly weaker effect than Fear had ties to one distinct topical category (Figure 5.4). For example, Topic 8 was tied to the “Profane” category, which could have been an indication that profanity in Topic 8 was representative of Fearful rather than Angry sentiment (Figure 5.4).

Analysis by degree centrality and edge density also revealed indirect ties to a topical category through other topics. For example, Topic 160 was directly linked to the topical category of topics discussing medically vulnerable persons, but it was also indirectly linked to the topical categories grouping topics about “Social Media” and the “Profane” topic category. Topic 160 was hand-coded into the “Social Media” category because of the high prevalence of words specific to social media, but this finding suggests that Topic 160 was more closely tied to medical vulnerability.

Example tweets generated using the text of the actual tweets falling into topic 160 that were identified as being emotionally “Angry,” provide evidence supporting that topic 160 had something to do with the idea of medical vulnerability. Specifically, Anger in topic 160 was aimed at denial and lack of understanding of medical vulnerability during COVID. Some Angry tweets lamented that people’s understanding of the risks COVID posed to medically vulnerable people was maligned with reality (Figure 5.4a). These included tweets about a general lack of understanding amongst the public that many felt was not due to any fault of the public themselves, but also tweets about intentional spread of misinformation by people in power who had more access to information than the public (Figure 5.4a).

Figure 5.4. Strength of Ties between Categories and Topics for which the Effect of "Anger" on Topical Prevalence was Significantly Different Than the Effect of "Fear"



Note: Larger nodes indicate higher degree centrality; Wider edges indicate greater edge density.

Other tweets indicated a sort of Angry shock over the activities other people were willing to engage in, given the high risk posed by COVID-19. For example, one example tweet in topic 160 indicated that some users would not agree that the chain diner “Denny’s” was worth the risk of getting COVID, but also that there were members of the public engaging in this behavior somewhat frequently (Figure 5.4a).

Analysis by degree centrality and edge density shows that Topic 35 was closely tied to Anger, even when accounting for ties to topical category (Figure 5.4). It also identified topic 35 as a highly central among topics where Anger had a significant effect on topical prevalence. Angry tweets in topic 35 were comprised of disagreements over risk mitigation during COVID (Figure 5.4b). This included users who felt the risk from COVID was overblown, but also users who felt the risk of COVID was underappreciated (Figure 5.4b).

The Hierarchical Random Graph (HRG) Model for topics where Anger had a significant effect on topical prevalence illustrates the probability of ties between 132 nodes in the network when it is split into two hierarchical subtrees (Figure 5.5a-b). The hierarchical random graph model examining the network of Anger, topics, and topical categories, projected 23 levels, identifying “Frontline Workers” as the lone root node connecting the two subtrees and an approximately 4% probability (Figure 5.5a).

Most of the groups were clustered in one subtree stemming from group 16 at level 2 of the hierarchy with an approximate probability of 3%, while the second subtree projected a 0% probability of group 21 at level 2, which contained the topical categories for “Social Media” and “Profane” topics (Figure 5.5a).

Figure 5.5a. Probability of Ties in a Fitted Hierarchical Random Graph Model Topical Categories, Topics, and Anger

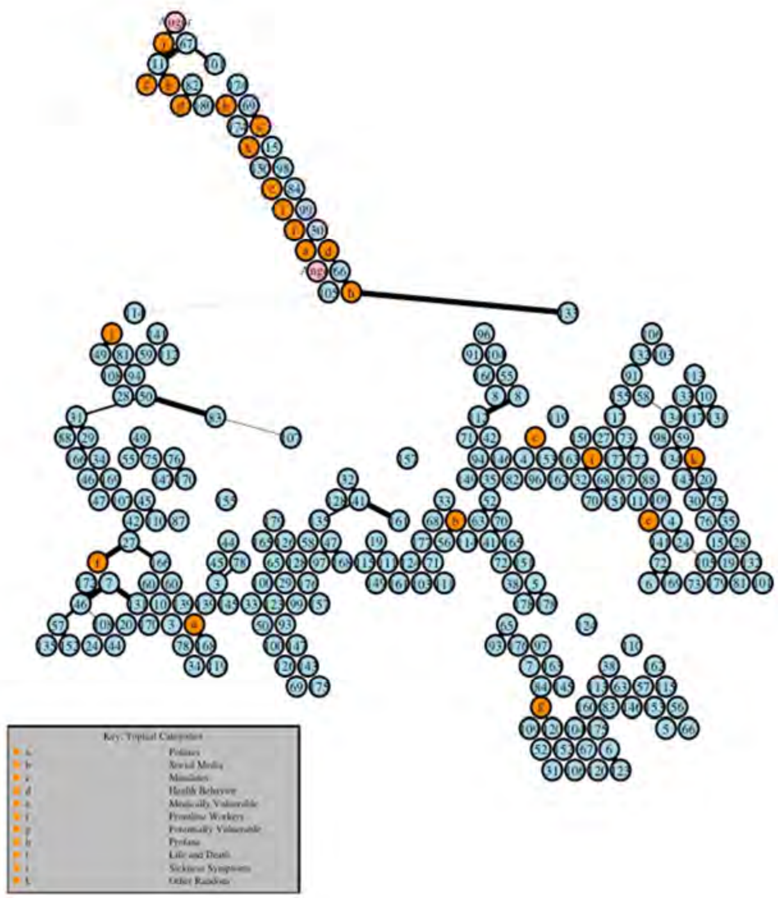


Figure 5.5b. Predicted Probability of Ties based on a Fitted Hierarchical Random Graph Model Topical Categories, Topics, and Anger

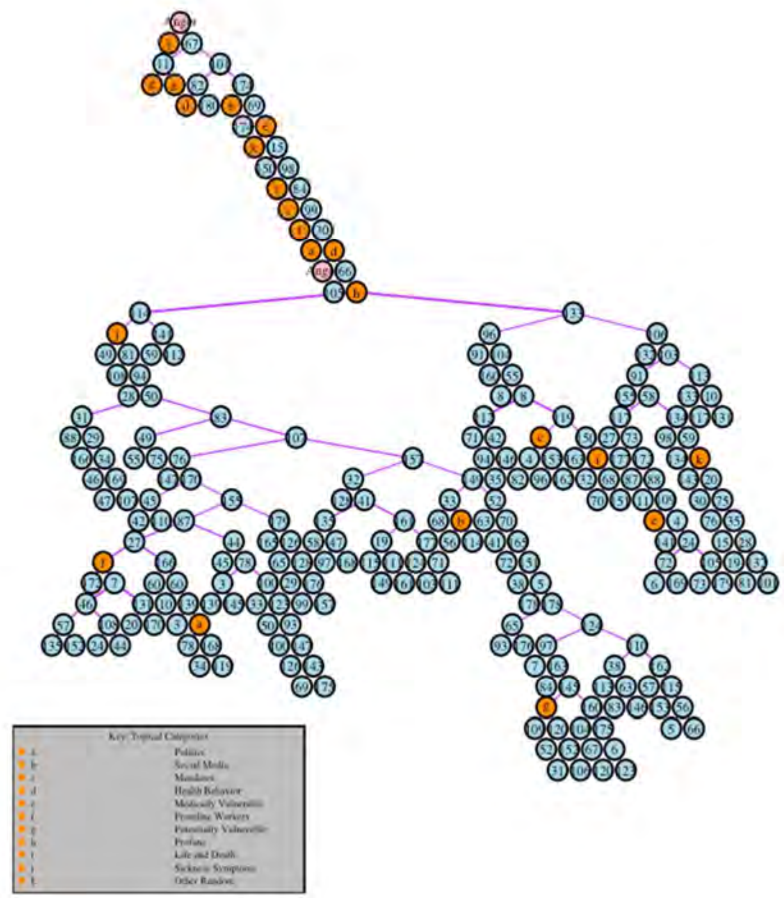
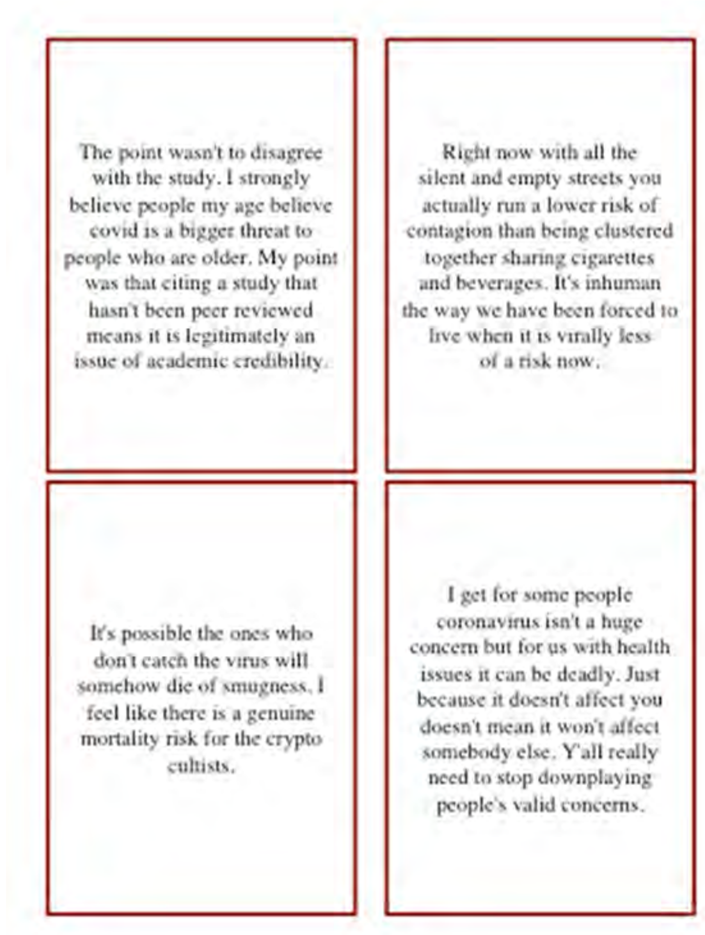


Figure 5.6a. Examples of 'Angry' Text in Topic 160 Tweets

Figure 5.6b. Examples of 'Angry' Text in Topic 35 Tweets



The predicted hierarchical random graph model revealed several additional possible missing ties, and the strength of predicted ties was diminished for ties that were very strong in the original hierarchical random graph model (Figure 5.5a-b). All of these ties occurred within subtrees, not between, which suggests the hierarchical random graph model was a fairly good fit, but that the strength of ties between nodes in each subtree is fairly consistent. The network may be more cohesive and less disjointed than the original hierarchical random graph might suggest, per the predicted hierarchical random graph model. This means that, regardless of topic and topical category, topics with similar levels of Angry sentiment are closely tied to each other.

The fitted and predicted probabilities for the Anger hierarchical random graph model indicate that many of the topics where Anger significantly effected topical prevalence were related to “Frontline Workers” (Figure 5.5a-b). However, considering the estimated effect of Anger on topics in the 180-topic structural topic model of general risk tweets being strongest when negative, this could be an indication that the absence of Angry sentiment played an important role in topical prevalence for topics containing tweets about frontline workers.

Anticipation

Anticipation had a significant effect on 104 of the 180 topics when compared with the effect of Fear (Figure 4), 38 of which were significantly less than the effect of Fear (Figure 4.1, Figure 6.1). There were 66 topics in which the effect of Anticipation was significantly larger than the effect of Fear, identified with green ties in the network graphs (Figure 4.2, Figure 6.1).

When adjusting the layout to reflect node centrality and strength of ties, several topics had stronger ties to Anticipation than others in the network, as shown by the longer ties in Figure 6.2. Edge density reflects degree centrality, with denser edges indicating that a topical node has more than one tie to Anticipation due to its association with other topics in the network (Figure

6.2). While Anger only had a few topics that were much more strongly tied to the emotion than other topics, Anticipation had strong ties to more than double that number of topics (Figure 5.2; Figure 6.2). I chose to focus on the topics that had strong ties to Anticipation and high degree centrality per the density of the edge between the topic and Anticipation. Topics 76, 96, 104, 110, 114, and 132 were strongly tied to Anticipation but also directly tied to many other topics (Figure 6.2).

A single word was representative of both Fearful and Anticipatory tweets in Topic 76, a topic for which the effect of Anticipation was significantly less than the effect of Fear (Figure 6.2). The word "COVID" characterized Fearful and Anticipatory tweets in Topic 76, but point estimates indicate that the word was most commonly Fearful (Figure 6.3a).

Other topics for which the effect of Anticipation was significantly less than Fear included topics 96 and 132 (Figure 6.2). Interestingly, unlike topic 76, these two topics had words that appeared most often in context of Anticipatory sentiment, including the word "COVID," which was classified as almost entirely Anticipatory in topic 132 (Figure 6.3f). There were many words appearing frequently in context of Fearful sentiment for both topics 96 and 132, though, which would suggest a higher prevalence of Fearful tweets in the topics overall paired with the use of certain words most often in context of Anticipation, not Fear (Figure 6.3b; 6.3f).

Topic 96 had many tweets using the words "age," "elderly," "death," and "group(s)" in a Fearful context (Figure 6.3b). When taken in context of the words used in an Anticipatory context, the words "young" and "less" here are a possible indication that there was Anticipation about whether there could be a lower level of Fear for younger people's risk of dying. They could also indicate that people were Fearful about the risk of COVID-19 for older people (Figure 6.3b).

Figure 6.1. Network of Topics for Which the Effect of Anticipation was Significant

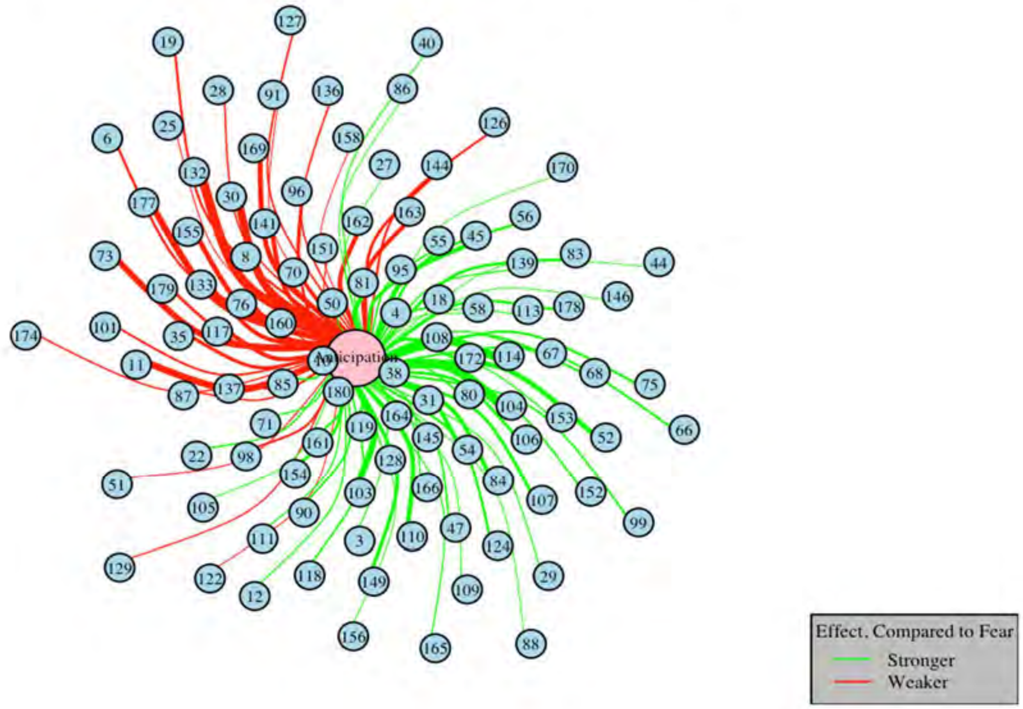
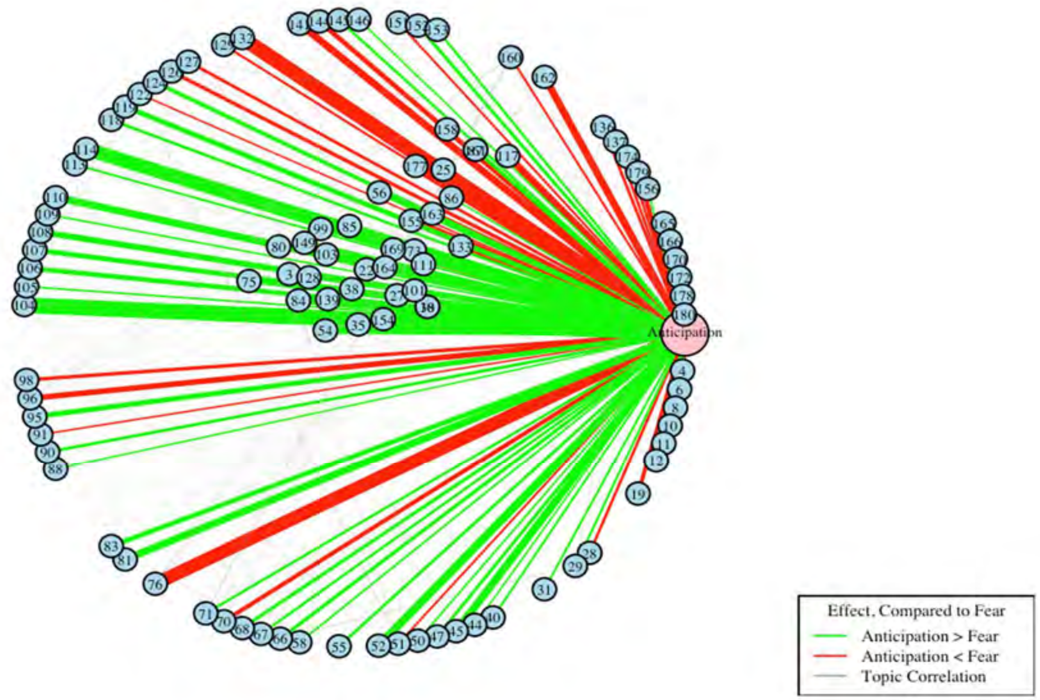


Figure 6.2. Strongest Effects and Correlation Between Topics in a Network of Topics for Which the Effect of Anticipation was Significant



Topic 132 had a similar focus on different levels of risk for different social groups. However, instead of primarily focusing on age-based risk like in topic 96 (Figure 6.3b), topic 132 indicated a sense of Fear for people with disabilities with words like “underlying,” “conditions,” and “adverse” included among those used frequently in a Fearful context (Figure 6.3f). Instead of anticipating instances in which Fear could be lower, as in topic 96 (Figure 6.3b), topic 132 tweets seemed to be anticipating an increasing Fear for the safety of people who are chronically ill (Figure 6.3f).

In topics 104, 110, and 114, the effect of Anticipation on topical prevalence was significantly greater than the effect of Fear (Figure 6.1-2). Only the word “will” was prevalent enough to be included among the highly prevalent Fearful and Anticipatory words in topic 110, and while it was used most often in an “Anticipatory” context, the absence of Fearful words in the comparison between Anticipation and Fear in topic 110 could be an indication that Anticipation was about something irrelevant to Fears over COVID risk in this topic (Figure 6.3d).

Topic 104 Fearful words included things like “ventilator” and “weeks” (Figure 6.3c). In context of the Anticipatory words “can” and “get,” topic 104 reveals possible Fear about how long people would be on a ventilator when in the hospital and Anticipation about their release back home (Figure 6.3c).

Topic 114 words high on Fear and Anticipation largely related to vaccination. Most of the words were used in about an equal number of Fearful and Anticipatory contexts, demonstrated by the words clustering near the center of the graph with a purple shade to indicate their equidistance between Fear (red) and Anticipation (blue) in Figure 6.3e. Smaller words are those used less often, with larger words appearing the most frequently among tweets in a topic.

Figure 6.3a. Prevalence of "Anticipatory" and "Fearful" Words in Topic 76

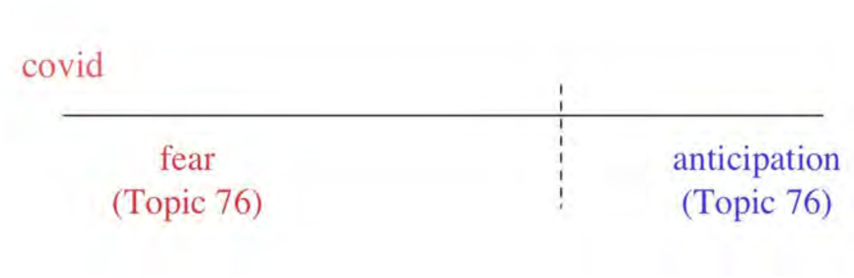


Figure 6.3b. Prevalence of "Anticipatory" and "Fearful" Words in Topic 96

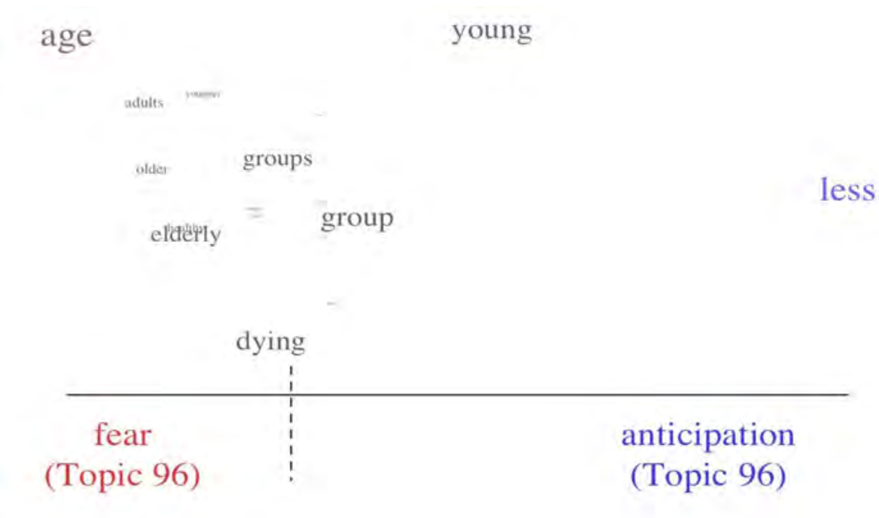


Figure 6.3c. Prevalence of “Anticipatory” and “Fearful” Words in Topic 104

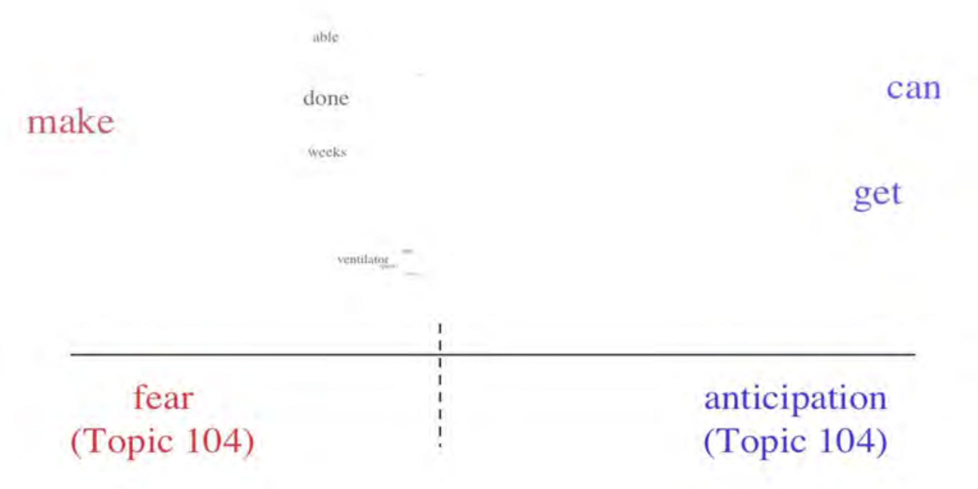


Figure 6.3d. Prevalence of "Anticipatory" and "Fearful" Words in Topic 110

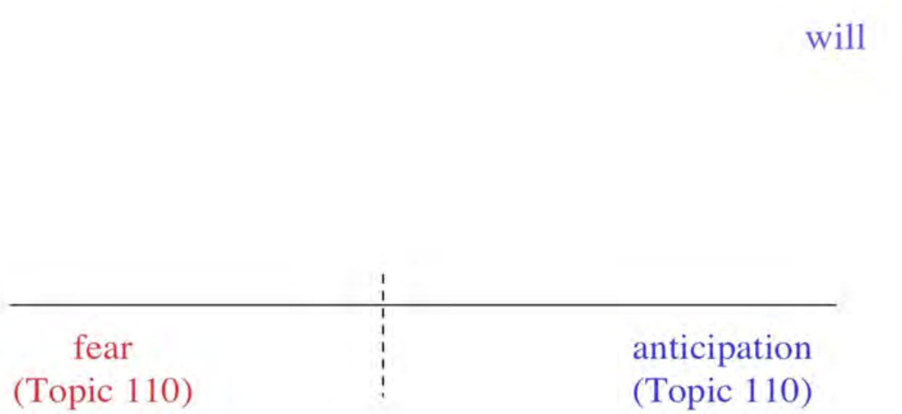


Figure 6.3e. Prevalence of “Anticipatory” and “Fearful” Words in Topic 114

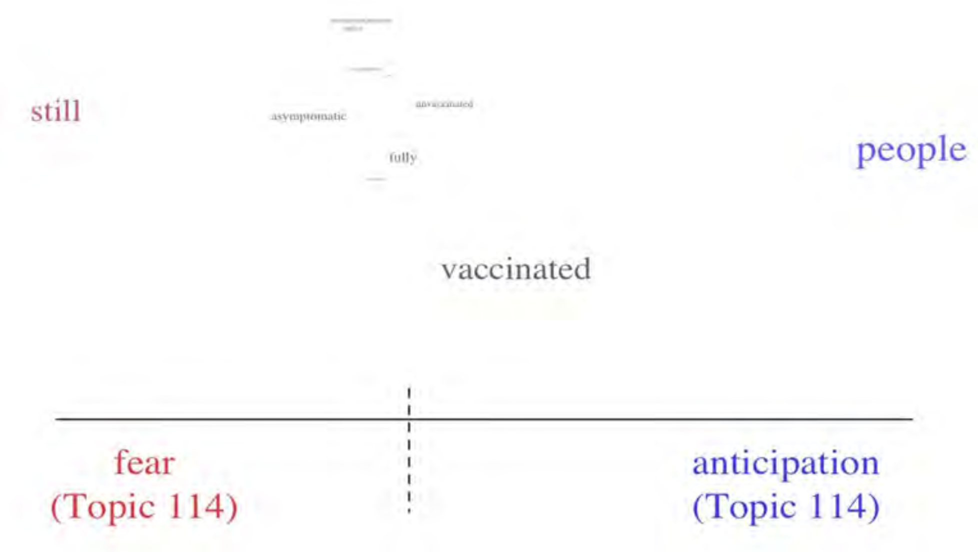
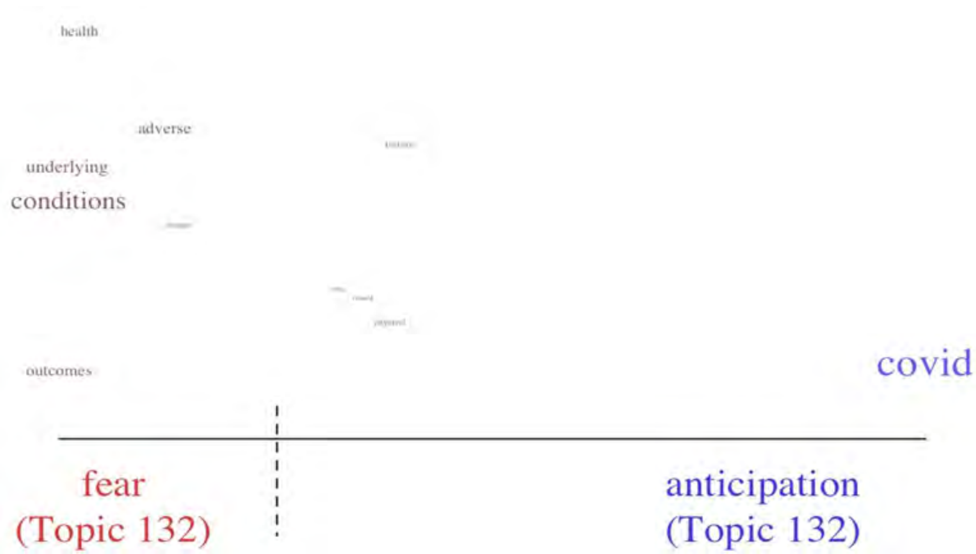


Figure 6.3f. Prevalence of "Anticipatory" and "Fearful" Words in Topic 132



The words “vaccinated,” “people,” and “still” stood out as most frequent compared to the other highly prevalent words for Anticipatory and Fearful contexts, which included words like “unvaccinated,” “fully,” and “asymptomatic” (Figure 6.3e). Topic 114 reveals possible Anticipation over the vaccine paired with Fear over people remaining unvaccinated, being under-vaccinated, and the potential to still spread COVID once vaccinated.

Upon addition of the topical categories to the network showing topics with significant ties to Anticipation, three topical categories had much higher degree centrality than the others, indicating more topics tied to Anticipation were tied to these topical categories than the other categories. There were more topics with significant ties to Anticipation in the “political” and “health behavior” categories than all others besides the “other/non-classified” category (Figure 6.4).

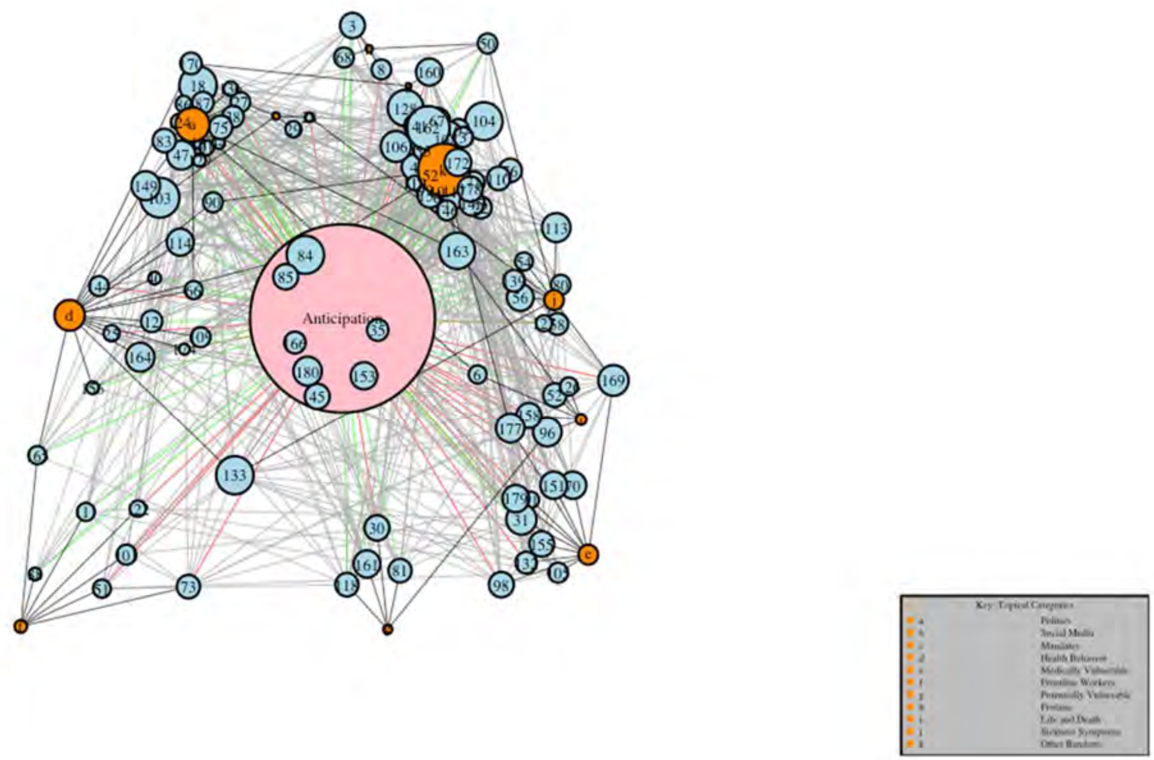
When accounting for hand-coded ties to topical categories, most of the topics with high degree centrality and strong ties to Anticipation were clustered around the “other/non-classified” topical category and other topics with the same classification (Figure 6.4). However, the nodes for topics 114 and 96 provide additional useful information for interpreting the meaning of Anticipation for different topics of conversation that are similar.

Topic 114 was strongly tied to the “health behavior” category (node “d” in Figure 6.4), but it was only tied to the other topical categories through its association with other topics. Given the evidence that topic 114 tweets were about vaccination, specifically getting or not getting vaccinated, this could be an indication that tweets in topic 114 discussed vaccination almost entirely as a health behavior. Topic 114 had many ties to topics clustered around the “political” and “sickness symptoms” categories, and because topic 114 was so focused on vaccines, it is possible the topics with which it is strongly associated are also about vaccines (Figure 6.4). If this is the case, some of the other focuses of vaccine-related topics where the effect of Anticipation on prevalence was significant could include politics surrounding vaccination, and the purpose behind vaccination, which was the mitigation of illness symptoms and severity.

Topic 96 was directly and strongly tied to two topical categories, “Life and Death” (node “i”) and “Potentially Vulnerable Groups” (node “g”) (Figure 6.4). Anticipation in topic 96 touched on the Anticipation of the risk the older age groups, which many people indicated was somewhat frightening (Figure 6.3b), so the strong tie between topic 96 and the broad topical category of “Life and Death” makes sense here. The strong tie to the broad topical category focused on “Potentially Vulnerable Groups” could be an indication that there is not firm consensus on whether the elderly should be classified as vulnerable. The network graph reveals that topic 96 is also indirectly tied to an additional topical category, though, through its association with topic 70. Topic 96 was indirectly tied to the “Medically Vulnerable” category (node “e”) through topic 70, which hints at a possible discussion of elder vulnerability in terms of whether and the extent to which elders are medically vulnerable (Figure 6.4).

There was no single root node in the hierarchical random graph models for Anticipation, topics, and topical categories (Figure 6.5a-b). Instead, there are two vertex groups at the first level, or comprising group 1 of the hierarchical random graph model (Figure 6.5a), with an approximately 3% ($P = 0.031$) probability that vertex pairs in the left tree (group 86) connect to the vertices in group 23 representing the “Social Media” and “Mandates” topical categories in the right tree. In the predicted model, the probability is much higher, about 94% ($P = 0.94$) (Figure 6.5b).

Figure 6.4. Strength of Ties between Categories and Topics for which the Effect of "Anticipation" on Topical Prevalence was Significantly Different Than the Effect of "Fear"



Note: Larger nodes indicate higher degree centrality; Wider edges indicate greater edge density.

Additionally, in the fitted model, the probability that the vertices in group 23 are connected to each other was 0 (Figure 6.5a), but the predicted model suggested that there was about a 40% probability (P = 0.4) that the “Social Media” and “Mandates” topical categories were linked (Figure 6.5b).

The left tree, or group 86, had two subgroups, group 114 and group 92, whose probability of being linked was 4.5% (P = 0.045) in the fitted model and 31% (P = 0.31) in the predicted model (Figure 6.5a-b). The predicted model provides some evidence that the fitted model placed too much emphasis on the links between the nodes in group 114, the largest group, while missing a possible link between the nodes in group 92. The fitted model projected a 95% probability (P = 0.95) that links exist between all nodes in subgroup 114 and a probability of 0 that the nodes in group 92 were tied to each other (Figure 6.5a). The predicted model indicated that the probability of the “Profane,” “Potentially Vulnerable Groups,” and “Life and Death” topical categories in group 92 were tied to each other was as high as 30% (P = 0.3) (Figure 6.5b). It also indicated that the probability that the nodes in the largest subgroup (group 114) were tied to each other was as low as 40% (P = 0.4) (Figure 6.5a-b).

Most notably, the “Anticipation” node fell into the large subgroup, group 114, and in the fitted model, there was a 95% probability (P = 0.95) it was linked to other nodes in the network only indirectly through their link to group 105, or the vertex pair for group 10 and “Risk Mitigating Behavior” (Figure 6.5a). This would suggest that “Anticipation” was only loosely tied to topics and topical categories in the network, except for “Risk Mitigating Behavior.”

**Figure 6.5a. Fitted Hierarchical Random Graph Model
Topical Categories, Topics, and Anticipation**

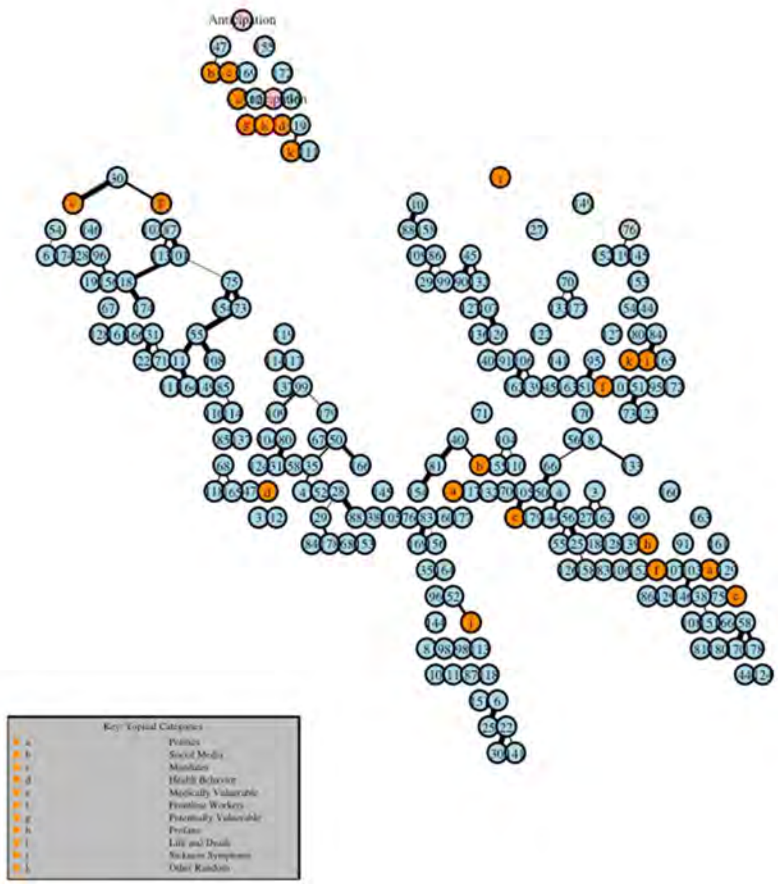
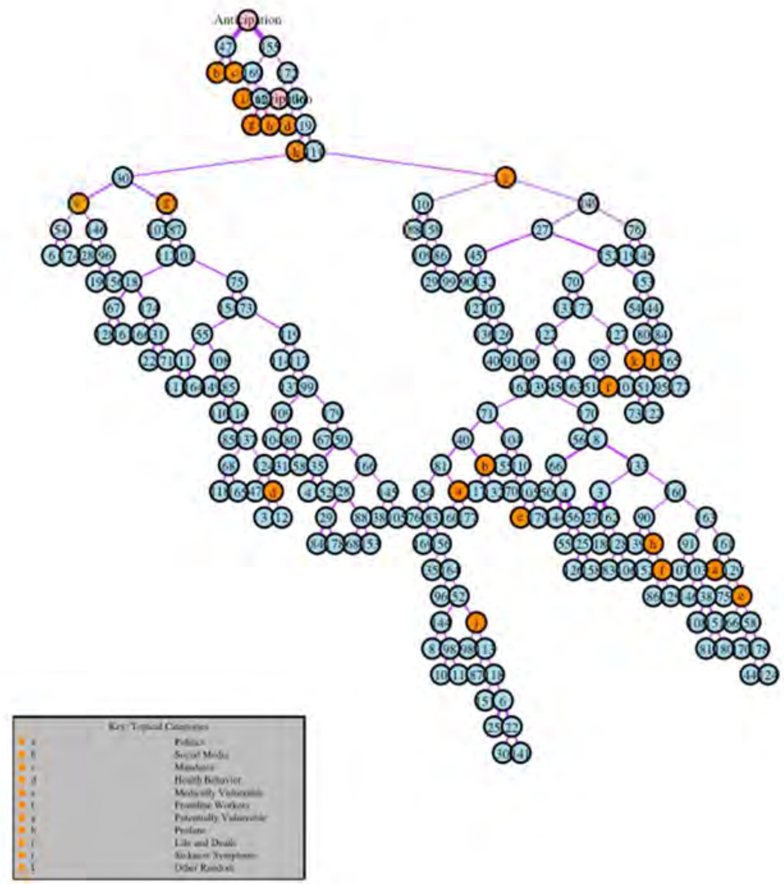


**Figure 6.5b. Predicted Hierarchical Random Graph Model
Topical Categories, Topics, and Anticipation**



The predicted probability was much lower at approximately 28% (P = 0.284), and the predicted model revealed possible direct ties between "Anticipation" and topics 47 and 155, and indirect ties between "Anticipation" and topics 3 and 12 through a mutual connection to the "Risk Mitigating Behavior" topical category (node "d") (Figure 6.5b).

These findings suggest that Anticipation in tweets about risk during COVID was most often in relation to risk mitigating behavior, and that topics 47, 155, 3, and 12, may be important representatives of Anticipatory sentiment during the first 19 months of the COVID-19 pandemic, and thus, warrant closer examination.

Example text generated using the real text of tweets in each topic reveals that the topics with possible direct ties to Anticipation per the predicted hierarchical random graph model both dealt with vaccination, but each had a slightly different focus. In topic 47, Anticipation related to vaccines was pre-emptive, with many discussing what the future of risk mitigation would look like after vaccination (Figure 6.6a). Anticipation in topic 155 also discussed what risk mitigation would look like after vaccination, but the tweets in topic 155, rather than asking about future risk mitigation as in topic 47, seemed to provide answers to some of the questions raised in topic 155. For example, one example generated from the text of tweets in topic 155 proposed that risk mitigation with vaccines would include the issuance of vaccine passports for the vaccinated to present as proof that they no longer needed additional mitigations like masks (Figure 6.6b).

Figure 6.6a. Text Representative of 'Anticipatory' Tweets in Topic 47

Look it's just three weeks. You need to remind yourself that we need to learn to live with the virus so we will have to continue to refine the ways we mitigate risk.	We can't have zero risk tolerance in public heath policy because of a want rather than a need for the public to buy in. I doubt fully vaxxed people will take off their masks any time soon they have avoided it so far they do not need another type of incentive as encouragement.
No jobs or houses or anything else you need to get. Just quarantine if you can we need to do anything to stop this huge emergency. Wear masks until summer we are talking cold weather you idiot.	Everyone supports valid medical exemptions, for example, children with cancer can not get live virus vaccines. Some children need real exemptions, the non-medical exemptions are the issue for children who need herd immunity. The antivaccine activists put them at risk.

Figure 6.6b. Text Representative of 'Anticipatory' Tweets in Topic 155

I am low risk. People with HIV can get it but frankly come the vaccine I think we will all get in line to kick the virus to the curb and honor the dead.	I agree there are a lot of recent cases in vaccinated individuals who are still testing. I think there is substantial evidence that before long vaccinated individuals will be able to carry the virus. I got J&J and still wouldn't risk such an awful situation.
The government will issue vaccination passports. It is for individuals who are vaccinated for covid were issued passports certifying they are longer at risk catching the virus and infecting anyone.	Those with pre-existing conditions who get the virus have a much higher risk of dying. The Moderna vaccine is effective but there is still a chance to get vaccinated. We need immunity it is the safest way bring things back to how they were.

Figure 6.7a. Text Representative of 'Anticipatory' Tweets in Topic 3

Head of safety and risk management @[university] campus said two persons have tested positive for covid but at present they are not on campus.

We have a plan to mitigate risk and limit the spread of covid on our campus. The @[university] community will succeed only if every student, faculty, and staff member commits to the appropriate public health behavior on campus.

@[hospital] staff charge was absolutely wonderful not mean at all yet students were denied if they were staying on campus because they are a health risk. Since I have worked healthcare I don't understand like how ironic.

It definitely feels a little gross for @[university] to be making players sign risk waivers. If you think they will get the virus by coming to campus don't bring them to campus and then decide they bear responsibility for themselves and not the university. Glad @[university] didn't follow suit.

Figure 6.7b. Text Representative of 'Anticipatory' Tweets in Topic 12

So what's DC going to do when the first cases of covid start hitting classrooms next week when children show up sick? Teachers will start finding other jobs if there is too much risk. Is DC willing to put children on the line?

This is a novel virus there is so much we don't know. Stop with the copouts, we have no data on covid risk in schools for kids and too many kids are sick bc of the irrational fear many held that unless they have at least one day a week in-person it isn't worth it.

Our schools have no definitive plans around the start of school. umm hello the start of school is in a few weeks. I think there is zero chance of Fall sports with this much risk and so much unknown about the virus.

Decisions from the state board, who are expected to meet next week, will affect all students who attend class. I don't know how Tennessee works but to be blunt there will be fallout if covid gets from the school into communities.

Topics 3 and 12 were possibly tied to Anticipation through the "Risk Mitigating Behavior" topical category (node "d", Figure 6.5a-b), and differently than topics 47 and 155 with prospective direct ties to Anticipation, topics 3 and 12 were not focused on a specific risk mitigating health behavior like vaccination. In fact, most of the example tweets generated for topics 3 and 12 did not mention any specific behaviors at all, but rather, criticized and questioned the response to COVID in schools (Figure 6.7a-b).

Expressly, topics 3 and 12 were focused on the responses by universities and in primary/secondary schooling, respectively (Figure 6.7a-b). These topics were focused on the response by institutions, including potential plans for mandatory and/or recommended risk mitigating health behavior, not the behaviors themselves.

Disgust

The effect of Disgust was significantly different than the effect of Fear for 116 of the 180 total topics (Figure 4; Figure 7.1). Disgust had a greater effect on the topical prevalence than Fear in 60 topics (Figure 4.2; Figure 7.1), and while it had a lesser effect on slightly fewer topics than it had a more powerful effect on, overall, there were about an equal number of topics for which the effect of Disgust on topical prevalence was significantly greater and significantly less than Fear (Figure 7.1). A total of 56 topics were significantly less impacted by Disgust than Fear (Figure 4.1; Figure 7.1).

Like the "Anger" subgraph, the "Disgust" subgraph revealed several topics that were more strongly tied to "Disgust" than other topics for which the effect if "Disgust" on topical prevalence was significantly different than the effect of "Fear" (Figure 7.2). The edges between "Disgust" and topics 8, 24, 35, 71, 88, 113, and 141 were dense and longer than the other edges, which indicated high degree centrality and a strong connection to “Disgust,” respectively, as shown by the cluster of nodes in Figure 7.2.

The prevalence of topics 8, 35, 71, and 141 was significantly less effected by “Disgust” than “Fear” (Figure 7.1-7.2). The most prevalent “Fearful” versus “Disgusted” words for each of these topics gives some insight as to what the topics were about. For example, in topic 8, highly prevalent and “Fearful” words included the lone word “infection,” which was much more prevalent than any of the other prevalent “Disgusted” words, demonstrated by the size of the text in Figure 7.3a where the word “infection” is much larger than words like “mouth,” “catching,” and “rather.”

Topic 8 tweets discussed the spread of infection, but tweets highlighting Fears over infection were significantly more likely than those expressing Disgust over infection or the means of infection with coronavirus. Similarly, Fearful terms, specifically the word “high,” stood out as highly prevalent in topic 71, whereas Disgusted terms like “vapor” and “worth” are barely visible, and indication that they were not very prevalent in topic 71 tweets (Figure 7.3d).

There were a couple of highly prevalent “Disgusted” words in topic 35, including “lower” and “eating” (Figure 7.3c). However, there were a higher quantity of prevalent “Fearful” words such as “study,” “vitamin,” “levels” and “found” in Topic 35, and because the effect of “Disgust” on topical prevalence was significantly lower than the effect of “Fear,” this suggests that in topic 35 there were many more tweets expressing Fears over newly released studies of SARS-CoV-2 than there were tweets expressing Disgust over behaviors like “eating” that could impact one’s risk from the virus.

Figure 7.1. Network of Topics for Which the Effect of Disgust was Significant

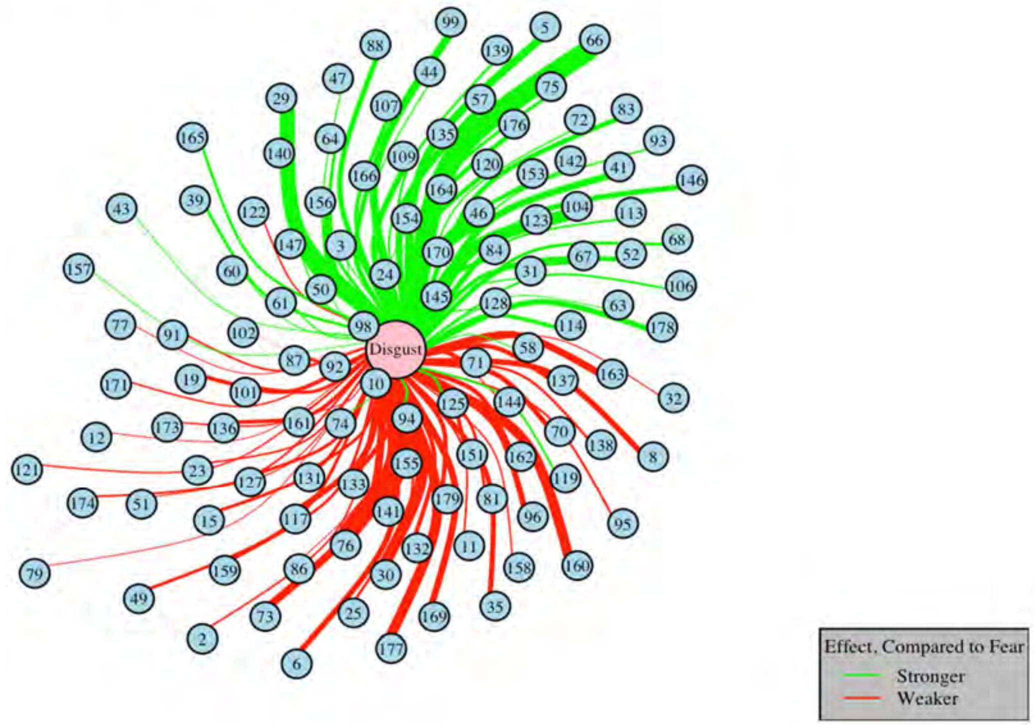
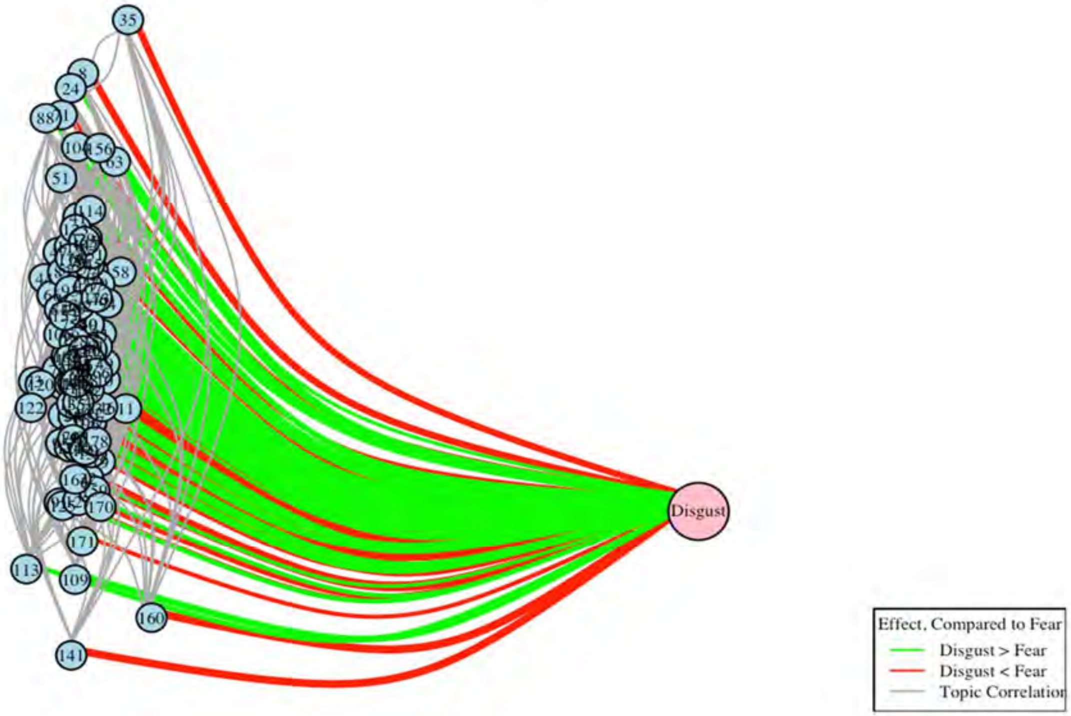


Figure 7.2. Strongest Effects and Correlation Between Topics in a Network of Topics for Which the Effect of Disgust was Significant



Of the topics for which the effect of “Disgust” on topical prevalence was significantly less than the effect of “Fear,” topic 141 had the largest quantity of prevalent “Disgusted” words (Figure 7.3g). Many of the Disgusted words in topic 114 were also somewhat Fearful, demonstrated by their positioning near the center of the graph and shade nearing purple in Figure 7.3g. Additionally, the highly prevalent Fearful words were much more specific, giving more information about the topic than the common words “using,” “along,” “great,” “personally,” “reduced,” and “shouldn’t” classified as being used primarily in a Disgusted context. The Fearful words in topic 141 like “respiratory” alongside “increased,” “associated,” and “rate” are indicative of a high prevalence of tweets exuding Fears over factors that increase risk and/or the rate of spread of SARS-CoV-2 throughout the community (Figure 7.3g).

The effect of “Disgust” on the prevalence of topics 24, 88, and 113 was significantly higher than the effect of “Fear.” Topic 113 included few Fearful and Disgusted words, and all being common words like “don’t,” there is a strong possibility that neither Fear nor Disgust was particularly relevant to tweets in topic 113. Other topics reveal the possibility of an interesting connection between emotional sentiment of tweets in a topic and the tweet type, though. It is possible that Disgusted tweets about risk during the first 19 months of the COVID pandemic were also somewhat confrontational when mentioning another user who is also a public figure, meaning they made use of the “cold call mention” by using the symbol “@” and the public figure’s username as opposed to passively mentioning the public figures by name.

Topic 24 is a good example of this dynamic (Figure 7.3b). The topic was clearly about a specific public figure, former President Donald Trump, who was president for approximately 13.5 months of the 19-month period of tweets included in the study. While most of the top Fearful and Disgusted terms fell towards the center of the graph but slightly closer to “Disgust” than “Fear,” the most prevalent terms were distinctly on the side of either “Fear” or “Disgust,” and except for the “Fearful” word “national,” were mentions of the president and his elected office (Figure 7.3b).

The other three most prevalent Fearful and Disgusted words in topic 24 were the use of “trump” and “president” in a Fearful context and “realdonaldtrump,” the former president’s twitter username, in a Disgusted context. Other words like “security,” “rallies,” “campaign,” “rally,” and the barely visible “biden,” indicate that topic 24 Fearful and Disgusted tweets tended to not only be about the former president, but specifically expressing Fear and Disgust over his behavior at political events surrounding the 2020 presidential election. It seems tweets directing this Disgust at the president himself via direct mention (@[username]) were more prevalent than those expressing Fear about the president to others without purposively engaging the president himself (Figure 7.3b).

The other topic for which the effect of “Disgust” on topical prevalence was significantly stronger than the effect of “Fear,” topic 88, dealt with the issue of protecting oneself from the risks of exposure in public places like retailers. Disgusted words like “gloves,” “hand,” and “sanitizer” suggest that tweets expressing Disgust over the potential to contract COVID infection via droplets on hard surfaces, known as fomites, were much more prevalent than tweets expressing Fear about fomites or behaviors used to avoid them (Figure 7.3e).

Upon analysis of the network with the addition of topical categories to the network of topics with significant connections to “Disgust,” the topical categories for “Politics” (node “a”) and “Risk Mitigating Behavior” (node “d”) had high degree centrality compared to the other meaningful topical categories. One of the topics for which the effect of “Disgust” on topical prevalence was significantly greater than the effect of “Fear,” topic 24, was tied to the “Politics” category (node “a”) (Figure 7.4), which makes sense in context of the top words for the topic, “trump,” “president,” and “realdonaldtrump” (Figure 7.3b).

The other notably Disgusted topic, topic 88, was not directly tied to either the “Politics” (node “a”) or “Risk Mitigating Behavior” (node “d”) topics. Instead, topic 88 had a direct tie to a the “Frontline Workers” category, with an indirect tie to the “Risk Mitigating Behavior” category through its strong association with topic 165 (Figure 7.4). This could be an indication that the behaviors mentioned in topic 88 were not the primary focus of the topic, despite being among the top words used in a “Disgusted” context (Figure 7.3e). Instead, it is possible that the Disgusted context for tweets in topic 88 was not Disgust over the need for risk mitigating behaviors, but rather, Disgust on behalf of frontline workers who would need to engage in these behaviors more frequently than the other people due to unavoidable employment-associated exposure to fomites and no option to work from home.

There was no single root node in the HRG models for “Disgust,” topics, and topical categories, which projected 127 subgroup pairs representing the subgroups of each internal node in the network. The root, group 1, had two subtrees, the smaller of which was group 90 containing the nodes for “Life and Death” (node “i”) and “Sickness Symptoms” (node “j”). In the fitted model, there was a 0 probability that the nodes in group 90 were linked (Figure 7.5a), but the predicted probability was 28% (P = 0.28), an indication that the absent tie between the two in the fitted model (Figure 7.5a) is a missed tie predicted to possibly exist (Figure 7.5b).

Figure 7.3a. Prevalence of "Disgusted" and "Fearful" Words in Topic 8

Figure 7.3b. Prevalence of “Disgusted” and “Fearful” Words in Topic 24

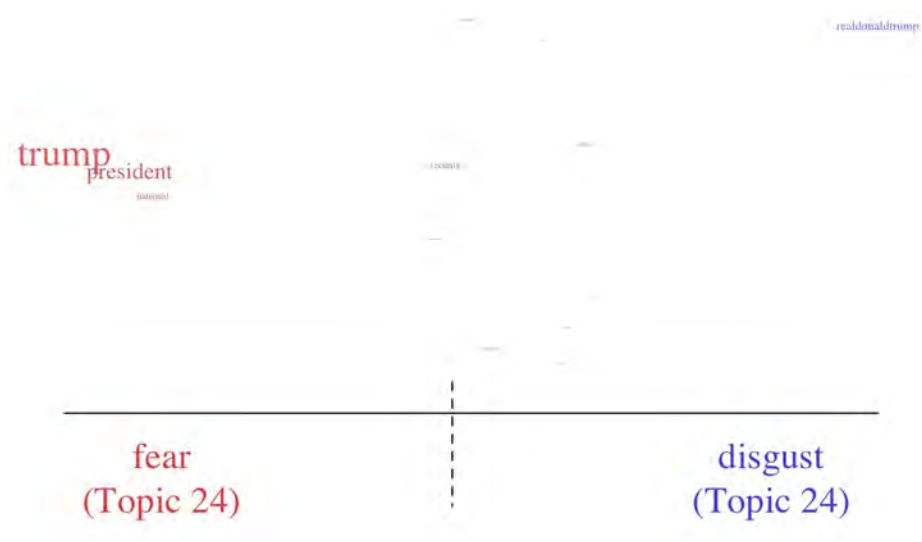


Figure 7.3c. Prevalence of "Disgusted" and "Fearful" Words in Topic 35

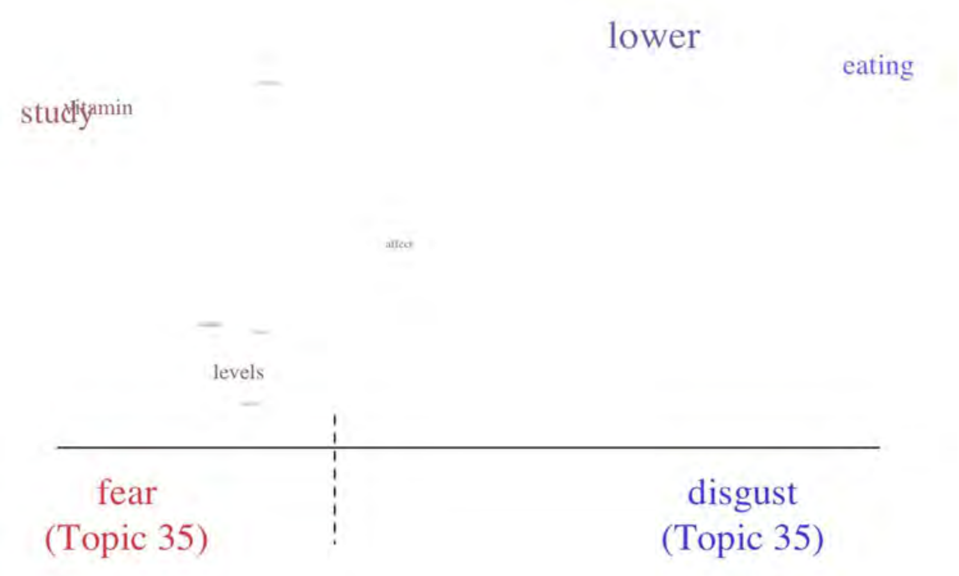


Figure 7.3d. Prevalence of "Disgusted" and "Fearful" Words in Topic 71

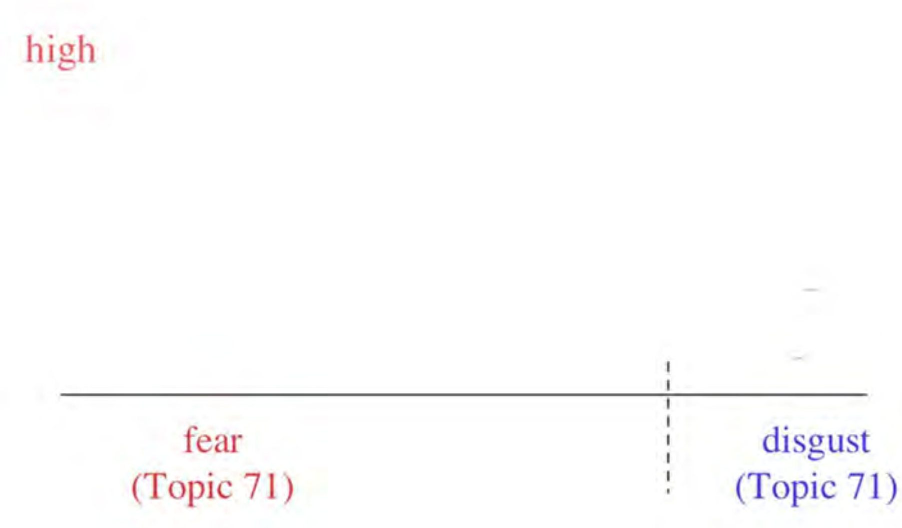


Figure 7.3e. Prevalence of "Disgusted" and "Fearful" Words in Topic 88

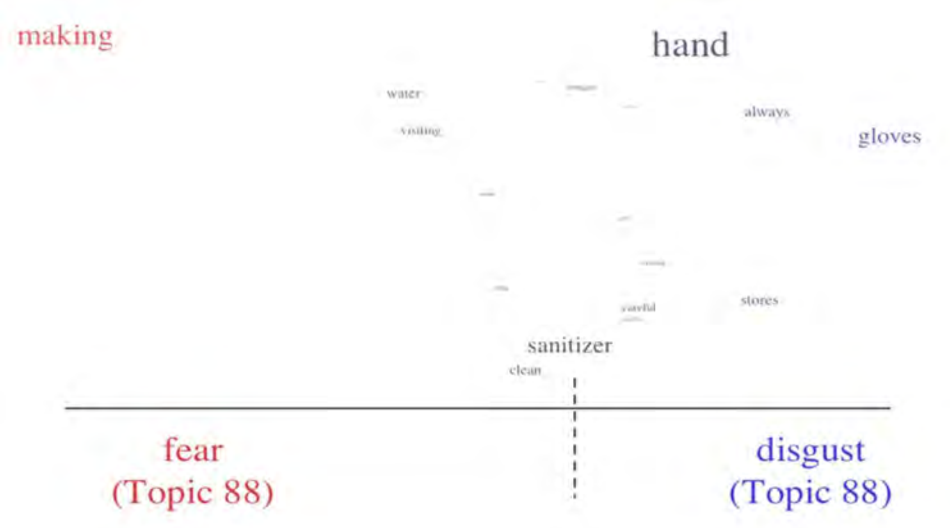


Figure 7.3f. Prevalence of “Disgusted” and “Fearful” Words in Topic 113

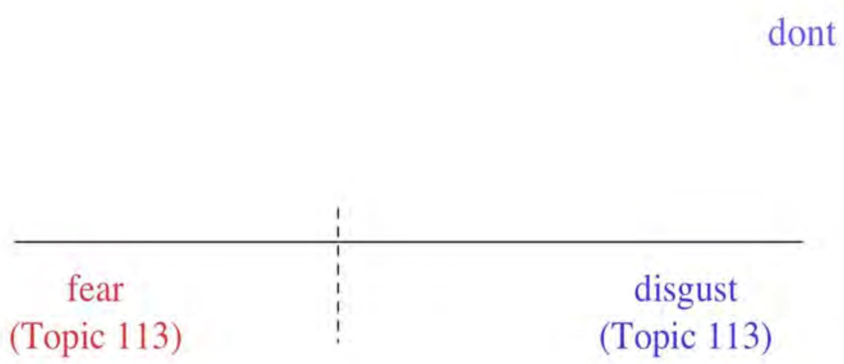


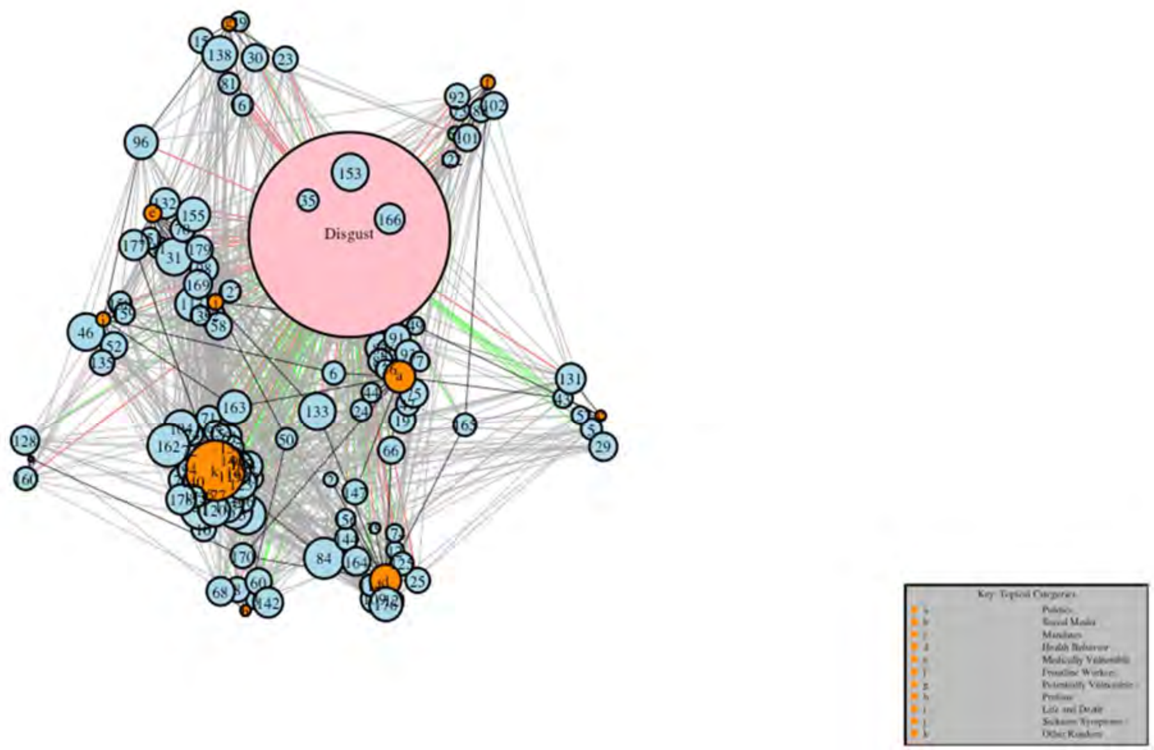
Figure 7.3g. Prevalence of "Disgusted" and "Fearful" Words in Topic 141

The other subtree, group 61, had a subgroup with a single vertex, the node for "Risk Mitigating Behavior," with a probability of 14% (P = 0.14) and a predicted probability of 30% (P = 0.30). Group 61 also contained a lower-level subgroup with the remaining vertices, with the probability of ties existing between nodes in group 112 of 6.5% (P = 0.065) in the fitted model (Figure 7.5a) and a predicted probability of 28% (P = 0.28) (Figure 7.5b). This included the vertex representing "Disgusted" sentiment, thus suggesting up to a 28% probability of "Disgusted" being tied to all nodes except the ones representing the "Life and Death" and "Sickness Symptoms" topical categories (Figure 7.5a-b).

The "Disgusted" vertex was also in the node pair group 119 alongside group 65, which places it within the closest proximity of nodes stemming from group 11. Group 11 included topic 87, and at lower levels, topics 19, 176, 58, 15, 29, 79, 64, 145, and 121. A third subgroup in group 11 was at an even lower level, containing topics 2 and 174.

Group 11 was directly connected to the "Risk Mitigating Behavior" topical category, and thus, there is a good chance that many of the "Disgusted" tweets about risk during the first 19-months of the COVID-19 pandemic dealt with health behaviors used to mitigate risk. (Figure 7.5a-b). The fitted hierarchical random graph model shows a strong probability of a connection between the "frontline workers" topical category (node "f") and other nodes in the network, but no direct or indirect ties from node "f" to Disgust. However, the node for topic 88, which was the gatekeeper connecting "Disgust" to "frontline workers," was not directly tied to "frontline workers" or "Disgust" in the fitted model (Figure 7.5a).

Figure 7.4. Strength of Ties between Categories and Topics for which the Effect of "Disgust" on Topical Prevalence was Significantly Different Than the Effect of "Fear"



Note: Larger nodes indicate higher degree centrality; Wider edges indicate greater edge density.

Figure 7.5a. Fitted Hierarchical Random Graph Model
Topical Categories, Topics, and Disgust

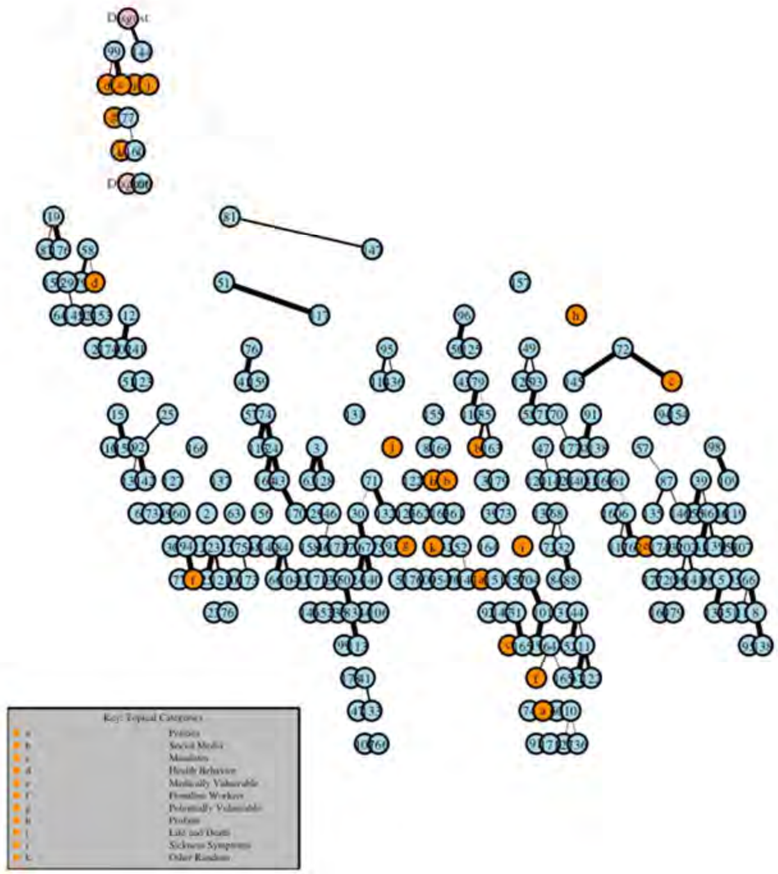
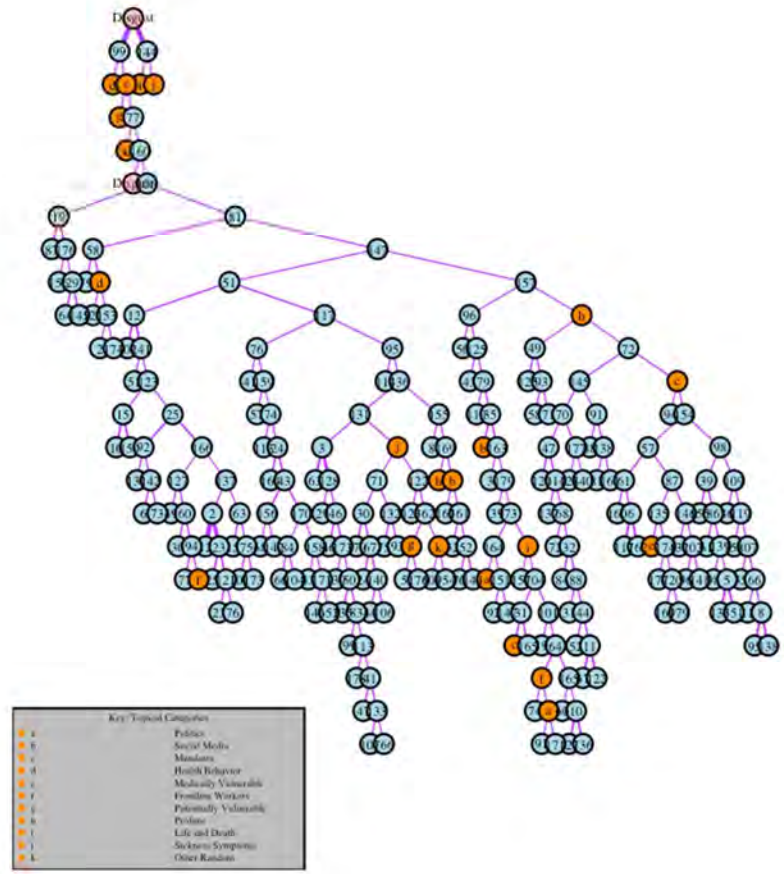


Figure 7.5b. Predicted Hierarchical Random Graph Model
Topical Categories, Topics, and Disgust



The predicted hierarchical random graph model reveals a possible pathway from topic 88 to “frontline workers,” and another, converging pathway, from “Disgust” to “frontline workers.” It appears that topics 147 and 157 may hold the ultimate gatekeeping roles for the ties between “frontline workers” and both “Disgust” and “topic 88” and may provide useful information about “Disgusted” sentiment related to the topic of frontline workers (Figure 7.5b).

A closer look at example text representing “Disgusted” tweets generated using the text of tweets in topics 147 and 157 indicates that, with respect to frontline workers, Disgust was often geared towards risk mitigation (Figure 7.6a-b). Topic 147 demonstrates one of two common themes of Disgusted sentiment about risk mitigation with regards to frontline workers, Disgust over lacking regard for the safety of workers, which was a common interpretation of the failure of many to participate in risk mitigation around frontline workers when doing things like going to the store (Figure 7.6a). The other theme, in stark contrast, is shown in topic 157.

Topic 157 provided evidence that there was possibly widespread Disgust over the idea that the public should have to engage in risk mitigation around frontline workers, with some suggesting that the risk was simply nonexistent and others suggesting that frontline workers were put in more danger by trying to enforce risk mitigating behaviors like masking, the idea being its enforcement could hurt worker’s earnings and also potentially lead to their physical harm (Figure 7.6b).

Figure 7.6a. Text Representative of 'Disgusted' Tweets in Topic 147

My anxiety is super high right now. I'm usually someone who has a hard time dealing with pressure and gets fucked in these situations. However, I know someone who works in public and lifting the mask mandate is putting my retail friend's life in danger.	So many people walking in and out of restaurants and Target without masks. If we continue to allow this kind of behavior we will continue to put people at risk. Frontline workers are at risk everyday we need to protect and respect them.
The one intervention needs many layers like cotton masks. They will continue to work as long as there are many other layers present eg being outdoors, only brief errands to higher risk settings e.g. indoors, and universal masking and making sure distancing is practiced when ventilation is poor and there are crowds.	Yes this is the way. It's facts and meant to minimize covid. You need to continue to take common sense precautions including working remotely if possible, washing hands frequently, and avoid close personal contact with large crowds especially if you are in a high risk group.

Figure 7.6b. Text Representative of 'Disgusted' Tweets in Topic 157

@[government official] you need to know corporate stores in Virginia Beach are not wanting to strictly enforce the mask rule. Not worth the money and can put the safety of employees at risk if corporate doesn't want enforce masks in stores statewide/elsewhere.	I think taking away Thanksgiving when others haven't even heard of a test shortage is mean. I don't mind the extra price, it is essential for delivering for businesses and it makes zero sense to enforce mask mandates when employees do not think they will put their family at risk.
The whole covid emergency is a scam designed to destroy America economy and churches and to train us to follow orders like sheeple. I am longer wearing a mask unless an individual business requires it. The governor can stick his order where the sun doesn't shine.	Meanwhile we will not enforce the masks ordinance or person limit for bars and clubs because compliance with not becoming high risk aren't in line with liquor license laws about following public health mandates. You want to only target bad actors right?

Joy

Joy had a significantly different effect on topical prevalence than Fear on 125 of the 180 topics about general risk during the first 19 months of the COVID-19 pandemic (Figure 4; Figure 8.1). The effect of Joy was significantly less than the effect of Fear on the prevalence of 60 topics (Figure 4.1; Figure 8.1).

Interestingly, the effect of Joy was significantly greater than Fear for most of the topics in which the effect of Joy was significantly different from Fear, though it was a small majority (n = 65) (Figure 4.2; Figure 8.1). Several of these topics were more strongly tied to "Joy" than others, each of which also had somewhat high degree centrality compared to other topic nodes in the network (Figure 8.2)

The prevalence of topics 88, 104, 109, and 113 was affected significantly more by "Joy" than by "Fear," and with the exception of topic 113 (Figure 8.3h), each of the topics provides some insight about what things gave people hope in light of the new, potentially frightening, risk posed by the novel coronavirus (Figure 8.1-8.2).

Figure 8.1. Network of Topics for Which the Effect of Joy was Significant

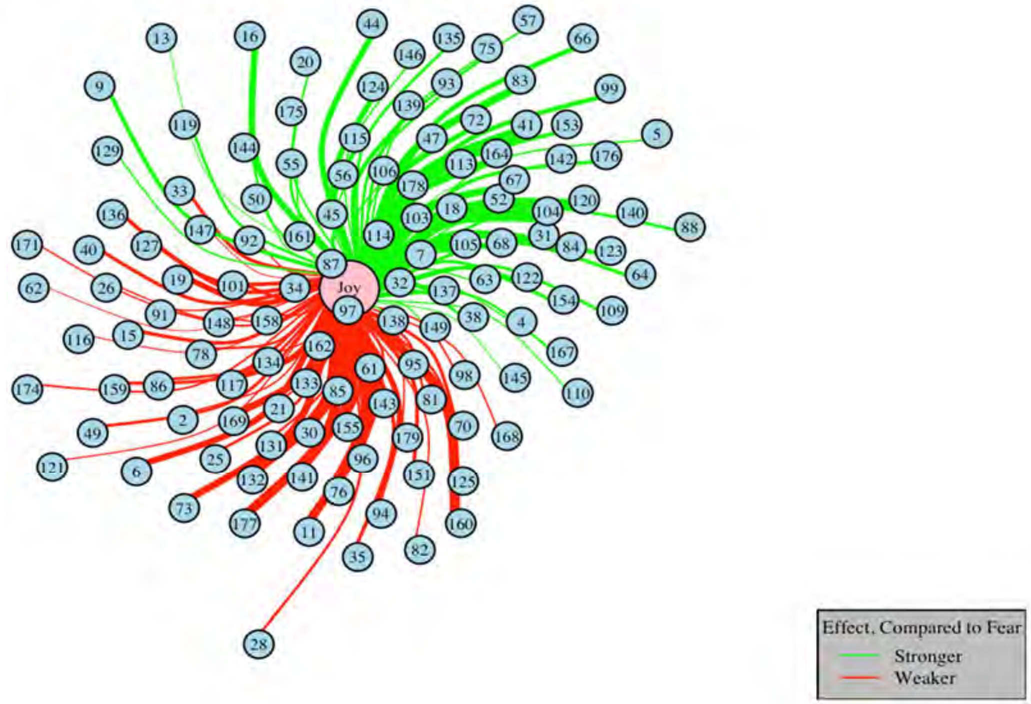
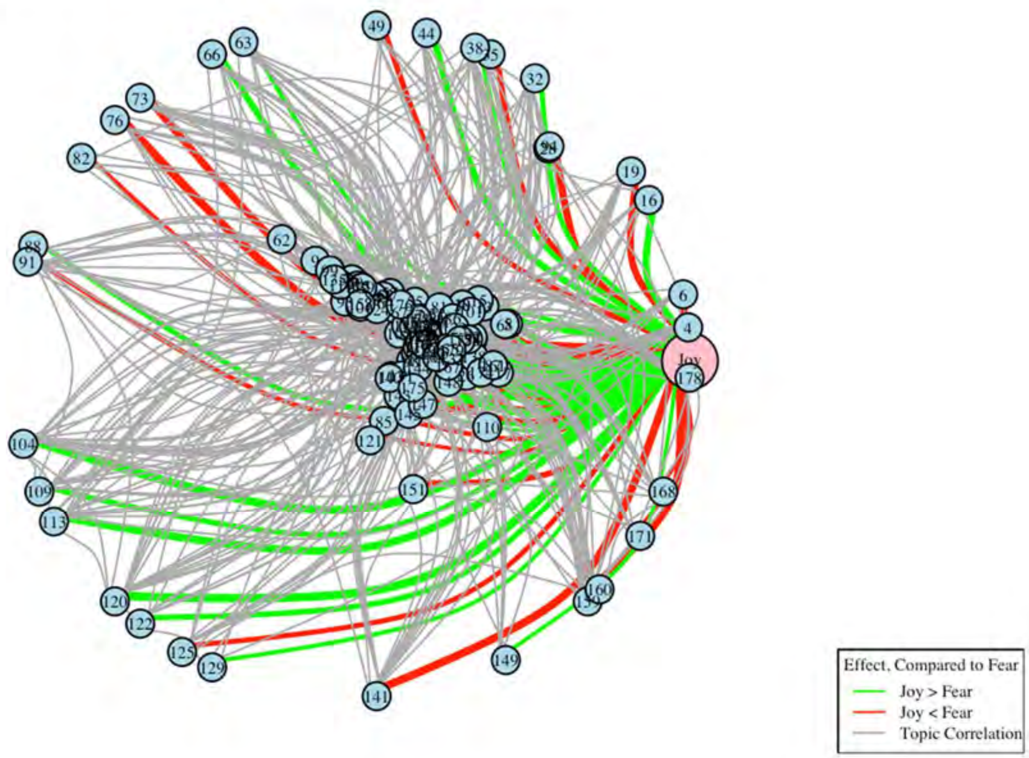


Figure 8.2. Strongest Effects and Correlation Between Topics in a Network of Topics for Which the Effect of Joy was Significant



For example, “Joy” had a significantly higher effect on the prevalence of topic 88 than “Fear” did (Figure 8.1-8.2). Top “Joyful” words in topic 88 like “grocery,” “store,” “trip,” “gloves,” and “shopping” alongside top “Fearful” words like “making,” “hand,” “sanitizer,” and “water” could be a sign that people were glad to have the opportunity to run errands, thanks in part, to the discovery and use of risk mitigating health behaviors, despite Fears that there may be shortages of important tools for engaging in those behaviors like hand sanitizer (Figure 8.3d).

The strong effect of “Joy” compared to “Fear” on the topical prevalence for topics 104 and 109 demonstrated the use of “Joy” was not necessarily because one felt hopeful. Instead, it was used as a tool for reassurance and encouragement that, despite potential Fears over COVID-19, a way forward was possible. For each of these topics, the top “Fearful” term versus the top term for “Joy” were common terms, providing little context without the less prevalent terms that tended to be used in an approximately equal number of contexts high on “Fear” and “Joy” (Figure 8.3f-g). Consider the words used in context of “Fear” and “Joy” for topic 109 clustered in the center of the graph (Figure 8.3g). The words “hands,” “wash,” “clean,” “ft” (representing the measurement unit “feet”), “touch,” “properly,” “apart,” and “masked,” appear alongside the lone term “keep” specific to contexts of “Joy” and “can’t” specific to contexts of “Fear” (Figure 8.3g). This could represent a back-and-forth whereby risk mitigating health behavior is discussed as something too frightening to possibly comprehend let alone accomplish, but also discussed using encouragement insisting that yes, we can keep this up, at least for the temporary future. In a similar fashion, topic 104 seems to include encouragement in response to Fears that people do not think they will be able to endure a ventilator and/or the duration of the stay-at-home order, the possible suggestion being that yes, you *can* endure, if you remember that you will get past this hardship (Figure 8.3f).

Figure 8.3a. Prevalence of "Joyful" and "Fearful" Words in Topic 73

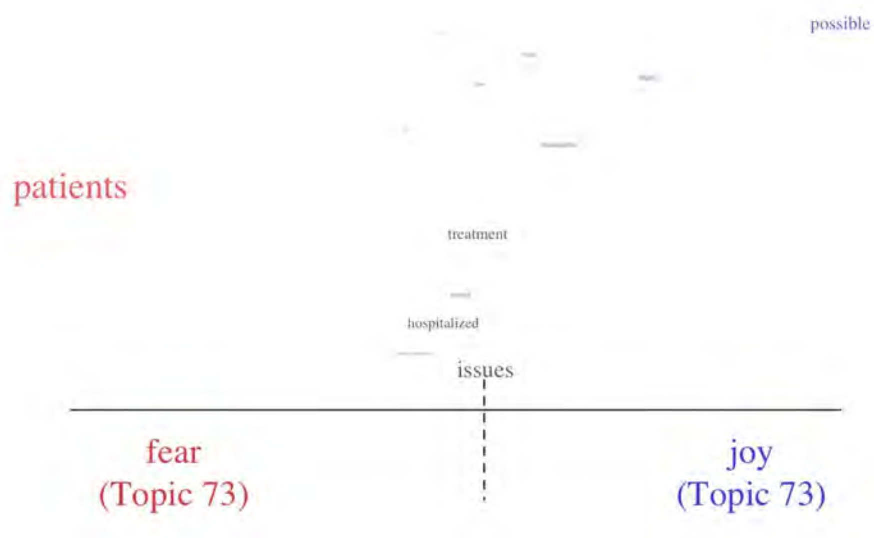


Figure 8.3b. Prevalence of “Joyful” and “Fearful” Words in Topic 76

Figure 8.3c. Prevalence of “Joyful” and “Fearful” Words in Topic 82

Figure 8.3d. Prevalence of "Joyful" and "Fearful" Words in Topic 88

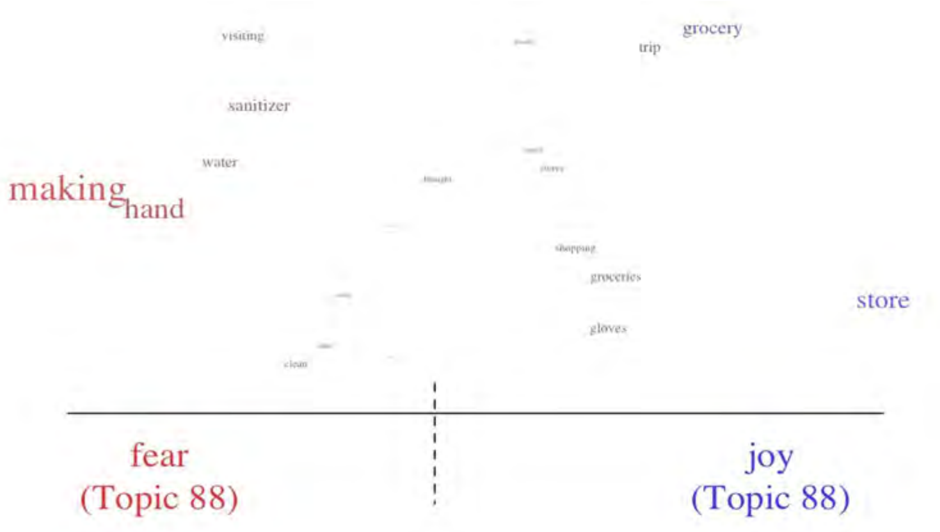


Figure 8.3e. Prevalence of “Joyful” and “Fearful” Words in Topic 91

Figure 8.3f. Prevalence of "Joyful" and "Fearful" Words in Topic 104

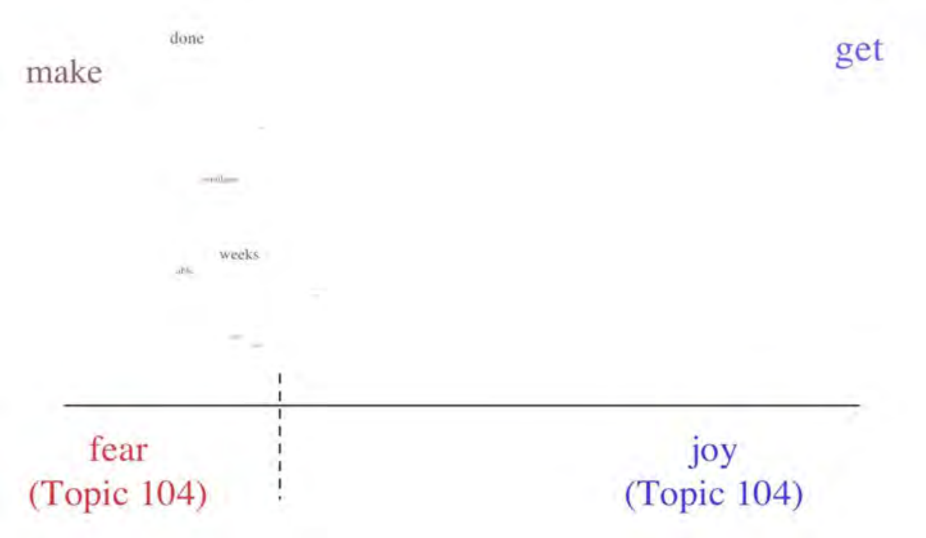


Figure 8.3g. Prevalence of "Joyful" and "Fearful" Words in Topic 109

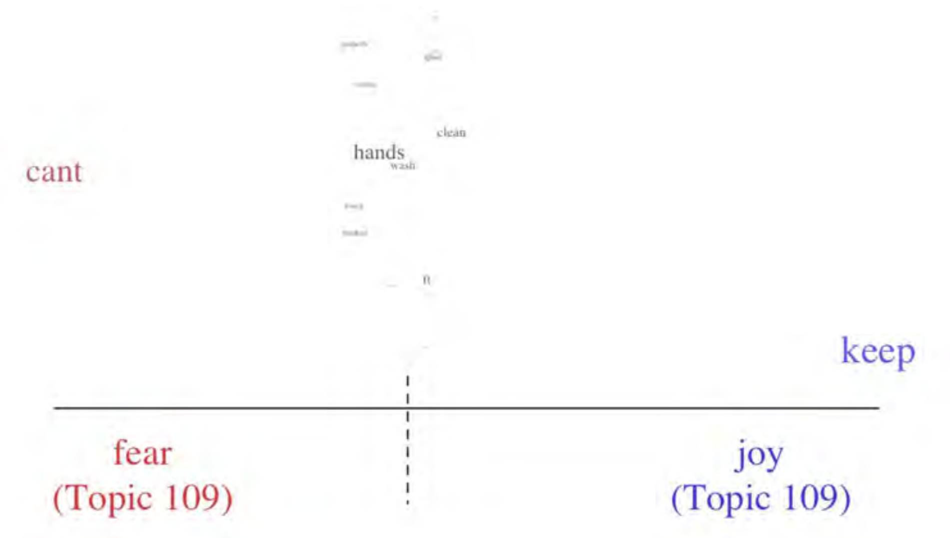
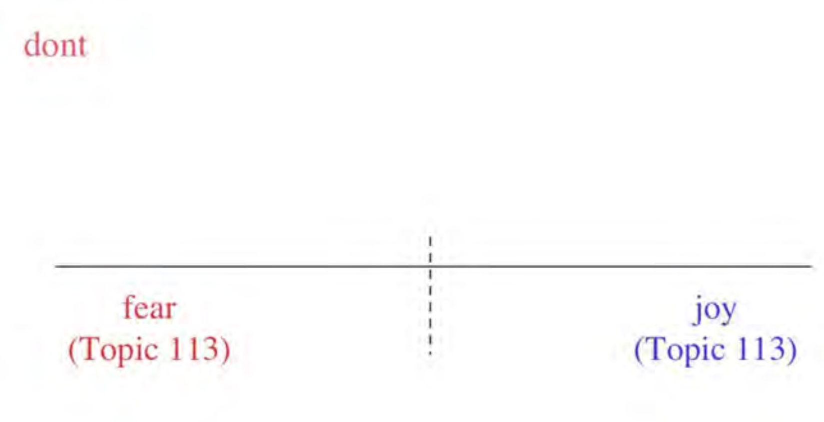


Figure 8.3h. Prevalence of "Joyful" and "Fearful" Words in Topic 113

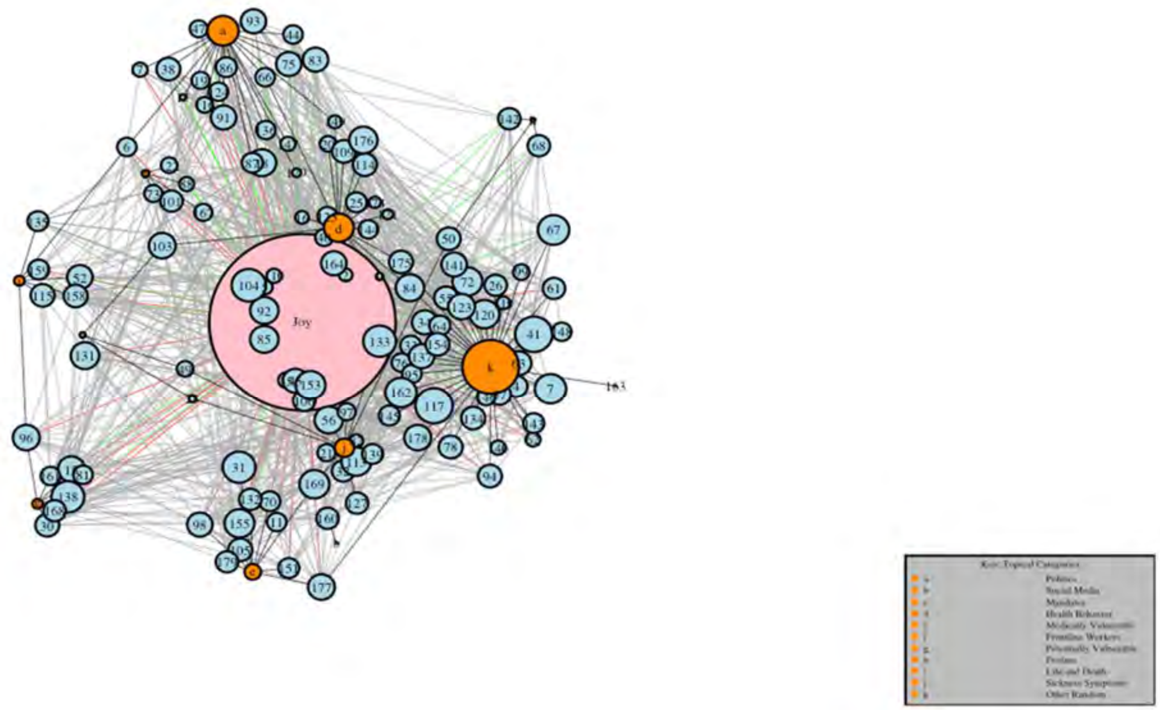


The effect of “Joy” on topical prevalence was significantly weaker than the effect of “Fear” for topics 73, 76, 82, and 91 (Figure 8.1-8.2). The top terms for “Joy” and “Fear” for these topics are useful for understanding Fears that many people would not perceive as overcomeable. If topics 104 and 109 included some sense of “yes, we can!” topics 73, 76, 82, and 91 exuded the opposite idea that, “no, we definitely cannot!”

The absence of words used in context of “Joy” alongside the lone word “COVID” used in context of “Fear” in topic 76 was a strong indication that users were unlikely to give encouragement or reassurance over Fears dealing with the general idea of COVID-19. Topics 73, 82, and 91 included terms used in context of “Joy,” but the implication was that these uses were not hugely popular among users tweeting about COVID-19 between December 2019—June 2021. For example, topic 73 seemed to highlight Fears over being a patient with COVID, both in and out of the hospital. There was also some evidence in topic 73 that encouragement via providing suggestions was somewhat unpopular. For instance, the word “possible” was used frequently in context of “Joy” in topic 73, but significantly less frequently than the expression of non-assuaged Fears about hospitalization and treatment for COVID (Figure 8.3a).

Topic 91 Fearful contexts often employed the terms “officials,” “residents,” “persons,” “county,” and “case,” which could be an indication that people expressed Fears over what was said by government officials with respect to whether the virus was spreading locally (Figure 8.3e). The words used in a “Joyful” context for this topic like “jail” and “area” suggest there was some, albeit limited, expression of reassurance that local spread was confined to areas with social undesirables, like jails (Figure 8.3e).

Figure 8.4. Strength of Ties between Categories and Topics for which the Effect of "Joy" on Topical Prevalence was Significantly Different Than the Effect of "Fear"



Note: Larger nodes indicate higher degree centrality; Wider edges indicate greater edge density.

Figure 8.5a. Fitted Hierarchical Random Graph Model
Topical Categories, Topics, and Joy

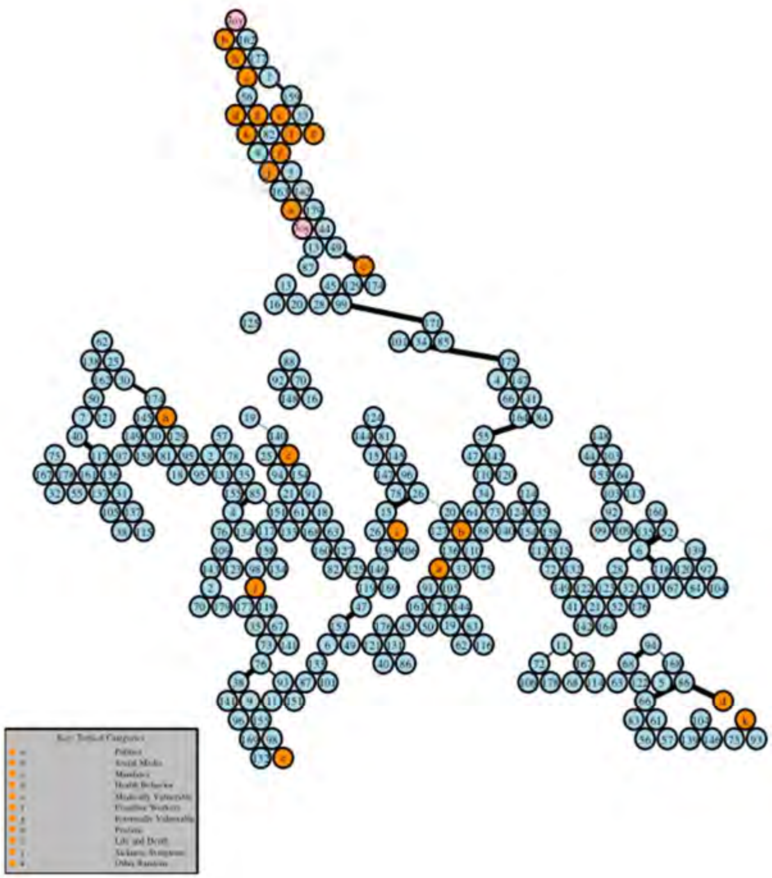
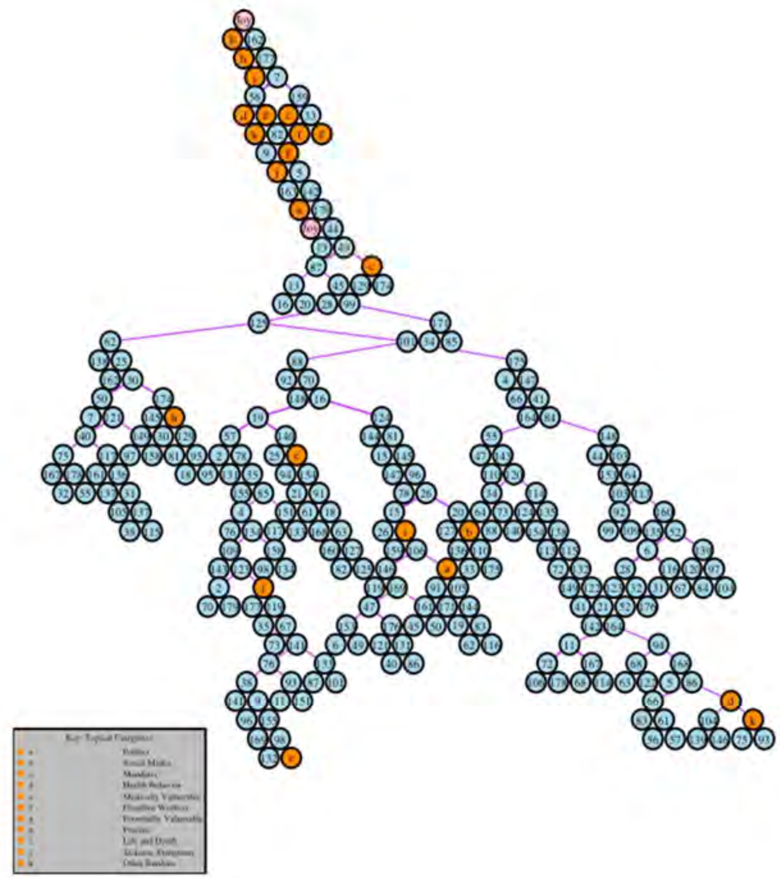


Figure 8.5b. Predicted Hierarchical Random Graph Model
Topical Categories, Topics, and Joy



Given the top words for “Fearful” contexts in topic 82 included “smoking,” “increases,” and “apparently,” topic 82 tweets likely included ones expressing Fears about a behavior already known to be harmful to one’s health potentially becoming more dangerous and forcing them to confront whether the desirability of the behavior still outweighed the risks (Figure 8.3c). The words used in context of “Joy” for the same topic included “drinking,” “inside,” “smart,” and “infection,” and given “infection” appeared in “Fearful” and “Disgusted” contexts for other topics, this could be an indication that the Joyful tweets in topic 82 provided reassurance that there were alternative behaviors to the desired one that may help achieve a similar effect (i.e. drinking instead of smoking), or encouragement to stop smoking with this new information because it was not the smart thing to do even before COVID (Figure 8.3c).

When the topical categories were added to the network linking the sentiment “Joy” with topics, four meaningful topical categories were more central than the others: the “Political” (node “a”) and “Risk Mitigating Behavior” (node “d”) categories, and the slightly less central “Mandates” (node “c”) and “Sickness Symptoms” (node “j”) categories (Figure 8.4). Topics 104 and 109 both dealt, to some extent, with risk mitigating health behavior (Figure 8.3f-g). Accordingly, these topics are directly tied to the “Risk Mitigating Behavior” topic (node “d”) (Figure 8.4). While the top words for contexts of “Fear” and “Joy” for topic 113 were uninformative (Figure 8.3h), the network graph shows a tie between topic 113 and the vertex for “Sickness Symptoms” (node “j”), and thus, provides further information about the subject matter of topic 113 tweets (Figure 8.4).

The root for the hierarchical random graph models examining the network ties between “Joy,” topical categories, and topics, included a single node representing the topical category for “Social Media,” and a second, lower-level subgroup (group 129) (Figure 8.5a-b). The fitted model estimated the probability of a tie between “Social Media” and the vertices in group 129 as less than 1% (P = 0.0073) (Figure 8.5a), but the predicted probability was much higher at 73% (P = 0.73) (Figure 8.5b). This was evidence of a possible missing tie between the “Social Media” vertex and the vertices in group 129.

Group 129 included two subgroups, the first with a single vertex representing the “Profane” topical category, the second a lower-level subgroup comprised of the vertices in group 117 (Figure 8.5a-b). The node representing “Joy” fell into this large, lowest level, subgroup (group 117). In the fitted hierarchical random graph model, estimates indicated there was about a 2% probability (P = 0.022) of a tie between “Joy” and the “Profane” topical category, and about a 5% probability (P = 0.052) of a tie between “Joy” and vertices other than “Social Media” and “Profane” (Figure 8.5a). The 27% (P = 0.27) predicted probability for a tie between group 117 and the “Profane” category was the same as the predicted probability that the vertices in group 117 were tied to each other (Figure 8.5b).

While the predicted hierarchical random graph model revealed several possible missing edges, the predicted probability of a tie for every one of the 137 vertex pairs in the predicted model was less than 1% (Figure 8.5b). This could be indicative of a low prevalence of “Joyful” tweets overall across topics.

Sadness

The effect of Sadness was significantly less than the effect of Fear on the prevalence of 49 topics (Figure 4.1; Figure 9.1). The effect of Sadness was significantly greater than the effect of Fear on the prevalence of slightly more topics, a total of 66 (Figure 4.2; Figure 9.1). In total, the effect of Sadness on prevalence was significantly different than that of Fear for a 115 of the 180 topics (Figure 4; Figure 9.1). In contrast to most of the other emotional sentiments, “Sadness” was strongly tied to many topics, which made for an extremely dense subgraph (Figure 9.2). The effect of “Sadness” on topical prevalence was strongest compared to “Fear” for topics 76, 78, 81, 82, 83, 84, 89, 90, 94, 98, 100, 105, 106, 108, 112, 116, 120, 122, and 125 (Figure 9.2).

The first notable observation of the top “Sad” versus “Fearful” words was for topic 76, where the word “COVID” was once again the sole prevalent term for the topic *and* used in a predominantly “Fearful” context (Figure 9.3a). Also, like other emotions, the effect of “Sadness” on the prevalence of topic 76 was significantly weaker than the effect of “Fear” (Figure 9.1-9.2). This consistent pattern through the analysis of six of the seven emotion subgraphs was a sign that the word “COVID” in topic 76 was used almost exclusively in contexts of “Fear.”

The effect of “Sadness” on topical prevalence was significantly lower than “Fear” for several other topics in addition to topic 76, including topic 78, 81, 82, 94, 98, 100, and 125 (Figure 9.1-9.2). Topic 78 top terms for “Sadness” and “Fear” indicated that Fear over the spread of COVID-19, particularly when spread was high, was more prevalent in topic 78 tweets than Sadness over specifics about where and when spread was the highest (Figure 9.3b).

There were several other things discussed more often in context of “Fear” than “Sadness.” One example was “Fear” about the dual threat of SARS-CoV-2 and climate change as more common than “Sadness” that many would not take either threat seriously in topic 100 tweets (Figure 9.3k). It was more common on Topic 125 to express Fear of being exposed than Sadness over the possibility that risk of exposure was unlikely to be reduced any time soon (Figure 9.3s). In topic 81, Sadness surrounding the return to school was less commonly expressed than Fear about what the return to school could mean for teachers or one’s own children in topic 81 (Figure 9.3c).

Figure 9.1. Network of Topics for Which the Effect of Sadness was Significant

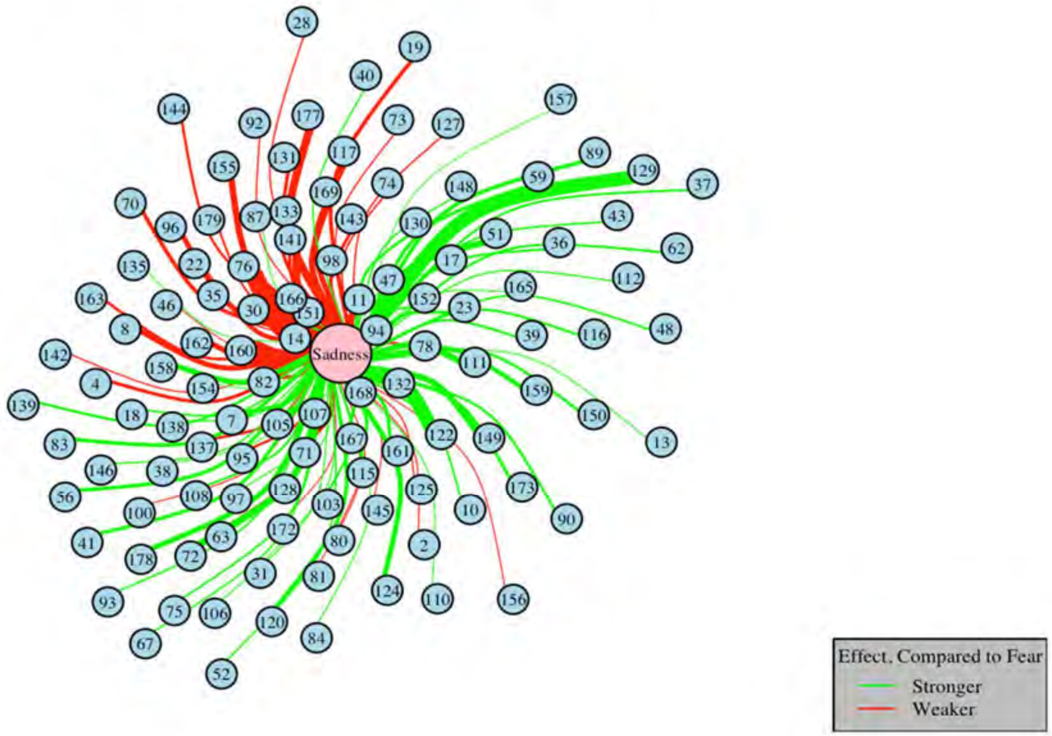
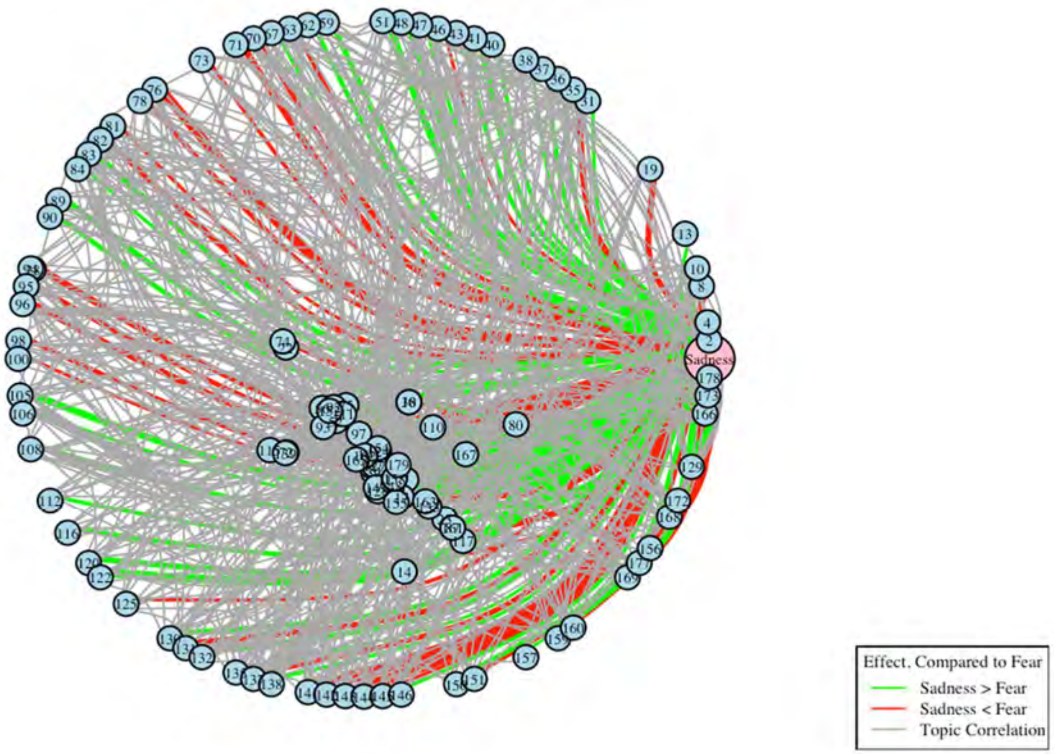


Figure 9.2. Strongest Effects and Correlation Between Topics in a Network of Topics for Which the Effect of Sadness was Significant



Topic 94 terms used in context of “Fear” and “Sadness” related to reducing transmission, but the significantly weaker effect of “Sadness” compared to “Fear” suggests that discussions about reducing transmission of the virus were more representative of “Fearful” contexts than “Sad” ones in this topic (Figure 9.3i). Topic 98 seemed to relate to people with heightened risk from infection with the SARS-CoV-2 virus due to a pre-existing chronic or temporary medical condition. For example, the high prevalence of the use of the words “pregnant” and “asthma” in a “Fearful” context in topic 98 could indicate somewhat widespread Fears about the risks specific to pregnant people and people with asthma (Figure 9.3j).

The effect of “Sadness” on topical prevalence was significantly stronger than the effect of “Fear” for the remaining topics: 83, 84, 89, 90, 105, 106, 108, 112, 116, 120, and 122 (Figure 9.1-2). There were two themes to the “Sad” contexts in these topics. The first theme indicated Sadness surrounding an apparent expectation that some social groups would not take the actions necessary to mitigate the risk of COVID. For example, topic 89 suggested there was an expectation and associated Sadness that states would not take necessary actions to successfully mitigate risk via collective and institutional action (Figure 9.3g), while topics 112 and 120 indicated there were similar feelings of Sadness surrounding the potential actions at the federal level, specifically “congress” in topic 112 (Figure 9.3o) and “Washington” in topic 120 (Figure 9.3q). Others took aim at “society” generally as unlikely to take necessary action to mitigate the risk of COVID, like in topics 83 (Figure 9.3e), 90 (Figure 9.3h), and 108 (Figure 9.3n). Smaller groups like “students” in topic 106 were also highlighted as potentially resisting risk mitigation efforts necessary to end the pandemic (Figure 9.3m).

Figure 9.3a. Prevalence of “Sad” and “Fearful” Words in Topic 76

Figure 9.3b. Prevalence of "Sad" and "Fearful" Words in Topic 78

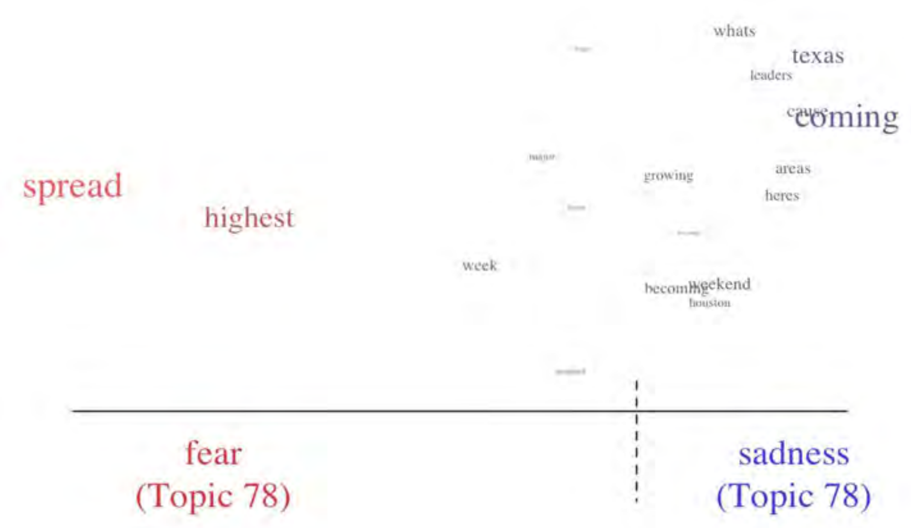


Figure 9.3c. Prevalence of "Sad" and "Fearful" Words in Topic 81

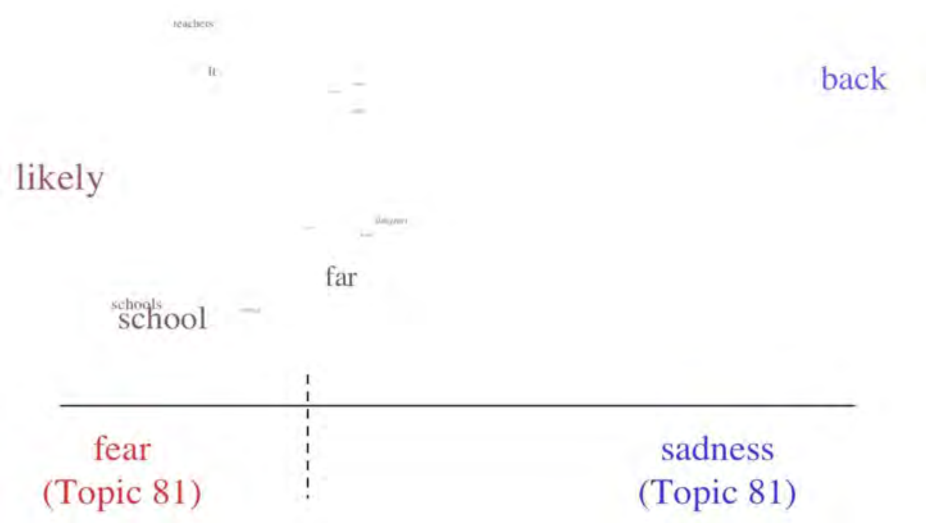


Figure 9.3d. Prevalence of "Sad" and "Fearful" Words in Topic 82

Figure 9.3e. Prevalence of "Sad" and "Fearful" Words in Topic 83

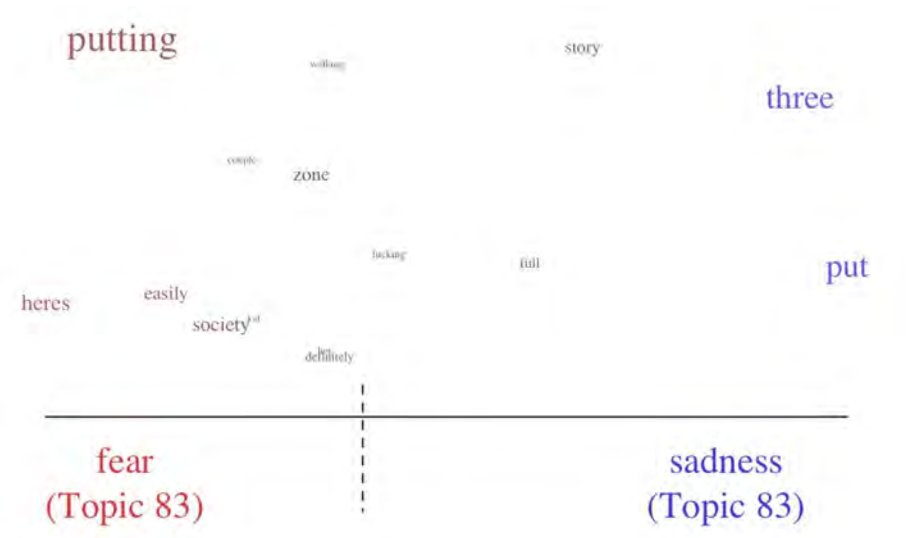


Figure 9.3f. Prevalence of "Sad" and "Fearful" Words in Topic 84

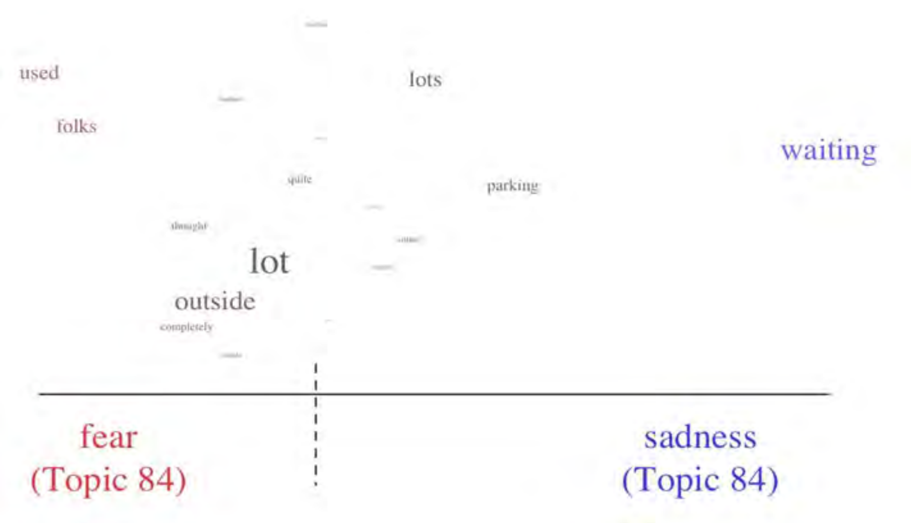


Figure 9.3g. Prevalence of “Sad” and “Fearful” Words in Topic 89

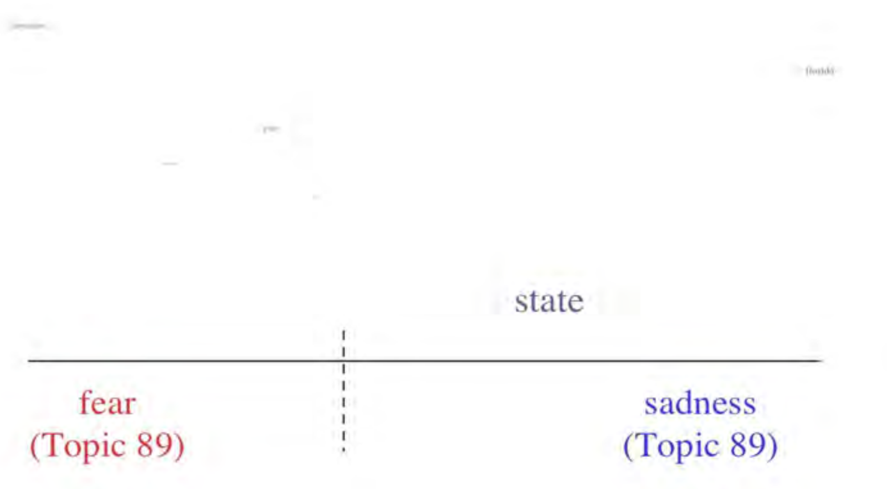


Figure 9.3h. Prevalence of "Sad" and "Fearful" Words in Topic 90

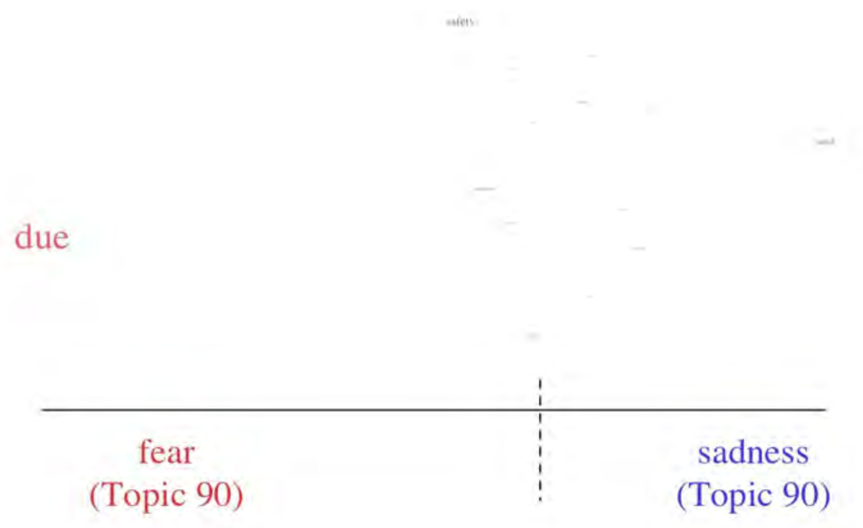


Figure 9.3i. Prevalence of "Sad" and "Fearful" Words in Topic 94

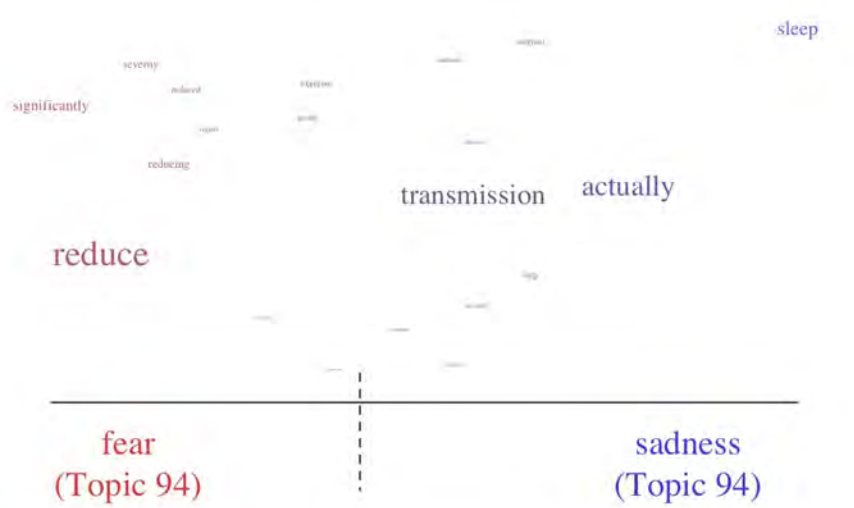


Figure 9.3j. Prevalence of "Sad" and "Fearful" Words in Topic 98

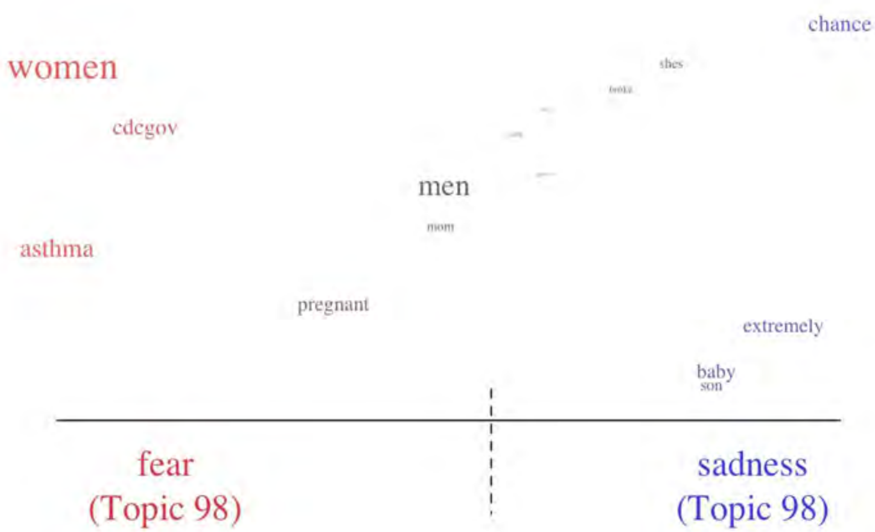


Figure 9.3k. Prevalence of "Sad" and "Fearful" Words in Topic 100

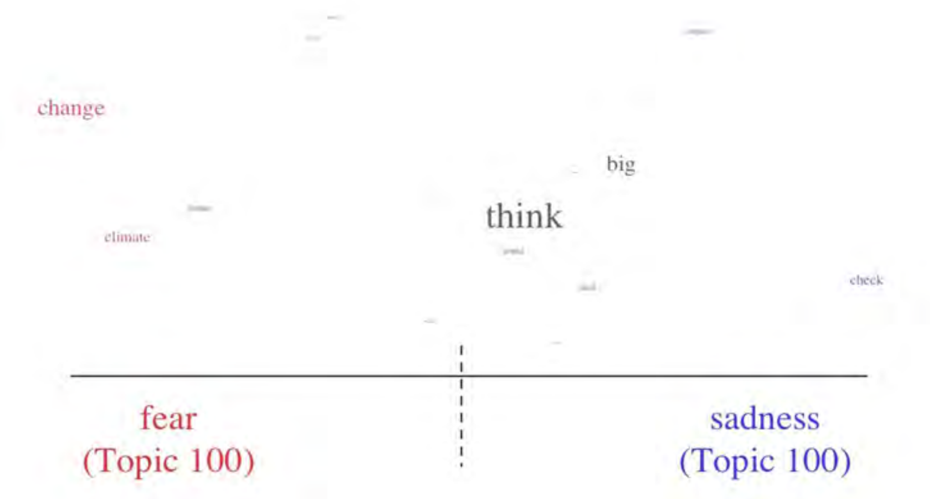


Figure 9.3l. Prevalence of "Sad" and "Fearful" Words in Topic 105

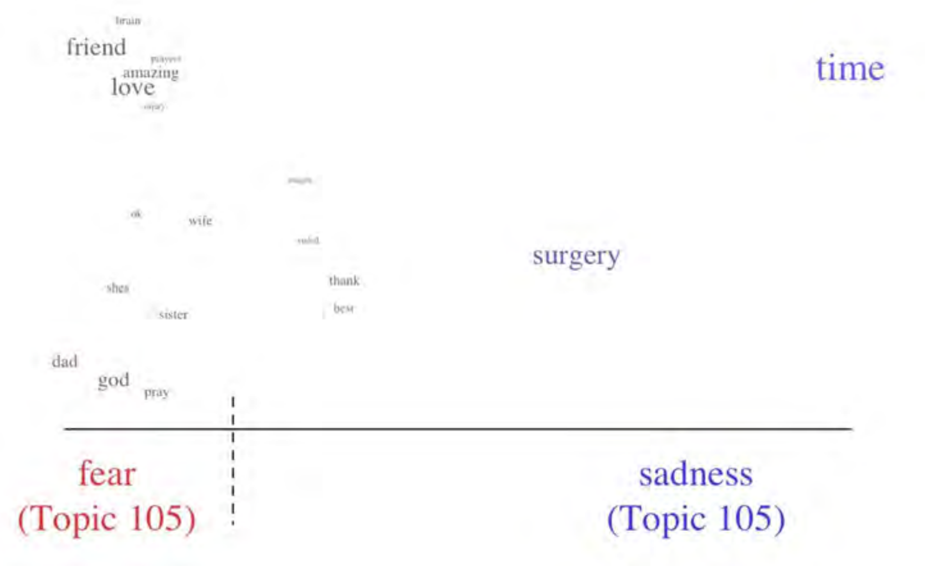


Figure 9.3m. Prevalence of "Sad" and "Fearful" Words in Topic 106

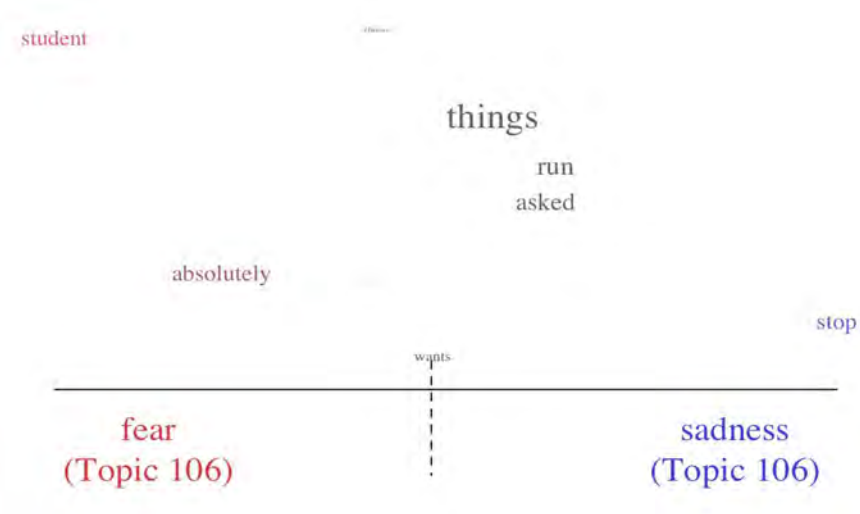


Figure 9.3n. Prevalence of "Sad" and "Fearful" Words in Topic 108

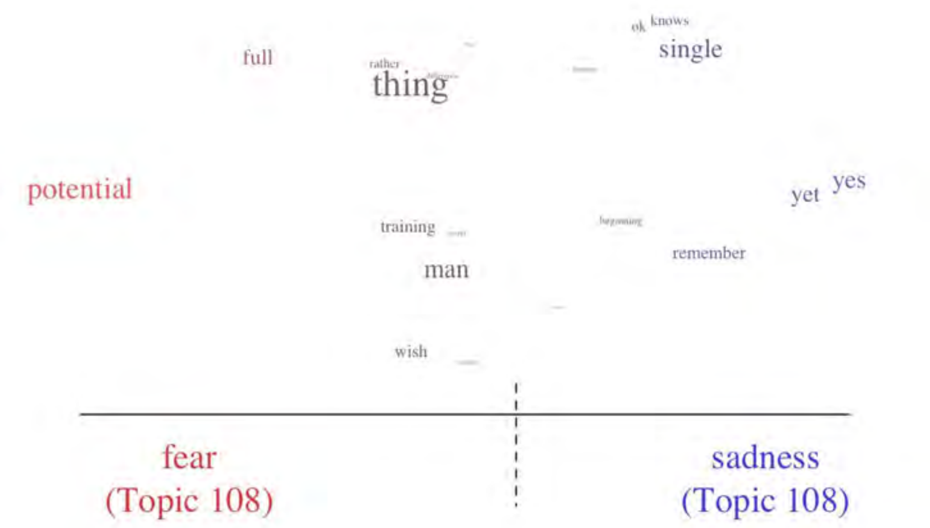


Figure 9.3o. Prevalence of “Sad” and “Fearful” Words in Topic 112

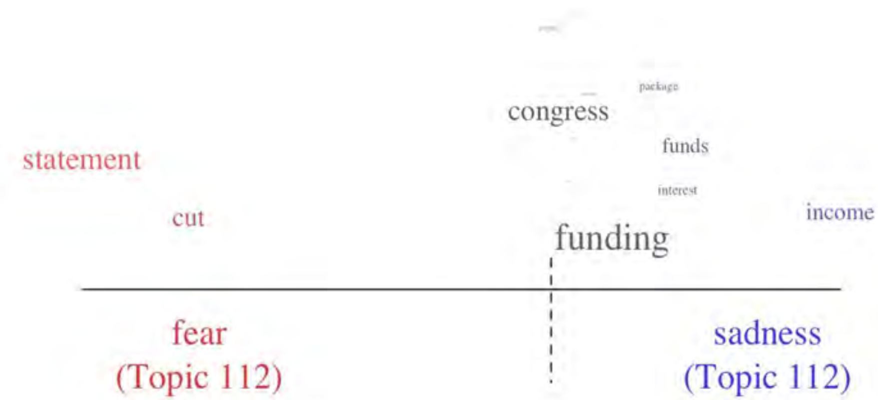


Figure 9.3p. Prevalence of "Sad" and "Fearful" Words in Topic 116

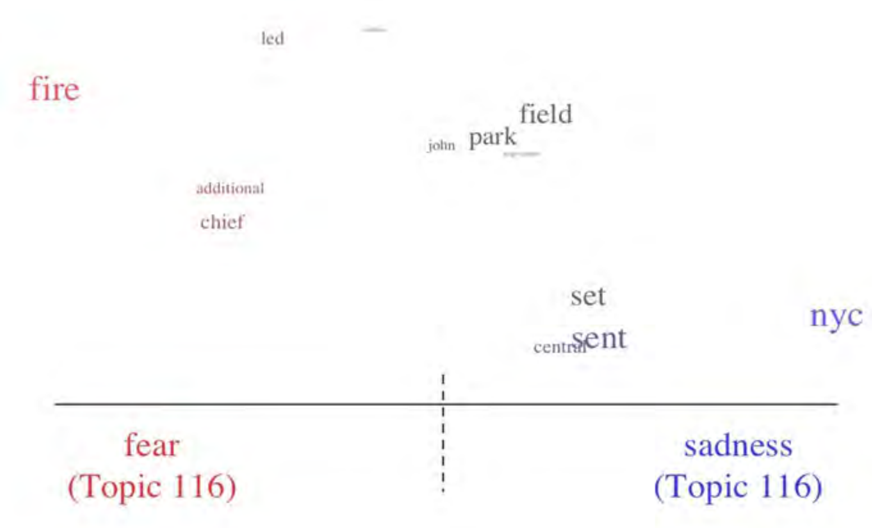


Figure 9.3q. Prevalence of “Sad” and “Fearful” Words in Topic 120

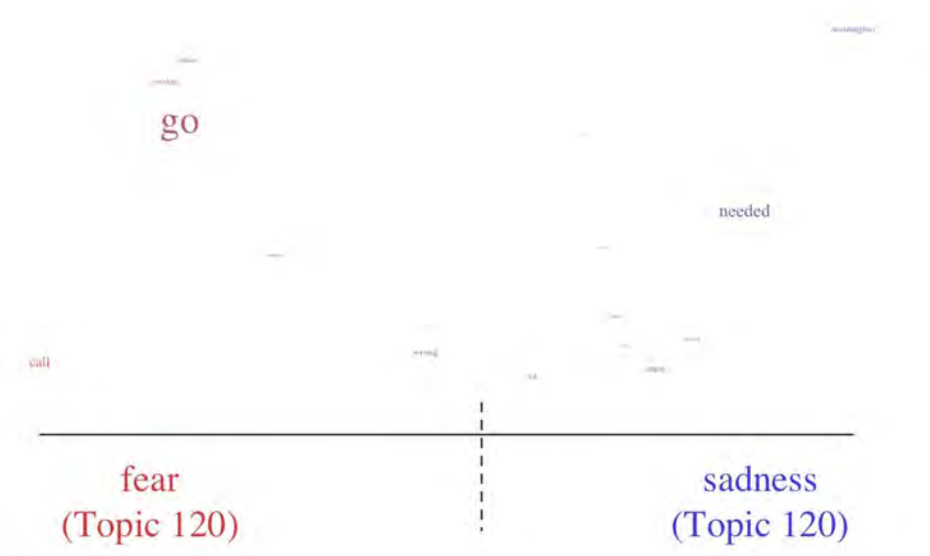


Figure 9.3r. Prevalence of "Sad" and "Fearful" Words in Topic 122

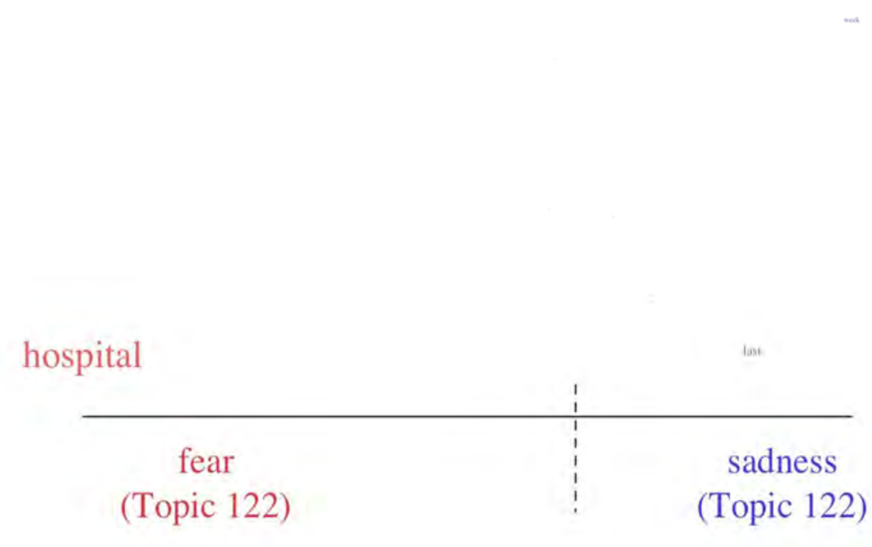
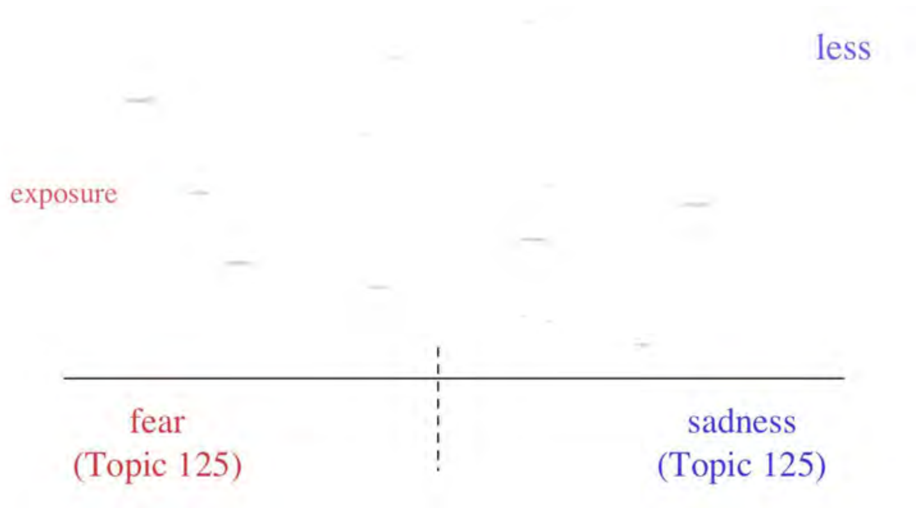


Figure 9.3s. Prevalence of “Sad” and “Fearful” Words in Topic 125

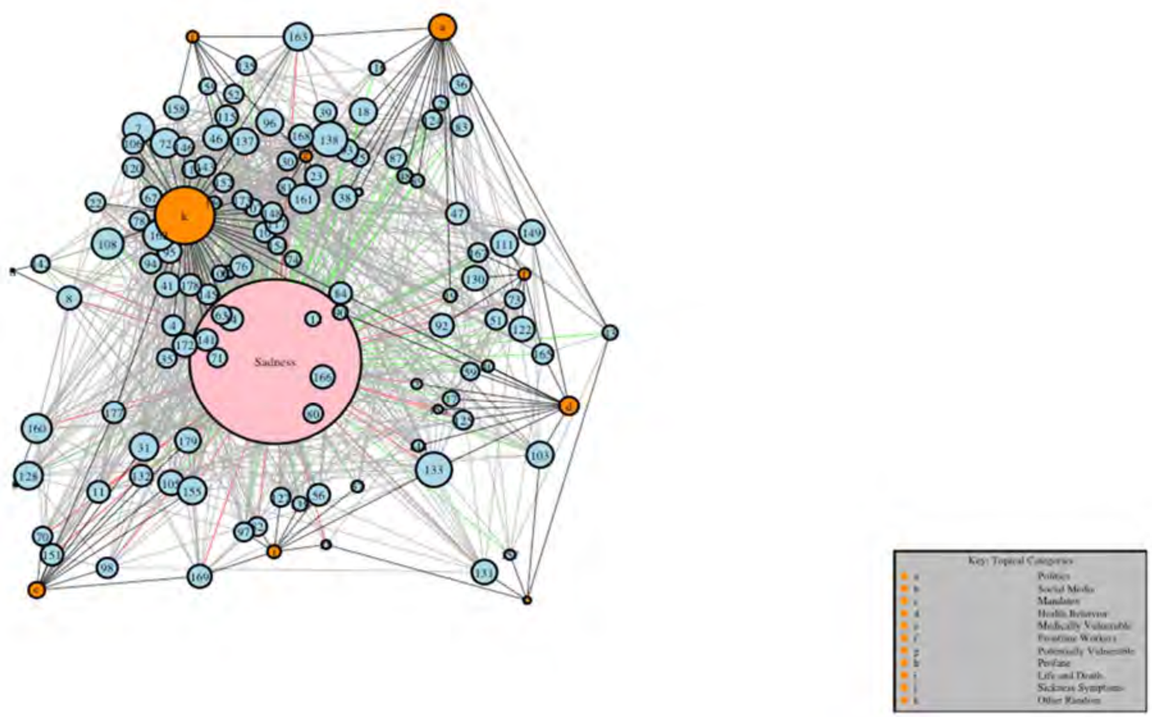


The other theme of “Sad” contexts was the expression of Sadness about the people, places, and services that would be impacted, should Fears about the virus come to fruition. These included public services like fire safety and recreation, as shown in topic 116 (Figure 9.3p). They also included discussions of health infrastructure like hospitals, mentioned in topics 105 (Figure 9.3l) and 122 (Figure 9.3r), and alluded to in topics 83 (Figure 9.3e) and 84 (Figure 9.3f).

The most central topical categories in the “Sadness” subnetwork were the “Political,” “Risk Mitigating Behaviors,” “Medically Vulnerable,” and “Life and Death” categories (Figure 9.4). The subnetwork for “Sadness” was also quite dense, with most of the possible ties between nodes being present (Figure 9.4).

The addition of the topical categories to the network revealed that there were pathways between some of the topical categories operating through topics for which the effect of “Sadness” was significantly different than “Fear.” For example, topics 84 and 90 provided indirect paths from the “Risk Mitigating Behavior” category and the “Other Random” category. Likewise, the effect of “Sadness” on topical prevalence was significantly stronger than the effect of “Fear” for both topics (Figure 9.4). Given the ties between several other topics and the “Other Random” category, and that many of these topics were strongly correlated to topics 90 and 84, the effect of “Sadness” compared to “Fear” could be a useful means of categorizing the topics in the “Other Random” category (Figure 9.4).

Figure 9.4. Strength of Ties between Categories and Topics for which the Effect of "Sadness" on Topical Prevalence was Significantly Different Than the Effect of "Fear"



Note: Larger nodes indicate higher degree centrality; Wider edges indicate greater edge density.

The hierarchical random graph model for the network of ties between "Sadness," topics, and topical categories had one root vertex, the one representing the "Profane" topical category, with one lower-level subgroup (Figure 9.5a-b). The probability that a tie existed between "Profane" and the remaining nodes comprising group 124 was just under 2% (P = 0.016) in the fitted model (Figure 9.5a), but the predicted probability of 98% (P = 0.98) provided evidence that there was a strong chance the tie existed (Figure 9.5b).

Group 124 had two subgroups that were estimated to have an approximately 2% probability of being tied to each other (P = 0.016) (Figure 9.5a). One consisted of the lone vertex for the "Social Media" topical category, and the other, lower level, subgroup contained the remaining nodes (group 3) (Figure 9.5a-b). The predicted probability that "Social Media" was tied to the remaining nodes, group 3, was slightly higher at 32% (P = 0.32) (Figure 9.5b).

Sadness was in group 10, a vertex pair containing "Sadness" and group 92 (Figure 9.5a-b). Group 92 was comprised of the vertex pair containing topic 28 and group 97 (Figure 9.5a-b). The estimated probability that "Sadness" was tied to group 92 was over 97% (P = 0.975) (Figure 9.5a), and though the predicted probability suggested the chance of a tie could be as low as 50% (P = 0.50) (Figure 9.5b), this still constituted strong evidence in both the fitted and predicted models that "Sadness" was near topic 28.

The hierarchical random graph model also indicated that "Sadness" was within four walks of topic 110, but the fitted model did not estimate a high enough probability that the necessary tie between topic 8 and topic 28 existed identify the shorter path from "Sadness" to topic 110 (Figure 9.5a). Instead, the fitted model suggests there is a 2% (P = 0.016) probability a much longer path between "Sadness" and topic 110 exists, operating through topic 161 and topic 43 (Figure 9.5a).

Figure 9.5a. Fitted Hierarchical Random Graph Model Topical Categories, Topics, and Sadness

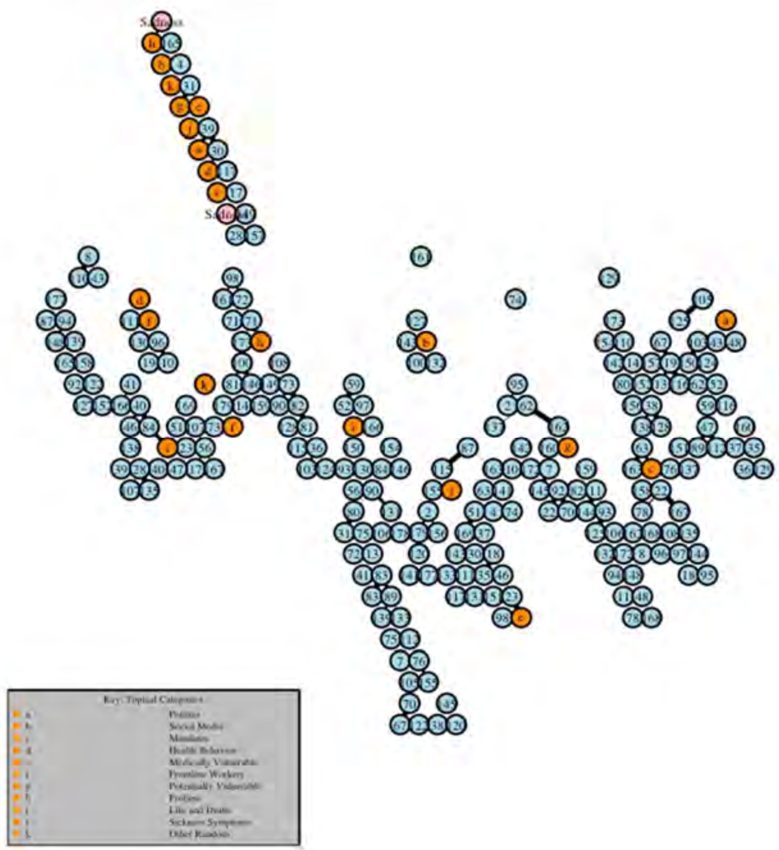


Figure 9.5b. Predicted Hierarchical Random Graph Model Topical Categories, Topics, and Sadness

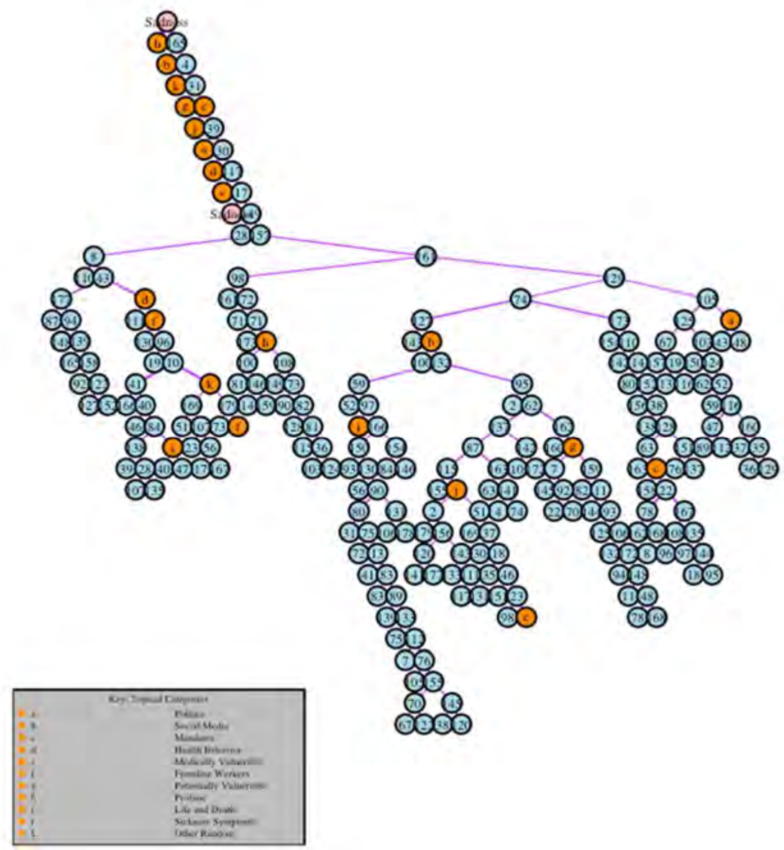


Figure 9.6a. Text Representative of 'Sad' Tweets in Topic 110, for which the effect of 'Sadness' on Prevalence is Significantly Stronger than 'Fear'

We are in this together: limited edition LA relief collection features Los Angeles inspired designs by @[artist]. All proceeds will support emergency relief for the covid crisis.	Just one week since launching the emergency relief fund and we have raised a whopping $1mil. I'll take it but damn this virus is so bad.
We are in this together: I'll be donating my sales to help weather the storm. Buy a necklace to support the United Way covid relief fund.	We another month. Suspend rent payments so tenants with lost income will not be forced to close their business due to the state of emergency. We will establish a coronavirus rental assistance fund. This is the third bill to set in motion emergency fund assisting small business and landlords.

Figure 9.6b. Text Representative of 'Sad' Tweets in Topic 28, for which the effect of 'Sadness' on Prevalence is Significantly Weaker than 'Fear'

Just now our local emergency room made a separate wing in the hospital just for covid patients. It's totally separated from the emergency room to keep people totally isolated. Every single room is thoroughly sterilized after each use.	3-ply cotton mask can be bad for workouts so I use 1-ply with an insertable filter. We need layers for hi-risk close contact inside but I can't maintain everywhere. Prob just some situations.
Yeah it makes a big difference I'm at the hospital and no one has been to visit or anything in days. It means I'm going to use a rescue inhaler like in my teen days at a soccer tourney to avoid the emergency room and long visit times.	At least Minnesota is getting a move on this thing. Mayo Clinic just ordered a bunch of fans for us to use in emergency hospitals.

The predicted model places the probability at a slightly higher approx. 30% probability (P = 0.31). However, it also predicts that a tie exists between topic 8 and 28, providing a more direct link from “Sadness” to topic 110 through topic 149, topic 28, and topic 8 (Figure 9.5b).

The results of the fitted versus predicted hierarchical random graph models supports the idea that topics 128 and 110 warrant closer examination, as Sadness may be an important factor for the prevalence of these topics. The prevalence of topic 110 was significantly more impacted by “Sadness” than “Fear,” and thus, may provide further insight as to what made people feel Sad during the first 19 months of the COVID-19 pandemic (Figure 9.1). In contrast to topic 110, “Sadness” had a significantly weaker effect on the prevalence of topic 128 than “Fear,” which means it may give some indication as to the things that were perceived as Sad regarding something that was overall more likely to frighten people than make them Sad (Figure 9.1).

Topic 110 concerned emergency relief for people who were economically vulnerable during the COVID-19 pandemic (Figure 9.6a). The implication is that there was a lot of Sadness surrounding the loss of finances during the COVID-19 pandemic. Topic 110 demonstrates that, for a seemingly frightening circumstance of sudden and widespread financial insecurity, many people also projected an overwhelming sense of Sadness compared to Fear about the widespread need for financial assistance due to the pandemic (Figure 9.6a).

Topic 28 involved the issue of mitigating the risk of infection and the difficulty many people faced when confronted with the need to mitigate the risk of infection with the SARS-CoV-2 virus in both hospital and non-healthcare public settings (Figure 9.6b).

The low effect of “Sadness” on topical prevalence compared to “Fear” for topic 28 would suggest that much more of the conversation in topic 28 involved Fears about risk mitigation in public settings than Sadness over mitigation efforts. When tweets in topic 28 were in a “Sad” context, they seemed to reflect Sadness that the risk of COVID-19 existed at all, Sadness that there was a need to mitigate COVID-19 risk, and Sadness that mitigation meant major changes to normal life (Figure 9.6b).

Surprise

The effect of "Surprise" was significantly different than the effect if "Fear" on the prevalence of 141 of the 180 topics, which was a larger number of topics than any other emotion (Figure 10.1). The prevalence of 82 of those topics was significantly less impacted by "Surprise" than "Fear" (Figure 4.1; Figure 10.1), while it was significantly more impacted by "Surprise" than "Fear" for fewer topics. The effect of Surprise on topical prevalence was only greater than the effect of Fear for 59 topics (Figure 4.2; Figure 10.1).

"Surprise" was most strongly tied to topics 35, 37, 58, 65, 68, 71, 73, 76, 89, 104, 112, 113, 129, 141, 150, and 160, most of which had high degree centrality (Figure 10.2). The effect of "Surprise" was significantly lower than the effect of "Fear" for many of these topics, including topics 35, 58, 68, 71, 73, 76, 104, 113, 141, and 160 (Figure 10.1-2).

The effect of "Surprise" on topical prevalence was significantly larger than "Fear" for topics 37, 65, 89, 112, 129, and 150 (Figure 10.1-2). All topics whose prevalence was more strongly impacted by "Surprise" than "Fear" related to the idea that COVID-19 constituted an emergency. The top terms for most of the topics indicated that there was a widespread sense of "Surprise" over emergency declarations, much more than there was "Fear," like the use of the word "emergency" in a "Surprised" context in topic 129 (Figure 10.3m). For example, top "Surprised" words for topic 37 included the highly prevalent word "declares," and the highly prevalent word "outbreak" used in about an equal amount of "Surprised" and "Fearful" contexts (Figure 10.3b).

Figure 10.1. Network of Topics for Which the Effect of Surprise was Significant

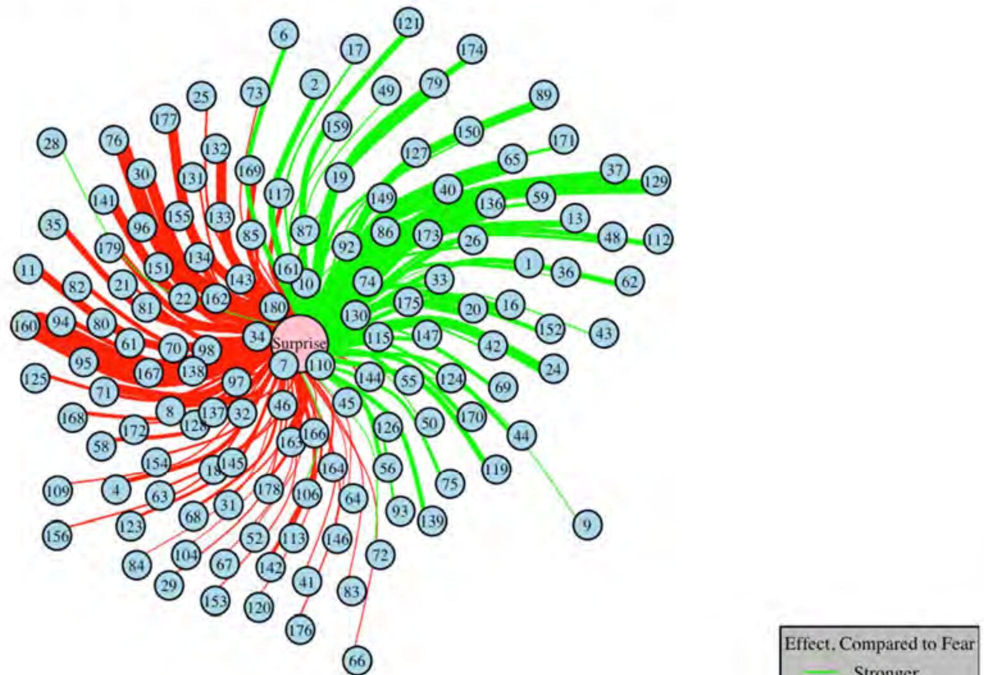
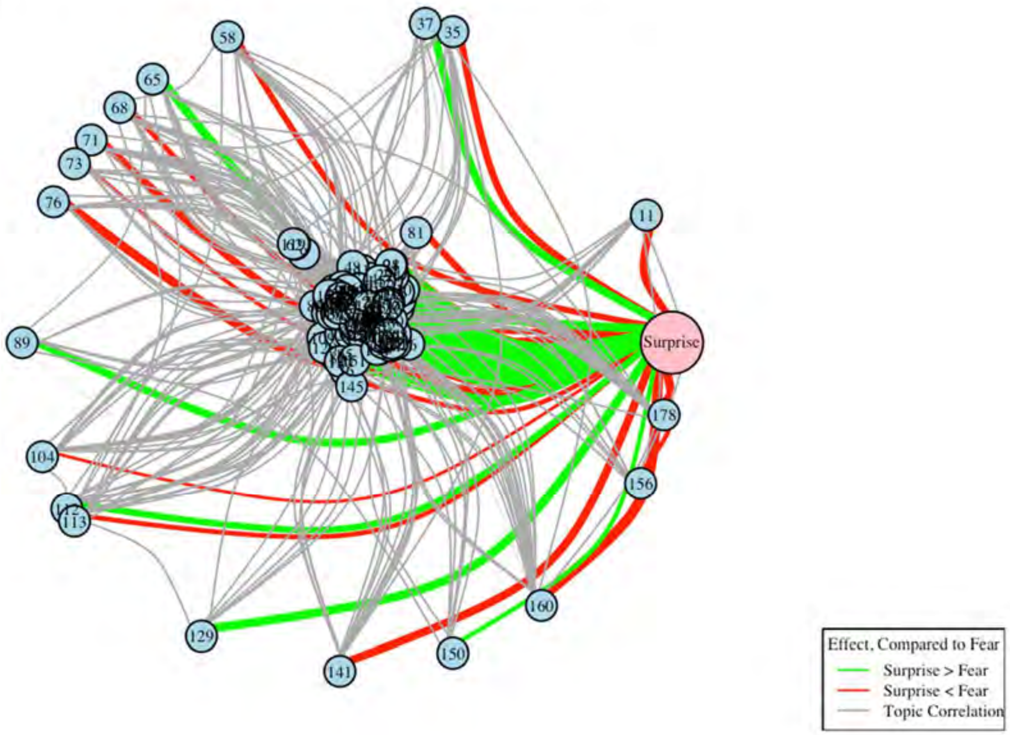


Figure 10.2. Strongest Effects and Correlation Between Topics in a Network of Topics for Which the Effect of Surprise was Significant



In Topic 65, the high prevalence of the word “hospitalization” in a “Fearful” context aligns with the idea that being hospitalized during a public health emergency could be frightening, but the higher effect of “Surprise” on topical prevalence and the use of the words “COVID” and “emergency” in an overwhelmingly “Surprised,” not “Fearful,” context could mean that many people were Surprised that the risk of hospitalization was such that COVID-19 constituted an emergency of global concern (Figure 10.3d).

There was also a high prevalence of other discussions related to the idea that COVID-19 was an emergency in urgent need of being addressed in a “Surprised” context. Topic 112 highlighted that many felt Surprised that action like proposing emergency “funding” were being taken by “congress” to address the COVID-19 emergency (Figure 10.3k). Topic 89 highlighted actions by state “governor[s],” also giving some indication that the word “governor” was used most often in a “Fearful” context in the topic (Figure 10.3i). This could relate to Fears that governors would act, but also Fears that they would fail to act when necessary. Other discussions related to the idea that COVID-19 was an emergency in urgent need of being addressed in a “Surprised” context. Take topic 112, for example, which highlighted that many felt Surprised that actions like proposing emergency “funding” were being taken by “congress” to address the COVID-19 emergency (Figure 10.3k).

Topic 150 provided evidence that people were also Surprised when emergency measures ended, which hints towards the possible importance of time for “Surprise” related to the COVID-19 emergency (Figure 10.3o). It could be the case that, after initial Surprise over the emergency, many people accepted that COVID-19 was indeed an emergency, and thus, were Surprised when the discussion changed to downplay its risk.

Figure 10.3a. Prevalence of "Surprised" and "Fearful" Words in Topic 35

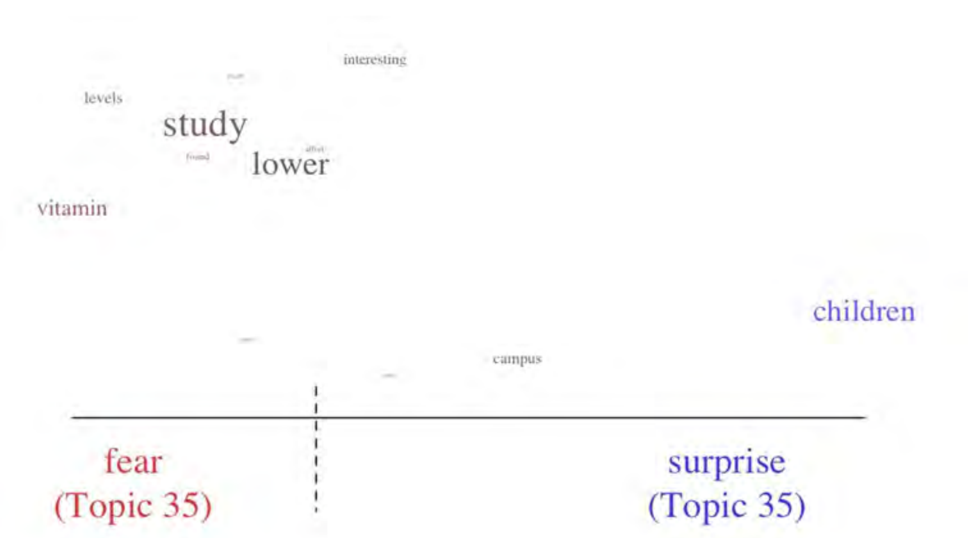


Figure 10.3b. Prevalence of "Surprised" and "Fearful" Words in Topic 37

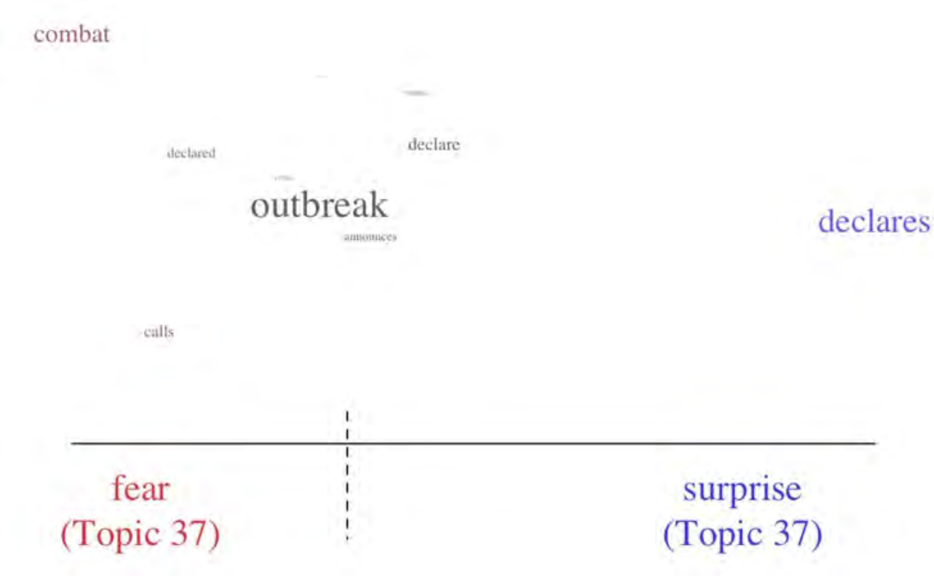


Figure 10.3c. Prevalence of “Surprised” and “Fearful” Words in Topic 58

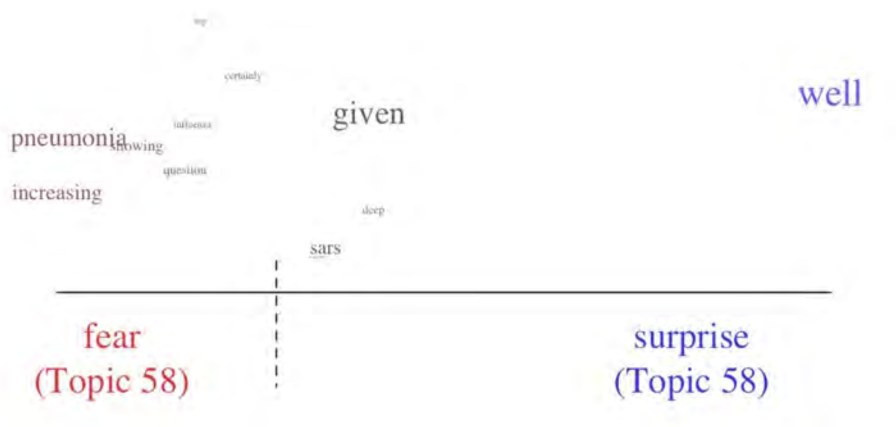


Figure 10.3d. Prevalence of "Surprised" and "Fearful" Words in Topic 65

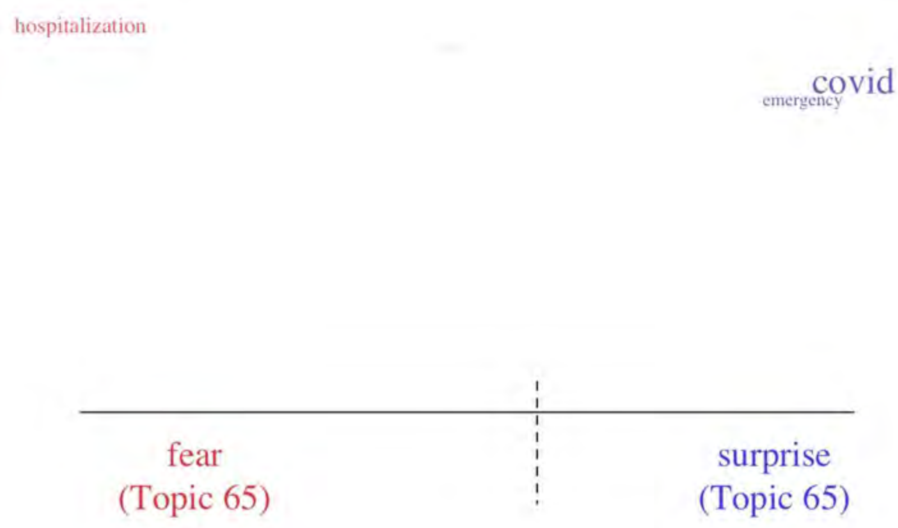


Figure 10.3e. Prevalence of "Surprised" and "Fearful" Words in Topic 68

Figure 10.3f. Prevalence of "Surprised" and "Fearful" Words in Topic 71

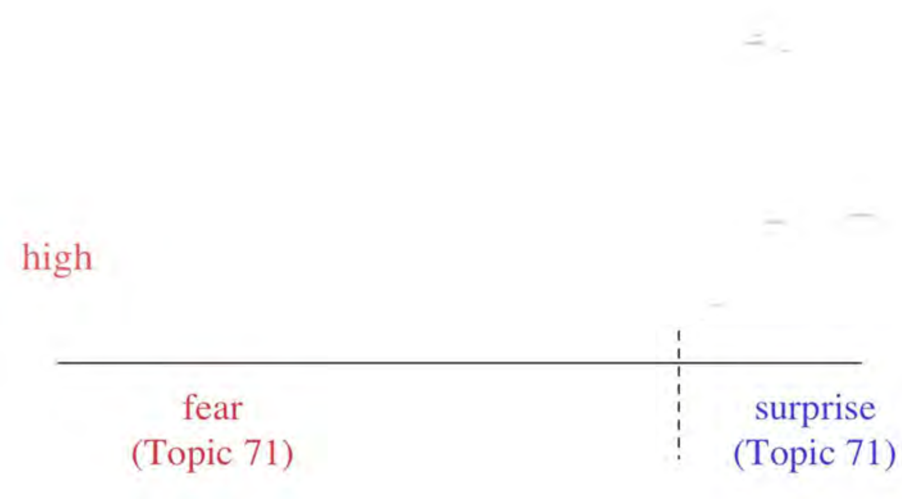


Figure 10.3g. Prevalence of "Surprised" and "Fearful" Words in Topic 73

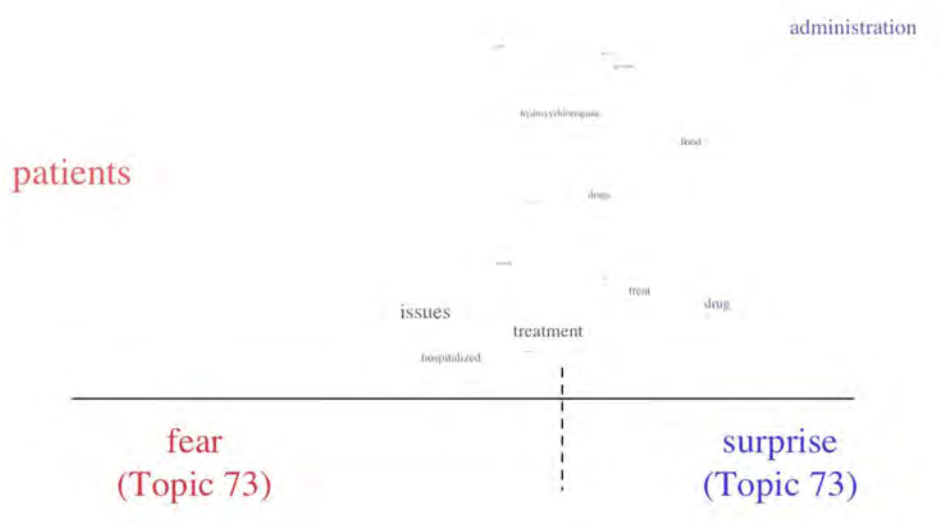


Figure 10.3h. Prevalence of "Surprised" and "Fearful" Words in Topic 76

Figure 10.3i. Prevalence of "Surprised" and "Fearful" Words in Topic 89

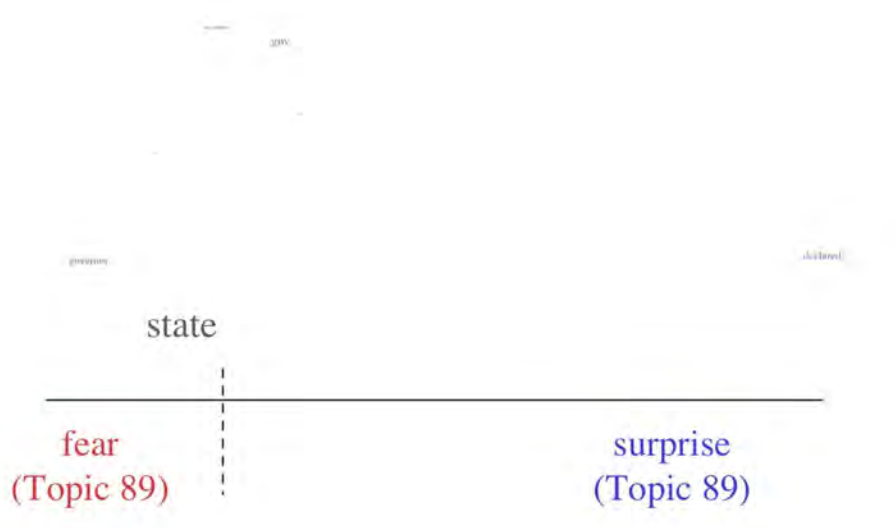


Figure 10.3j. Prevalence of "Surprised" and "Fearful" Words in Topic 104

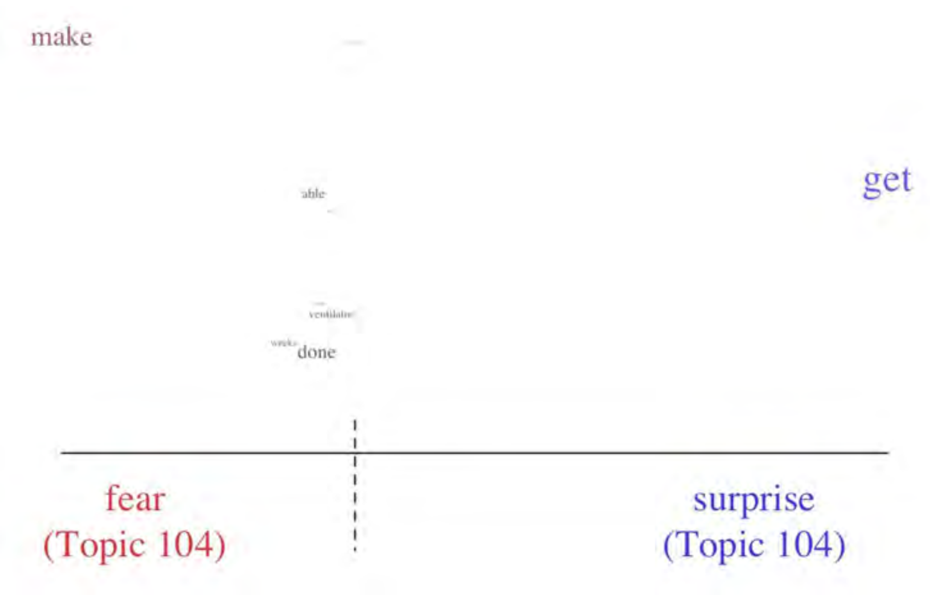


Figure 10.3k. Prevalence of "Surprised" and "Fearful" Words in Topic 112

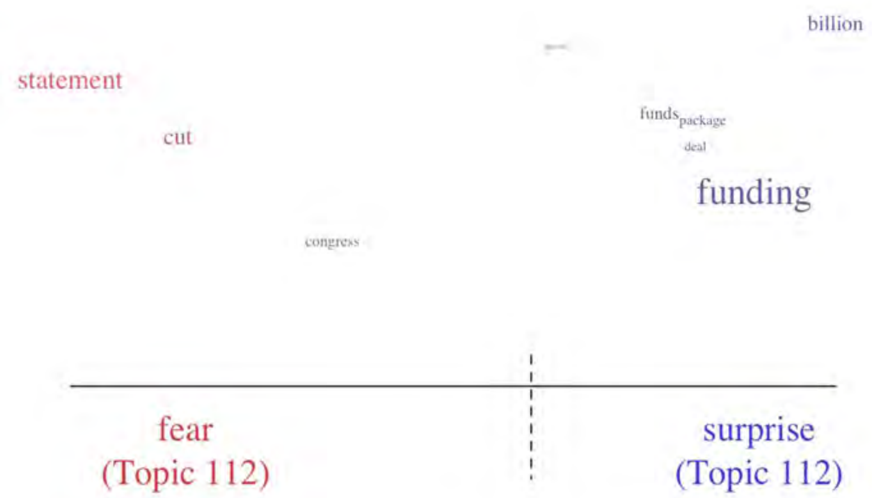


Figure 10.3l. Prevalence of "Surprised" and "Fearful" Words in Topic 113

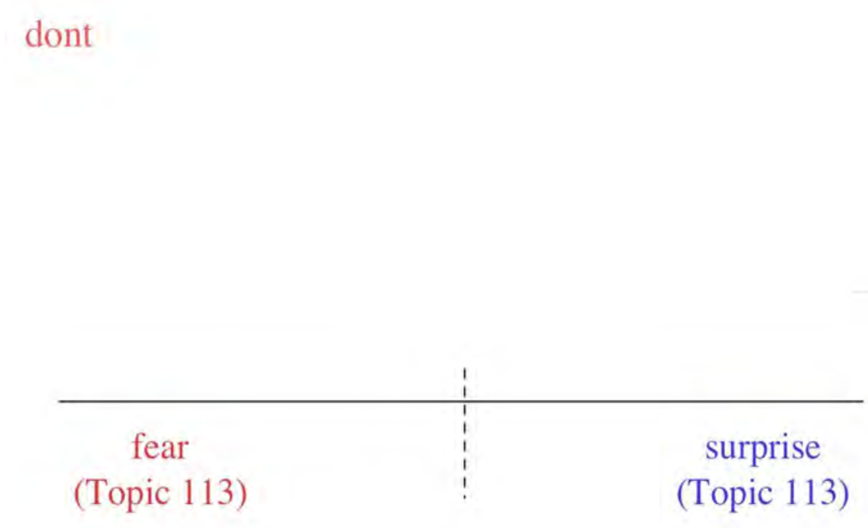


Figure 10.3m. Prevalence of "Surprised" and "Fearful" Words in Topic 129

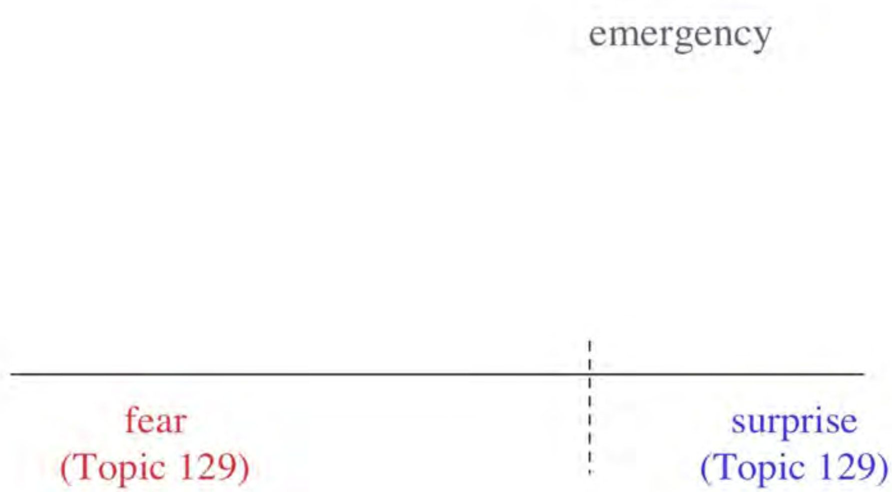


Figure 10.3n. Prevalence of "Surprised" and "Fearful" Words in Topic 141

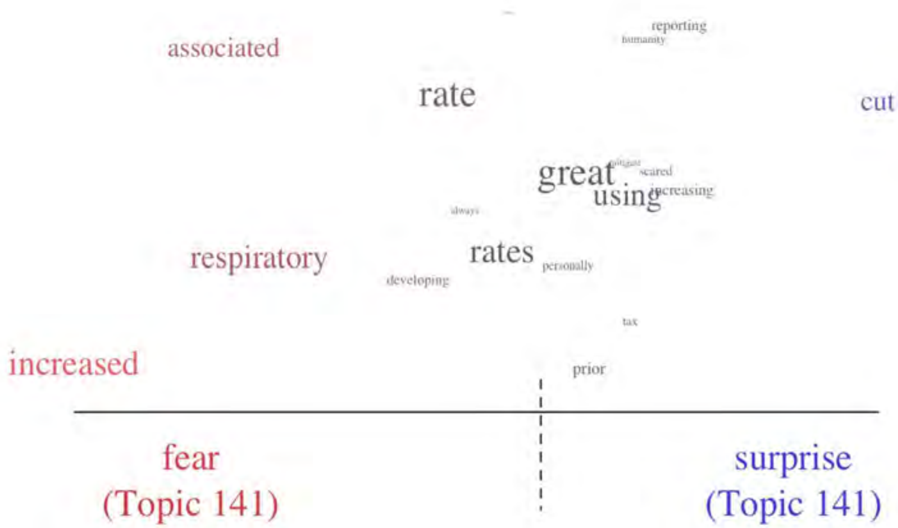


Figure 10.3o. Prevalence of "Surprised" and "Fearful" Words in Topic 150

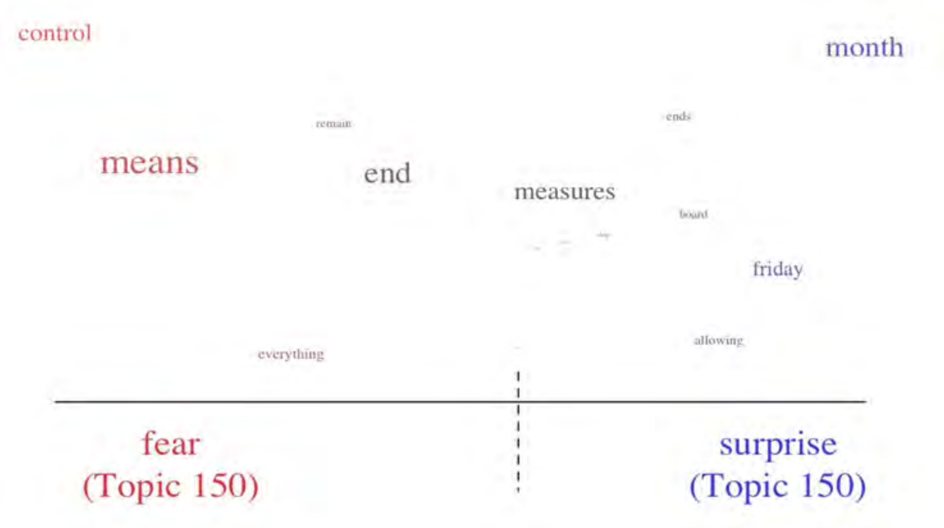
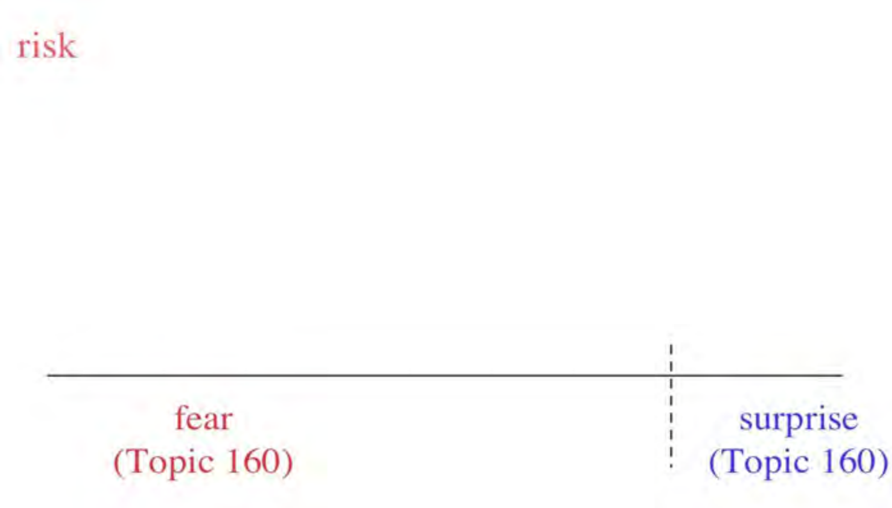


Figure 10.3p. Prevalence of "Surprised" and "Fearful" Words in Topic 160

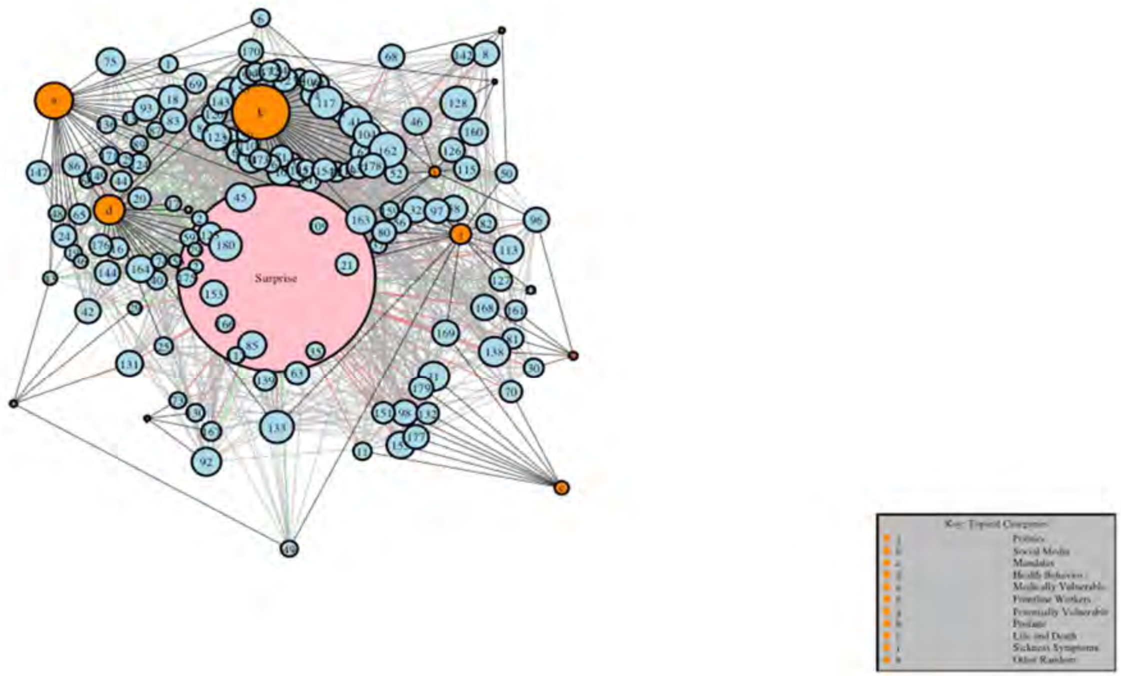


In contrast to the topics where “Surprised” contexts were more prevalent than “Fearful ones suggesting there was much more “Surprise” than “Fear” that the emergency existed, topics where “Fearful” contexts were more prevalent than “Surprised” ones indicated that many people were frightened by the idea of “risk” generally, like in topic 160 (Figure 10.3p). Other topics gave additional insight, for example, the suggestion in topic 76 that people were specifically frightened by the existence of “COVID” (Figure 10.3h). The persistent predominant use of the word “COVID in a “Fearful” context in topic 76 regardless of which emotion “Fear” was compared to is a good indication that many people were frightened by COVID itself (Figure 5.3c; Figure 6.3a; Figure 8.3b; Figure 9.3a; Figure 10.3h).

Top “Fearful” terms like “patient” in topic 73, “high” in topic 71, and the words “increasing” and “pneumonia” in topic 58, alongside the significantly lower effect of “Surprise” on prevalence for these topics, hinted that the expression of “Fear” for the risk to medically vulnerable populations was more common than the expression of “Surprise” in all three topics. This suggests that, even though the circumstance could be considered frightening, there was some degree of expectation that groups like the elderly and people with chronic illnesses would be more vulnerable to complications from COVID-19 infection than younger people with no diagnosed or suspected chronic illness.

The addition of the topical categories to the “Surprise” subnetwork revealed the “Political” and “Risk Mitigating Behaviors” topical categories were highly central, in addition to the less meaningful “Other” category (Figure 10.4). While this was somewhat expected given these nodes remained highly central across the subnetworks for other emotions (Figure 5.4; Figure 6.4; Figure 7.4; Figure 8.4; Figure 9.4), it was notable that another topical category was also highly central to the subnetwork connecting topics and topical categories to “Surprise.”

Figure 10.4. Strength of Ties between Categories and Topics for which the Effect of "Surprise" on Topical Prevalence was Significantly Different Than the Effect of "Fear"



Note: Larger nodes indicate higher degree centrality; Wider edges indicate greater edge density.

Figure 10.5a. Fitted Hierarchical Random Graph Model
Topical Categories, Topics, and Surprise

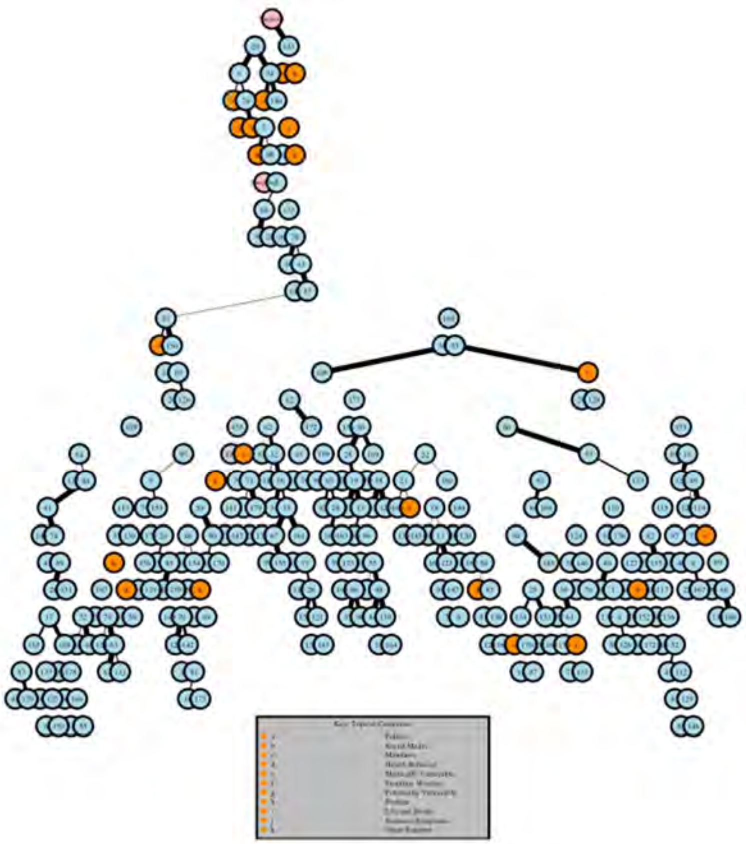
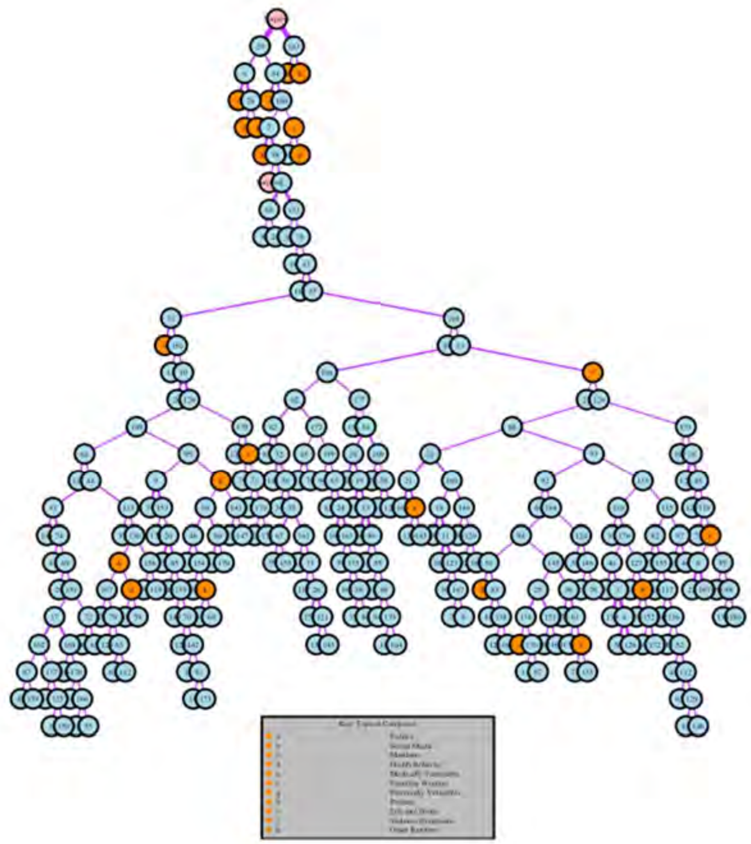


Figure 10.5b. Predicted Hierarchical Random Graph Model
Topical Categories, Topics, and Surprise



The category for topics related to “Sickness Symptoms” (node “j”) was also highly central for the “Surprise” subnetwork (Figure 10.4). Taken in context of the high prevalence of “Surprise” in topics discussing the notion that COVID-19 posed a widespread and potentially dire threat, this could indicate that many people were Surprised about the symptoms of COVID-19 and/or their severity (Figure 10.3a-p).

Also notable was that only one of the six topics for which the effect of “Surprise” on prevalence was significantly stronger than the effect of “Fear” was tied to a topical category other than “Political” topics (node “a”) and “Sickness Symptoms” (node “j”). Topic 150 was tied only to the “other” category (node “k”) (Figure 10.4). Additionally, despite its high degree centrality due to having ties to many nodes in the network, none of the topics for which the effect of “Surprise” on topical prevalence was significantly stronger than “Fear” were tied to the “Risk Mitigating Behavior” category (node “d”). Instead, most were tied to the “Political” category (node “a”), including topics 65, 89, 112, and 129 (Figure 10.4). The remaining topic, topic 37, was tied to the “Sickness Symptoms” category, providing support for the idea that people may have been Surprised at the symptoms of SARS-CoV-2 infection and/or their severity (Figure 10.4).

The root of the hierarchical random graph model for the “Surprise” subnetwork included one subgroup comprised of groups 29 and 23. Group 29 represented the vertex pair with the “Social Media” and “Profane” categories. The smaller of group 23’s subgroups was group 5, which contained the nodes representing the “Mandates,” “Life and Death,” and “Frontline Workers” topical categories. The larger subgroup under group 23, group 28, contained the remaining nodes, including the node for “Surprise” and every one of the 141 topics in the network. (Figure 10.5a-b)

The fitted model estimated a low, 2%, probability of a tie between the subgroups in group 1 (P = 0.023) (Figure 10.5a), but the predicted probability of 97% (P = 0.97) was a good indication that the nodes in group 29 for the "Profane" and "Social Media" categories were not completely isolated from the remaining nodes in the network. This could mean the "Profane" and "Social Media" categories were somewhat correlated to "Surprised" emotional sentiment, just not strongly so (Figure 10.5b).

Trust

Of the topics for which the effect of "Trust" on topical prevalence was significantly different from the effect of "Fear," the effect of "Trust" was significantly *stronger* than the effect of "Fear" for 66 topics (Figure 4.2; Figure 11.1), while it was significantly *weaker* than the effect of "Fear" for 59 topics (Figure 4.1; Figure 11.1).

The effect of "Trust" on topical prevalence was significantly different than the effect of "Fear" for the same number of topics as one other emotion, Joy (n = 125) (Figure 8.1; Figure 11.1). Trust and Joy are also the two emotions that are most easily separated from the upsetting or somewhat negative connotation of "Fear," with other emotions like "Sadness," "Disgust," and "Anger" often also used in a negative context or to denote feeling upset, and emotions like "Surprise" and "Anticipation" being more neutral or used to express about an equal amount of positive sentiment as negative sentiment. There is some overlap among topics in the "Joy" and "Trust" subnetworks. However, there was not *complete* overlap between topics whose prevalence was significantly more effected by "Trust" than "Fear," and those for which the effect of "Joy" was significantly stronger than the effect of "Fear" (Figure 11.1; Figure 8.1). It could be the case that the similar number of topics in the "Joy" and "Trust" subnetworks was entirely coincidental.

While the subnetworks for "Joy" and "Trust" shared 86 of their 125 topics[3], the topics for which the effects of both "Joy" and "Trust" on topical prevalence was significantly greater than "Fear" are potentially the most useful for understanding unintuitively optimistic topics of conversation surrounding risk during the COVID-19 pandemic (Figure 8.1; Figure 11.1). The effect of both "Joy" and "Trust" on topical prevalence was significantly higher than the effect of "Fear" for only 24[4] of the 86 topics found in both the "Joy" and "Trust" subnetworks (Figure 8.1; Figure 11.1). Furthermore, 39 of the 125 topics in each subnetwork were unique to either the "Joy" or "Trust" subnetworks, and for the "Trust" subnetwork, the effect on topical prevalence was significantly greater than "Fear" for a vast majority of the topics. The effect of "Trust" on topical prevalence was significantly larger than the effect of "Fear" for 30 of the total 39 topics unique to the "Trust" network (Figure 11.1).

The best indication of a lacking similarity between topics where "Joy" and "Trust" had a stronger effect on prevalence than "Fear" was found in the topics most strongly tied to "Trust" in its subnetwork. The ties between "Trust" and 5 topics in the subnetwork, topics 37, 89, 113, 122, and 160, were visibly stronger than the ties between "Trust" and each of the other 120 topics in the subnetwork, shown by the longer red and green edges in Figure 11.2.

Topics 113 and 160, for which the effect of "Trust" on topical prevalence was significantly weaker than "Fear," also appeared in the "Joy" subnetwork but the negative effect of "Trust" on topical prevalence compared to "Fear" was only shared by "Joy" for topic 160 (Figure 8.1; Figure 11.2).

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[3] topics 2, 4, 5, 6, 7, 9, 11, 13, 19, 21, 25, 26, 28, 30, 32, 33, 35, 38, 40, 41, 44, 46, 50, 57, 62, 63, 64, 66, 68, 70, 73, 76, 81, 82, 85, 86, 87, 91, 92, 94, 95, 96, 98, 99, 101, 103, 110, 113, 114, 115, 116, 117, 119, 122, 123, 124, 125, 129, 132, 133, 136, 137, 138, 139, 141, 142, 143, 145, 149, 151, 155, 159, 160, 161, 162, 163, 164, 167, 168, 169, 171, 175, 176, 177, 178, 179

[4] topics 5, 9, 13, 44, 50, 57, 64, 66, 99, 103, 110, 115, 119, 122, 123, 129, 139, 145, 149, 161, 164, 167, 175, 176

Figure 11.1. Network of Topics for Which the Effect of Trust was Significant

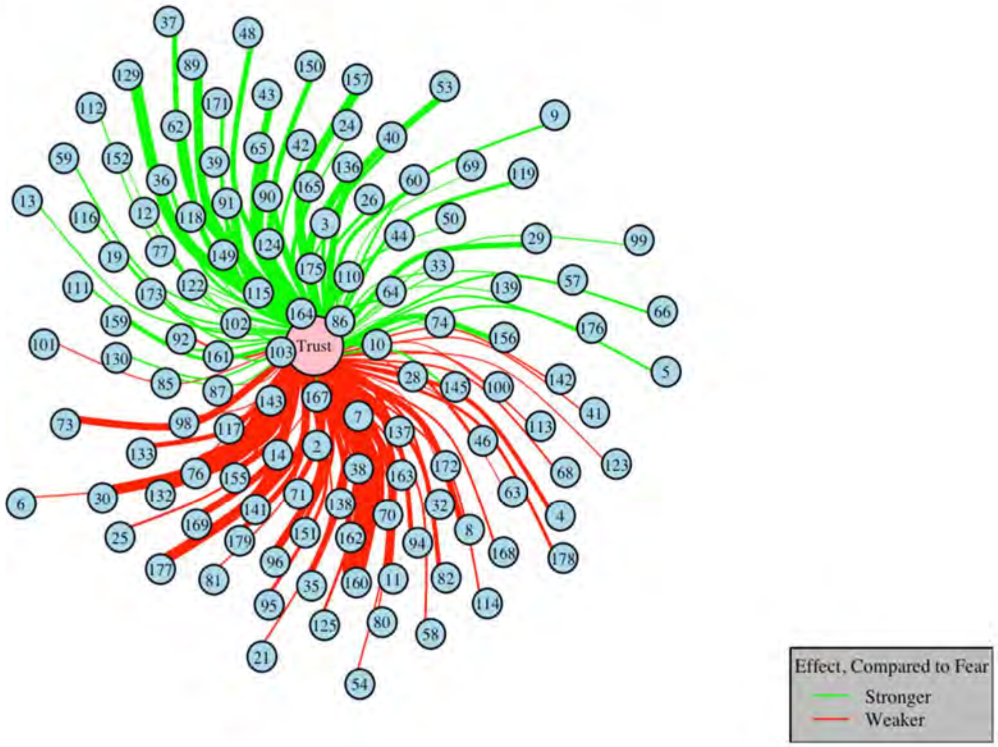
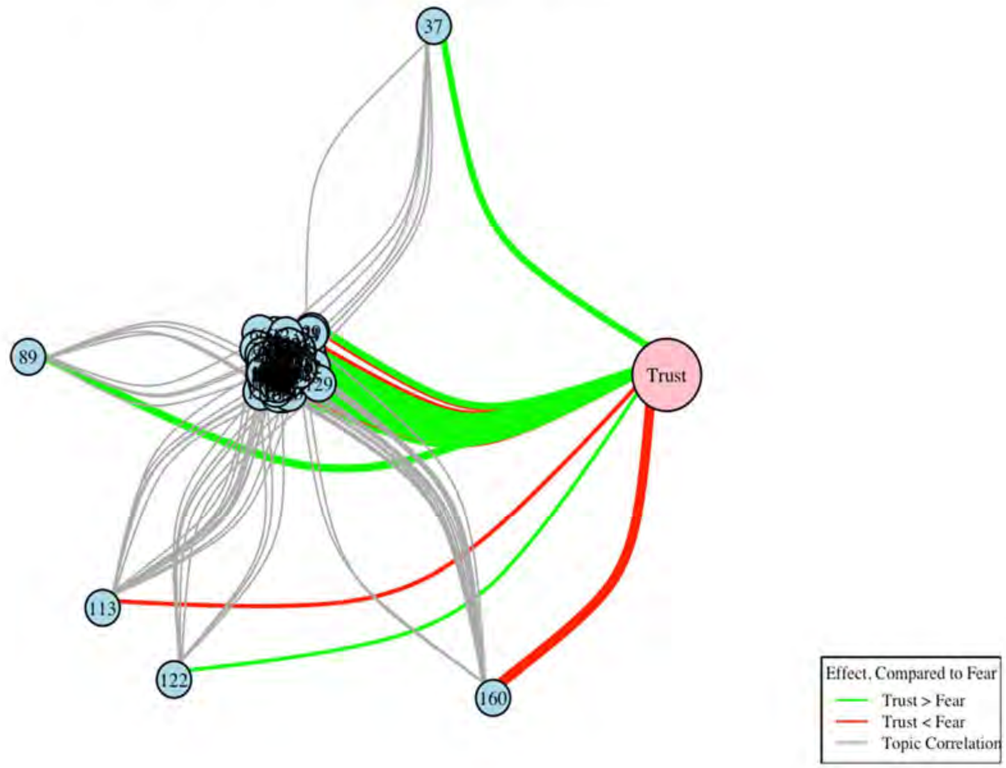


Figure 11.2. Strongest Effects and Correlation Between Topics in a Network of Topics for Which the Effect of Trust was Significant



Topic 160 was not among the topics most strongly tied to “Joy” (Figure 8.2; Figure 8.3a-h), and while Topic 113 was among topics with the strongest ties to “Joy,” the effect of “Joy” on the prevalence of topic 113 was significantly *stronger* than the effect of “Fear” in stark contrast to the effect of “Trust compared to “Fear” for the same topic (Figure 8.2; Figure 11.2). Additionally, the only word prevalent enough in either “Fearful” or “Trusting” contexts to appear for topic 113 was the word “don’t” in a “Trusting” context, a likely indication that neither “Trust” nor “Fear” was particularly important for the overall prevalence of topic 113 (Figure 11.3c).

The only node with a strong tie to “Trust” also present in the “Joy” subnetwork and for which the effect of “Joy” on topical prevalence was significantly larger than the effect of “Fear” was topic 122 (Figure 11.2), but the topic was not among those most strongly tied to “Joy” (Figure 8.2; 8.3a-h). The words that appeared most often in a “Trusting” rather than “Fearful” context in topic 122 included “last,” “power,” and the barely visible “night,” alongside the common use of the word “hospital” in a “Fearful” context (Figure 11.3d). This could be a sign that many people felt a sense of Trust when the end to a hospitalization was near, despite the frightening circumstance of hospitalization.

Figure 11.3a. Prevalence of “Trusting” and “Fearful” Words in Topic 37

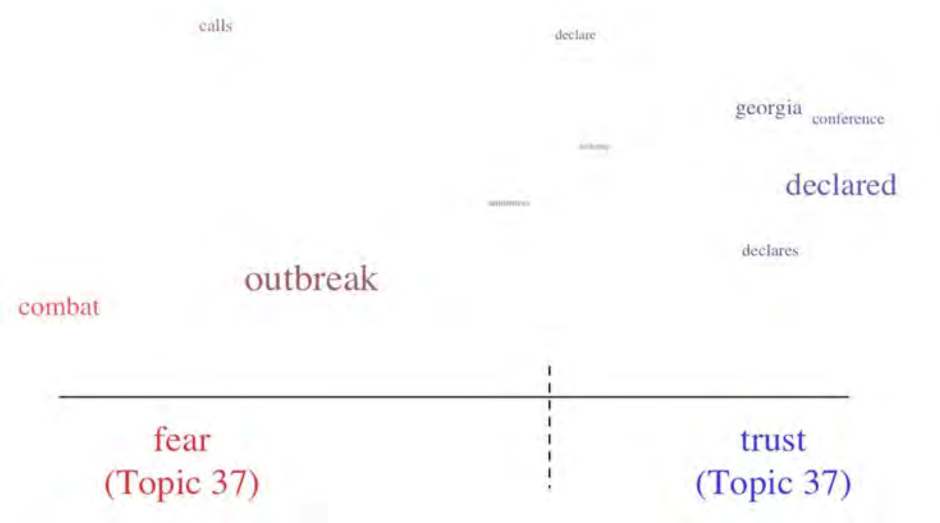


Figure 11.3b. Prevalence of "Trusting" and "Fearful" Words in Topic 89

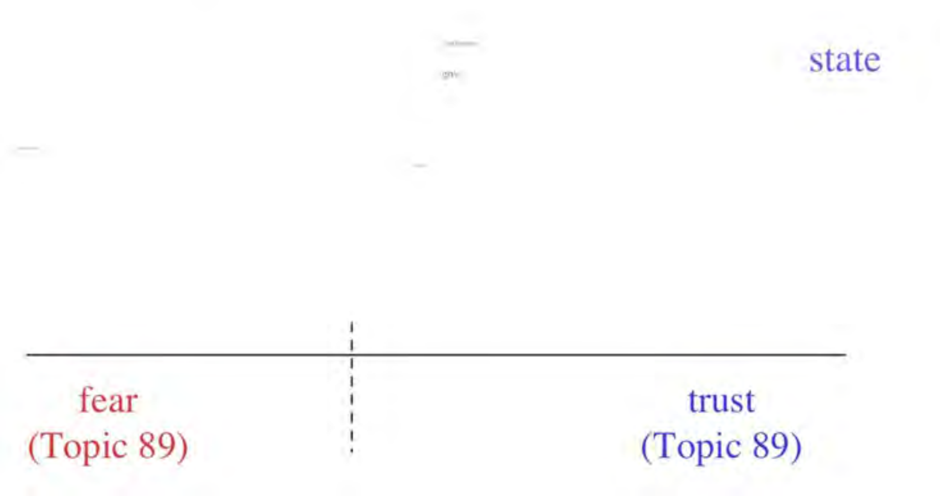


Figure 11.3c. Prevalence of “Trusting” and “Fearful” Words in Topic 113

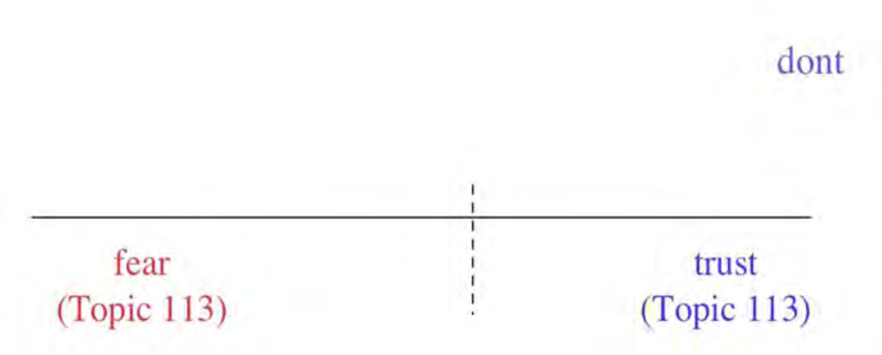


Figure 11.3d. Prevalence of "Trusting" and "Fearful" Words in Topic 122

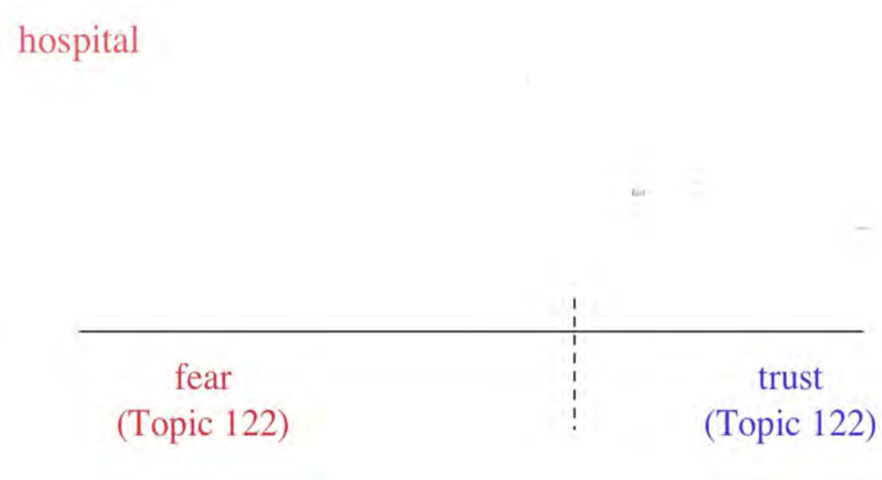


Figure 11.3e. Prevalence of "Trusting" and "Fearful" Words in Topic 160

The other topics with strong ties to “Trust” whose prevalence was more strongly impacted by “Trust” than “Fear” included topics 37 and 89 (Figure 11.2). Top words for topic 89 like “governor” in a “Fearful” context and the words “gov,” “declaration,” and “state” in a “Trusting” context give merit to the possibility that, considering the frightening circumstances surrounding the COVID-19 pandemic, declarations by government officials could invoke a sense of “Trust” (Figure 11.3b). The prevalent use of the words “outbreak” and “combat” in a “Fearful” context alongside the common use of words like “Georgia,” “conferences,” and several variations of the word “declare” in a “Trusting” context in topic 37, shed light on one of the lesser-emphasized consequences of the state of Georgia’s early reopening compared to other states (Figure 11.3a).

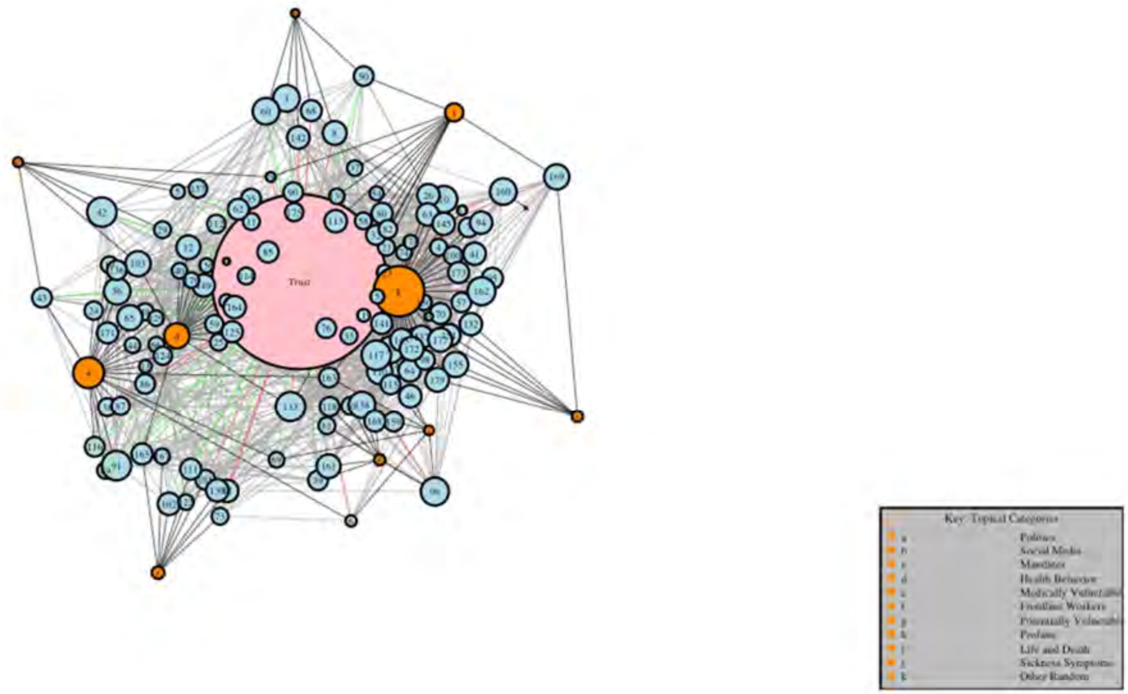
The top words for “Fearful” versus “Trusting” contexts in topic 37 reveal a possible sense of Trust in the State of Georgia, which is counter to the accusations that the state was acting against the wishes of much of the U.S. The Trust seemed to stem from Georgia being among the first to reopen after initial stay at home orders issued during March 2020 across most of the United States. Topic 37 shows that Georgia’s early reopening may have provided some guidance and an ongoing example of a path forward when few others existed (Figure 11.3a). Georgia’s reopening was heavily criticized by many scientists, health professionals, and journalists with large public platforms. This finding provides a different picture of the Fear surrounding Georgia’s reopening. It is possible that Georgia’s reopening assuaged Fears about the uncertainty of reopening by showing it was possible and providing a roadmap for other states to follow.

There is also some evidence favoring the idea that discussions of Georgia’s reopening in a “Trusting” context were apolitical, despite involving conversations about state governance, a distinctly political phenomenon (Figure 11.3a). While the similar topic 89 was directly and strongly tied to the highly central “Political” category (node “a”), topic 37 was directly and strongly tied to the “Sickness Symptoms” category (Figure 11.4). This could be an indication that much of the conversation surrounding Georgia’s reopening on Twitter focused on the reopening as a rational and necessary step in response to the perceived diminished threat of severe symptoms for most of the U.S. population, and *not* as a politically motivated process dealing with the political affiliations of Georgia politicians in charge of reopening.

In the hierarchical random graph models for the “Trust” subnetwork, group 1 had one root subgroup with a single vertex, the “Profane” category (node “h”), with an estimated 4% probability (P = 0.044) of a tie to one lower-level subgroup, group 58 (Figure 11.5a). Group 58 had one subgroup with a single vertex, the “Social Media” category (node “b”), with an estimated 7% probability (P = 0.074) of a tie to the lower-level subgroup containing all nodes except for “Profane” and “Social Media,” group 51 (Figure 11.5a).

The predicted hierarchical random graph model (Figure 11.5b) identified several possible missing edges in the fitted model (Figure 11.5a). The potentially missing edges included a 60% predicted probability (P = 0.60) of the presence of edges connecting topic 160 to the rest of the network (Figure 11.5b). This was important because topic 160 was an isolate in the fitted model (Figure 11.5a), despite its supposedly strong tie to “Trust” (Figure 11.2).

Figure 11.4. Strength of Ties between Categories and Topics for which the Effect of "Trust" on Topical Prevalence was Significantly Different Than the Effect of "Fear"



Note: Larger nodes indicate higher degree centrality; Wider edges indicate greater edge density.

Figure 11.5a. Fitted Hierarchical Random Graph Model Topical Categories, Topics, and Trust

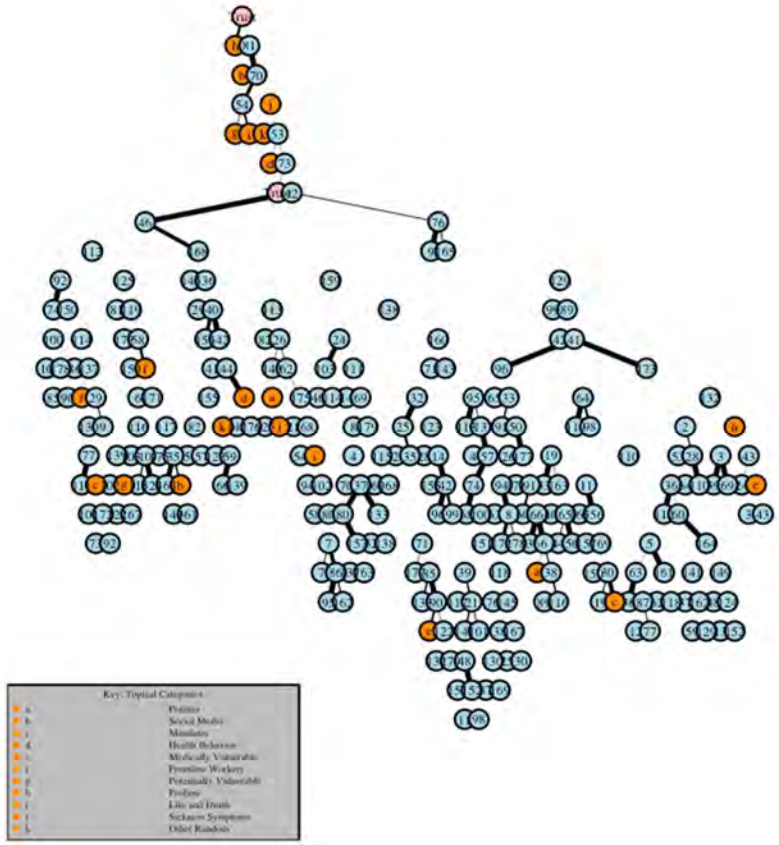
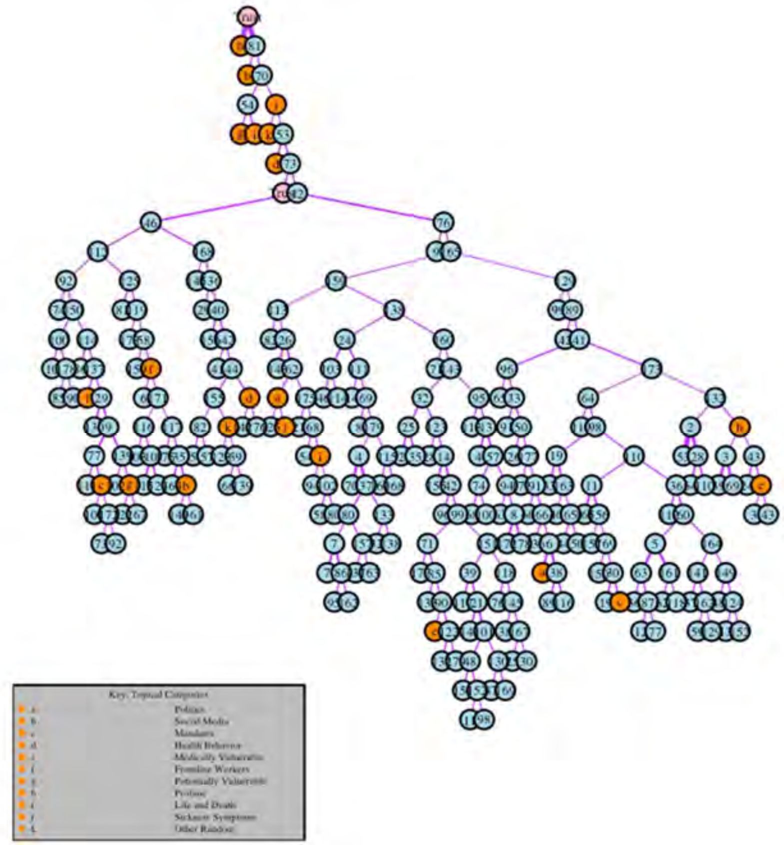


Figure 11.5b. Predicted Hierarchical Random Graph Model Topical Categories, Topics, and Trust



TIME SERIES ANALYSIS: ESTIMATED EFFECT OF TIME ON TOPIC PREVALENCE

The period in question consisted of 19 months across three calendar years from December 2019—June 2021, so it was important to assess the effect of time (cumulative days) on topical prevalence. Figure 12.1 shows the expected change in topic proportions over the 19 months for all 180 topics included in the best-fitting structural topic model of general risk tweets.

Visually, several topics do appear to have large changes in prevalence, with some appearing to decrease as time passed and others increasing to become among the topics with the highest estimated proportion by the end of June 2021 (Figure 12.1). Time did not have a significant effect on the prevalence of every topic in the model, though. Time only had a significant effect on the prevalence of 108 of the total 180 topics (Figure 12.2). Of those 108 topics (Figure 12.2), estimations indicated that the prevalence of 39 topics increased significantly between December 2019—June 2021 (Figure 12.3a). The effect of time on topical prevalence was negative for 69 of the 108 topics for which it was significant, indicating a significant decrease in prevalence over time for these topics (Figure 12.3b).

Figure 12.1. Estimated Proportion of Topics over 19 Months

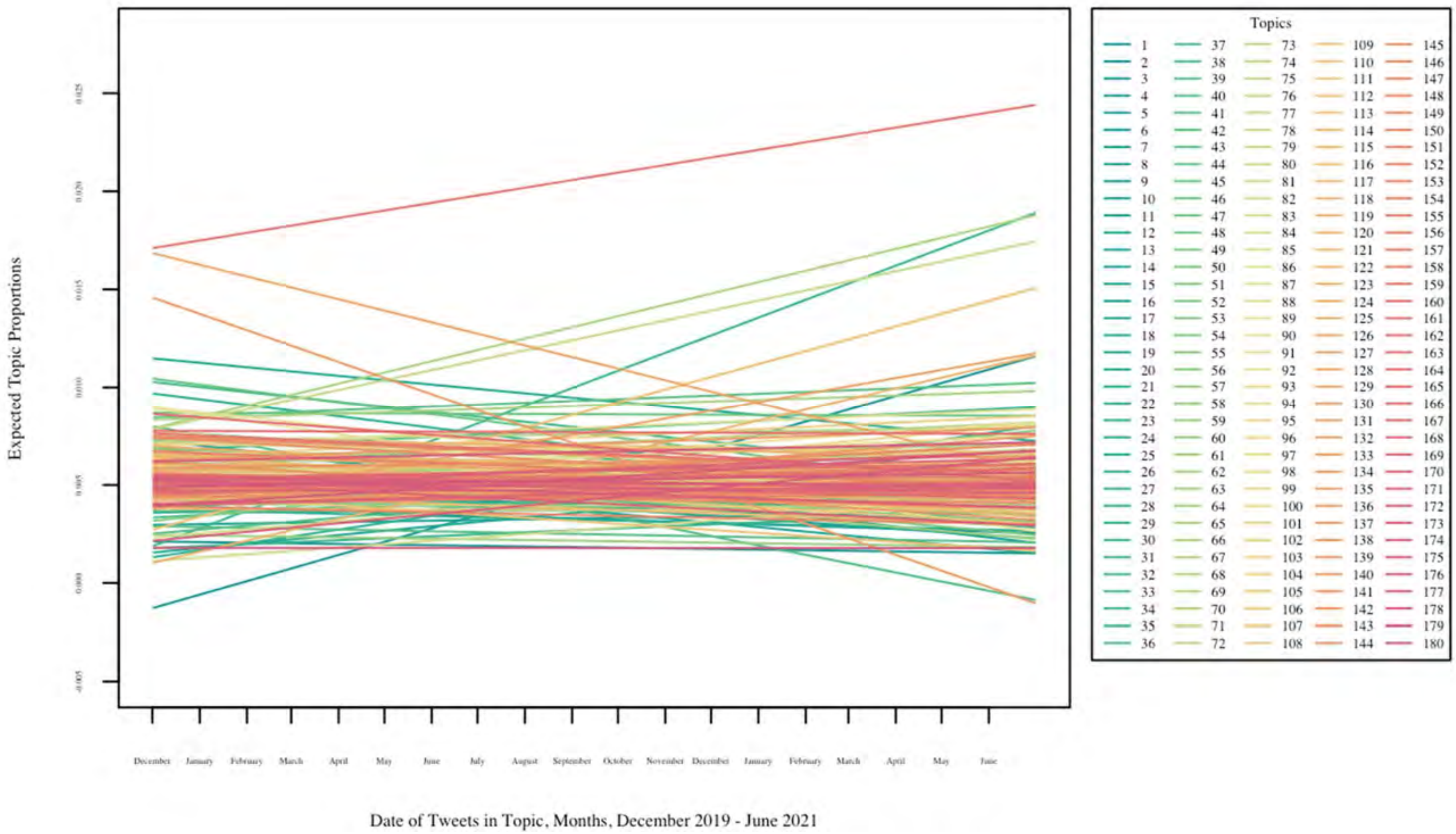


Figure 12.2. Estimated Proportion over 19 Months for Topics where the Effect of Time on Prevalence was Significant

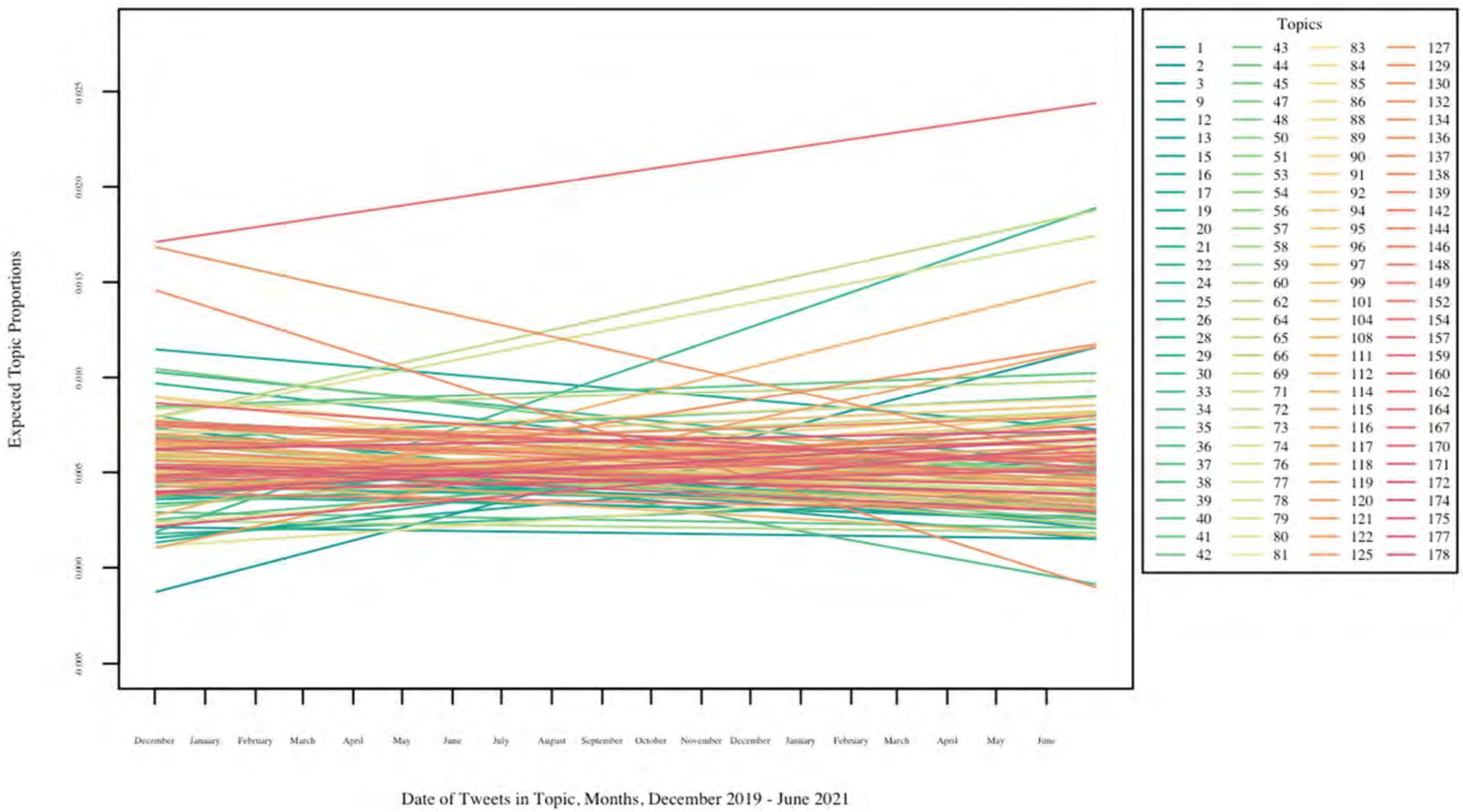


Figure 12.3a. Estimated Increase in Topic Proportion over 19 Months for Topics where the Effect of Time on Prevalence was Significant and Positive

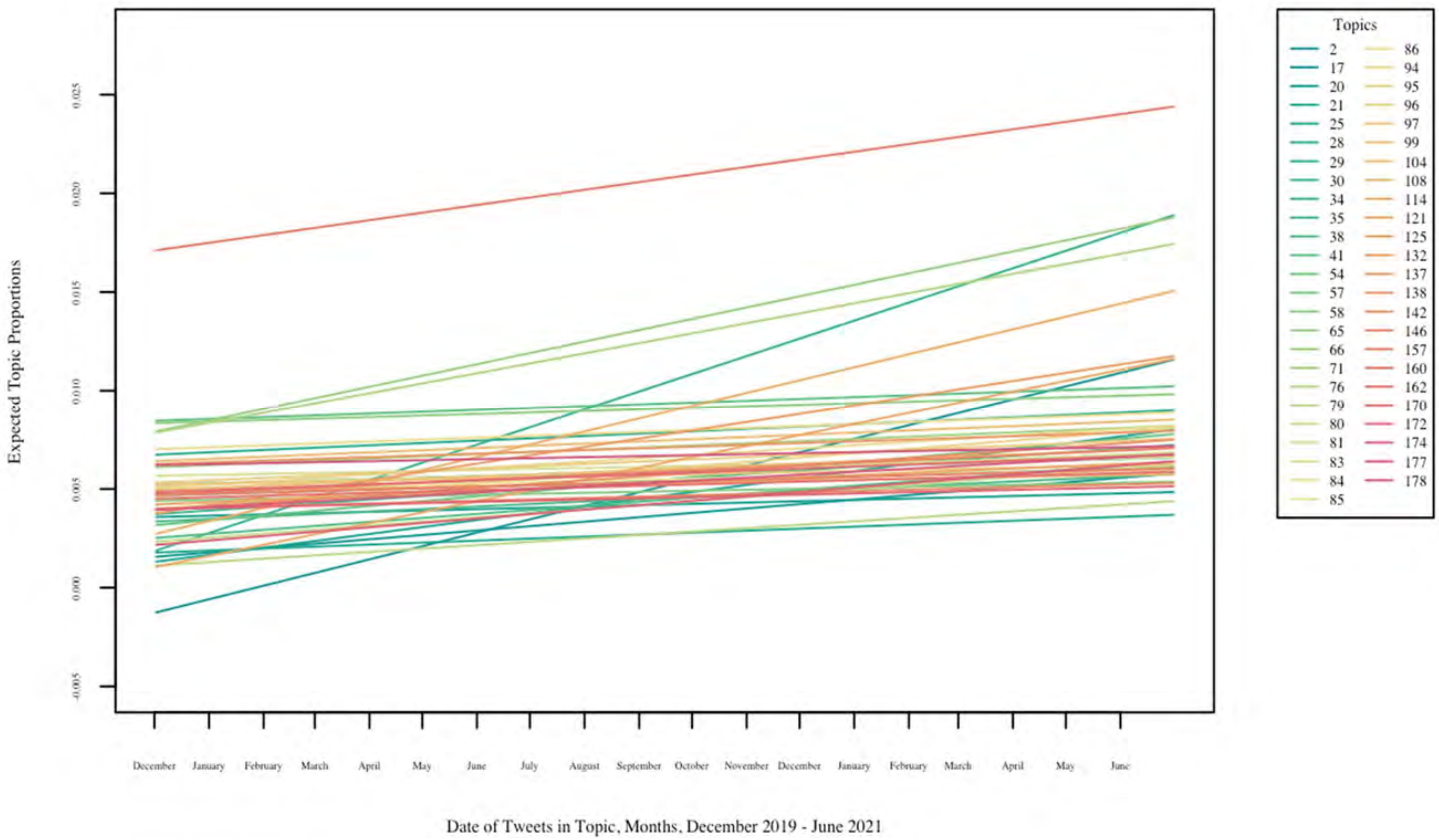
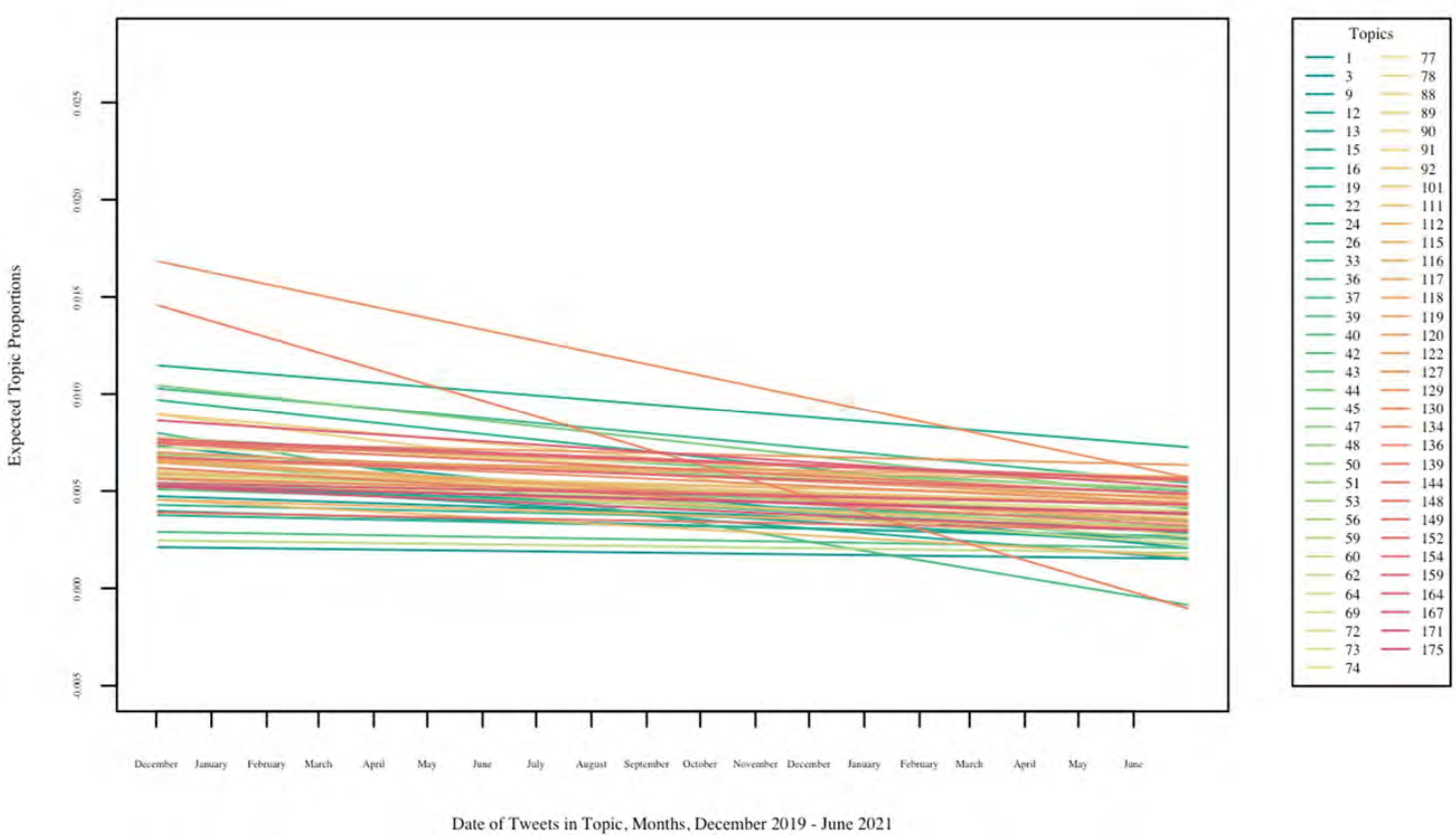


Figure 12.3b. Estimated Decrease in Topic Proportion over 19 Months for Topics where the Effect of Time on Prevalence was Significant and Negative



The linear estimations for the effect of "day" (cumulative) project only the mean change over time for each topic, and thus, do not provide a picture of how the prevalence of topics varies day-to-day or month-to-month. Plotting the estimation using a splined transformation of the "day" variable is useful for making sense of what these significant increases and decreases in topical prevalence looked like by providing a visualization of their fluctuation in the days between December 1, 2019, and June 30, 2021, the days marking the start and end of the 19-month period (Figure 12.4a-b). There were interesting differences in the patterns of fluctuation among topics that saw significant increases versus significant decreases over time. There was a lot of day-to-day, month-to-month, variation in the prevalence of topics that saw significant increases over time (Figure 12.4a), whereas similar fluctuation in topics that saw significant decreases over time was predominantly clustered towards the beginning of the 19-months, with many reaching a fairly stable prevalence by July 1, 2020, and lasting the remainder of the time period (Figure 12.4b).

There were topics that saw significant increases in prevalence over time that were highly prevalent at the start of the period and even more so towards the end alongside several with extremely low prevalence in the early months of the pandemic with steep increases to be highly prevalence by the end of June 2021(Figure 12.3a; Figure 12.4a). For example, Topic 160, a topic pertaining to "Social Media," was significantly more prevalent in June 2021 than December 2019, but it also had the highest expected topic proportion of any topic for most of the remaining duration of the 19 months in question (Figure 12.3a; Figure 12.4a).

Top words for topic 160 tweets like "risk," "Facebook," "COVID," "time," and "thought," and the fact that Topic 160 was the most prevalent of the three topics in the "Social Media" category, indicated that many discussions about risk on Twitter during the first 19-

months of the pandemic involved discussions of the happenings on other social networking and social media platforms, namely Facebook (Figure 3.3b). The persistently high prevalence of topic 160 could be a nod to widespread and increasing interest in the spread of information about COVID-19 online among members of the non-expert public (Figure 3.3b; Figure 12.4a).

In contrast, topic 38 was estimated to account for under 1% of tweets about general risk in December 2019 at the start of the duration but was one of the most prevalent topics with a significant change over time by the end of data collection in June 2021 (Figure 12.4a). On the plot of the linear estimation over time (cumulative days), topic 160 appeared to remain at a higher prevalence than all other topics through the end of June 2021 (Figure 12.3a), but the splined projection shows that topic 38 may have actually surpassed topic 160 by around the middle of that same month (Figure 12.4a). Topic 38 was a "political" topic with top words like "got," "already," "cdc," "buy," and "phase" (Figure 3.3a). The top terms for topic 38 suggested that the topic involved discussions about the phased approach to reopening as the risk of COVID-19 decreased, which was headed by the Centers for Disease Control and Prevention (CDC) in collaboration with the federal coronavirus emergency response team. In May 2021, the CDC announced that it would recommend transitioning to a new "phase" for vaccinated people in the United States over the coming months, at which point most of the United States adult population was to be considered safe to reduce their engagement in risk mitigation efforts like wearing masks (Lovelace Jr. 2021). The State of California ended its mask mandate on June 15, 2021, marking the last official transition to this new phase of reduced efforts to mitigate risks associated with COVID-19 infection. The sharp increase in the prevalence of topic 38 between May and June 2021 could be a symptom of the CDC's announcement of a new approach to risk mitigation around the same time (Figure 12.4a).

One other topic, topic 29, also appeared to surpass topic 160 in prevalence by the end of the 19-month period in question (Figure 12.4a). The increase in topic 29's prevalence over time provides further evidence supporting the idea that there was much discussion of the CDC's announcement of new guidance for handling the pandemic in the summer months of 2021. Topic 29 top words included "masks," "face," "required," "require," and "covering," which point to discussions of mandated risk mitigating behaviors during COVID in topic 29, specifically mandates requiring people to wear masks (Figure 3.3c). Considering the CDC's new guidance issued in May 2021 included specific guidance that vaccinated people in the United States were safe to stop masking in public, there is a good possibility that the large increase in the prevalence of topic 29 by the end of June 2021 had something to do with discussions of this new guidance (Figure 3.3c; Figure 12.4a).

One other pattern of fluctuation observable for the topics with significantly increasing prevalence between December 2019 and June 2021 was topics with an initially low prevalence, a sharp increase that peaked early, and a small decrease prior to another steady increase, followed by what appears to be the start of a sharp decrease towards the end of the time frame in June 2021 (Figure 12.4a). This was the case for topic 66, a topic that involved mandated risk mitigation that was categorized as "Political," with top words like "mask," "wear," "wearing," "mandate," and "tx," the abbreviation for the state of Texas (Figure 3.3a; Figure 12.4a). Topic 66 saw a rapid and steep increase in prevalence between March 2020 and July 2020, peaking again in November 2020 and once more around May 2021 (Figure 12.4a).

Figure 12.4a. Estimated Increase in Topic Proportion over 19 Months, Smoothed, for Topics where the Effect of Time on Prevalence was Significant and Positive

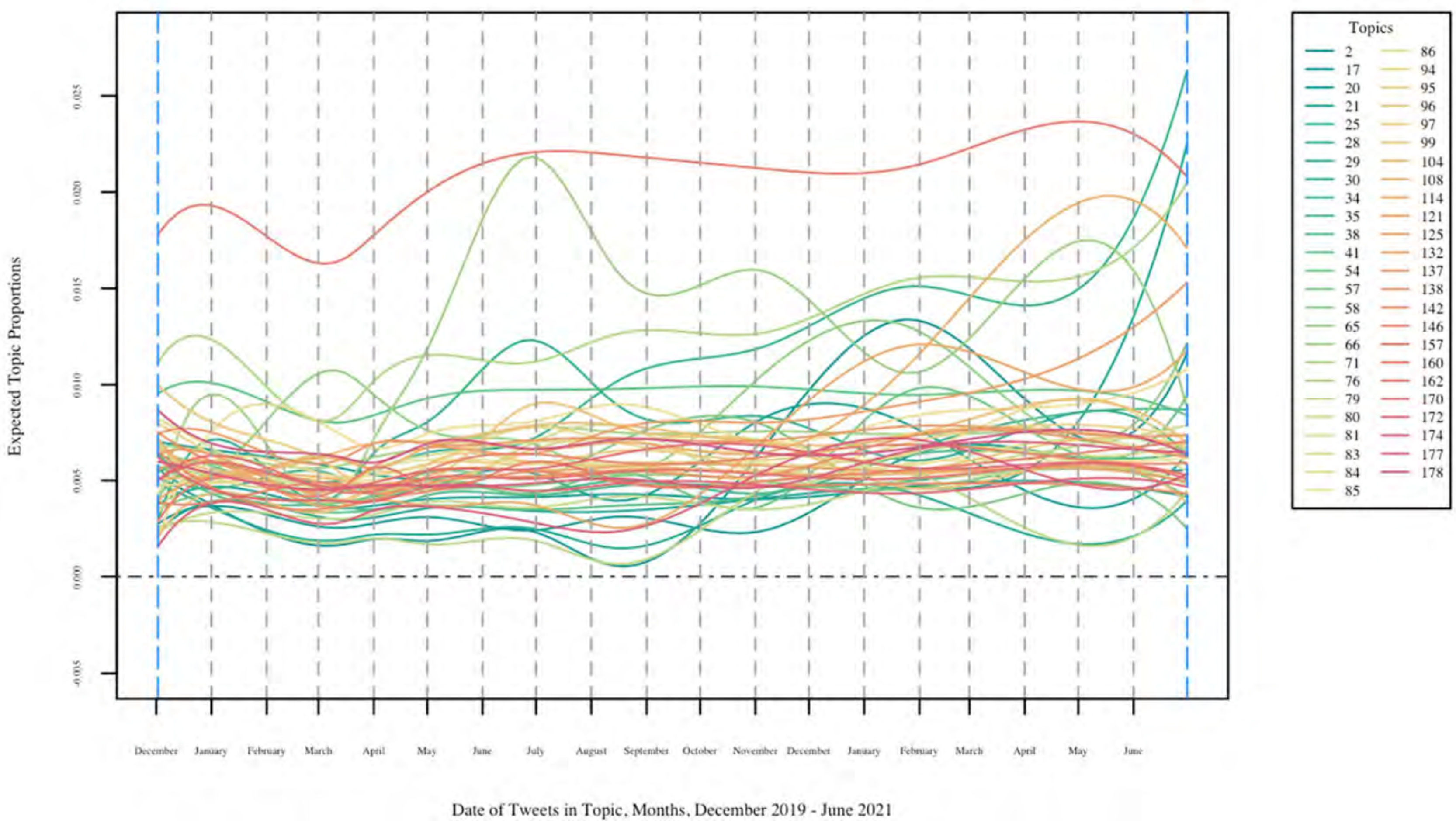
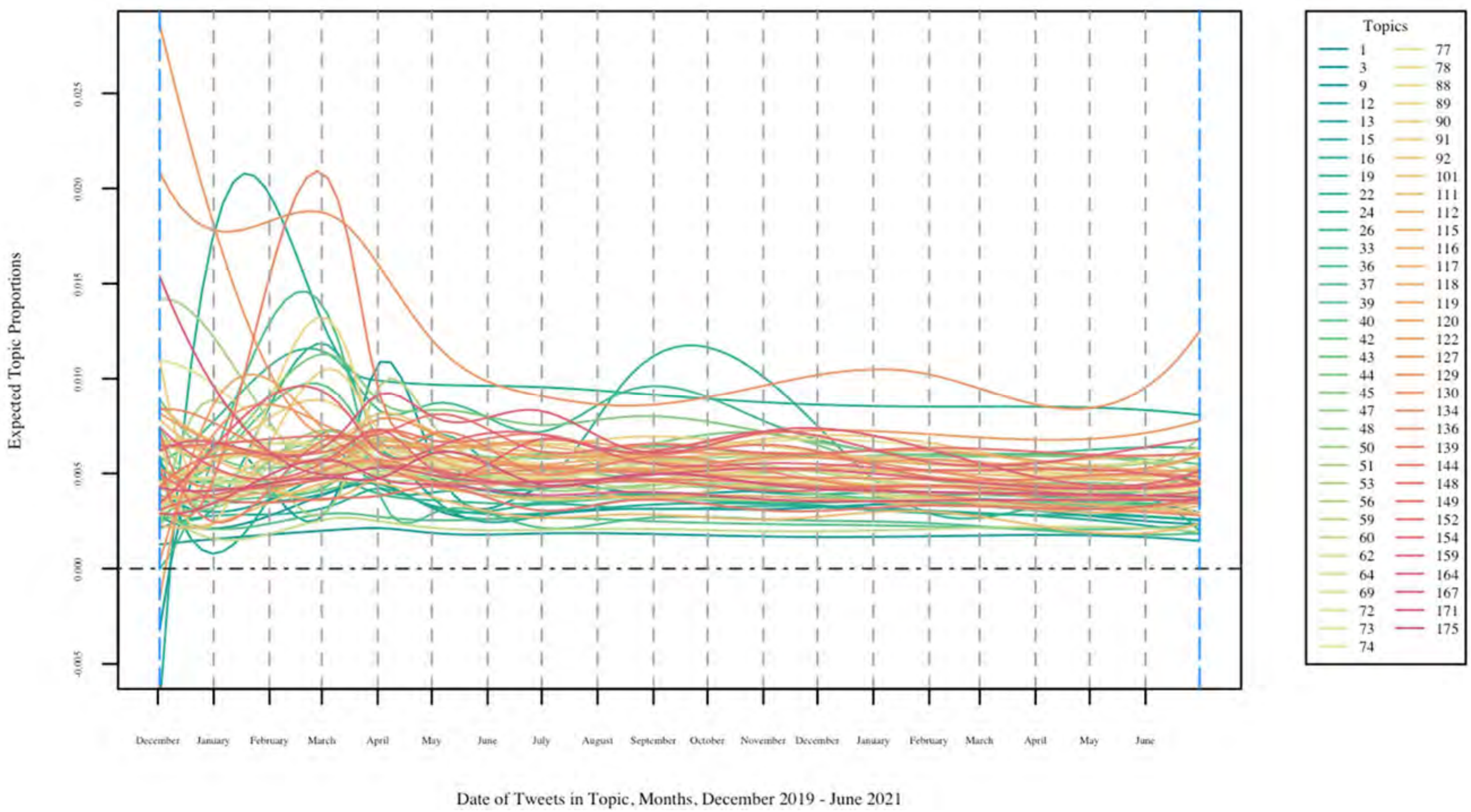


Figure 12.4b. Estimated Decrease in Topic Proportion over 19 Months, Smoothed, for Topics where the Effect of Time on Prevalence was Significant and Negative



The state of Texas followed the state of Georgia's early reopening, with neither state implementing a long-term statewide mask mandate. These decisions were considered highly controversial, particularly so in Texas, and thus, the observed pattern of fluctuation in the prevalence of topic 66 over time could be picking up on the arguments surrounding the issue of mask mandates in Texas. If so, the topic's decreasing prevalence by June 2021 could indicate that the CDC's guidance that most vaccinated people no longer needed to mask in public to mitigate the risk of COVID-19 led many to cease arguing over a need for mask mandates (Figure 12.4a).

Most of the topics seeing significant decreases over time were highly prevalent in the early months of the pandemic and only moderately prevalent by the end of June 2021 (Figure 12.3b; Figure 12.4b). Some exceptions included topic 22, which saw an initial spike early in the pandemic just prior to April 2020, a second lagging spike beginning in June 2020 and peaking between September and October 2020, and a third, more modest, spike beginning in March 2021, peaking around the beginning of May 2021, and diminishing to a minimal level by the end of June 2021 (Figure 12.4b). The top words for topic 22 were "watch," "talk," "consider," "delivery," and "tv" (Figure 3.3k). Considering the dips and peaks in the prevalence of estimated prevalence for topic 22 over time align well with the four "waves" of COVID-19 outbreaks in the U.S. occurring between December 2019 and June 2021 (CDC 2023), topic 22 may have included many tweets from people discussing their time at home during stay-at-home orders and/or periods of quarantine and isolation due to being diagnosed with or exposed to someone known to have tested positive for COVID-19 infection.

Other topics, like topic 130, saw initial increases in prevalence in the earlier days/months of the pandemic that diminished and plateaued at a level that meant their prevalence remained higher than other topics (Figure 12.4b). Topic 130 was a topic in the “frontline workers” category, characterized by top words like “care,” “working,” “allowed,” “critical,” and “access” (Figure 3.3f). It was somewhat notable, then, that despite a significant decrease over time, topic 130 remained highly prevalent compared to other topics, whose prevalence was diminished with time (Figure 12.4b). Topic 130 continuing to account for a large proportion of tweets compared to other topics that were discussed much less frequently as the pandemic stretched into a second year provides evidence that conversations about frontline workers, particularly those working in critical areas like health care, remained moderately prevalent when tweets about risk related to COVID-19 were becoming less common (Figure 12.4b).

CHAPTER 4

RESULTS PART II: ASSESSING THE ROLE OF EMOTIONAL UNDERTONES IN TOPIC CONTENT WITH REGARD TO TOPIC PREVALENCE

Topical prevalence was impacted by the emotional undertones of tweet content, meaning the prevalence of tweets in each topic varied depending on the dominant emotion expressed in the tweet. After controlling for emotional sentiment as a content covariate, the prevalence varied quite a bit between topics for which the effect of time was significant (Figure 13.1a-b). The patterns of fluctuation on prevalence among topics that became much more prevalent over time tended to remain consistent when controlling for emotional sentiment as a content covariate, but the moderated model revealed that the differences between the topics' proportions over time may have been much larger than were initially observed (Figure 12.4a; Figure 13.1a).

The significance of the effect of time on topic prevalence also changed after controlling for emotion in topic content for several topics. For instance, the effect of time on topical prevalence became significant only after controlling for emotion for topics 11, 100, 109, 123, 128, 140, 150, and 151 (Table 3). Additionally, the effect of time was no longer a significant predictor of topical prevalence for several topics upon controlling for the emotional undertones of the tweet content. The effect of time on the prevalence of topics 1, 3, 26, 43, 58, 85, 97, 104, 108, 122, 162, 172, and 178 was no longer significant after controlling for emotional sentiment as a content covariate (Table 4), observed in the little fluctuation over time in Figure 13.1c.

Table 4. Estimated Prevalence for Topics where the Effect of Time on Prevalence was Significant only After Controlling for the Effect of Emotional Sentiment on Topic Content

	Topic 11			Topic 100			Topic 109			Topic 123			Topic 128			Topic 140			Topic 150			Topic 151		
Covariate	β	σ	p	β	σ	p	β	σ	p	β	σ	p	β	σ	p	β	σ	p	β	σ	p	β	σ	p
Fear	0.0143	0.0006	***	0.0060	0.0004	***	0.0036	0.0004	***	0.0055	0.0004	***	0.0047	0.0004	***	0.0040	0.0004	***	0.0034	0.0003	***	0.0102	0.0006	***
Time	0.0000	0.0000	**	0.0000	0.0000	*	0.0000	0.0000	*	0.0000	0.0000	*	0.0000	0.0000	*	0.0000	0.0000	**	0.0000	0.0000	*	0.0000	0.0000	**
Anger	-0.0091	0.0006	***	0.0034	0.0004	***	0.0012	0.0005	*	0.0009	0.0005	.	0.0014	0.0005	**	0.0006	0.0005		0.0010	0.0004	**	-0.0044	0.0008	***
Anticipation	-0.0087	0.0006	***	0.0003	0.0004		0.0013	0.0005	*	0.0004	0.0005		0.0018	0.0006	**	0.0010	0.0005	*	0.0006	0.0003	.	-0.0022	0.0009	*
Disgust	-0.0029	0.0007	***	0.0002	0.0005		0.0085	0.0006	***	0.0040	0.0005	***	0.0016	0.0006	**	0.0051	0.0006	***	0.0006	0.0003	.	-0.0054	0.0007	***
Joy	-0.0100	0.0006	***	0.0005	0.0005		0.0033	0.0005	***	0.0051	0.0005	***	0.0006	0.0005		0.0017	0.0005	***	0.0002	0.0004		-0.0052	0.0007	***
Negative	-0.0093	0.0006	***	0.0028	0.0005	***	0.0005	0.0005		-0.0002	0.0004		0.0001	0.0006		-0.0001	0.0004		0.0000	0.0003		-0.0028	0.0007	***
Positive	-0.0100	0.0006	***	-0.0013	0.0004	**	0.0030	0.0006	***	-0.0003	0.0005		0.0002	0.0005		0.0026	0.0006	***	-0.0001	0.0003		-0.0057	0.0007	***
Sadness	-0.0085	0.0007	***	-0.0008	0.0004	*	-0.0003	0.0005		-0.0007	0.0005		0.0013	0.0006	*	0.0002	0.0005		0.0023	0.0004	***	-0.0057	0.0007	***
Surprise	-0.0106	0.0006	***	0.0000	0.0004		-0.0016	0.0005	***	-0.0028	0.0004	***	-0.0023	0.0005	***	-0.0008	0.0004	.	0.0015	0.0003	***	-0.0079	0.0007	***
Trust	-0.0102	0.0006	***	-0.0009	0.0004	*	0.0005	0.0005		-0.0012	0.0004	**	-0.0001	0.0005		-0.0008	0.0005		0.0051	0.0004	***	-0.0057	0.0007	***

Topic 160 was the most prevalent of the topics seeing a significant increase over time for most of the 19 months prior to controlling for emotional sentiment as a content covariate (Figure 12.4a). After controlling for emotion, topic 160 remained the most prevalent topic for the entire duration from December 2019 to June 2021 (Figure 13.1a), unlike the prior instance where topic 160 appeared to be ultimately surpassed in prevalence by topics 38 and 29 (Figure 12.4a).

Topic 66 was the other topic with a consistently high prevalence for most of the 19-month duration before controlling for emotional content of the tweets in each topic (Figure 12.4a). The prevalence for topic 66 was similarly high for the duration of the 19 months in question after controlling for emotional undertones of the tweet content (Figure 13.1a). However, controlling for emotional sentiment reveals a possible earlier peak in topic 66's prevalence in January 2020 (Figure 13.1a), two months earlier than the initial large peak in the base model for time (Figure 12.4a).

While topics 38 and 29 no longer surpassed topic 160 in prevalence by the end of June 2021 after controlling for emotional sentiment, both topics still saw similar patterns of steady increase with small fluctuations for most of the period, followed by a sharp increase around May 2021 (Figure 13.1a). In the base model for time, topic 38 had an estimated prevalence that was slightly higher than topic 29 by the end of June 2021 (Figure 12.4a). The opposite occurred after controlling for emotion, with topic 29 estimated to be slightly more prevalent than topic 38 by the end of June 2021 (Figure 13.1a). Considering the similarity between the two topics, with both classified as "Political" and involving recommendations for risk-mitigating behavior based on guidance from the CDC (Figure 3.3a), this suggests that emotional undertones distinguish tweets in the two topics from each other (Figure 13.1a).

Table 5. Estimated Prevalence for Topics where the Effect of Time was No Longer Significant After Controlling for the Effect of Emotional sentiment on Topic Content

	Fear			Time			Anger			Anticipation			Disgust			Joy		
Topic	β	σ	p	β	σ	p	β	σ	p	β	σ	p	β	σ	p	β	σ	p
1	0.0027	0.0004	***	0	0		0.0001	0.0005		-0.0002	0.0005		0.0004	0.0005		0.0014	0.0005	**
3	0.0016	0.0002	***	0	0	.	0.0007	0.0003	*	0.0006	0.0002	*	0.0006	0.0002	*	0.0004	0.0002	.
26	0.0036	0.0004	***	0	0		0.0004	0.0004		0.0008	0.0004	.	-0.0005	0.0004		-0.0012	0.0004	**
43	0.0036	0.0005	***	0	0		0.0000	0.0005		-0.0005	0.0005		0.0013	0.0005	*	0.0003	0.0005	
53	0.0049	0.0005	***	0	0		0.0010	0.0007		0.0007	0.0007		0.0008	0.0007		0.0009	0.0007	
58	0.0052	0.0004	***	0	0		0.0009	0.0005	*	0.0010	0.0005	*	0.0010	0.0005	*	-0.0005	0.0005	
60	0.0018	0.0002	***	0	0		0.0007	0.0003	*	0.0000	0.0003		0.0007	0.0003	*	0.0000	0.0003	
85	0.0055	0.0004	***	0	0		0.0003	0.0005		0.0029	0.0006	***	-0.0010	0.0005	*	-0.0019	0.0005	***
96	0.0131	0.0005	***	0	0	.	-0.0070	0.0005	***	-0.0047	0.0006	***	-0.0076	0.0006	***	-0.0091	0.0005	***
97	0.0054	0.0005	***	0	0		0.0013	0.0005	*	0.0003	0.0007		0.0008	0.0006		-0.0011	0.0006	*
104	0.0033	0.0003	***	0	0		0.0036	0.0004	***	0.0098	0.0005	***	0.0098	0.0004	***	0.0101	0.0005	***
108	0.0039	0.0003	***	0	0		0.0024	0.0004	***	0.0033	0.0004	***	0.0000	0.0004		0.0006	0.0003	.
122	0.0058	0.0004	***	0	0		0.0000	0.0005		-0.0010	0.0005	*	-0.0014	0.0004	**	0.0030	0.0004	***
162	0.0082	0.0004	***	0	0	.	-0.0030	0.0004	***	-0.0037	0.0005	***	-0.0039	0.0004	***	-0.0025	0.0004	***
172	0.0034	0.0003	***	0	0	.	0.0027	0.0005	***	0.0031	0.0005	***	0.0001	0.0004		0.0006	0.0004	
178	0.0046	0.0003	***	0	0		0.0051	0.0004	***	0.0022	0.0004	***	0.0043	0.0004	***	0.0047	0.0005	***

	Negative			Positive			Sadness			Surprise			Trust		
Topic	β	σ	p	β	σ	p	β	σ	p	β	σ	p	β	σ	p
1	-0.0003	0.0004		0.0014	0.0005	**	0.0008	0.0005	.	0.0052	0.0006	***	0.0005	0.0005	
3	0.0003	0.0002		0.0005	0.0003	.	0.0002	0.0002		0.0003	0.0002		0.0011	0.0003	***
26	-0.0004	0.0004		-0.0005	0.0004		0.0002	0.0004		0.0032	0.0005	***	0.0031	0.0005	***
43	-0.0008	0.0005		0.0022	0.0006	***	0.0020	0.0006	***	0.0016	0.0005	**	0.0104	0.0008	***
53	0.0021	0.0007	**	-0.0003	0.0007		0.0005	0.0007		-0.0001	0.0007		0.0113	0.0008	***
58	-0.0008	0.0005	.	-0.0016	0.0004	***	-0.0008	0.0004	.	-0.0027	0.0004	***	-0.0017	0.0004	***
60	0.0004	0.0003		0.0000	0.0003		-0.0001	0.0003		0.0002	0.0003		0.0031	0.0004	***
85	-0.0023	0.0005	***	0.0016	0.0005	**	-0.0008	0.0005		-0.0029	0.0005	***	0.0016	0.0006	**
96	-0.0068	0.0006	***	-0.0085	0.0006	***	-0.0074	0.0006	***	-0.0104	0.0005	***	-0.0103	0.0005	***
97	0.0029	0.0007	***	-0.0021	0.0007	**	0.0013	0.0006	*	-0.0029	0.0006	***	-0.0009	0.0006	
104	0.0045	0.0004	***	-0.0002	0.0003		-0.0003	0.0003		-0.0007	0.0003	*	-0.0005	0.0003	
108	0.0022	0.0003	***	0.0000	0.0004		0.0019	0.0004	***	-0.0001	0.0004		0.0007	0.0003	*
122	-0.0020	0.0004	***	0.0009	0.0004	*	0.0185	0.0007	***	-0.0007	0.0004		0.0012	0.0004	**
162	-0.0030	0.0004	***	-0.0052	0.0004	***	-0.0043	0.0004	***	-0.0049	0.0005	***	-0.0048	0.0004	***
172	0.0040	0.0004	***	-0.0008	0.0003	*	-0.0008	0.0004	*	-0.0014	0.0003	***	-0.0008	0.0004	*
178	0.0038	0.0004	***	-0.0017	0.0004	***	0.0039	0.0004	***	-0.0021	0.0004	***	-0.0022	0.0004	***

Topics whose prevalence significantly decreased over time were more sensitive to the introduction of emotion to the model as a content covariate than topics that significantly increased over time (Figure 12.4a-b; Figure 13.1a-b).

The pattern of prevalence for topic 47 was drastically different after controlling for emotional sentiment, having extremely and consistently high prevalence from December 2019 through June 2021 compared to other topics seeing significant decreases over the 19-month period (Figure 13.1b). In the base model, topic 47 had the fourth highest prevalence of the topics seeing significant decreases over time at the start of the period in December 2019 but was indistinguishable from most other topics by the end of the period in June 2021 (Figure 12.4b). Taken together, these findings are a good indication that topic 47 could be more prevalent than any other topic whose prevalence significantly decreased over time, depending on the emotional undertones of the tweets (Figure 13.1b). This was despite topic 47's overall low prevalence for most of the 19-months (12.4b; 13.1b).

Other topics whose prevalence initially appeared to coincide with the waves of increasing and decreasing rates of COVID-19 infection in the U.S. population did not fluctuate as drastically from day-to-day/month-to-month as the base model would have suggested (Figure 12.4b). Topic 22, which included random discussions related to the newly popular activities like binge-watching "tv" in the era of stay-at-home orders and quarantine (Figure 3.3k), initially appeared to rise and fall around the same time that COVID-19 levels rose and fell in the United States (Figure 12.4b). Additionally, the fluctuations in topic 22's prevalence over time appeared somewhat drastic, decreasing quite a bit between the peaks (Figure 12.4b).

Figure 13.1a. Estimated Increase in Topic Proportion over 19 Months, Smoothed, for Topics where the Effect of Time on Prevalence was Significant and Positive when Controlling for the Effect of Emotion on Topic Content

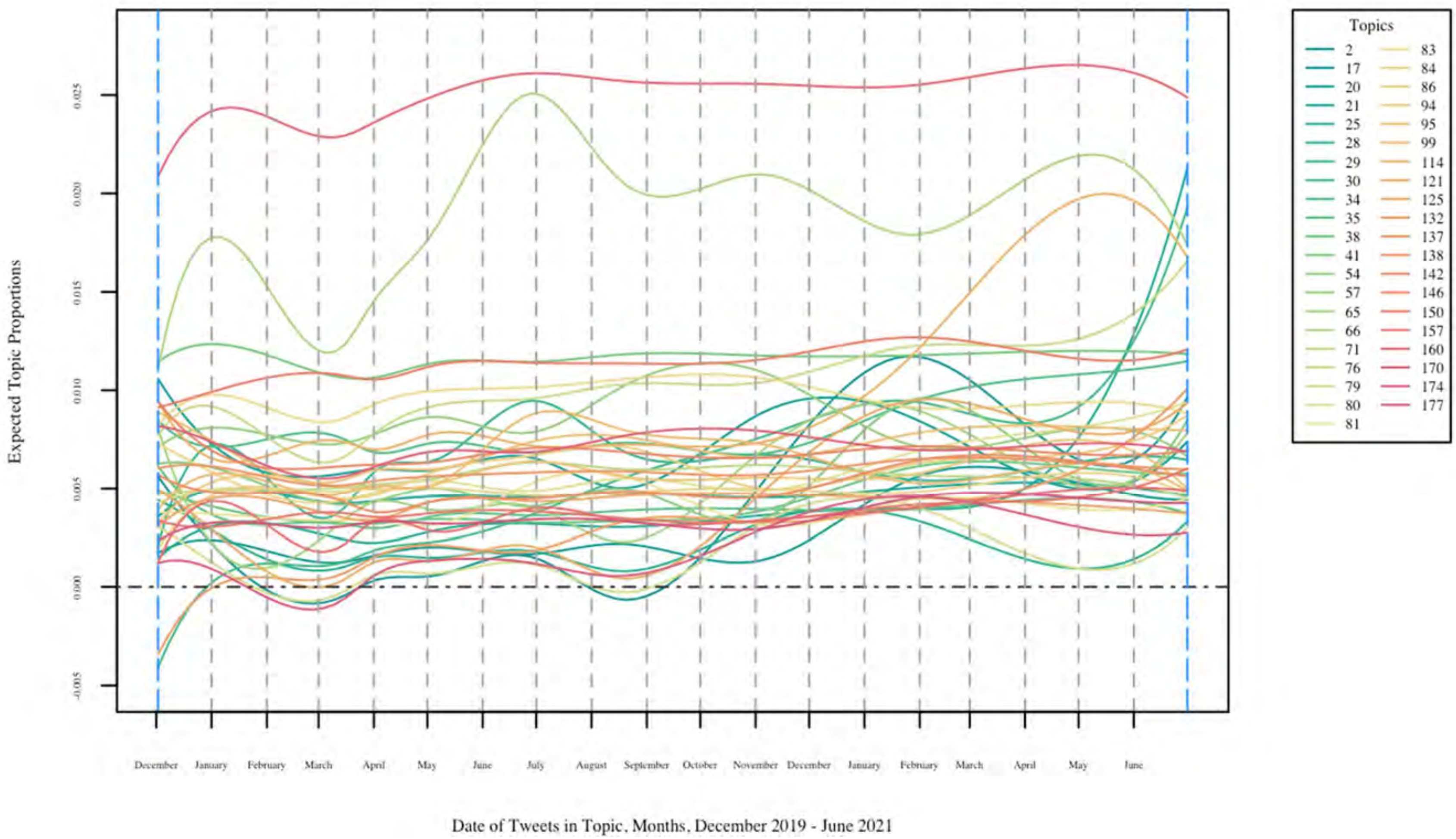


Figure 13.1b. Estimated Decrease in Topic Proportion over 19 Months, Smoothed, for Topics where the Effect of Time on Prevalence was Significant and Negative when Controlling for the Effect of Emotion on Topic Content

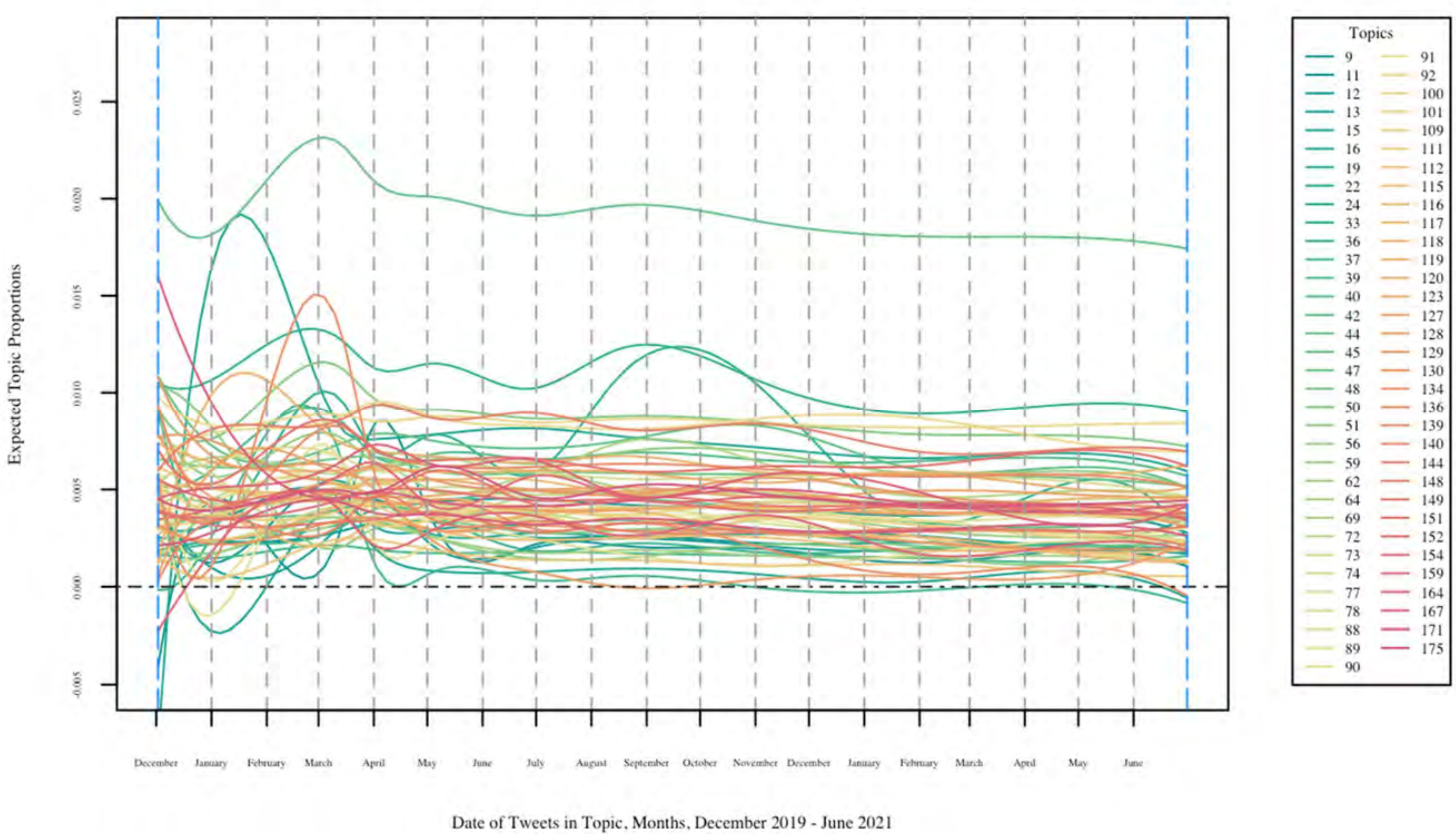
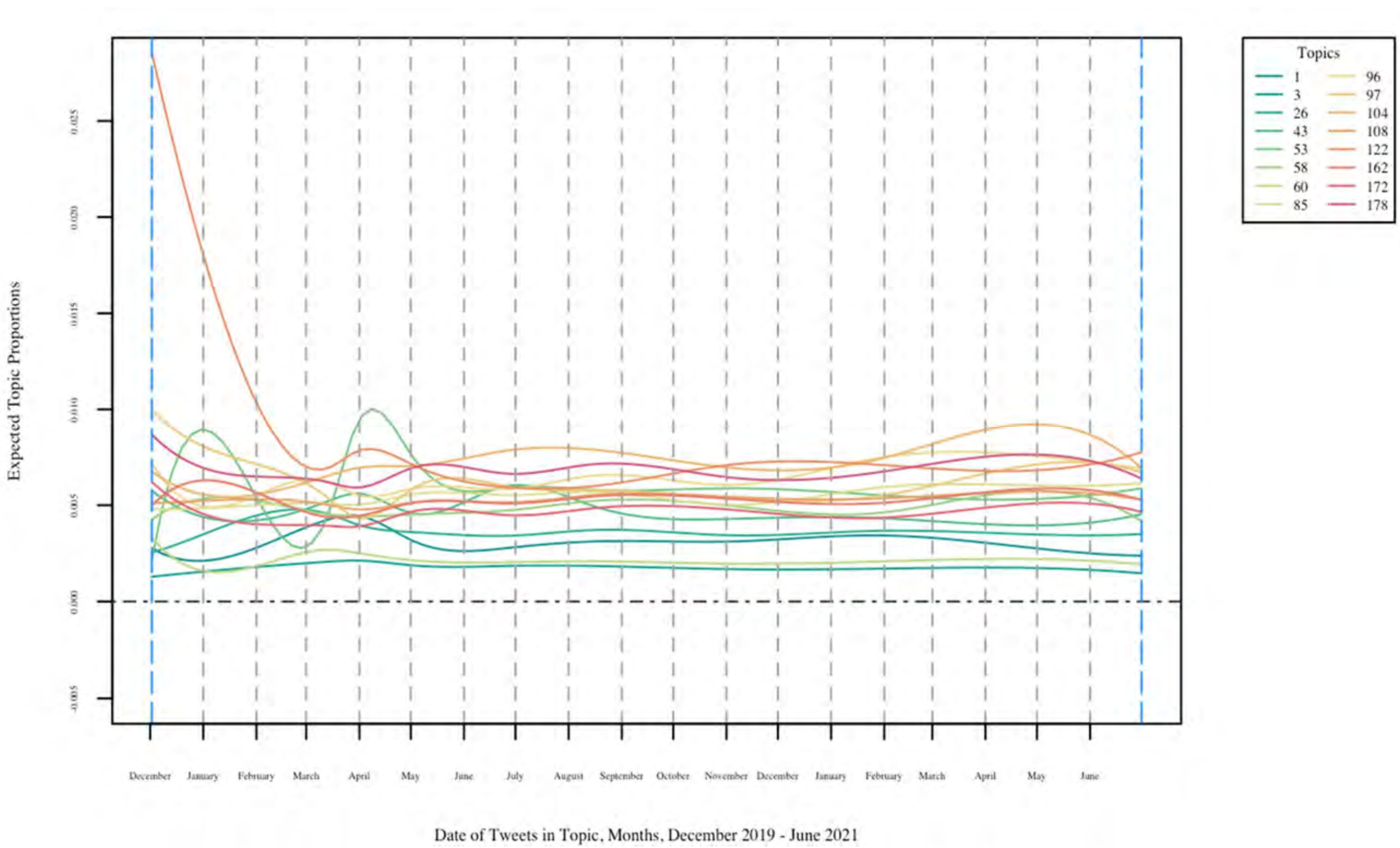


Figure 13.1c. Estimated Change in Topic Proportion over 19 Months, Smoothed, for Topics where the Effect of Time on Prevalence was No Longer Significant when Controlling for the Effect of Emotion on Topic Content



Upon controlling for emotional sentiment in the content of topic 22 tweets, the topic still saw a significant decrease over time, but its prevalence remained much steadier. Topic 22's prevalence hovered between about 1-1.5% until November 2020, at which point the estimated prevalence dropped to slightly below 1% for the remainder of the time through the end of June 2021 (Figure 13.1b). This could be an indication that tweets in the topic were predominantly reflective of a specific emotional context, and that discussions in this context took place at a consistent rate for at least the first 12-months of the 19-month period (Figure 13.1b).

Topic 130 was among the most prevalent of the topics seeing significant decreases over time prior to controlling for emotional sentiment in tweets, seeing little fluctuation on a day-to-day/month-to-month basis and instead decreasing steadily over the course of 19 months (Figure 12.4b). Topic 130 saw a similarly steady decrease in prevalence with little fluctuation after controlling for emotional sentiment (Figure 13.1b). However, the topic no longer stood out as highly prevalent compared to most other topics that significantly decreased over time after controlling for emotional sentiment (Figure 13.1b).

Tweets in topic 130 tended to discuss issues related to frontline workers (Figure 3.3f). Some of the findings from the network and base time series analyses are reinforced by the results for topic 130 after controlling for emotion's effect on topic content. For instance, the evidence that discussions about frontline workers did not decrease or fluctuate quite as much as other topics even after controlling for emotional sentiment reinforces the notion that frontline workers were important to conversations of risk in the early months of the pandemic and remained so, despite changing social conditions surrounding their risk. The lower overall prevalence of topic 130 after controlling for emotion could be an indication that discussions of frontline workers were less prevalent when they reflected strong emotional responses to something impacting this population. It is possible that many of the tweets in this topic highlighted that frontline workers existed and were important, but did not express strong feelings about what that meant and did not tend to instigate conflict with other users.

TOPICS WHERE EMOTIONAL SENTIMENT HAD A SIGNIFICANT EFFECT ON CONTENT, BUT NOT PREVALENCE

There were several topics for which the effect of at least one emotional sentiment moderated the significant effect of time on topical prevalence but whose prevalence was not significantly shaped by the same emotions (Figure 13.2a-g). There were also several topics under each emotion where that emotion had a significant effect on topical content, but topical prevalence was impacted by neither “time” nor that same emotion. As such, “Angry” tweet content was a significant moderator of “time” (cumulative days) for topics 80 and 119, and the effect of “Anger” on content for topic “102” was significant despite the lack of significant effect of either “Anger” or “time” on topical prevalence (Figure 13.2a).

Topic 102 was about being grateful for frontline workers, with top words like “first,” “staff,” “thank,” “doctors,” and “line” (Figure 3.f). Given the effect of “Anger” on topical content was positive, this hints at some Anger related to thanking frontline workers, presumably Anger over a lack of gratitude towards healthcare workers like doctors.

Topic 119 Angry tweets increased sharply between December 2019—January 2020, peaking between January 2020 and February 2020 before decreasing sharply and remaining at a consistent prevalence near 0.5% for the remainder of the period (Figure 13.2a). The pattern of prevalence over time for topic 119 in context of the positive effect of “Anger” on topical content and top words for the topic like “China,” “human,” “world,” “started,” and “Chinese,” this could be an indication that some American Twitter users felt Anger towards China related to the outbreak's initial discovery in the Wuhan province (Figure 3.3k).

"Anger" had a significant and positive effect on the content of Topic 80 in the "Sickness/Symptoms" category (Figure 3.3j), becoming significantly more prevalent over time (Figure 13.2a). Based on top words for topic 80 like "point," "immunity," "become," "easily," and "herd," there were strong undertones of "Anger" over the concept of herd immunity (Figure 3.3j). The prevalence of topic 80 in context of "Anger" began to increase more rapidly around December 2020, providing evidence that the expression of Anger over herd immunity on Twitter became more common among U.S. Twitter users after vaccines became available in the United States (Figure 13.2a).

The effect of "Anticipation" on topical content was significant for topics 27, 102, 134, and 140, but the effect of "Anticipation" on topical prevalence for these topics was not significant (Figure 6.1; Figure 13.2b). Of these, the effect of "time" only had a significant effect on the prevalence for topic 140, and only after controlling for emotion (Figure 12.1-2; Figure 13.1b; Figure 13.2b). Top words for topic 140 like "keep," "safe," "lack," "protective," and "step" hint that there was some sense of Anticipation surrounding whether and what protective measures would be taken in response to the discovery of SARS-CoV-2 (Figure 3.3k). There was a significant decrease in the prevalence of tweets in topic 140 over time (Figure 13.1b). The significant and negative effect of "time" on the prevalence of topic 140 and the significant and positive effect of "Anticipation" on topical content would suggest that Anticipation about risk mitigation was highest around the estimated peak prevalence of Anticipatory tweets in topic 140 in April 2020 (Figure 13.2b). This implies that people had a good idea of what risk mitigation during the pandemic would look like by April 2020.

Figure 13.2a. Estimated Prevalence over Time for Topics where the Effect of “Anger” on Topical Content was Significant and “Anger” had No Significant Effect on Topical Prevalence Compared to “Fear”

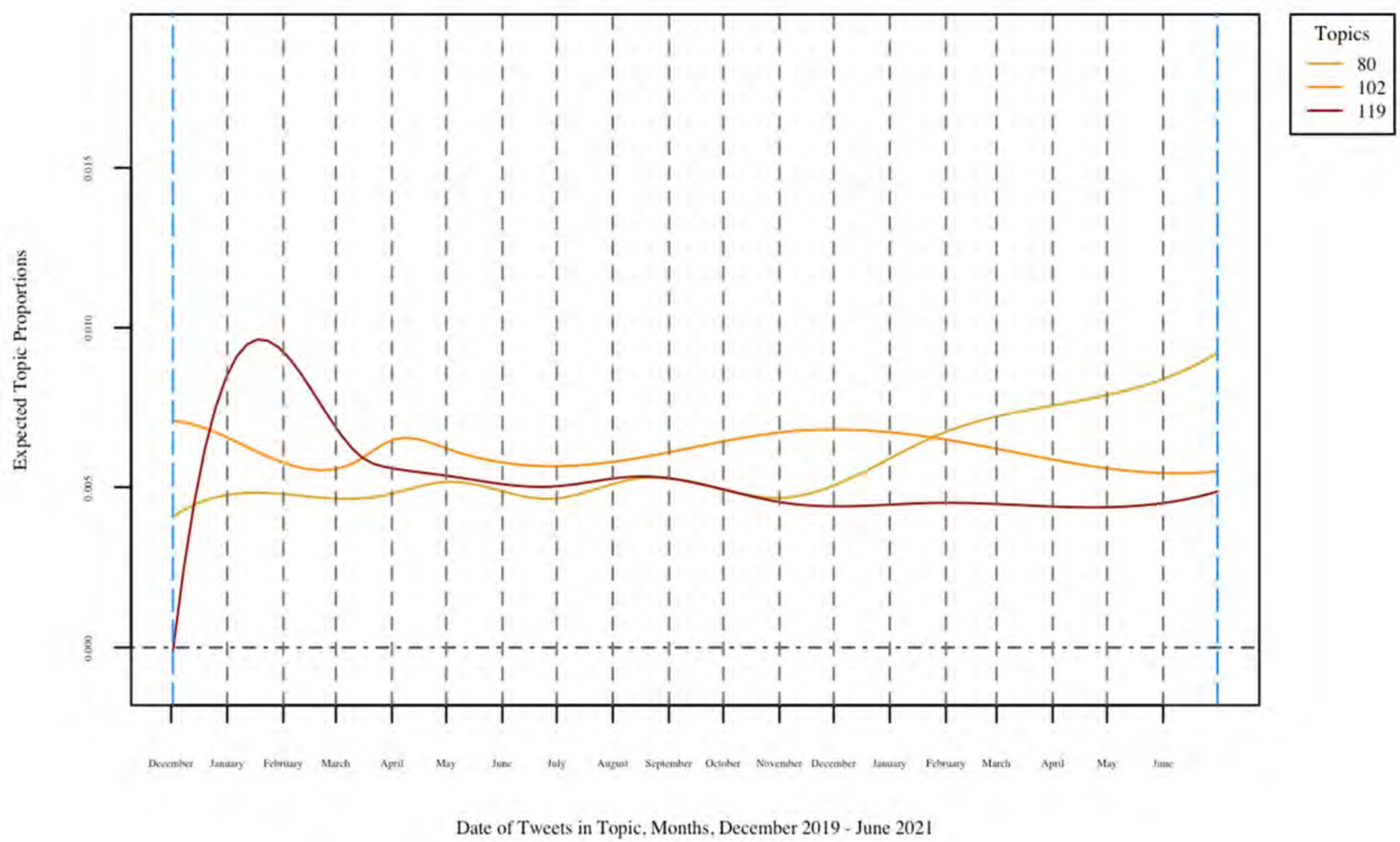


Figure 13.2b. Estimated Prevalence over Time for Topics where the Effect of “Anticipation” on Topical Content was Significant and “Anticipation” had No Significant Effect on Topical Prevalence Compared to “Fear”

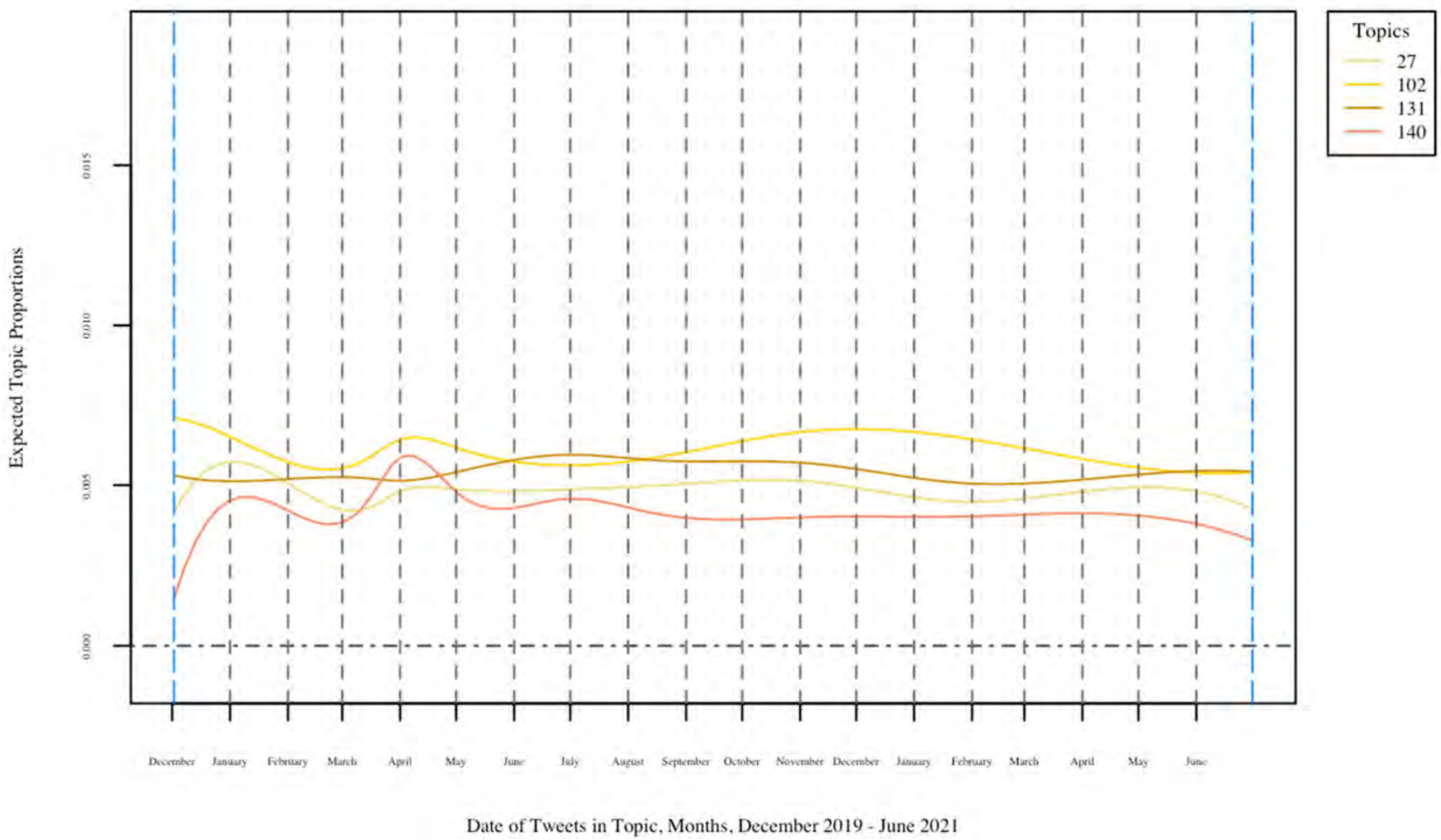


Figure 13.2c. Estimated Prevalence over Time for Topics where the Effect of "Disgust" on Topical Content was Significant and "Disgust" had No Significant Effect on Topical Prevalence Compared to "Fear"

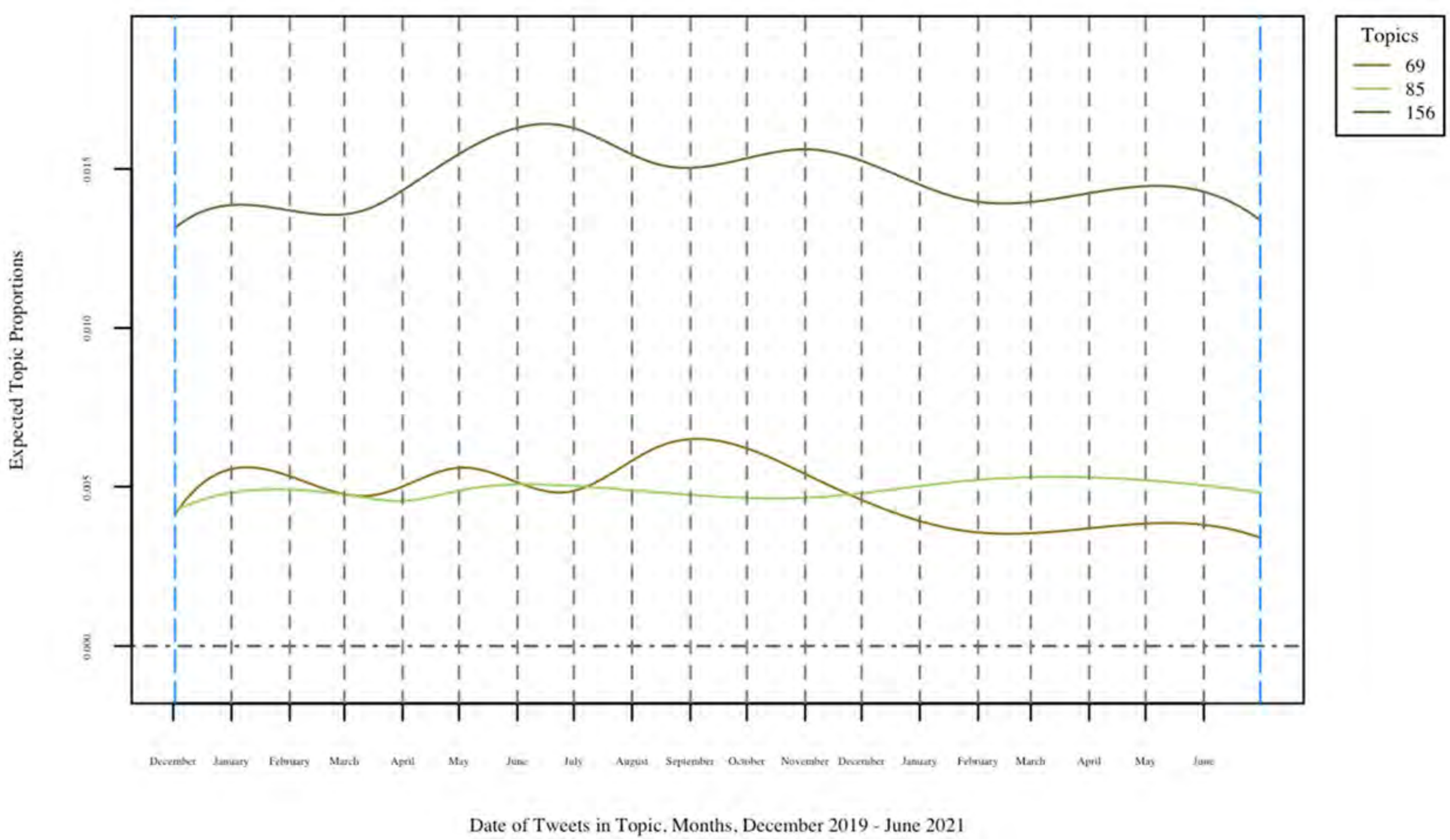


Figure 13.2d. Estimated Prevalence over Time for Topics where the Effect of "Joy" on Topical Content was Significant and "Joy" had No Significant Effect on Topical Prevalence Compared to "Fear"

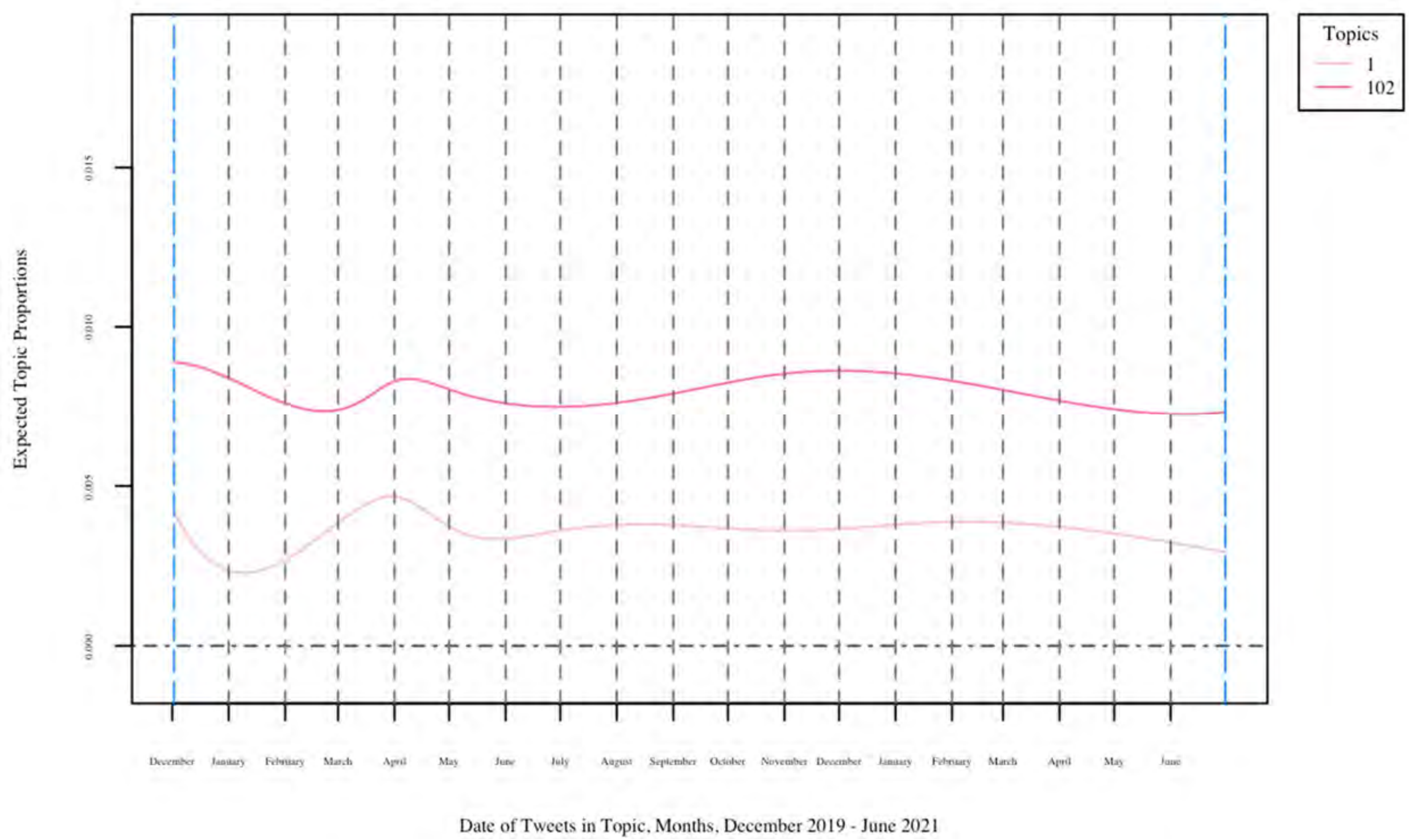


Figure 13.2e. Estimated Prevalence over Time for Topics where the Effect of "Sadness" on Topical Content was Significant and "Sadness" had No Significant Effect on Topical Prevalence Compared to "Fear"

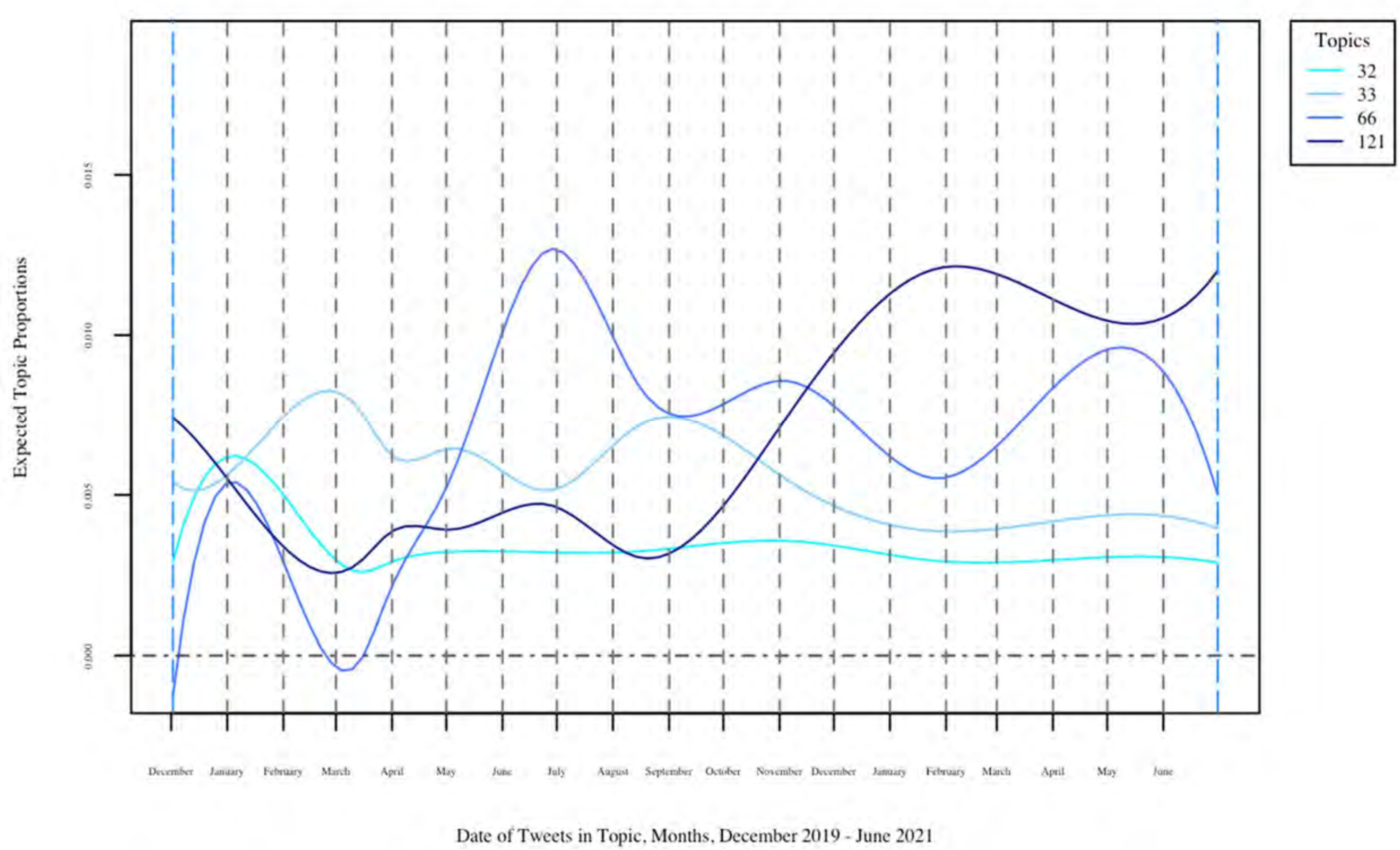


Figure 13.2f. Estimated Prevalence over Time for Topics where the Effect of "Surprise" on Topical Content was Significant and "Surprise" had No Significant Effect on Topical Prevalence Compared to "Fear"

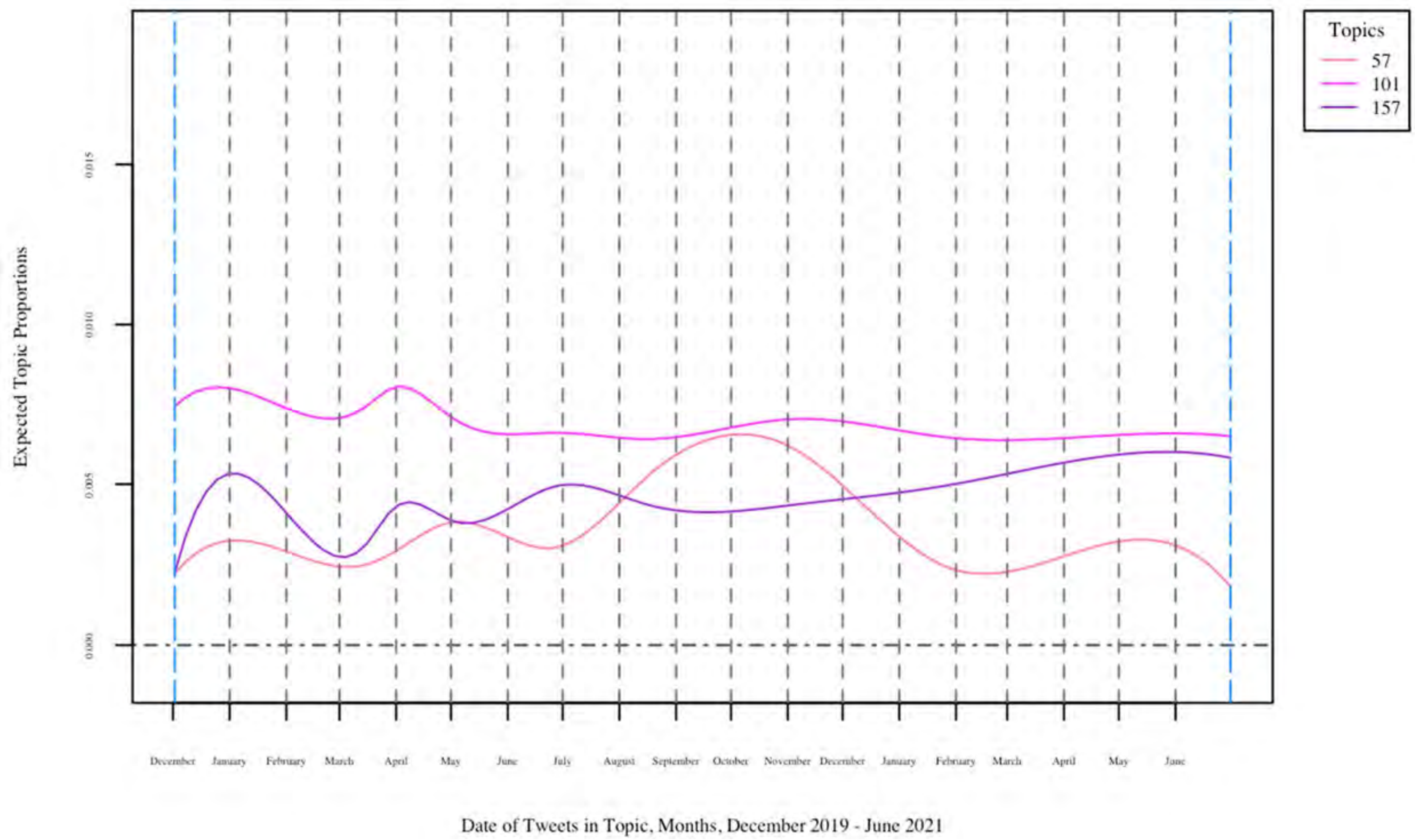
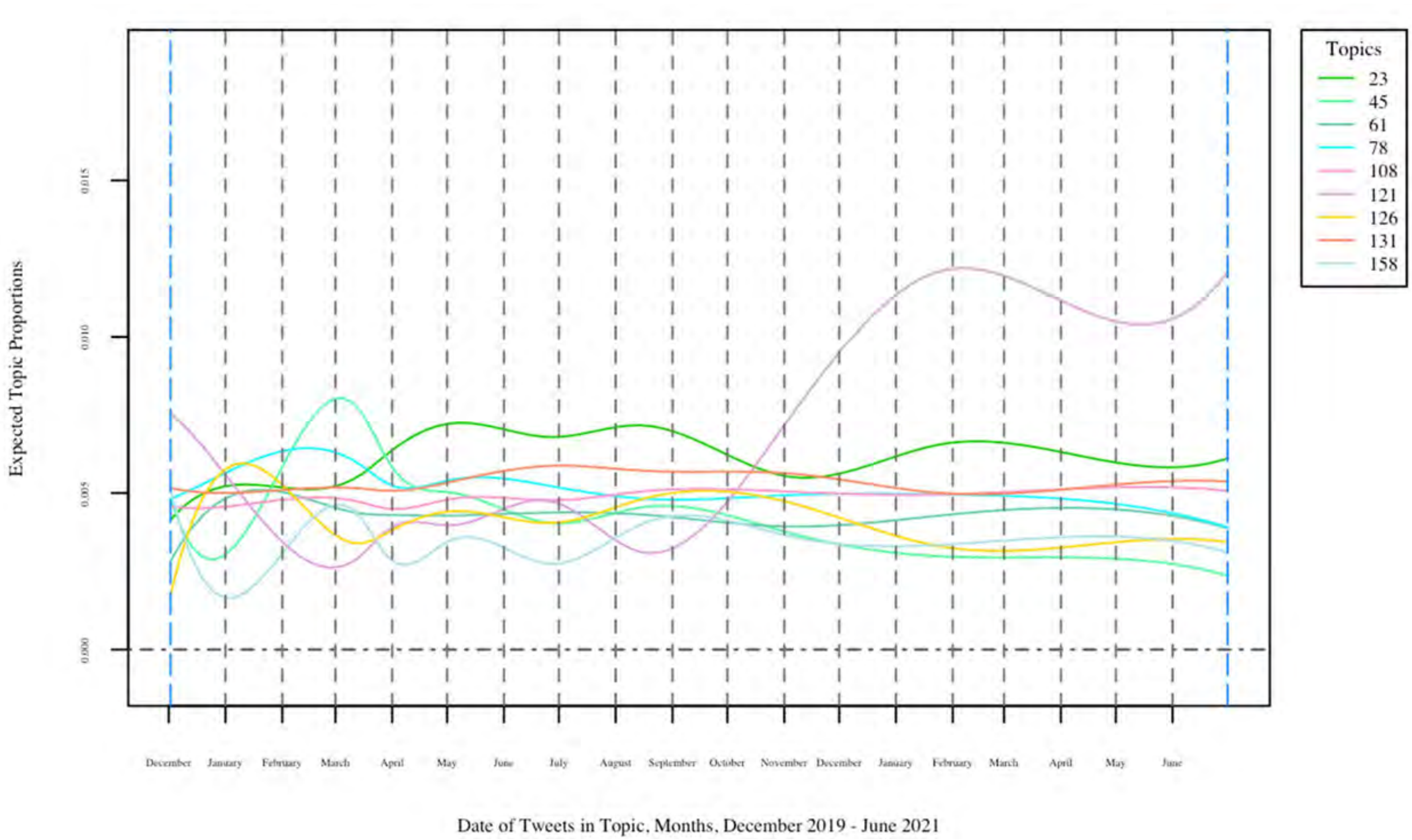


Figure 13.2g. Estimated Prevalence over Time for Topics where the Effect of "Trust" on Topical Content was Significant and "Trust" had No Significant Effect on Topical Prevalence Compared to "Fear"



The positive effect of “Anticipation” on the content of topic 102 (Figure 13.2b), which pertained to frontline health care workers (Figure 3.3f), indicates some degree of Anticipation surrounding this population compared to other emotions. Conversely, the negative effect of “Anticipation” on the content of topic 131 about mandated mitigation (Figure 13.2b), whose top words included things like “information,” “avoid,” “follow,” “potential,” and “guidelines” (Figure 3.3c), points to a lack of Anticipatory sentiment in topic 131 discussions compared to other emotions. It appears that access to information may have quelled Anticipation among American Twitter users regarding risk and risk mitigation during COVID-19.

The effect of “Disgust” was significant for the content of topics 69, 85, and 156 but not their prevalence (Figure 7.1; Figure 13.2c). Of these topics, the effect of time was only significant when controlling for emotional sentiment for the prevalence of topic 69, which significantly decreased over the course of 19 months (Figure 13.1b; Figure 13.2c). Topic 85 tweets were significantly less likely to contain “Disgusted” undertones than other emotions (Figure 13.2c). Taken in context of top words for topic 85 like “community,” “data,” “level,” “look,” and “looking” (Figure 3.3k), this finding indicates a lack of Disgust in data-driven conversations about the level of COVID-19 transmission in U.S. communities compared to other emotions. Topics 69 and 156 tweets were much more likely to contain undertones of “Disgust” compared to other emotions (Figure 13.2c). Topic 69 was a topic pertaining to matters of life and death, and its top words included “deadly,” “economy,” “worse,” “knew,” and “action” (Figure 3.3i). While it seems U.S. Twitter users were significantly more likely to express “Disgust” over the issue of the economy given the high risk of death from coronavirus infection than they were to express other emotions, the significant and negative effect of “Time” on the prevalence of topic 69 when controlling for topical prevalence is an indication that these expressions became less common over time (Figure 13.1b). For “Disgusted” tweets in topic 69, the decrease in prevalence appeared to occur around September 2021 (Figure 13.2c).

While the prevalence of topic 156 was not significantly shaped by “time” after controlling for emotional sentiment, the significant and positive effect of “Disgust” on content in topic 156 indicates discussions in the topic were significantly more likely to express “Disgust” than other emotions (Figure 13.1; Figure 13.2c). Considering topic 156 top words included “social,” “distancing,” “distance,” “practice,” and “physical” (Figure 3.3d), it seems that Twitter users in the United States commonly expressed Disgust over the issue of social (physical) distancing.

Time had a significant and negative effect on the prevalence of topic 1 until controlling for the emotional undertones of the tweets in the topic, at which point the effect of time on topical prevalence was no longer significant (Table 4; Figure 13.1c). The effect of “Joy” on topical prevalence for topic 1 was not significant, but the moderative model revealed that tweets in topic 1 were much more likely to contain emotional undertones of “Joy” than other emotions (Figure 13.2d). This was interesting, considering topic 1 was a political topic with top words like “GOP,” “Republicans,” “Senate,” “Address,” and “Democrats” (Figure 3.3a), and suggests that regardless of the tendency for many news media reports to characterize the political climate during COVID-19 as hostile, heated, etc., there were many conversations related to political parties and institutions in the United States taking place on Twitter that did not have emotional undertones that could be considered distinctly bad/negative/undesirable.

The content of topic 102 tweets was also significantly more likely to exude “Joy” than other emotions, but the prevalence of the topic was not significantly shaped by either time or “Joy” (Figure 8.1; Figure 12.2; Figure 13.1a-b); Figure 13.2d). The overall estimated prevalence of topic 102 was higher than topic 1, and even though the effect of neither time nor “Joy” on topic 102 prevalence was significant, it was still notable that more tweets seemed to discuss frontline workers, the focus of topic 102, in a Joyful context than political parties and institutions (Figure 13.2d). The implication is that sentiments of Joy tied to hospital workers on the frontline were more common than sentiments of Joy about members of either political party or institutions like the United States Senate (Figure 3.3a; Figure 3.3c).

The emotional sentiment “Sadness” had no significant effect on the prevalence of topics 32, 33, 66, and 121 compared to “Fear” but was found to have a significant effect on the content of all four topics. In addition to not being significantly impacted by “Sadness,” the prevalence of topic 32 was also not significantly shaped by time after controlling for emotional undertones of tweet content. Topic 32 had a low overall prevalence compared to other topics in the full model, but also comparatively low prevalence compared to other topics specifically pertaining to symptoms of sickness when infected with COVID-19 (Figure 3.3j). Top words for topic 32 included “ppl,” a common abbreviation for “people,” and words like “problem,” “contagious,” “highly,” and “harm,” so the significant and negative effect of “Sadness” on topical content would suggest that people were much less likely to express Sadness over the issue of contagion being possibly harmful to others than they were to express other emotions (Figure 3.3j; Figure 13.2e).

Topic 33 tweets were significantly less likely to be in a “Sad” context than other emotional contexts, and the topic saw a significant decrease in prevalence over time after controlling for emotional sentiment (Figure 13.1b; Figure 13.2e). This could mean that top words like “threat,” “longer,” “greatest,” “posed,” and “book” are characteristic of tweets about the threat subsiding (Figure 3.3k).

Topic 66 tweets saw a significant increase over time even after controlling for the effect of emotional sentiment on topical content (Figure 12.4a; Figure 13.1a). A significantly higher proportion of the tweets in this "Political" topic pertaining to mask mandates in the state of Texas also expressed "Sadness" than expressed other emotions (Figure 3.3a; Figure 13.2c). Similarly, there was a significant increase in the prevalence of topic 121 over time, and the effect of "Sadness" on the content of tweets in this topic was significant and positive, indicating that there were a higher proportion of "Sad" tweets than tweets expressing other emotions in this topic (Figure 13.1a; Figure 13.2c).

This provides some interesting insight into nuance surrounding discussions of vaccines in the U.S. when taken in context of top words for the risk mitigating behavior-related topic like "vaccines," "effective" "second," "takes," and "Pfizer," one of three pharmaceutical companies producing a COVID-19 vaccine that had received federal approval through the Food and Drug Administration (FDA) for use in the United States by the end of June 2021 (Figure 3.3d). This topic captures that discussions expressing Sadness related to vaccine efficacy and protocols for vaccination were included among the increasingly prevalent discussions across several topics about changed risk after the approval of vaccines in the U.S. and the subsequent announcement by the CDC that the U.S. was preparing to enter a new phase of reduced risk for vaccinated individuals.

The effect of "Surprise" on the prevalence of topics 57, 101, and 157 was not significant, but the effect of the emotion on content was estimated to be significant and positive for topics 57 and 157 and significant and negative for topic 101 (Figure 13.2f). The direction of the effect of "Surprise" on content for each of these topics corresponded with the direction of the significant effect of "time" on their prevalence, with significant increases in topics 57 and 157 over time alongside an increased proportion of "Surprised" undertones compared to other emotions, and a significant decrease in topic 101, which was much less likely to express "Surprise" than other emotions.

Topic 101 was in the "frontline workers" category of topics (Figure 3.3f). Top words for topic 101 like "medical," "idea," "supplies," "later," and "heard" coupled with the significant decrease in topical prevalence over time when controlling for emotion indicate a lack of Surprise over the issue of medical supplies compared to other emotions, but also that this topic became less common, and thus, seemingly less important to Twitter users in the United States, over time (Figure 3.3f; Figure 13.1b; Figure 13.2f). In contrast, there was a lot of "Surprise" compared to other emotions in topics 57 and 157, and these topics became much more prevalent over time when controlling for emotional sentiment in tweet content (Figure 13.1a; Figure 13.2f). Top words like "others," "service," "selfish," "potentially," and "irresponsible" indicate that in topic 57 this Surprise may have related to the perception of other people's behavior as selfish and/or irresponsible, and it would seem the issue of selfish and/or irresponsible behavior became more relevant to discussions about risk taking place among Twitter users in the U.S. over the duration of the early phase of the pandemic (Figure 3.3k; Figure 13.1a; Figure 13.2f).

It would also seem that conversations about mandates, more often in a Surprised context than in context of other emotions, became more prevalent among U.S. Twitter users over the first 19 months of the COVID-19 pandemic. This was evidenced by top words for topic 157 including "orders," "law," "mandates," "everywhere," and "private" (Figure 3.3c). It could be the case that people in the United States were Surprised about the widespread applicability of mandates to include private businesses.

There were a larger number of topics whose content, but not prevalence, was significantly impacted by “Trust” compared to other emotions (Figure 13.2a-g). However, the effect of time on topical prevalence was also non-significant after controlling for emotion for most of these topics, including topics 23, 61, 108, 126, 131, and 158 (Figure 13.1a-b). Top words for topic 23 about potentially vulnerable social groups like “million,” “lost,” “program,” “assistance,” and “economic” are a good indication of heightened Trust compared to other emotions in discussions about potential solutions to economic vulnerability during the COVID-19 pandemic (Figure 3.3g). Topic 108 top words were less informative, including words like “thing,” “man,” “whole,” “single,” and “wish,” but the heightened level of “Trust” in content of topic 108 tweets compared to other emotions could represent Trust over a desire coming to fruition and/or Trust that a desired outcome was possible (Figure 3.3k).

Topics whose tweets were less representative of “Trust” than other emotions touched included those related to matters of life and death, like topic 126 with the top words “danger,” “stop,” “poses,” “grave,” and “rest” and topic 158 with the top words “americans,” “months,” “died,” “calling,” and “dead” (Figure 3.3i), and mandates and recommendations, as per topic 131 (Figure 3.3c). Others, like topic 61, discussed things like the size of the population and one’s positionality relative to others in the population, with the top words “population,” “increase,” “general,” “personal,” and “course” (Figure 3.3k).

TOPICS WHERE EMOTIONAL SENTIMENT HAD A SIGNIFICANT EFFECT ON PREVALENCE, BUT NOT CONTENT

Just as there were several topics where the effect of some emotion was significant for topical content but not prevalence, there were several topics for each emotion where the given emotion had a significant effect on prevalence but did not serve to significantly moderate the effect of time by having a significant effect on topical content.

In some instances, the effect of time on topical prevalence was non-significant alongside the non-significant effect of a given emotion on topical content. In these cases, the emotion in question provides important information about what shaped the prevalence of the topic, given the prevalence was not significantly impacted by time when controlling for emotion as a content covariate (Figure 13.3a-g). The prevalence of topic 27, for example, was significantly shaped by "Anger," but not by "time," which suggests that there was not much fluctuation in the prevalence of topic 27 over time and that "Anger" had a significantly different effect on topical prevalence than "Fear" (Figure 13.1a-b; Figure 13.3a). Other examples include the effect of "Disgust" as a main predictor of the prevalence of topics 63 and 102, given the effect of time was not a significant predictor of prevalence for either topic (Figure 13.1a-b; Figure 13.3c). The same was true for the effect of "Joy" on the prevalence of topic 145 (Figure 13.3d), "Sadness" on the prevalence of topic 87 (Figure 13.3e), and the effect of "Surprise" on the prevalence of topics 10 and 161 (Figure 13.3f).

Figure 13.3a. Estimated Prevalence over Time for Topics where the Effect of "Anger" on Content did not Interact with the Significant Effects of Time and "Anger" on Prevalence

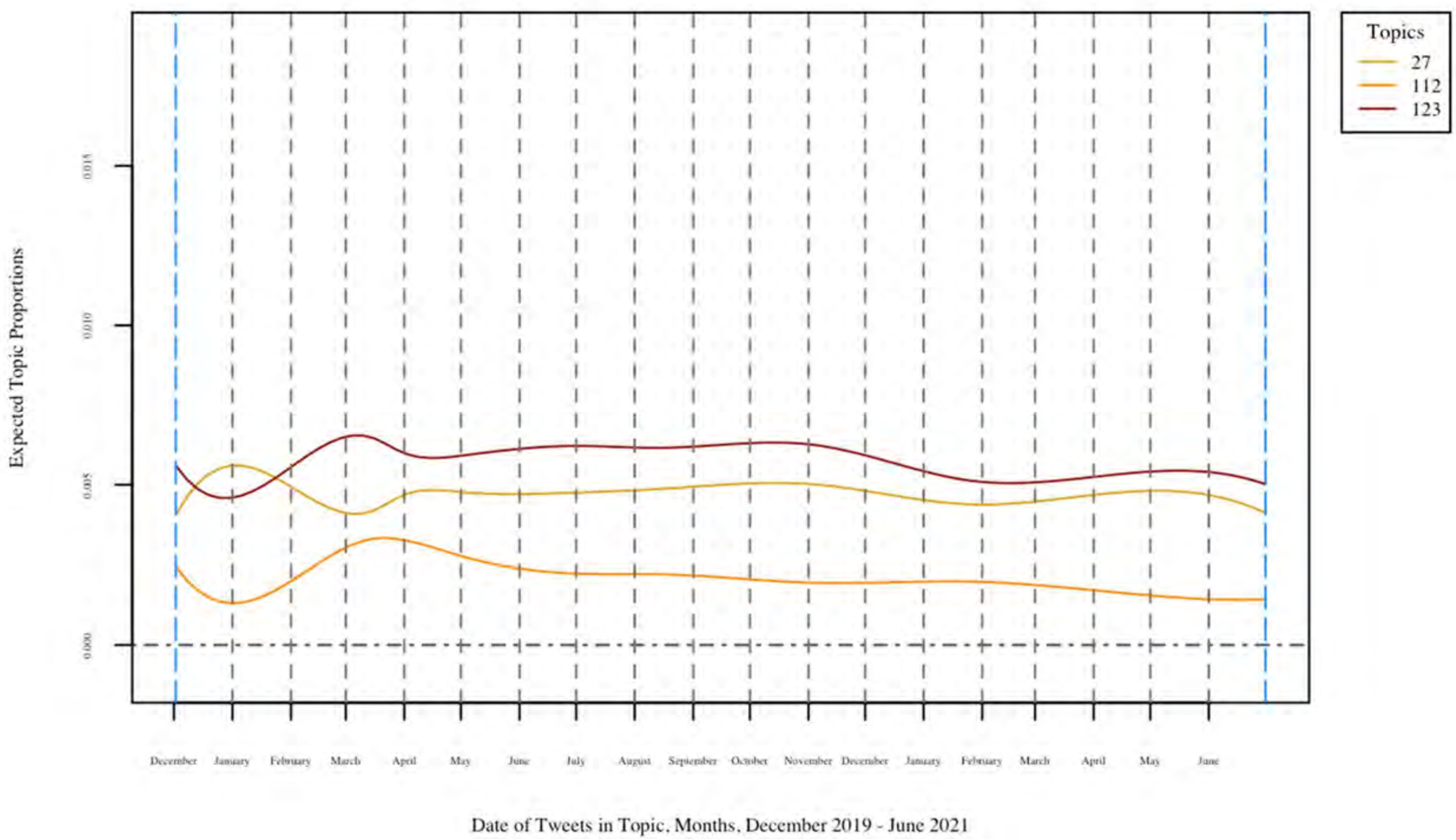


Figure 13.3b. Estimated Prevalence over Time for Topics where the Effect of "Anticipation" on Content did not Interact with the Significant Effects of Time and "Anticipation" on Prevalence

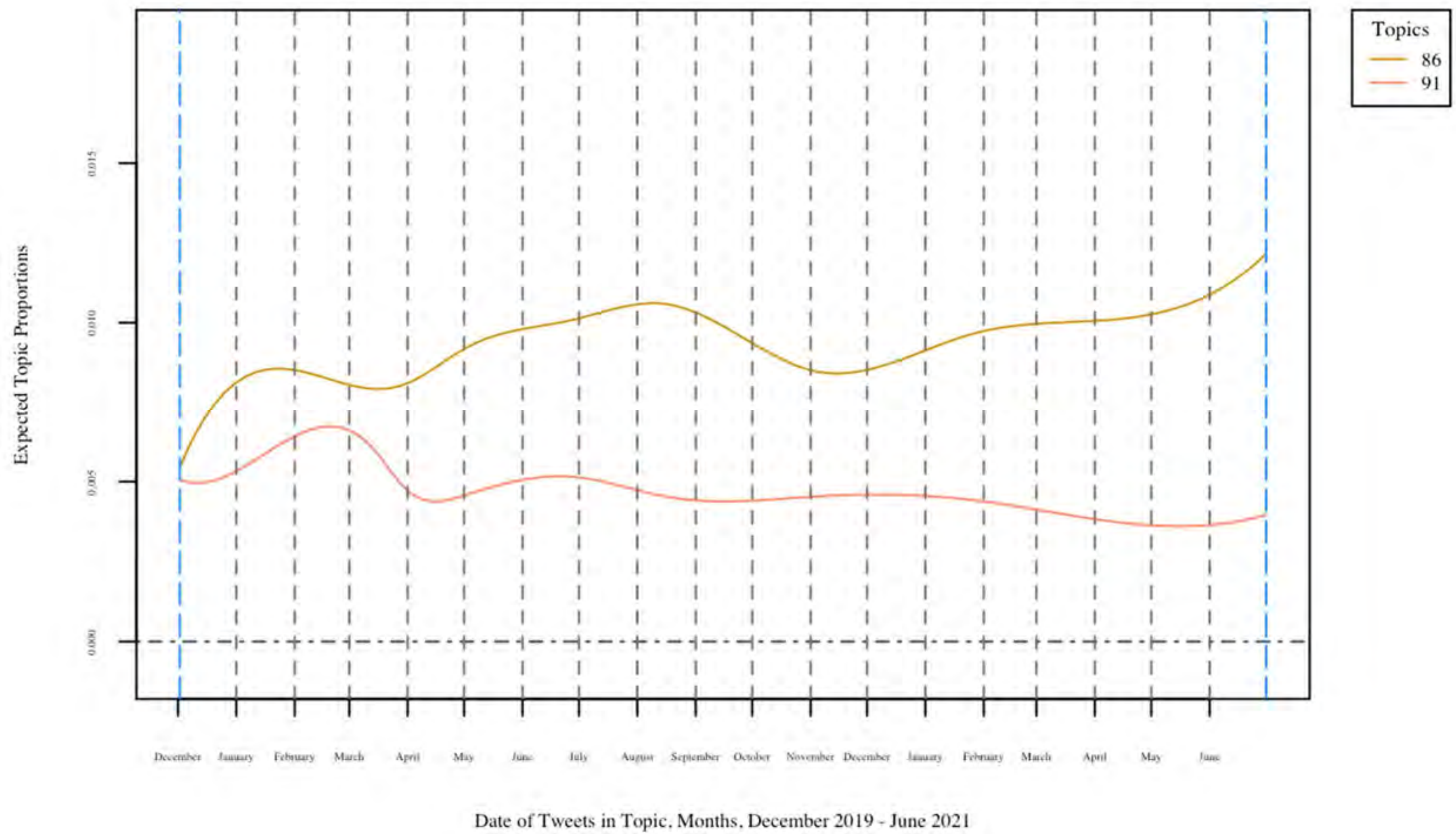


Figure 13.3c. Estimated Prevalence over Time for Topics where the Effect of "Disgust" on Content did not Interact with the Significant Effects of Time and "Disgust" on Prevalence

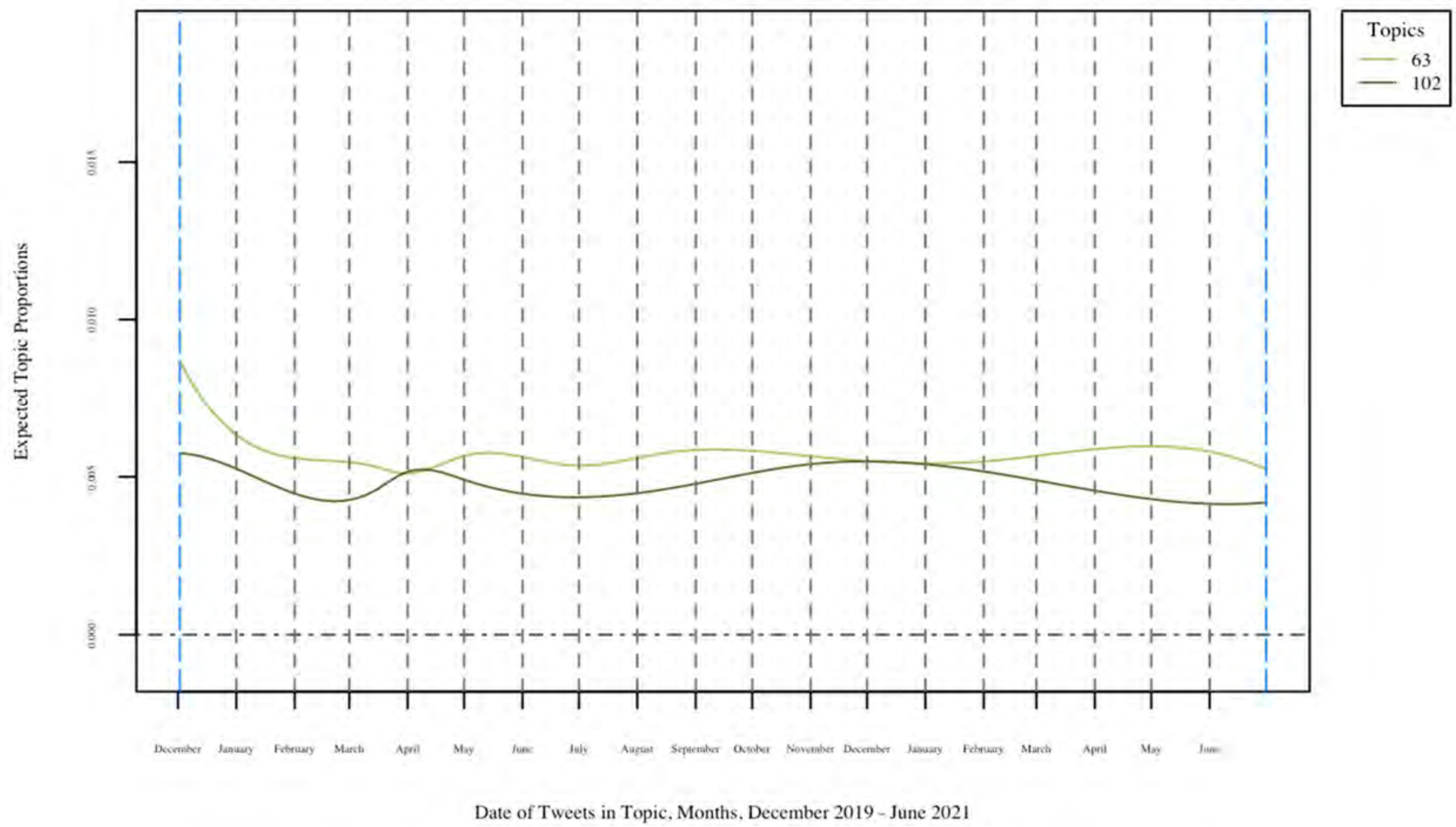


Figure 13.3d. Estimated Prevalence over Time for Topics where the Effect of "Joy" on Content did not Interact with the Significant Effects of Time and "Joy" on Prevalence

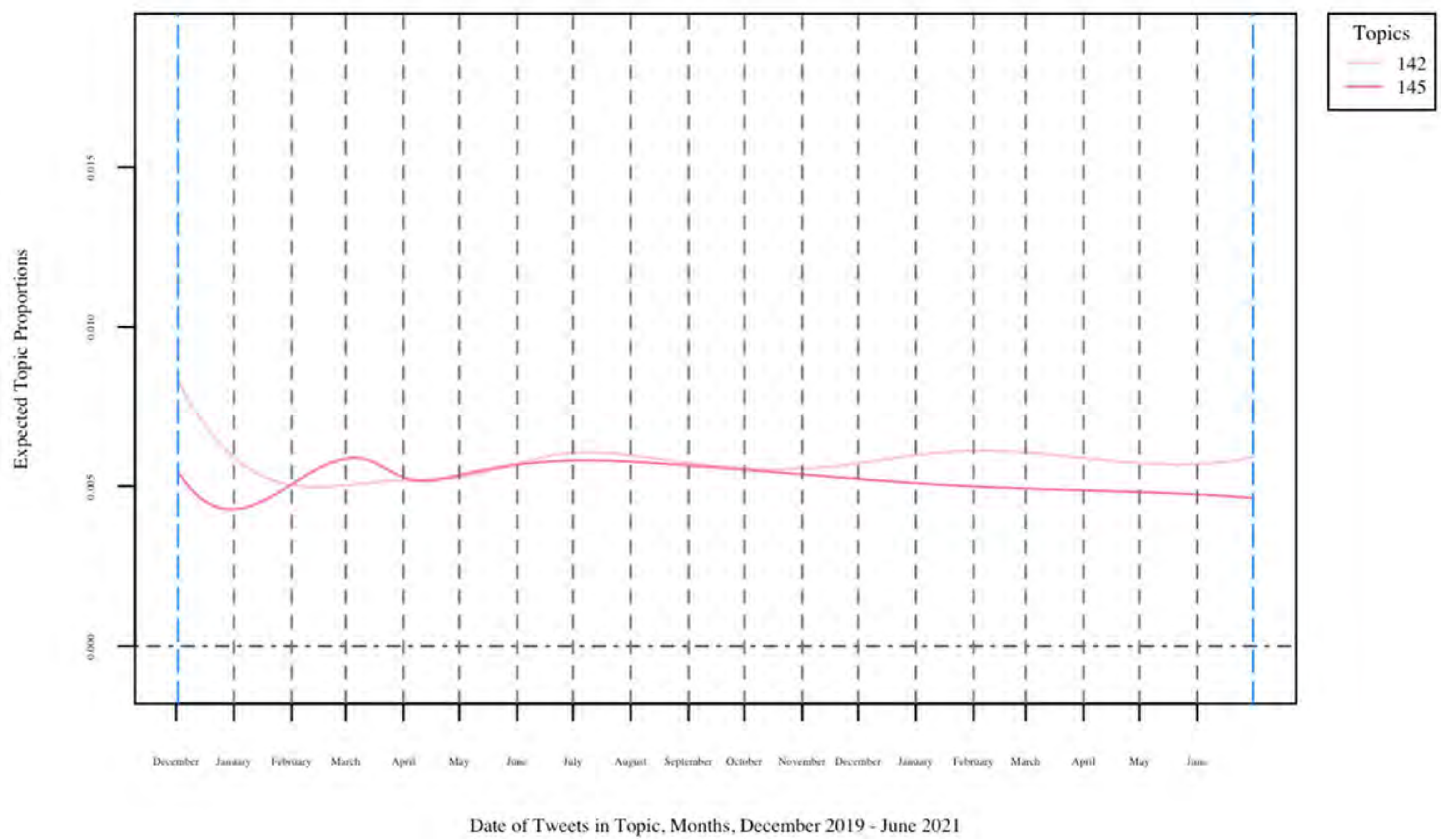


Figure 13.3e. Estimated Prevalence over Time for Topics where the Effect of "Sadness" on Content did not Interact with the Significant Effects of Time and "Sadness" on Prevalence

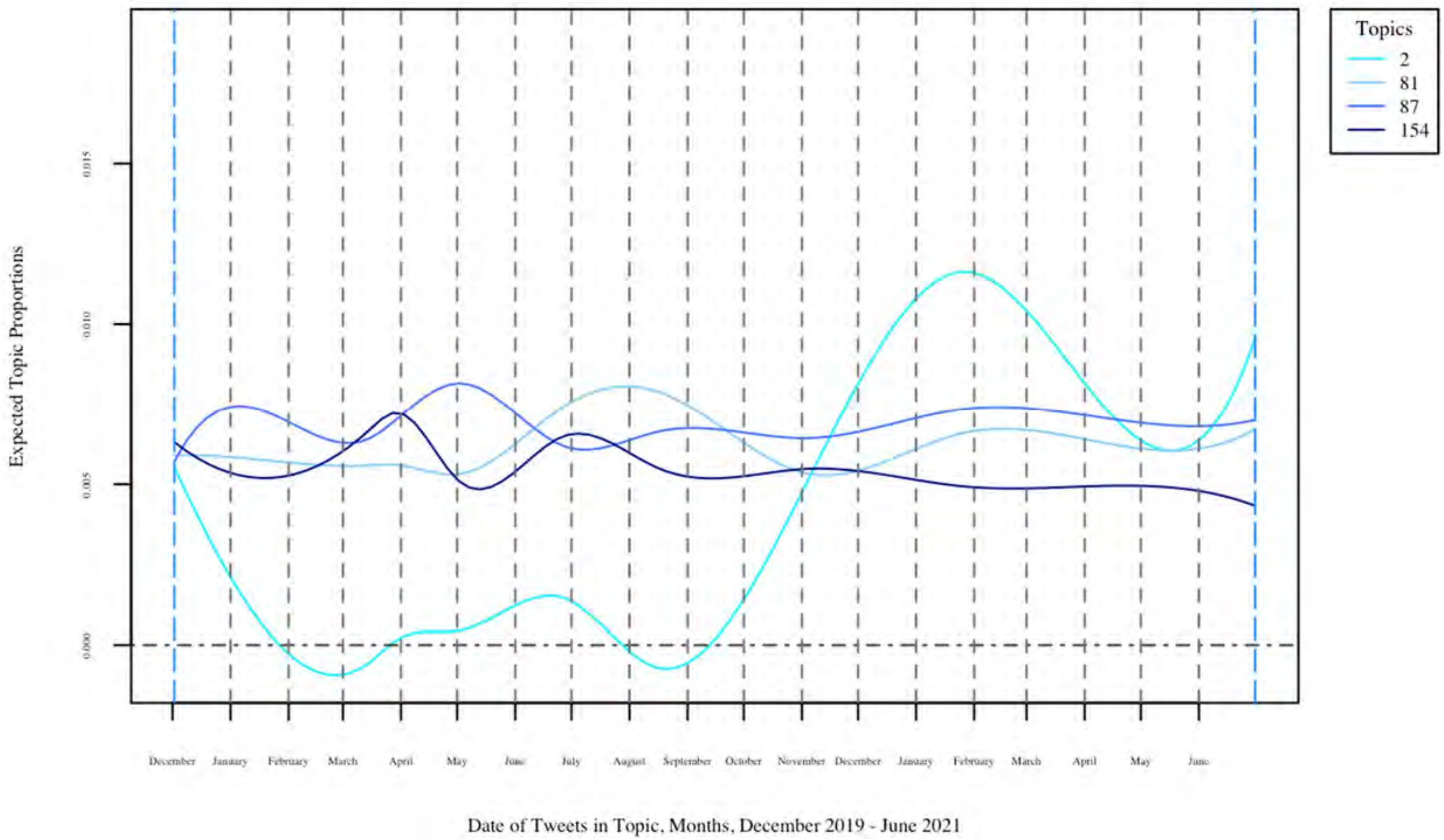


Figure 13.3f. Estimated Prevalence over Time for Topics where the Effect of "Surprise" on Content did not Interact with the Significant Effects of Time and "Surprise" on Prevalence

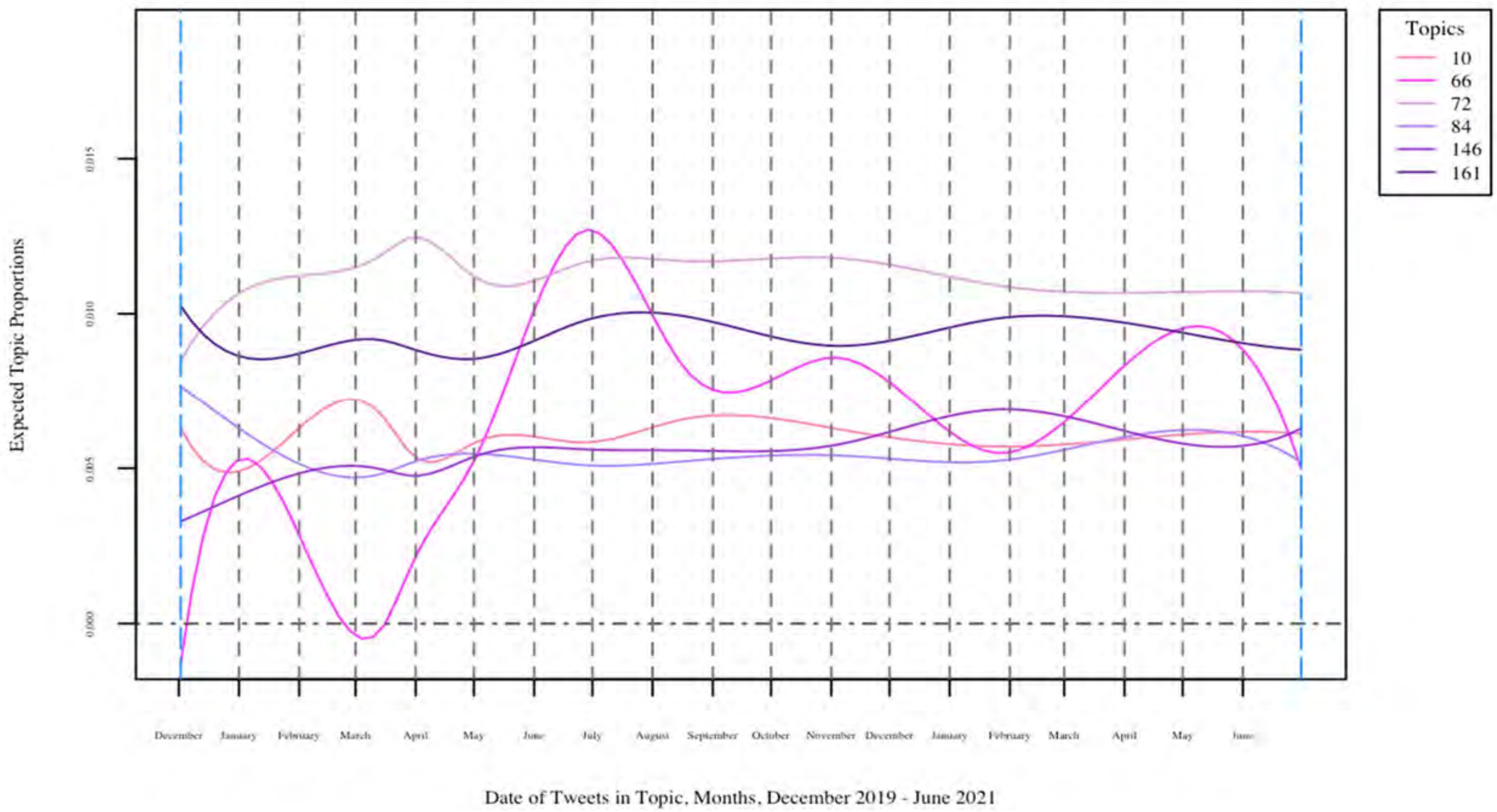
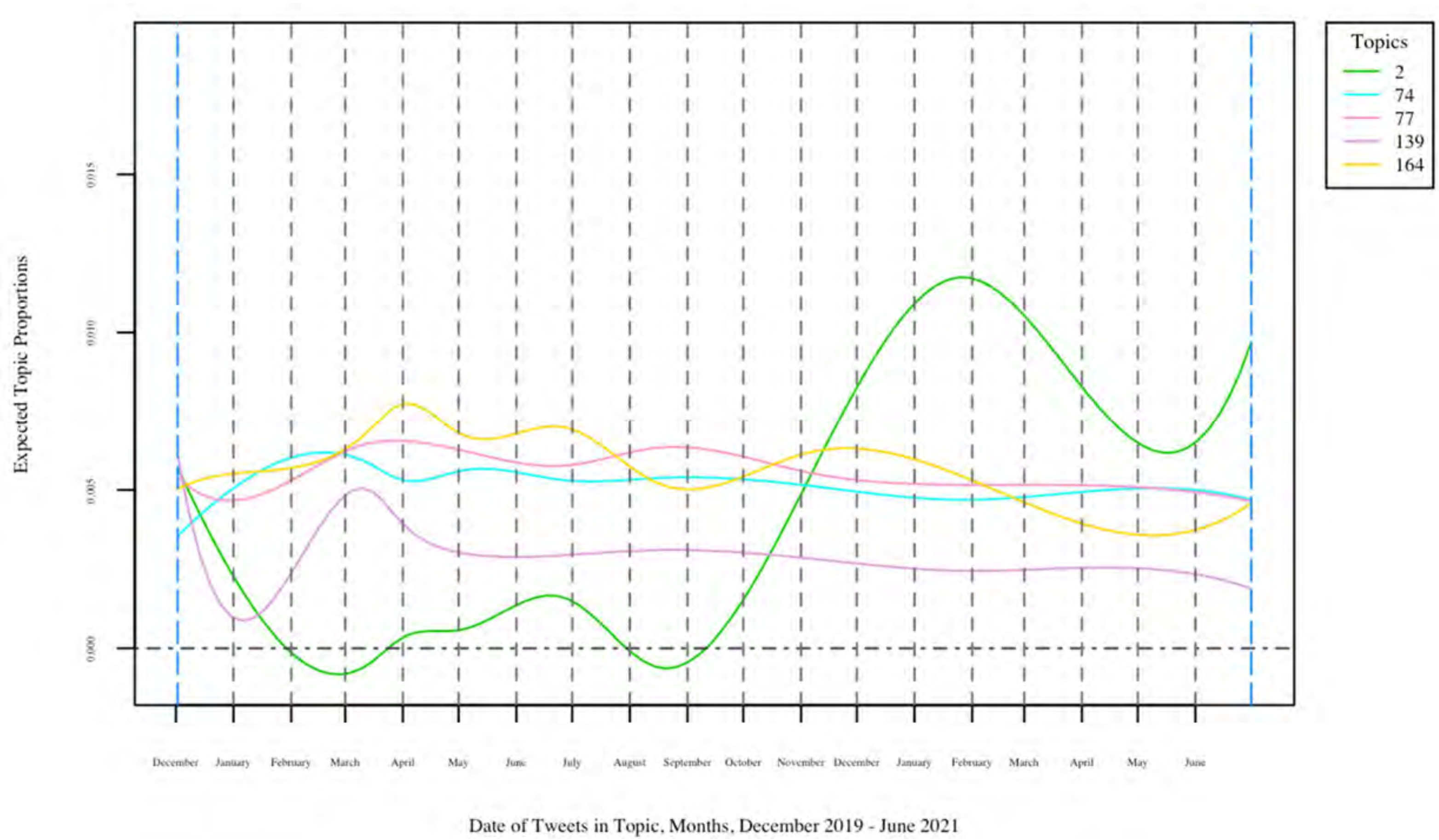


Figure 13.3g. Estimated Prevalence over Time for Topics where the Effect of “Trust” on Content did not Interact with the Significant Effects of Time and “Trust” on Prevalence



For topics where the effect of time was significant, there was a possible interactive effect between emotion and time for emotions that did not have significant effects on topical content but had significant effects on topic prevalence. For example, it is possible that the positive effect of “Anger” on the prevalence of topics 112 and 123 was counteracted by the significant and negative effect of “time” (Figure 13.1b; Figure 13.3a). The effect of “Sadness” may have buffered, or diminished the positive effect, of “time” for topics 2 and 81, having a significant and negative effect on the prevalence of both topics (Figure 13.3f). Additionally, the negative effect of “time” on the prevalence of topic 154 may have seen a lesser reduction in “Surprised” versus “Fearful” contexts (Figure 3.3f).

Time had a significant effect on the prevalence of both topics for which the effect of “Anticipation” was significant for topical prevalence but not topical content (Figure 13.3b). However, the interactions between “Anticipation” and “time” for both topics may have served to amplify, not buffer, the effect of the other. This is because the effects of “time” and “Anticipation” were either similarly positive or similarly negative. Consider topic 86, for instance, where the effect of “time” on topical prevalence was significant and positive, as was the effect of “Anticipation” compared to “Fear” (Figure 13.1a; Figure 13.3b). It could be the case that tweets in topic 86 became significantly more prevalent over time, but also that this increase may be larger for contexts of “Anticipation” compared to contexts of “Fear.” The effects operated in the opposite direction for topic 91, which saw a significant decrease in prevalence over time and for which the effect of “Anticipation” on topical prevalence was significantly weaker than “Fear” (Figure 13.1b; Figure 13.3b). When compared to “Fear,” the already significant decrease in the prevalence of topic 91 over time may have been even larger in context of “Anticipation.”

Other topics for which the significant effect of "time" on topical prevalence was potentially magnified by the significant effect of some emotion included a stronger increase over time for topic 146 for "Joyful" as opposed to "Fearful" contexts (Figure 3.3d) and topic 2 in a "Trusting" as opposed to "Fearful" context (Figure 3.3g).

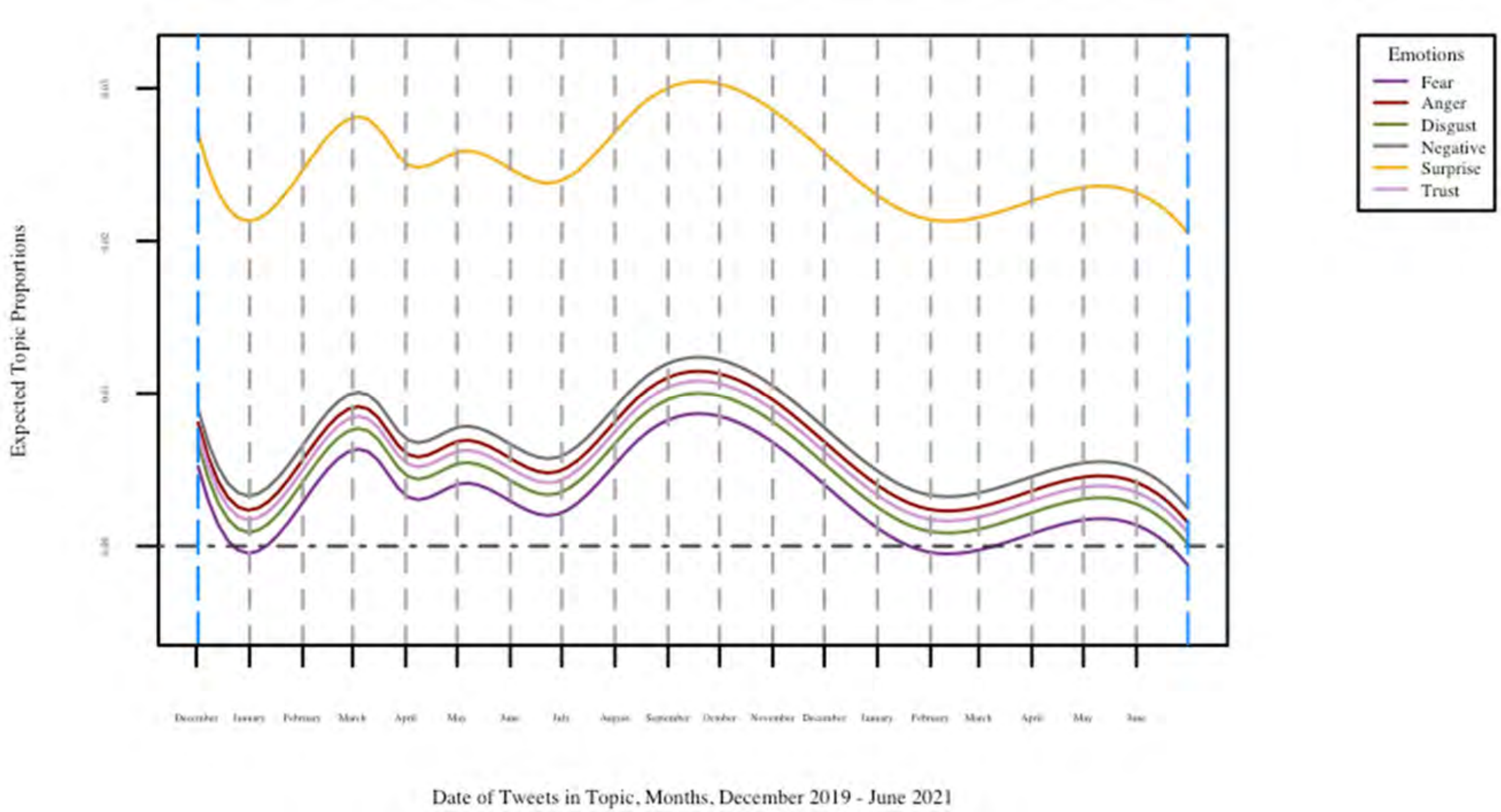
EXAMINING DIFFERENCES IN TWEET CONTENT BY TOPIC AND EMOTION

Topics where Time had a Significant Effect on Topical Prevalence both Before and After Controlling for Emotional Sentiment

The effect of time remained significant for most topics after controlling for emotion (Figure 12.2; Figure 13.1a-b), but the effect of time was moderated by the effect of emotional sentiment for all topics for which the effect of time was significant when controlling for the emotional undertones of a topic's tweets. Plotting the change in topical prevalence over time for each emotion with a significant effect on topical content provides the fullest picture of how people felt about each topic while also giving context as to when each topic was most prevalent among Tweets from Twitter users in the United States. In this section, I will focus most heavily on the content representing text of tweets for the most prevalent emotions with a significant effect on topical content.

Figure 13.4a demonstrates the difference in the estimated decrease of topic 24 over time depending on the emotional context underlying the content of the tweet. While there were several emotions with significant effects on the content of topic 24, the emotional context of "Surprise" stands out as much more prevalent than emotional contexts of "Anger," "Disgust," "Trust," or general "Negative" sentiment (Figure 13.4a).

Figure 13.4a. Estimated Change in Topic Prevalence over Time for Topic 24, Smoothed, by Emotions with Significant Effects on Tweet Content



The example text for topic 24 in all emotional contexts indicates that topic 24 tweets were political and specific to the context of President Trump's time in office (Figure 13.4b-c). Consider the peak prevalence for all significant emotional contexts of topic 24, which occurred between September 2020—October 2020 (Figure 13.4a). President Trump did not win the November 2020 presidential election. Not only does the main decrease in the prevalence of topic 24 coincide with the beginning of the Biden administration in late January 2021, and thus, a period in which President Trump's response to the coronavirus would have been increasingly irrelevant, it occurs around the same time the president's personal Twitter account "@realdonaldtrump" was forcibly inactivated for violating Twitter policy.

The dominant emotional context of "Surprise" in topic 24 is a good indication that many tweets in topic 24 expressed Surprise over the president's response to the pandemic. Example text generated from "Surprised" tweets in topic 24 like "Coronavirus: US President Donald Trump declares national emergency," and "Overdue. Hope it doesn't translate into panic over coronavirus" point to an overwhelming feeling of Surprise about one of the former president's specific responses to the pandemic, declaring it a national emergency (Figure 13.4b).

Tweets in other significant emotional contexts for topic 24 including "Anger," "Disgust," "Negative" and "Trust" were somewhat alike, and both were distinctly different than "Surprise," overwhelmingly focusing on the perception that then President Trump's response to the pandemic was inappropriate or nonexistent (Figure 13.4c).

Figure 13.4b. Text Representative of 'Surprised' Tweets in Topic 24

Coronavirus: US President Donald Trump declares national emergency.

Overdue. Better hope it doesn't translate into panic over coronavirus.

Can't believe the president ever belittled the threat of coronavirus. vice president told him not to cry wolf. Pence standards for VP are unstinting supporter of President Donald Trump. Pretty Bad.

President taking swift action on covid while democrats trying to impeach President Trump for restricted travel. Democrats calling him a dictator. Trump called for a national emergency stop over reacting. The president stopped lives from being lost

Figure 13.4c. Text Representative of 'Fearful', 'Angry', 'Disgusted', 'Negative', and 'Trusting' Tweets in Topic 24

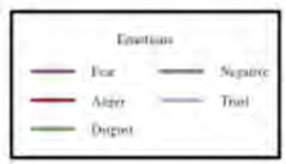
Pray! POTUS & FLOTUS diagnosed w/covid, president's age puts him at particularly high risk. It doesnt matter if you are a supporter or opponent. The president must be able to rise above politics in the moment.

Trump continues to crave attention even in the hospital. Had the idea to leave the hospital to greet supporters via motorcade. Reckless, selfish, and stupid and puts people at risk of being infected like others in the administration.

@[several users] exactly! We are supposed to be able to trust the president to lead us in crisis with competence and swift action. Instead we have a president whose biggest concern over coronavirus is whether it'll hurt his campaign and the election

President Donald Trump signs coronavirus relief package into law, invokes emergency powers.

@[several public officals] remember yesterday morning Trump held a hate rally surrounded by unmasked ppl. Keep talking while Trump is still not leading properly, puttng secret service at risk. Pleading but who cares? Rallying today!



Surprise was also the dominant emotion for topic 37, which saw a significant decrease over time (Figure 13.5a). In similar fashion to topic 24, tweets in topic 37 were focused on responses to the coronavirus pandemic by those in with institutional and/or political positions of power (Figure 13.5b-c). While the president of the United States (POTUS) was among the powerful entities mentioned in example text for topic 37 tweets, the president was not the primary focus of the topic. There was little to no exclusive focus on former President Trump specifically in the examples generated for topic 37, and this was true for all emotional contexts (Figure 13.5b-c).

Examples of what “Surprised” tweets in topic 37 looked like each touch on a different powerful entity declaring that the SARS-CoV-2 outbreak was an emergency of global concern, including “POTUS,” “Hong Kong,” “New York,” and “WHO,” the abbreviation for the World Health Organization (Figure 13.5b). Considering the prevalence for topic 37 only saw one large peak occurring between December 2019 and April 2020, this topic likely concerned only the initial declarations of emergency and not the renewals issued at later points in the pandemic (Figure 13.5a).

Topic 37 tweets provide evidence that Surprise over the declaration of a state of emergency due to coronavirus was not exclusive to Surprise that then President Trump took an important action that many expected him to forego (Figure 13.4b). Instead, it seems that many people were also simply Surprised to learn that SARS-CoV-2 constituted an emergency, a type of emergency that many Westerners had never encountered (Figure 13.5b).

Figure 13.5a. Estimated Change in Topic Prevalence over Time for Topic 37, Smoothed, by Emotions with Significant Effects on Tweet Content

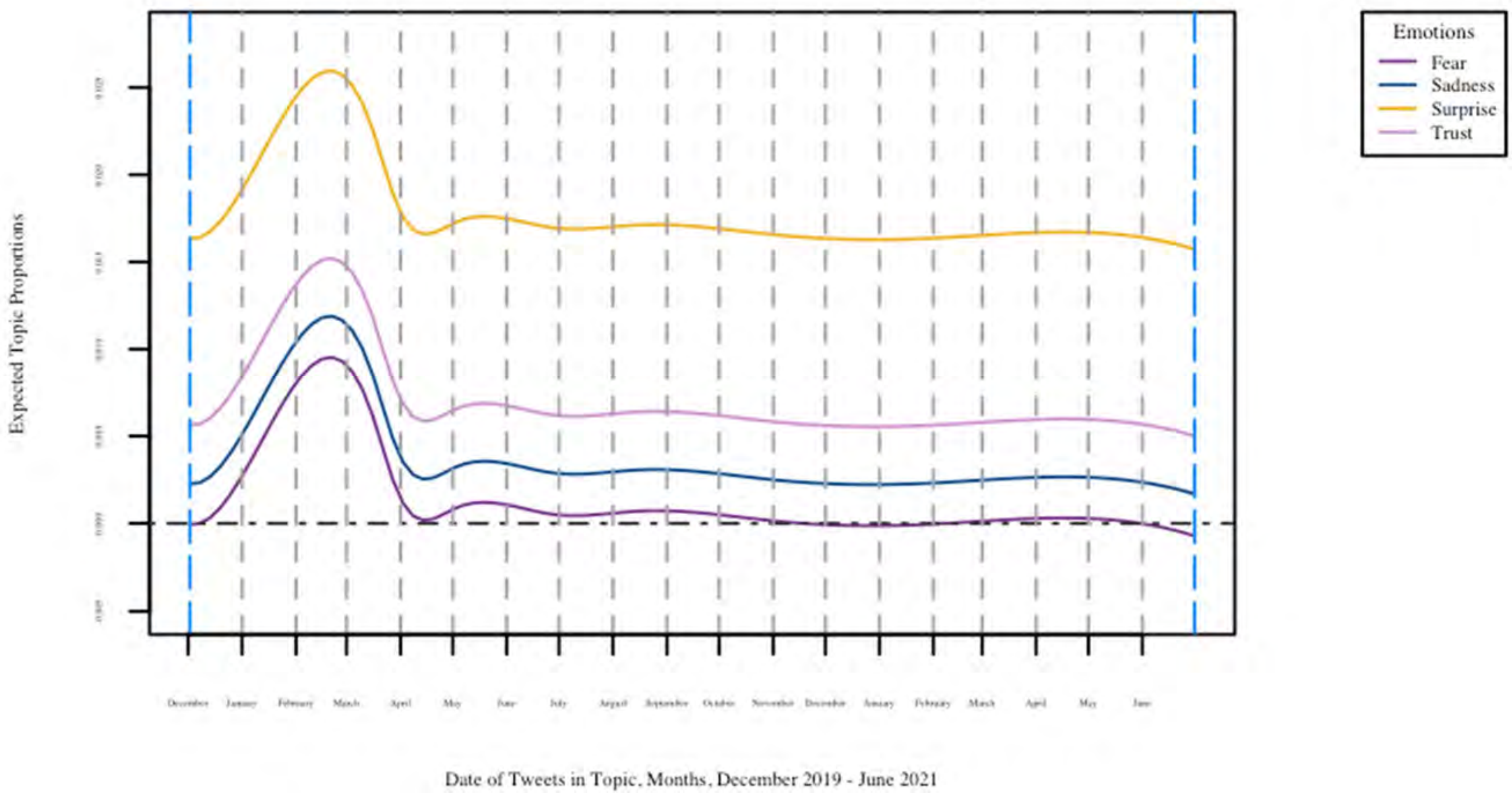


Figure 13.5b. Text Representative of 'Surprised' Tweets in Topic 37

Breaking: POTUS declares national emergency amid covid outbreak.

WHO has declared the coronavirus outbreak a global health emergency.

Hong Kong declares coronavirus outbreak emergency.

New York City declares a state of emergency due to coronavirus, details to come.

Figure 13.5c. Text Representative of 'Fearful', 'Sad', and 'Trusting' Tweets in Topic 37

Snohomish county first responders were the first in the nation to see the covid outbreak months ago, now tracking alarming new trend spike in emergency calls for covid like illness. Higher than any time during the pandemic.

Today's wants: intended to celebrate world magic day and math pi day. However, the country declared a national emergency over coronavirus so I won't eat pie this year. No pi day this march means [tearful emoji]

Hey tribe! After much consideration we have made the difficult decision to cancel the [national organization] Conference in light of the state of emergency declared in nys due to the spread of covid.

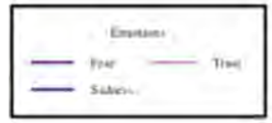


Figure 13.6a. Estimated Change in Topic Prevalence over Time for Topic 65, Smoothed, by Emotions with Significant Effects on Tweet Content

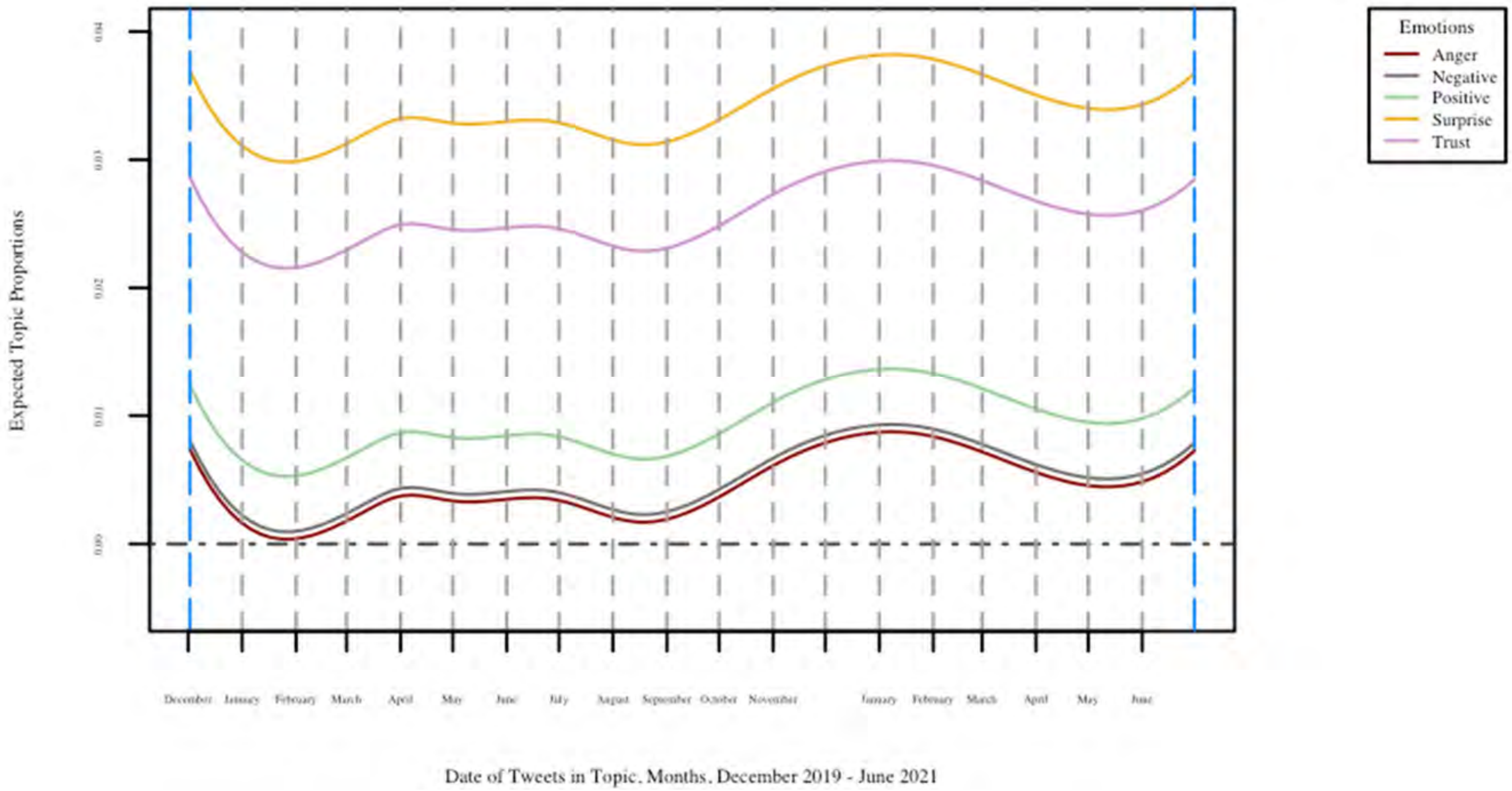


Figure 13.6b. Text Representative of 'Surprised' Tweets in Topic 65

FDA authorizes Pfizer covid vaccine for emergency use!

FDA takes key action in the fight against covid by issuing an emergency use authorization for the first covid vaccine.

FDA committee endorses emergency use for covid vaccine shot.

If its meant to treat covid it means its prob covid. Wow: @[news source] FDA ends emergency use authorization of hydroxychloroquine to treat covid

Figure 13.6c. Text Representative of 'Angry', 'Negative', 'Positive', and 'Trusting' Tweets in Topic 65

Topic 65 “Surprised” tweets, which were the predominant emotional context for the topic (Figure 13.6a), reveal that people were Surprised over preventives and treatments for COVID-19. These included mentions of vaccines and treatments authorized for emergency use to treat COVID-19 infection like “hydroxychloroquine” (Figure 13.6b).

The significant increase in the prevalence of topic 65 over time makes sense considering the absence of treatments for COVID-19 in the initial days of the pandemic and preventives until the approval of vaccines in late 2020.

Topic 71 saw a significant increase over time, and the effect of all emotions on topical content was significant apart from “Joy,” including significant effects of “Anger,” “Anticipation,” “Disgust,” “Fear,” “Joy,” “Negative,” “Positive,” “Sadness,” “Surprise,” and “Trust” (Figure 13.7a). The prevalence was highest in context of “Anticipation,” though, and this was true for the duration of the 19-month period from December 2019 through June 2021 (Figure 13.7a). Examples of “Anticipatory” tweets in topic 71 indicate Anticipation surrounding the potentially limited effectiveness of risk mitigation plans for reducing the risk of infection with the SARS-CoV-2 virus, and some Anticipation linked to high-risk locations like churches (Figure 13.7b). Other emotional contexts of topic 71 tweets were similarly focused on high-risk locations and the potentially limited effectiveness of risk mitigation plans for reducing risk of exposure (Figure 13.7c). Given the significant effect of all 10 emotions on topical content, this suggests that syntax and word use were important indicators of how emotion could vary quite drastically among tweets about the issues of mitigation effectiveness and risk tied to location (Figure 13.7b-c). The topic’s increasing prevalence over time suggests that the issues of location-based risk and of potentially ineffective mitigation steadily gained importance over the first 19 months of the pandemic (Figure 13.7a).

Figure 13.7a. Estimated Change in Topic Prevalence over Time for Topic 71, Smoothed, by Emotions with Significant Effects on Tweet Content

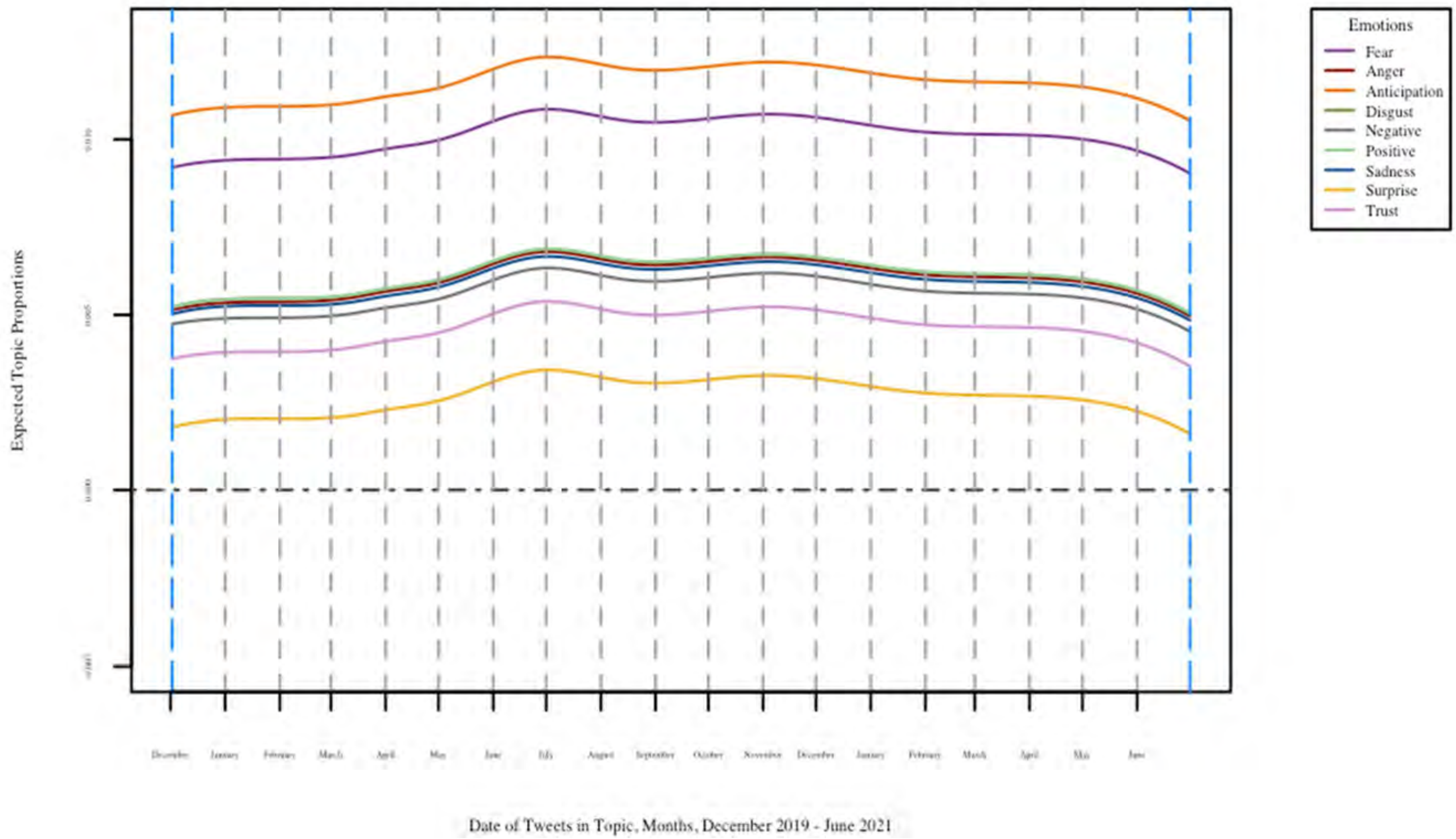


Figure 13.7b. Text Representative of 'Anticipatory' Tweets in Topic 71

Georgia Tech created a pandemic risk assessment tool to predict likely-hood of coming in contact with a covid positive person based on location and crowd size.	Tri-state area in high-risk category for infections despite aggressive precautionary measures.
Contact tracing shows a high risk of coronavirus spread in churches.	@[user] Idk if I want to risk elective surgery in my location. High viral load for an unknown virus with an un-reasonably high mortality rate?

Figure 13.7c. Text Representative of 'Fearful', 'Angry', 'Disgusted', 'Negative', 'Positive', 'Sad', 'Surprised', and 'Trusting' Tweets in Topic 71.

All 10 emotions had a significant effect on the content of topic 73 (Figure 13.8a), including "Joy," which was the lone sentiment with a non-significant effect on the content of topic 71 (Figure 13.7a). Topic 73 significantly decreased over the course of 19 months, peaking prior to the start of the pandemic in December 2019, and once more in April 2020 (Figure 13.8a). "Fearful" tweets were the most characteristic of topic 73, seeming to reveal a sense of Fear about the lacking clarity on who was at risk for serious illness from COVID-19 infection and the range of seriousness for COVID infections depending on factors like being medically vulnerable and the availability of therapeutics to manage symptoms of illness (Figure 13.8b).

Tweets with non-Fearful contexts in topic 73 shed light on some of the significant but less prevalent feelings expressed about the clarity of information about COVID-19 risk (Figure 13.8c). While the tweets about the clarity surrounding the true extent of risk posed by COVID-19 were most often expressions of "Fear" that there was not clarity, they also included other perceptions and feelings about the alleged clarity (or lack thereof) about the risks of COVID-19. For example, some people did not feel there was lacking clarity about who was at risk for severe illness if infected with COVID-19.

When this was the case, some tweets expressed "Anger" aimed at those who did not seem to understand what they felt was obvious, that risk was only high for medically vulnerable people (Figure 13.8c). Not everyone who agreed that the medically vulnerable were those facing the biggest threat from the virus expressed "Anger" at others who contested this fact, though. Instead, others simply expressed a general "Negative" sentiment towards people who touted the fact as a means of excusing their lacking engagement with risk mitigation, suggesting that those celebrating their own low risk should not discount the worth of vulnerable people's lives (Figure 13.8c).

Figure 13.8a. Estimated Change in Topic Prevalence over Time for Topic 73, Smoothed, by Emotions with Significant Effects on Tweet Content

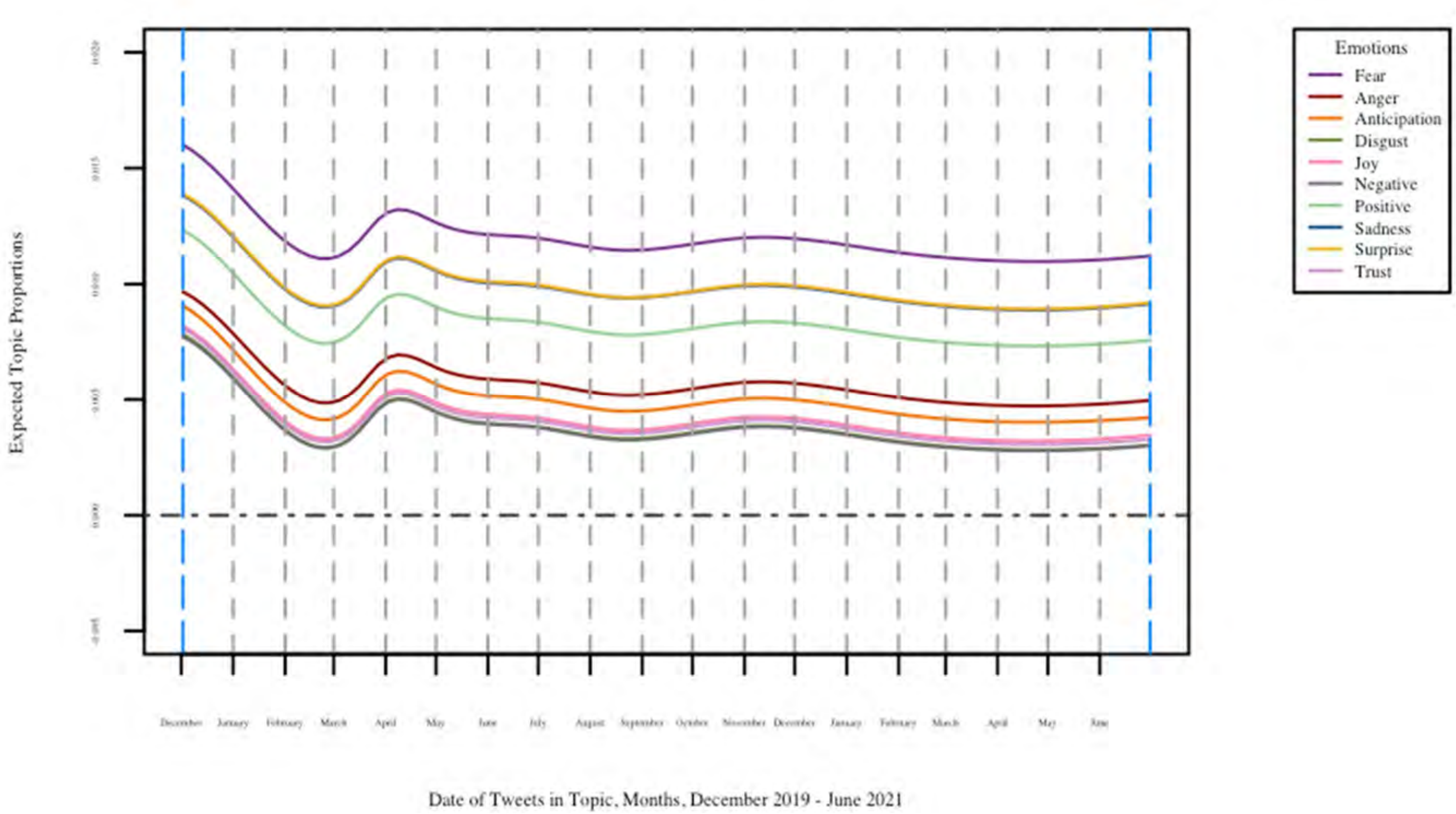


Figure 13.8b. Text Representative of 'Fearful' Tweets in Topic 73

A study of hospitalized coronavirus patients on six continents found those who received hydroxychloroquine were at significantly higher risk of death compared to those who did not.

This would suggest patients with cardiac diseases like hypertension and diabetes being treated with ace increasing drugs are higher risk for severe covid infection. therefore, should be monitored on ace modulating medications like ace inhibitors via @[medical research journal]

Trump claimed without evidence that convalescent plasma helped coronavirus patients who received the treatment.

@[user] the CDC website says adults hospitalized for flu-like illness in studies reported early antiviral treatment can reduce the risk of death.

Figure 13.8c. Text Representative of ‘Angry’, ‘Anticipatory’, ‘Disgusted’, ‘Joyful’, ‘Negative’, ‘Positive’, ‘Sad’, ‘Surprised’, and ‘Trusting’ Tweets in Topic 73

Another perception on COVID-19 risk found in topic 73 was that the risk was possibly severe but ultimately temporary. While some tweets expressed “Surprise” over measures meant to ensure the risk of COVID-19 was temporary like the FDA authorization of therapeutics on an emergency basis allowing them to forego the clinical trial process for authorization to treat a specific condition, others expressed a general sense of “Positivity” about the FDA “finally” using its emergency authorization power (Figure 13.8c). There were also expressions of “Anticipation” in discussions of the “short term shelter in place” orders issued to keep hospitals from being overwhelmed in the early months of the pandemic, and expressions of “Joy” over the bravery of frontline health care workers in face of the immediate risk of COVID-19 and implying an eventual end to a need for this alleged bravery (Figure 3.8c).

Topic 76 also saw significant effects of all 10 emotions on topical content, and it was increasingly more prevalent over time (Figure 13.9a). Topic 76 was like topic 73 in that it highlighted a lacking consensus over who was at risk from COVID-19 and what the extent of that risk truly was (Figure 13.8b-c; Figure 13.9b-c). The largest proportion of tweets in topic 76 contained emotional undertones of “Fear” (Figure 13.9a-b).

The significant increase in the prevalence of topic 76 over time could indicate a shift from uncertainty about the proximity of COVID-19 risk during the beginning of the pandemic and the mistaken hope that the risk would be short-term, to a period of heightened certainty that COVID-19 was something ineradicable and disagreement about whether that also meant there was an enduring risk to the general population.

Figure 13.9a. Estimated Change in Topic Prevalence over Time for Topic 76, Smoothed, by Emotions with Significant Effects on Tweet Content

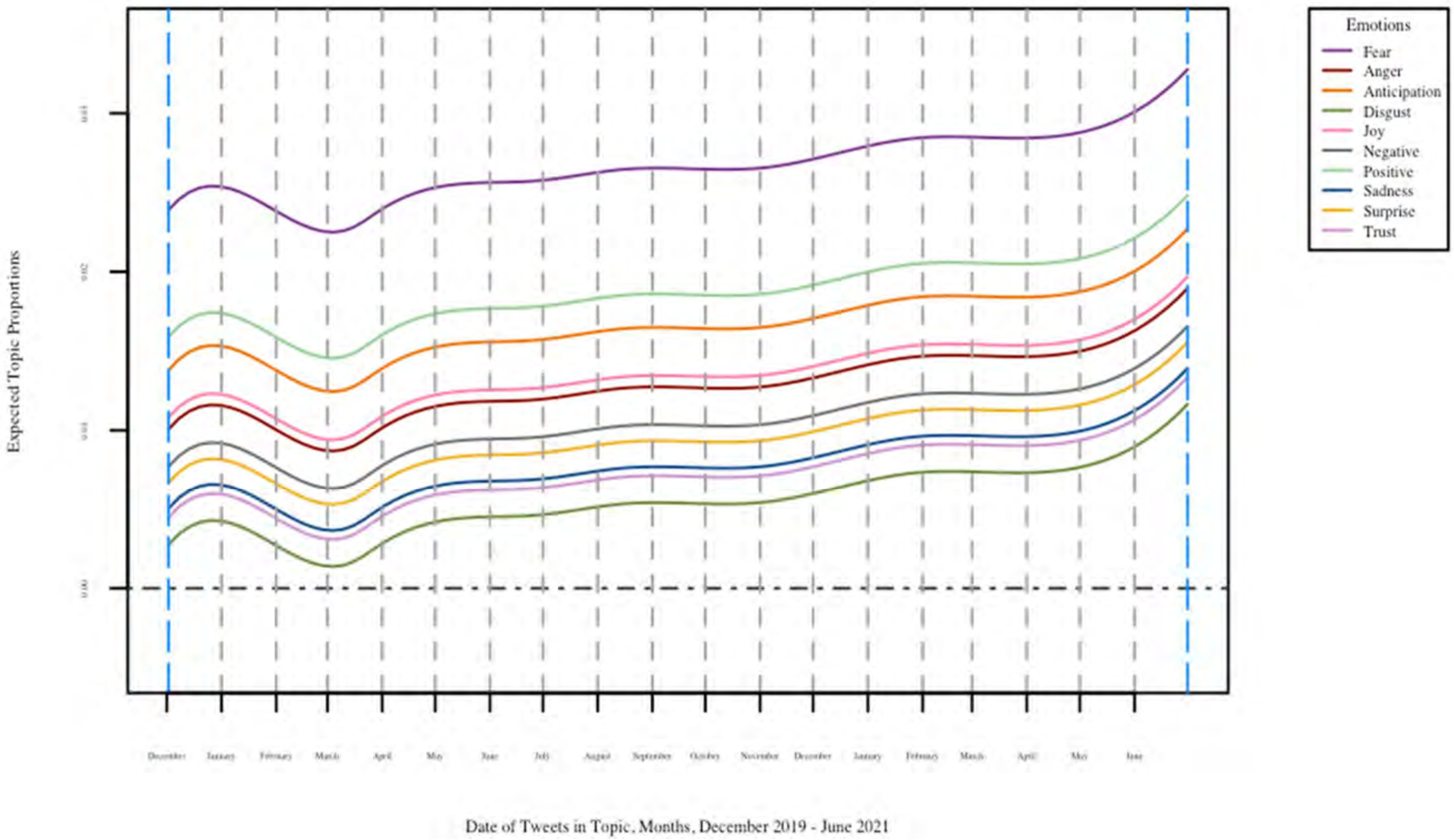
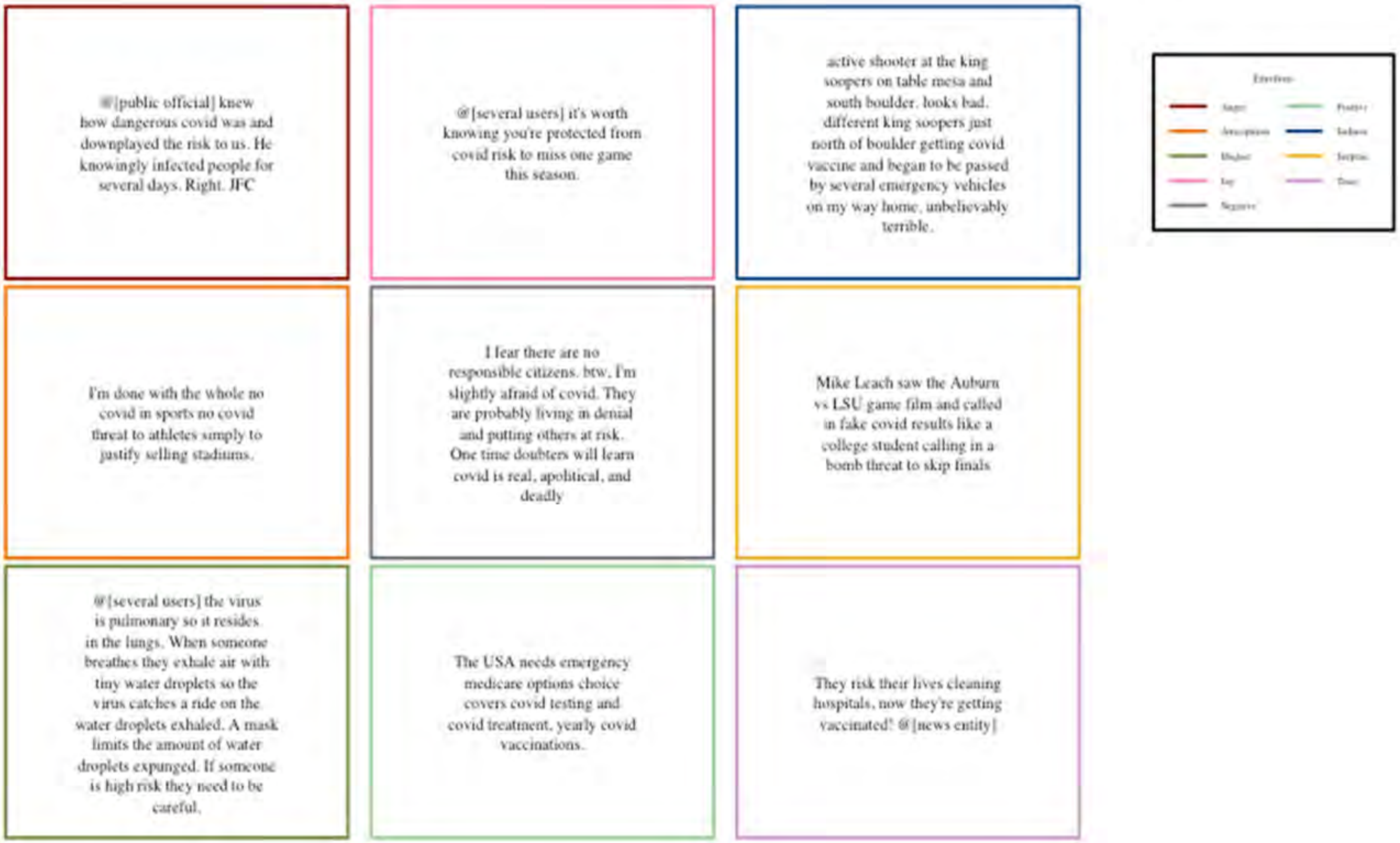


Figure 13.9b. Text Representative of 'Fearful' Tweets in Topic 76

@[user] great faith in the human immune system. If covid was triggered, the risk of severe covid will be near zero whether vaccination or infection. I'm personally not as worried about covid as the covid vaccines. Rather get vaccinated with an approved vaccine.	This means children are several times more likely to die of non-covid causes than the pandemic. Covid puts the risk of covid death for children in the ballpark of deaths from lightning.
Is the covid vaccine or covid the big threat?	There appears to be a grave danger of being exposed to covid in dental settings, particularly as the pandemic is decelerating.

Figure 13.9c. Text Representative of ‘Angry’, ‘Anticipatory’, ‘Disgusted’, ‘Joyful’, ‘Negative’, ‘Positive’, ‘Sad’, ‘Surprised’, and ‘Trusting’ Tweets in Topic 76



The predominant emotional undertone of tweets in topic 78 was "Anger" (Figure 13.10a). However, unlike other topics for which the significant effect of "Time" on topical prevalence was moderated by the effect of emotional sentiment on topical content, the prevalence of tweets in several other emotions were visually indistinguishable from each other in topic 78. These included the contexts of "Joy," "Positive" sentiment, and "Sadness" (Figure 13.10a). While the prevalence of tweets expressing "Fear" and "Trust" was lower than the prevalence of tweets expressing "Anger," the two emotions stood out for having a higher prevalence that was visually distinct from the prevalence of tweets expressing "Joy," "Positive" sentiment, or "Sadness" (Figure 13.10a).

"Angry" tweets in topic 78 took aim at people who felt the risk of COVID-19 was serious enough that the entire U.S. population should partake in mitigatory efforts, sometimes going so far as to mock others by calling them demeaning names like "stupid" and invalidating their Fears by labeling them as "hysteria" (Figure 13.10b).

The example text of "Fearful" tweets in topic 78 gives merit to this idea by providing evidence that people did express Fears about the risk of COVID-19. Sometimes the expression of "Fear" in topic 78 were direct expressions of Fear while mocking others for even considering behavior that could be considered risky with a side note that the user tweeting would not engage in that behavior (Figure 13.10c). Tweets using this approach also implied a sort of moral superiority over those who chose to expose themselves to COVID-19 (Figure 13.10c). Other expressions of Fear were indirect, implying that "Fear" about risk from the virus existed by identifying circumstances where action was taken to mitigate risk, such as the suspension of "obligations for holy week" by leaders of the Catholic church (Figure 13.10c).

Figure 13.10a. Estimated Change in Topic Prevalence over Time for Topic 78, Smoothed, by Emotions with Significant Effects on Tweet Content

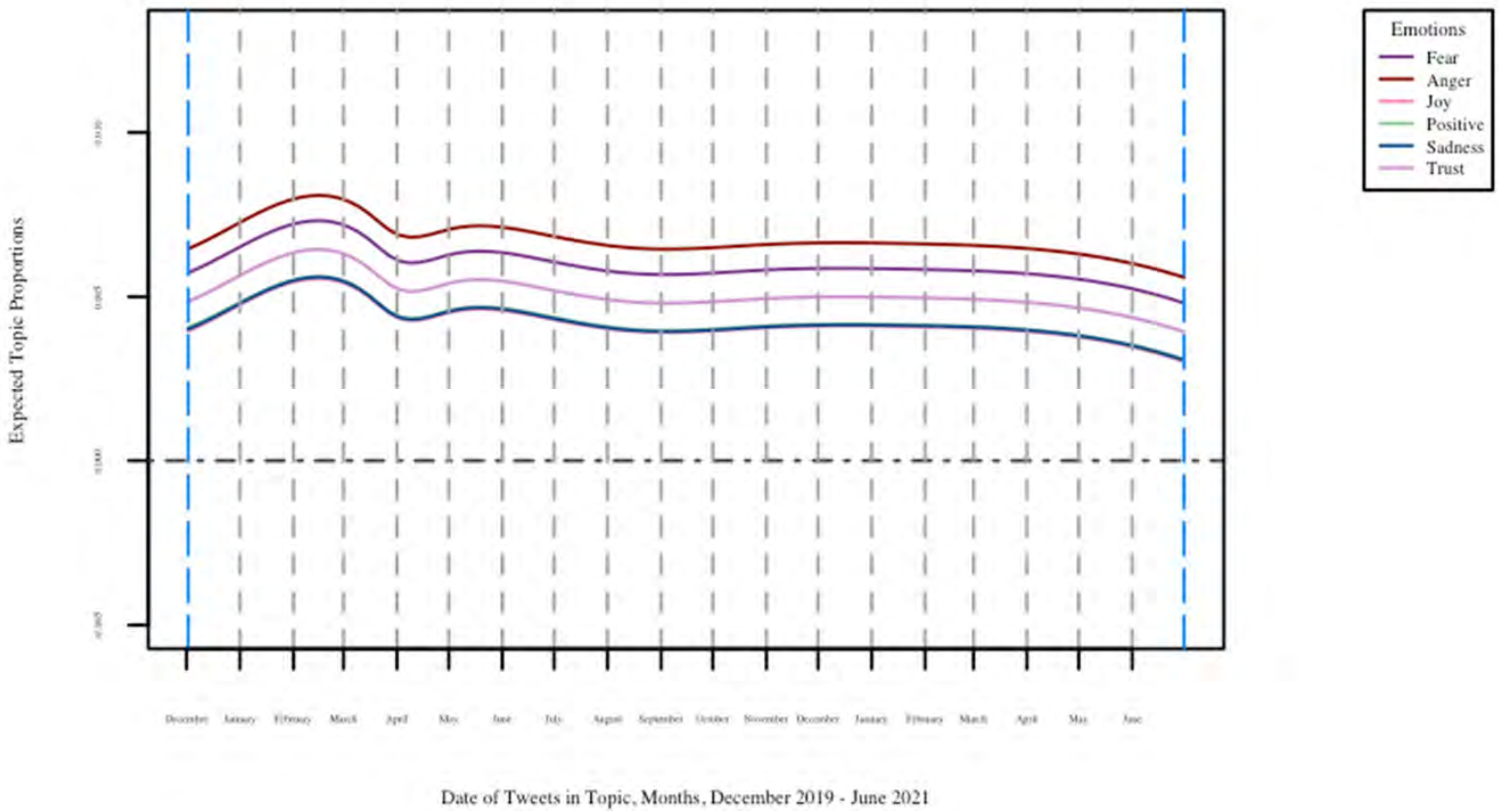


Figure 13.10b. Text Representative of 'Angry' Tweets in Topic 78

You should just take one for the team. If every vulnerable senior removes themself the risk of infection goes down and gives the economy a slightly better chance at recovering successfully. Isn't what's most important the economy?

@[professional basketball player] chose to opt out of the Orlando NBA bubble plan for family reasons cause he said one of his sons won't be allowed to go since he'll be the most at risk for covid cause of his respiratory illness. I don't blame him one bit, it's what's best for the family.

hard discern whats legitimate concern about corona and whats just hysteria

@[user] you sound stupid lol better to never find out and drive in your car cause the risk is actually lower and the survival rate higher than corona. You have a better chance at eating making you choke and die.

Figure 13.10c. Text Representative of 'Fearful' Tweets in Topic 78

The nation's top health officials warn recent travelers of increased risk of spreading covid coming home from the holiday weekend.

Bishops in Ohio canceled the obligation to do mass on holy week due to extreme concern of virus spread. Of course when I'm excused from mass I want to attend.

I've watched them lose week after week. If I was a season ticket holde I'd be fuckin livid to risk my health to see Carr throwing rd long-screen passes and throw aways. They lose and you catch rona!

Having the highest cases and deaths and being the quickest reopening country means we are at the highest risk for an additional spike in cases. All the poisoning from bad suggestions shows the poorest handling of the virus.

Figure 13.10d. Text Representative of 'Trusting' Tweets in Topic 78

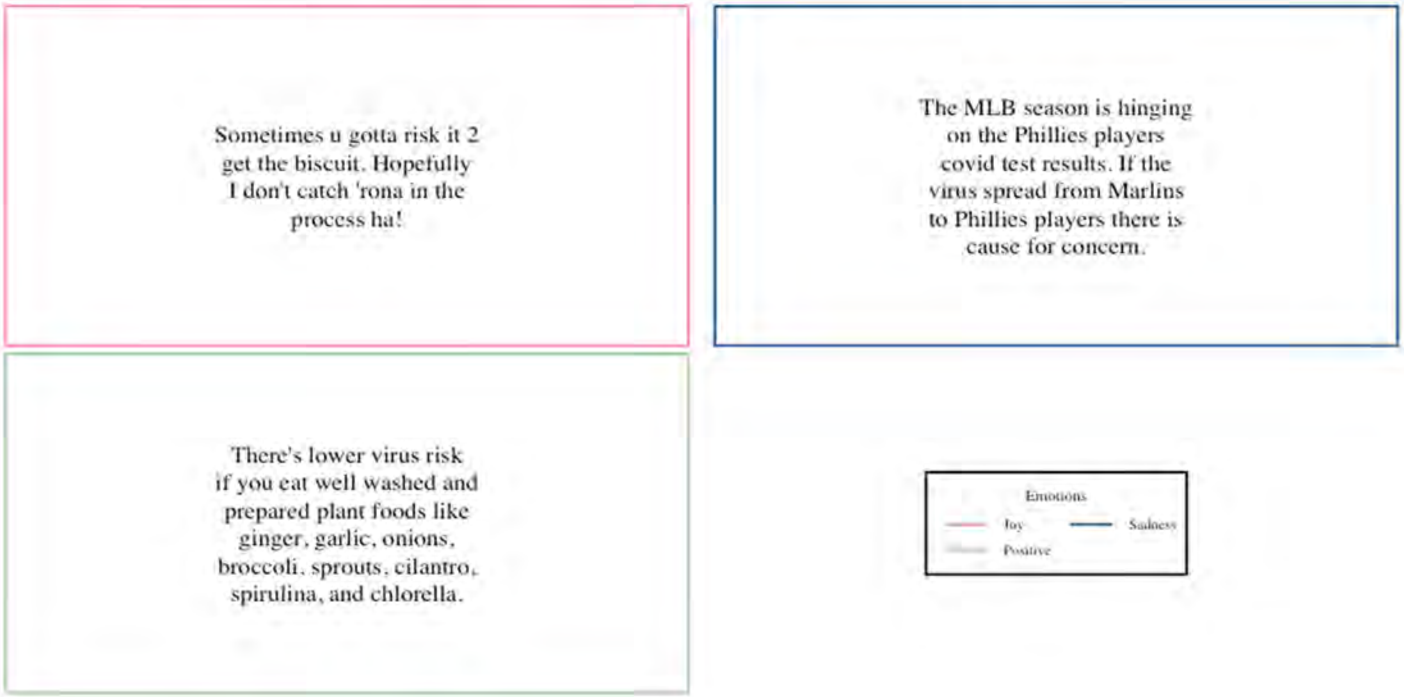
Houston is uniquely situated to be better prepared for the coronavirus threat.

One Texas county sends an emergency text alert to residents requesting they cancel holiday gatherings amidst covid surge.

Face mask on deck. OG. Will be ready for my rotation this weekend.

Texas department of criminal justice announced on Wednesday that it is locking down all prisons in response to the coronavirus crisis.

Figure 13.10e. Text Representative of 'Joyful','Positive', and 'Sad' Tweets in Topic 78



"Trusting" tweets in topic 78 were almost exclusively dealing with the state of Texas' response to the threat of coronavirus (Figure 13.10d). The expression of "Trust" related to Houston being "uniquely prepared" points to that city as a possible exception to the alleged unsafe handling of the virus by Texas generally (Figure 13.10d). There were also expressions of "Trust" about statewide actions to mitigate the risk of COVID-19 in Texas, which suggests that, regardless of judgements about its general handling of the pandemic, the state did take several actions that were well-received by its critics. These included things like the use of the emergency text alert system to provide residents updates about COVID-19, and "locking down all prisons" (Figure 13.10d). When it responded in a way that critics felt was appropriate, the state of Texas invoked a sense of "Trust" in its response to the pandemic.

The example text representing tweets with other strong emotional sentiments in topic 78 indicated that there was not a lot of animosity in tweets with "Joyful," "Positive," and "Sad" emotional undertones. Tweets in a "Joyful" context hint that some people felt a sense of "Joy" over making the decision to face the risk of COVID-19 head-on, like the example text declaring that "Sometimes u gotta risk it 2 get the biscuit" followed by acknowledgement that the risk was specific to COVID-19 with text like "Hopefully I don't catch 'rona[5] in the process!" (Figure 13.10e). Other tweets in topic 78 indicated there was a general sense of "Positivity" about the possibility that lifestyle choices like diet and exercise could reduce one's risk of COVID-19 infection and complications from infection to a minimal level.

A final trend for topic 78 tweets was the expression of "Sadness" over the realization of possible super spreader events. For example, topic 78 "Sad" tweet text highlighted discussions about the potential spread of COVID-19 infection between players of two major league baseball

[5] Several slang nicknames for COVID-19 emerged over the course of the pandemic, including "'rona," "Miss 'rona," "COVID," "cvid," and "corona."

(MLB) teams during a game. They also referenced a real super spreader MLB event that occurred when the Philadelphia Phillies played the Miami Marlins in the summer of 2020, when the Marlins had a known exposure to infected players on the Washington Nationals during their previous series. The outbreak was so severe that the Phillies' next series, an "away" series against the New York Yankees, had to be postponed, and the entire Marlins organization was shut down for an entire week after the series against Philadelphia to keep the outbreak from spreading further (Pingue and Carroll 2020). (Figure 13.10e)

Most of the tweets in topic 81 pertained to the risk of COVID-19 for children, indicating a range of emotions surrounding things like sending children to school and scientific studies assessing the risk coronavirus infection posed to children (Figure 13.11b-c).

There was a significant increase in the prevalence of tweets in topic 81 over time. Considering the increase for topic 81 did not seem to begin until about May 2020 around the end of the 2019-2020 academic year and start of summer break for students, this could be a symptom of the implementation of virtual schooling for much of the Spring semester of the 2019-2020 academic year for students from kindergarten through higher education in the United States (Figure 13.11a).

Anticipatory tweets were dominant in topic 81, and they specifically highlighted Anticipation of the risk to children when they went "back to school" for the 2020-2021 academic year, and thus, gave even more merit to the idea that the trajectory of prevalence for topic 81 had something to do with timing of school semesters and breaks (Figure 13.11a-b).

The predominant emotional context for tweets in topic 83 was "Negative," but it was only slightly predominant over "Joy," with the prevalence of other significant emotional predictors of topical content remaining much lower (Figure 13.12a).

Figure 13.11a. Estimated Change in Topic Prevalence over Time for Topic 81, Smoothed, by Emotions with Significant Effects on Tweet Content

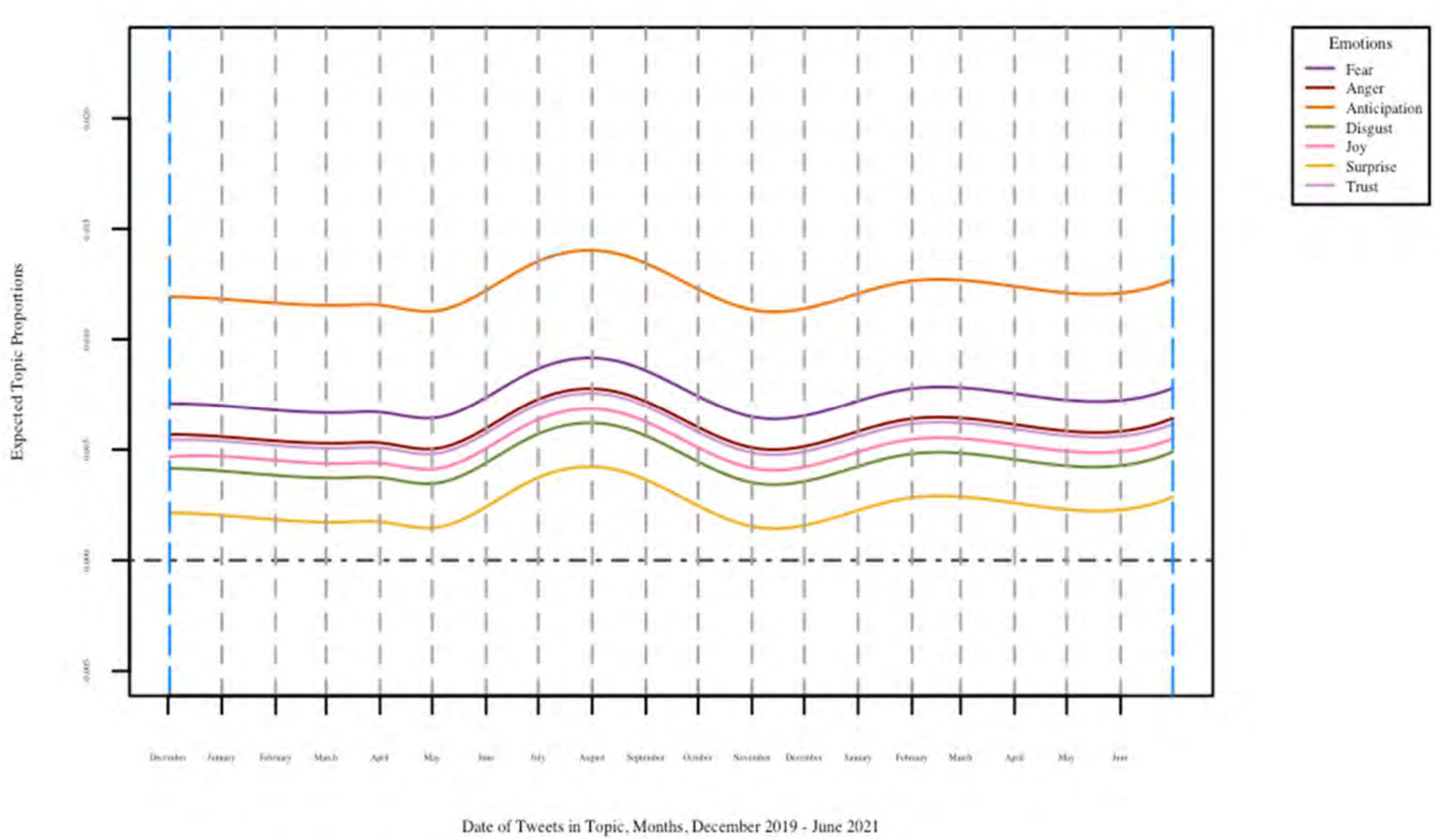
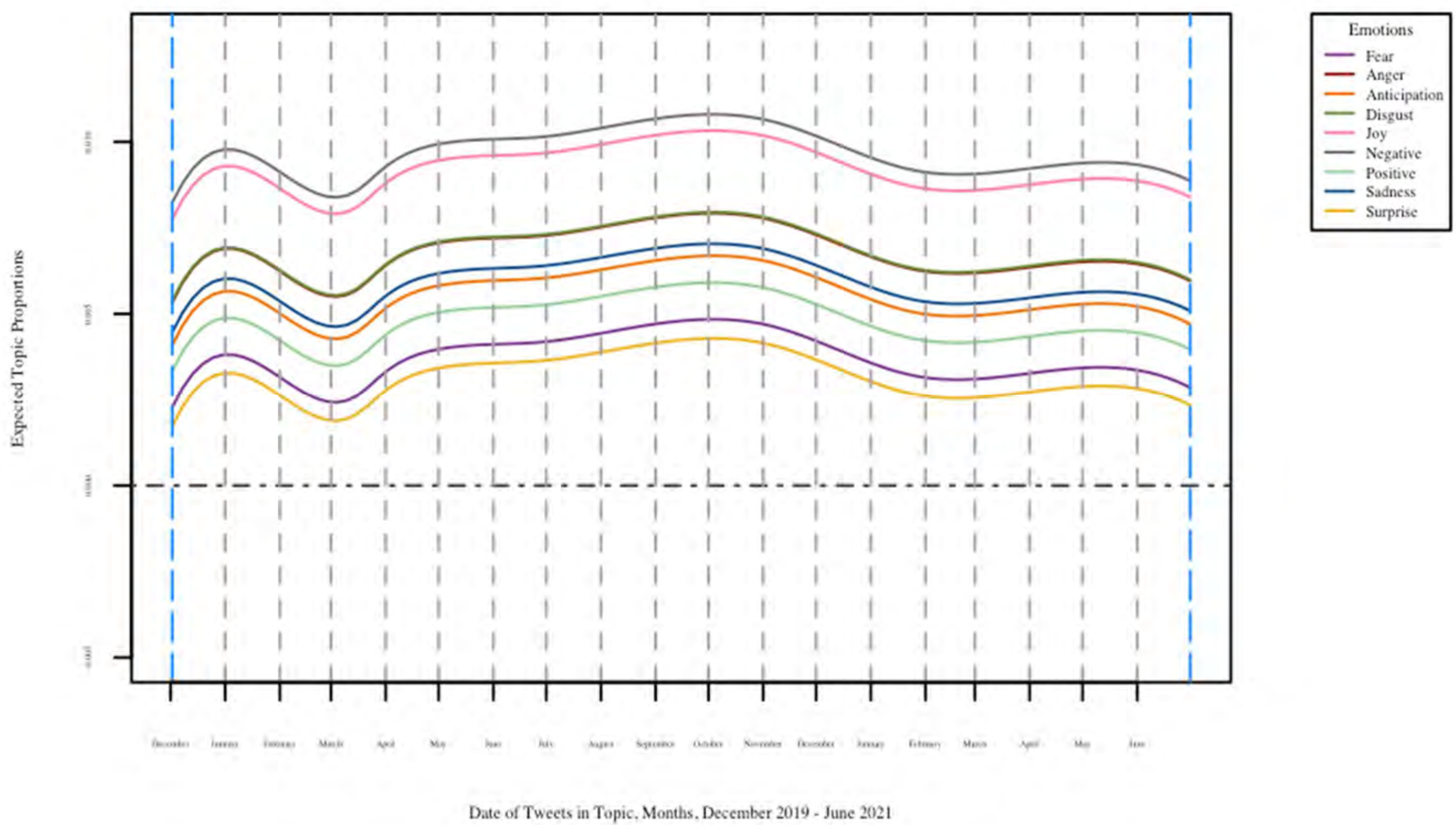


Figure 13.11b. Text Representative of 'Anticipatory' Tweets in Topic 81

I'm putting my kids in class. The risk of covid is rarely fatal in young people. Sure they will be infected howver closing schools risks dropouts. Kids falling far behind never catch up. Kids getting in trouble are at greater risk when closing schools so they should at least open part time.	I have repeatedly heard that science says children are less likely to get the virus. Ok, so they go to school, but there are adults at school. It's a risk to their families
@[user] I agree that's a tough one. How do you draw the line of a greater risk in hockey vs kids school? My kids also spend time at daycare cause I work full time. At daycare they are extremely close w/no masks so seems just likely it will spread.	Good luck to all the children and students going back school! Remember the risk of leaving school has a far greater effect on life prospects than covid.

Figure 13.11c. Text Representative of 'Fearful', 'Angry', 'Disgusted', 'Joyful', 'Surprised', and 'Trusting' Tweets in Topic 81.

Figure 13.12a. Estimated Change in Topic Prevalence over Time for Topic 83, Smoothed, by Emotions with Significant Effects on Tweet Content



Both “Negative” and “Joyful” tweets in topic 83 were somewhat provocative in the conflict sense, making great use of profane and inflammatory language to criticize ways other people handled risk mitigation (Figure 13. 12b-c).

Some of the uses were general exclamations declaring one’s strong feelings that a certain behavior or perception was wrong, typically “Negative” tweets (Figure 13.12b), or that a certain behavior or perception was the only morally correct one, typically tweets with “Joyful” undertones (Figure 13.12c). One example includes the text for a “Negative” tweet in topic 83 declaring that “the danger is dumb talking heads who watch other dumb talking heads,” or another that exclaims that the user is currently playing witness to “a bunch of Karens[6]” at the grocery store “refusing to wear masks,” the implication being that only the most privileged yet disrespectful of white women would complain about protecting someone else (Figure 13.12b).

In context of “Joy,” these exclamations included things like “fuck COVID stupidity. If you are sick stay home and don’t put others at risk” (Figure 13.12c). They also included declarations that appropriate behavior included participating in things you despised, like the example tweet of a user proclaiming they “fucking hate masks” that goes on to say that the user wears them anyways because “not putting my family at risk is the right kind of patriotism” (Figure 13.12c). This implied that people who could not get over their hate for masks were not truly patriotic, that the sacrifice of masking was a mark of superiority (Figure 13.12c).

Other tweets in topic 83 were not so passively critical, instead using profanity as a means of name-calling, like one example of “Negative” tweet text calling another user a “dumb ass,” citing the user’s behavior as “putting everyone at risk” (Figure 13.12b)

[6] “Karen” is a slang term used to identify white women who exercise their privilege at the expense of others, often with no understanding that others may find this offensive.

Figure 13.12b. Text Representative of 'Negative' Tweets in Topic 83

The danger is dumb talking heads who watch other dumb talking heads	@[several users] dumb ass you're putting everyone at risk. The pandemic and covid are real and people are dying
Spreading the virus around and putting others in danger is a careless and selfish attitude that can turn into hiking covid numbers and taking up hospital beds. Thanks for putting my family at risk and putting everyone at risk	A bunch of selfish karens @[grocery chain] refusing to follow signs asking them to wear masks and are putting us at risk in line behind us and invading the 6ft zone. This is why I dont shop on weekends.

Figure 13.12c. Text Representative of 'Joyful' Tweets in Topic 83

I will keep my fucking mask on for another year if I have to. I don't trust this shit and I'm not putting my mom at risk.

fuck covid stupidity if you're fucking sick stay home and don't put others at risk

ppl walking around the office in a mask not wanting to put other at risk of covid should not be seen as unreasonable, ha!

@several users I fucking hate wearing mask but my daughter is recovering from cancer, my wife already survived it, son asthmatic. Not putting my family at risk is the right kind of patriotism.

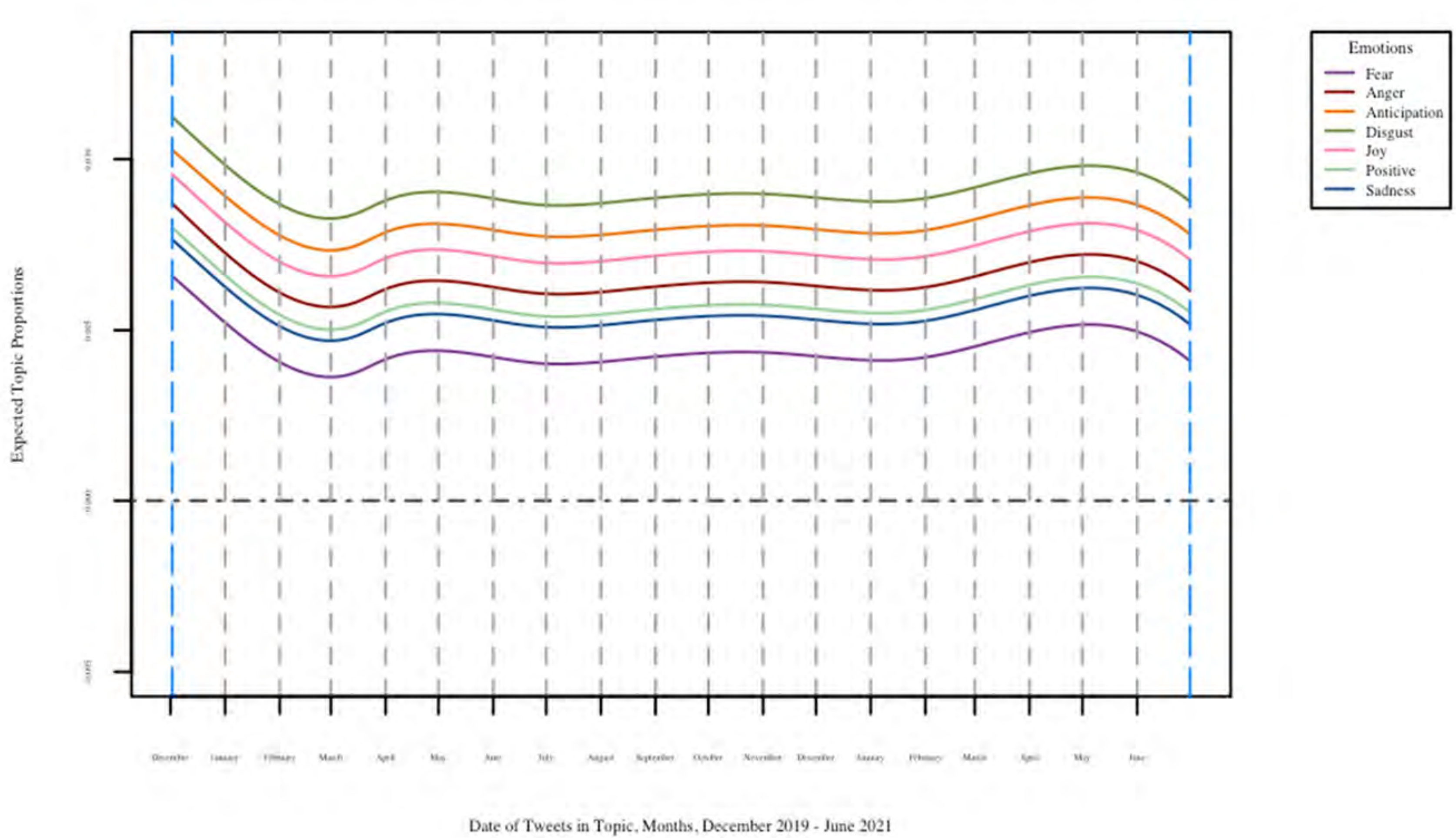
Figure 13.12d. Text Representative of 'Fearful', 'Angry', 'Anticipatory', 'Disgusted', 'Positive', 'Sad', and 'Surprised' Tweets in Topic 83

Tweets representing emotional contexts other than "Joy" and general "Negativity," while critical, were less inflammatory and were not obvious attempts to instigate conflict. For example, some of the more confrontational contexts outside of "Joy" and "Negative" sentiment were among the "Fearful" tweets in topic 83. These examples were still less confrontational than the examples for "Joy" and "Negative" sentiment. While there were examples of text from "Fearful" tweets in topic 83 that included profanity, the context of its use was not to demean others, as was the case with profanity in many "Negative" and "Joyful" contexts in the same topic.

This is seen in one example of text from a "Fearful" context where a user gives a strong assertion making their stance on what the correct approach to risk behavior should be very clear by referring to pre-kindergarten as a "biological war zone" and declaring that nobody will take away their free will as a parent, but especially not the teachers who "throw up way too many fucking hands when kids are already in danger of getting chicken pox and butt worms" (Figure 13.12d). The implication in this example is that taking appropriate steps to protect children from COVID-19 should not include the decision that addressing risk is futile and the subsequent decision to give up trying. The "Fearful" undertone of this kind of tweet suggests some level of "Fear" that others would do things like decide risk mitigation was futile and give up trying.

The significant increase in the prevalence of topic 83 over time supports the accusation that Americans became more polarized in their values as the pandemic endured, including values about mitigating COVID-19 risk (Figure 13.12a). Relatedly, there was a dip in the prevalence of topic 83 that occurred in March 2020 and only lasted through the end of that month (Figure 13.12a). March 2020 was a time many have characterized as one of great unity, so it would make sense if there were fewer inflammatory tweets criticizing others during that time.

Figure 13.13a. Estimated Change in Topic Prevalence over Time for Topic 84, Smoothed, by Emotions with Significant Effects on Tweet Content



Topic 84 was another topic highlighting contention related to disagreement with how others perceived COVID-19 risk and/or behaved to mitigate that risk. Like other topics highlighting this contention, there was a significant increase in the prevalence of topic 84 over time that aligns with accusations of increased polarization among Americans over the course of the pandemic (Figure 13.13a). Instead of using profanity to hail insults at others via name-calling, topic 84 tweets tended to insult others by providing a sarcastic recommendation for an alternative behavior that would be unquestioningly uncomfortable for most people (Figure 13.13b-c).

This was most often in context of "Disgust," where tweet text included things like stating disbelief over another person's behavior in response to risk, implying disagreement, followed by the ironic suggestion that the other person should actually just continue doing the wrong thing. One example of this is found in the suggestion that people who stay indoors when the weather conditions are favorable, and the risk of COVID-19 is low, should "go back inside and stfu[7]" (Figure 13.13b).

Other examples in topic 84 included the expression of "Disgust" by criticizing some person or behavior with an underhanded comment about what superior action they would have taken if faced with the same situation, like the example of text from a "Disgusted" tweet in topic 84 starting off with a snide remark about a "narcissistic teacher" followed by the recommendation that, since "I don't care that I've spent the last 11 months locked inside of [the] house because I don't want to infect my high risk fam," the person in question should also not care if they would like to be characterized as something other than a narcissist (Figure 13.13b).

[7] "STFU" is an acronym for "shut the fuck up."

Figure 13.13b. Text Representative of 'Disgusted' Tweets in Topic 84

Oh wow what a narcissistic teacher. I don't care that I've spent the past 11 months locked inside of house because I don't want to infect my high risk fam.

@[several users] yeah outside you don't need a mask but inside masks should be required if for a long time and breathing in someone's face. If you test and are outside you shouldn't threat as bad.

@[user] the concern for covid safety inside the whitehouse and outside the whitehouse.

Still trying to find out how when it is amazing outside you can sit sit on your asses even when we get covid under control rather than risk being outside with somebody checking symptoms? You really do need to go back inside and stfu.

Figure 13.13c. Text Representative of 'Fearful', 'Angry', 'Anticipatory', 'Joyful', 'Positive', and 'Sad' Tweets in Topic 84

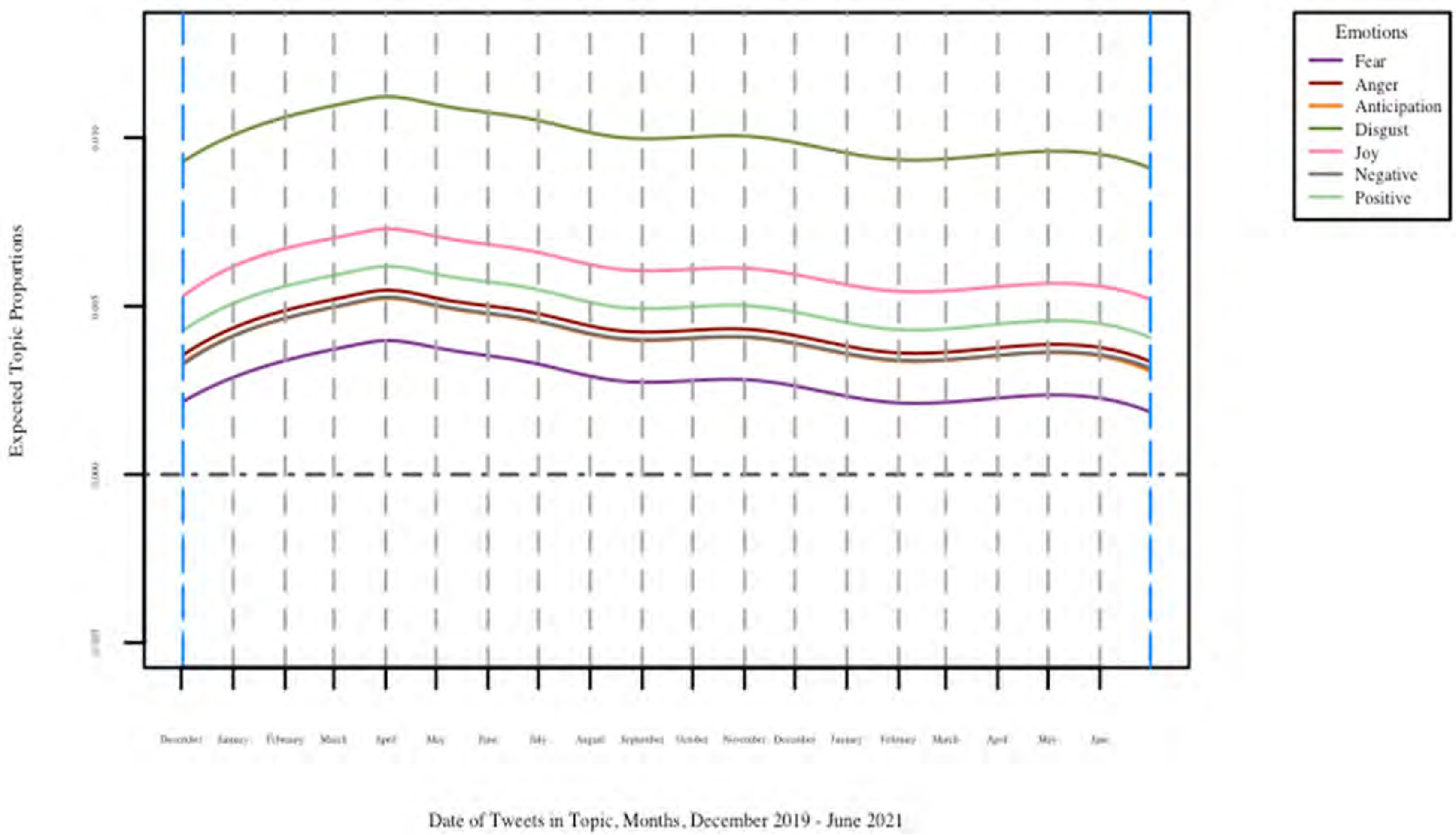
The prevalence of tweets in topic 88 decreased significantly over time, peaking around the beginning of April 2020 (Figure 13.14a). The highest proportion of tweets in topic 88 Topic 88 expressed “Disgust” over the possible risk of exposure to COVID-19 through contact with fomites[8] (Figure 13.14a-b). There is now substantial evidence that COVID-19 infection is transmitted via aerosols, not fomites, so this paints a picture of the uncertainty about how SARS-CoV-2 infection was transmitted in the earliest months of the pandemic when most of the United States was subject to stay-at-home and shelter-in-place orders.

Tweets in topic 88 highlighted the measures people took because there was a widespread belief that they were necessary to mitigate risk of fomite exposure (Figure 13.2b-c). Example text from “Disgusted” tweets in topic 88 include conversations where users give recommendations to other users to “wear gloves,” be “constantly cleaning,” wear a “mask,” and have “hand sanitizer” on hand, the implication being that the risk of exposure to fomites was perceived as “Disgusting” and therefore something to be avoided (Figure 13.14b).

Example text for other emotional contexts in topic 88 also touched on the widespread shortages of cleaning supplies like hand sanitizer and surface disinfectants and personal protective equipment (PPE) like gloves and masks. “Fearful” tweets announcing things like local distilleries transitioning to manufacture hand sanitizer to help with supply shortages show how frightening it was for many people to face the possibility of unmitigable exposure because the tools for mitigation like cleaning supplies and PPE had limited availability (Figure 13.14c).

[8] Fomites are objects, like hard surfaces, that are reservoirs for infection by things like viruses and bacteria.

Figure 13.14a. Estimated Change in Topic Prevalence over Time for Topic 88, Smoothed, by Emotions with Significant Effects on Tweet Content



Tweets in other emotional contexts in topic 88 also hinted at a sense of "Fear" surrounding the possibility of exposure to COVID-19 while doing everyday life activities like grocery shopping. For example, "Positive" sentiment was found in text indicating that many felt the need to pray for others safety while running errands, like "May god bless you and keep those in Costco[9] and working at grocery stores…safe," suggesting it is a "moral obligation" for the public to mitigate risk (Figure 13.14c). Others like "Anticipatory" tweets tried to place parameters around risk, like the suggestion that "the virus will live longer on metal than paper or fabric so coins are a higher risk than dollar bills," hinting that there was some Fear about fomite exposure via cash payment (Figure 13.14c).

Some tweets in other emotional contexts even went as far as to acknowledge there was some "Fear" about exposure to the virus, like the "Angry" text stating, "yes the virus is scary and this makes it worse" (Figure 13.14c). This also indicated that many felt "Angry" when people took actions that were counterproductive to the effort to fight COVID-19, including "Anger" at people hoarding goods, which was perceived as one of the factors leading to supply shortages in the United States (Figure 13.14c). "Joyful" tweets expressed a sense of relief when able to secure supplies, like the example text expressing "Joy" over the fact that "my sister came home from Target with hand sanitizer, tissues, face masks, Tylenol, a thermometer, and soup" (Figure 13.14c). The wide range of supplies people felt relieved to secure shows just how widespread the supply shortages were at certain points in the pandemic, including the point in time during which topic 88 was most prevalent between March 2020 and May 2020 (Figure 13.14a).

[9] COSTCO is a popular, membership-only, bulk retailer in the United States.

Figure 13.14b. Text Representative of 'Disgusted' Tweets in Topic 88

@[user] in grocery stores bring sanitizer wipes and wear gloves and a mask. One other thing is to stay clear of anyone sick or who appears sick. Honestly there's always going to be a risk but its low risk if you're constantly cleaning

@[several users] my neighbor has copd and she's walking everyday in a mask and gloves, no one can pat her dog, has to get groceries delivered to minimize the risk.

People protesting in the middle of a fucking pandemic are putting us at risk. Can they at least equip them with protective gear including masks, gloves, hand sanitizer?

My next door neighbors keep going outside and running errands without gloves or masks. The high risk population just dropped and left out. No gloves, no masks, and they are excited! I tried. *hug* *sigh*

Figure 13.14c. Text Representative of 'Fearful', 'Angry', 'Anticipatory', 'Negative', and 'Positive' Tweets in Topic 88

Figure 13.15a. Estimated Change in Topic Prevalence over Time for Topic 89, Smoothed, by Emotions with Significant Effects on Tweet Content

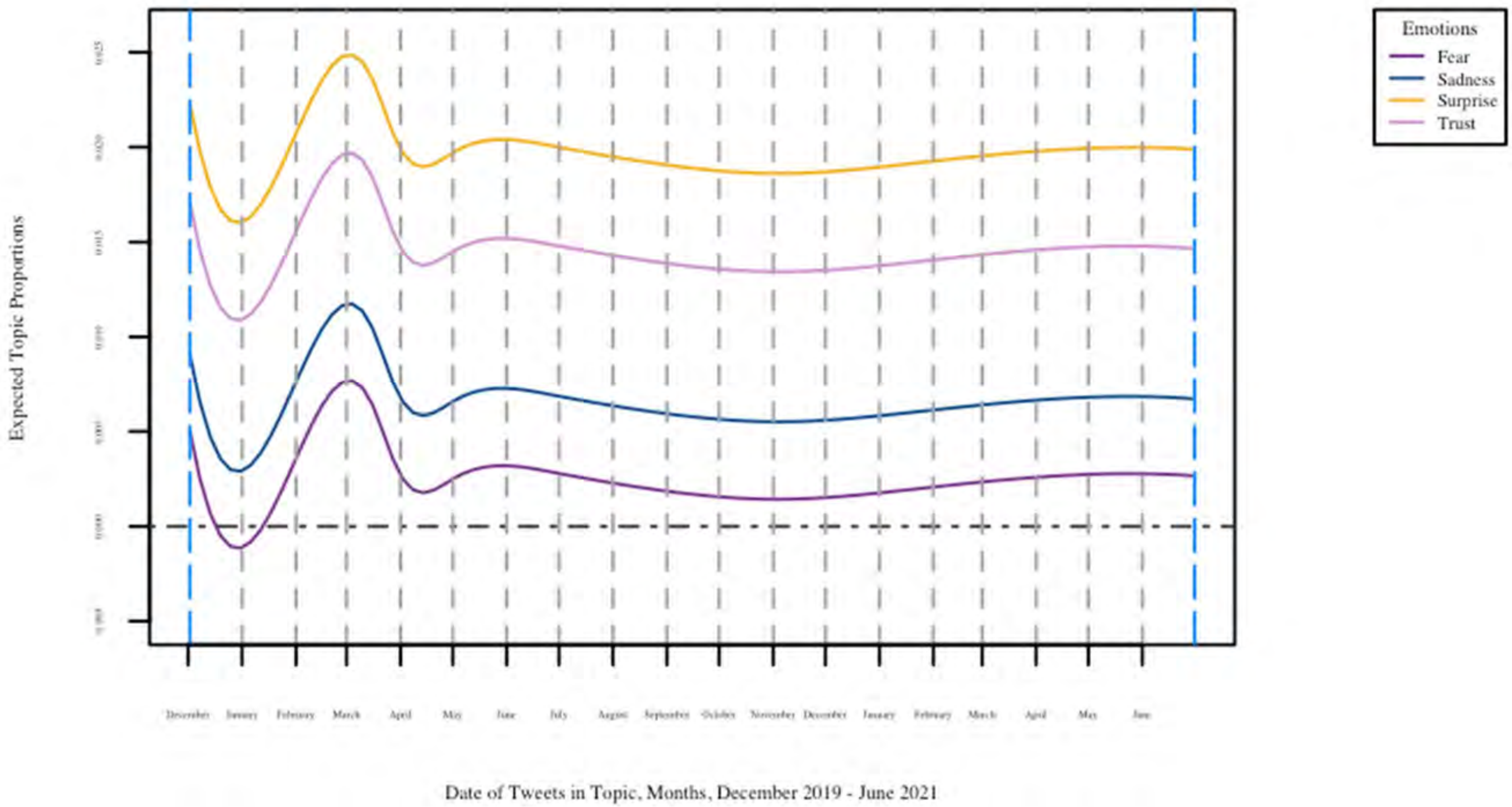


Figure 13.15b. Text Representative of 'Anticipatory' Tweets in Topic 89

The state will extend the covid state of emergency clause allowing South Carolinians to participate by mail in absentee voting.	An armed fascist mob of whites storm the state house to intimidate the governor with unmasked protesters. The Michigan governor extends state of emergency amid protests at the state house.
Massachusetts finds coronavirus: Boston conference is the epicenter of a state outbreak. Governor declares state of emergency @[news entity].	Japan on Friday declared a state of emergency to curb the rapid coronavirus resurgence. This is its third since the pandemic began.

Figure 13.15c. Text Representative of 'Fearful', 'Sad', and 'Trusting' Tweets in Topic 89

Faced with mounting infections California gov Gavin Newsom on Sunday issued sweeping new restrictions in California calling for home isolation for everyone in the state age 70+ or in a high risk population group.

A judge has ruled that gov Whitmer has the right to extend Michigan's stay at home order under the state of emergency after republican state legislators filed a lawsuit to challenge her emergency powers in response to the ongoing covid pandemic.

Populous South Florida hospital officials have reported that emergency rooms and intensive care units are nearing capacity. On Sunday Florida reported cases totaling a new state daily record and has now surpassed New York's April peak.

Topic 89 dealt with the declarations of emergency, and the example text generated from tweets in all emotional contexts with a significant effect on topical content suggests that topic 89 was an informative topic consisting largely of journalistic reports (Figure 13.15b-c). It could be the case that “Surprised” sentiment was tied to reports of breaking news for topic 89 tweets (Figure 13.15b).

Further evidence that topic 89 consisted primarily of news reports, specifically, and not emergency declarations generally, is the significant decrease in topic 89 over time paired with the peak in March 2020, when initial states of emergency were declared in the U.S. and most other countries (Figure 13.15a).

Topic 90 was another topic most prevalent in March 2020, seeing a significant decrease for the remainder of the period ending in June 2021 (Figure 13.16a). It sheds light on how many events were cancelled, and how widespread the cancellations were across industries, when the emergence of SARS-CoV-2 was first declared an emergency of global concern by the WHO. Most of the tweets exuded “Trust,” indicating that many people expressed feeling somewhat thankful that the event cancellations seemed to stem from concern for their safety and that a firm decision had been made, providing clarity for event attendees (Figure 13.16a-b). The “Trusting” sentiment was not uniform, though, despite being most common among tweets in the topic.

Other, less commonly expressed, feelings in topic 90 included “Sadness” over missed events because they had been something to look forward to, and “Anticipation” over whether events would be cancelled (Figure 13.16a-c).

Figure 13.16a. Estimated Change in Topic Prevalence over Time for Topic 90, Smoothed, by Emotions with Significant Effects on Tweet Content

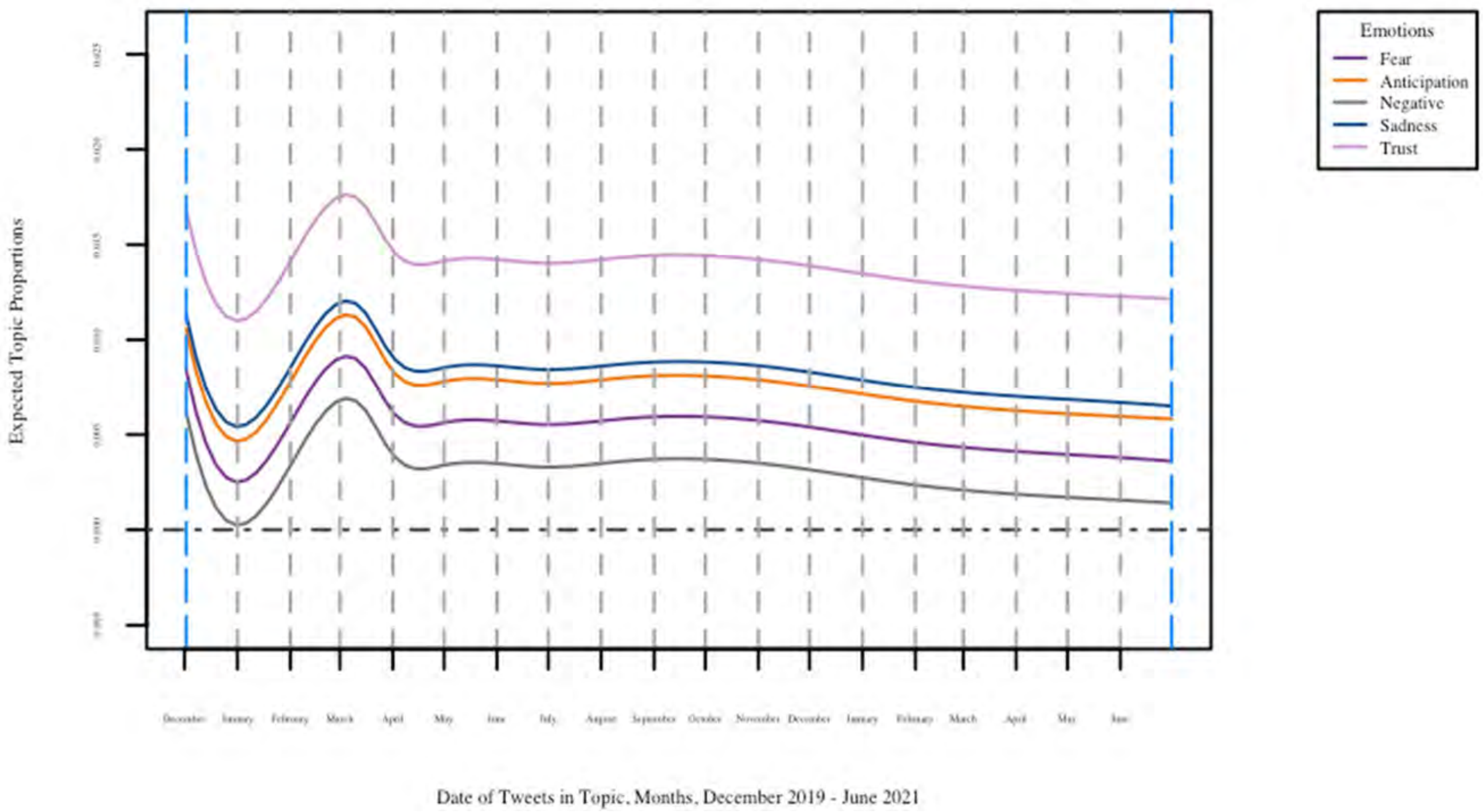
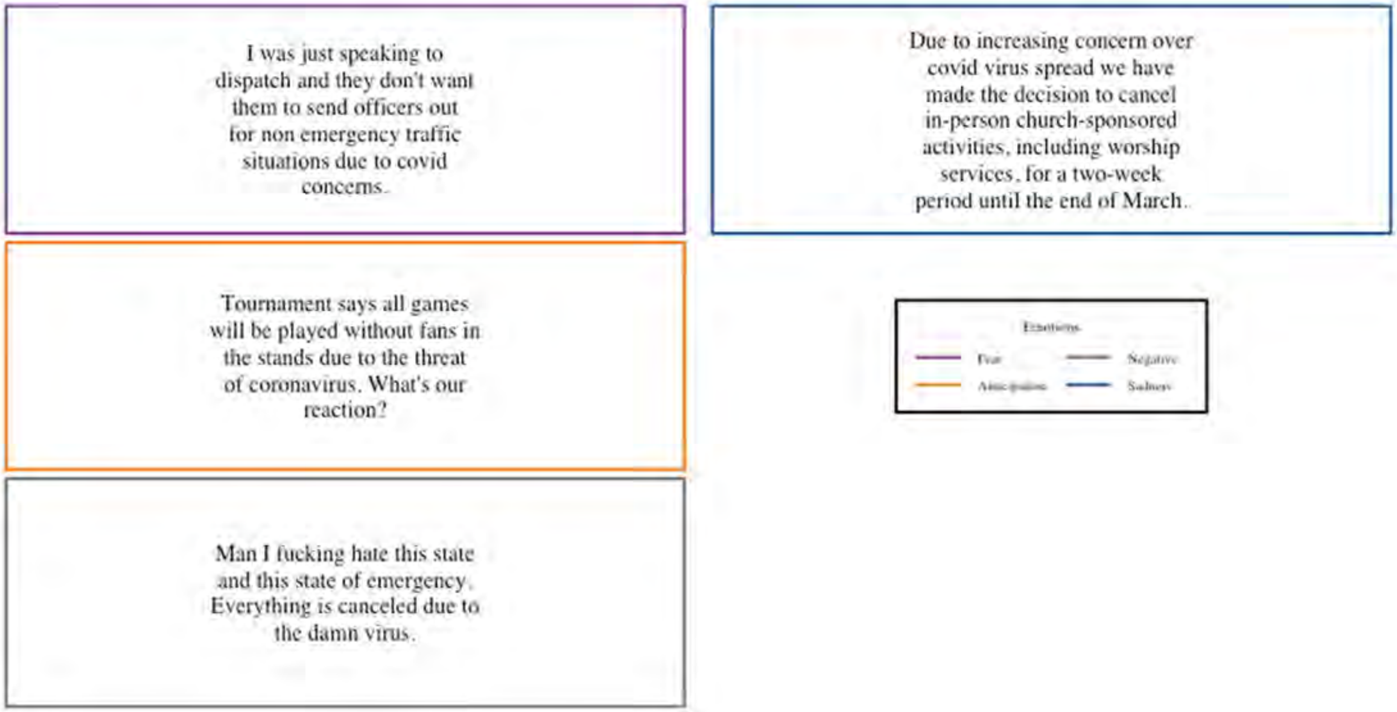


Figure 13.16b. Text Representative of 'Trusting' Tweets in Topic 90

Due to covid and the coronavirus pandemic and concerns for health and safety we have decided to cancel the scholarship breakfast. We are still accepting donations towards the scholarship.	This weeks games are cancelled due to the ongoing threat of covid. The situation will be re-evaluated at the end of the week.
NCAA tournament canceled due to the threat of coronavirus.	Just announced by treasury secretary Steven Mnuchin: due to ongoing coronavirus emergency the filing deadline in April has officially been moved to July

Figure 13.16c. Text Representative of 'Fearful', 'Anticipatory', 'Negative', and 'Sad' Tweets in Topic 90



There were also expressions of "Negative" sentiment over event cancellations in topic 90 tweets, indicating a sense of frustration over missing out with profanity in statements like "Man I fucking hate this state and this state of emergency. Everything is canceled due to the damn virus" (Figure 13.16c). In this case, the use of the word "hate" demonstrates just how strong the "Negative" sentiments about cancelled events could be.

While the significant decrease in topic 90's prevalence over time could represent the end of event cancellations, because the decrease begins in March 2020, reaching a plateau by about mid-April 2020, it could also be the case that people felt less compelled to discuss their thoughts on event cancellations when they became more common and expected with more information available about COVID-19 risk (Figure 13.16a).

Topic 91, another predominantly "Trusting" topic, provided an example of another action besides event cancellations that invoked a sense of Trust (Figure 13. 17a). Example text including announcements about the reducing of a county's threat level "from red to orange" and the reports of officials assuring the public that the risk remains low and that "there is no immediate threat to the public," indicate that people felt Trusting when reassured (Figure 13.17b).

Text examples from tweets in other emotional contexts in topic 91 provide some evidence that it was not simply the expression of "Trust" related to reassurance in topic 91, but rather, a sense of "Trust" in others when presented with information suggesting the threat of COVID-19 had disappeared or been reduced to a nonserious level.

Figure 13.17a. Estimated Change in Topic Prevalence over Time for Topic 91, Smoothed, by Emotions with Significant Effects on Tweet Content

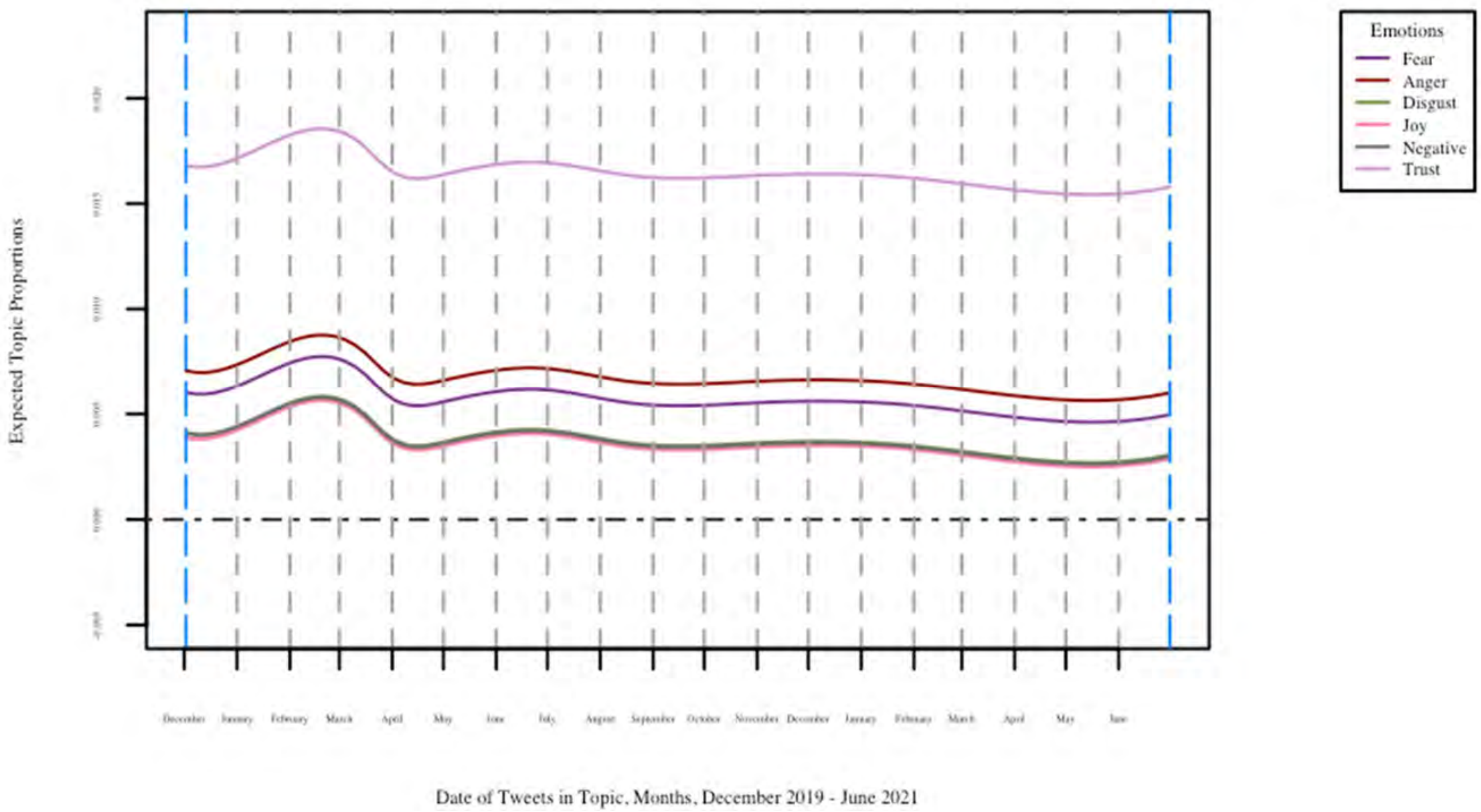
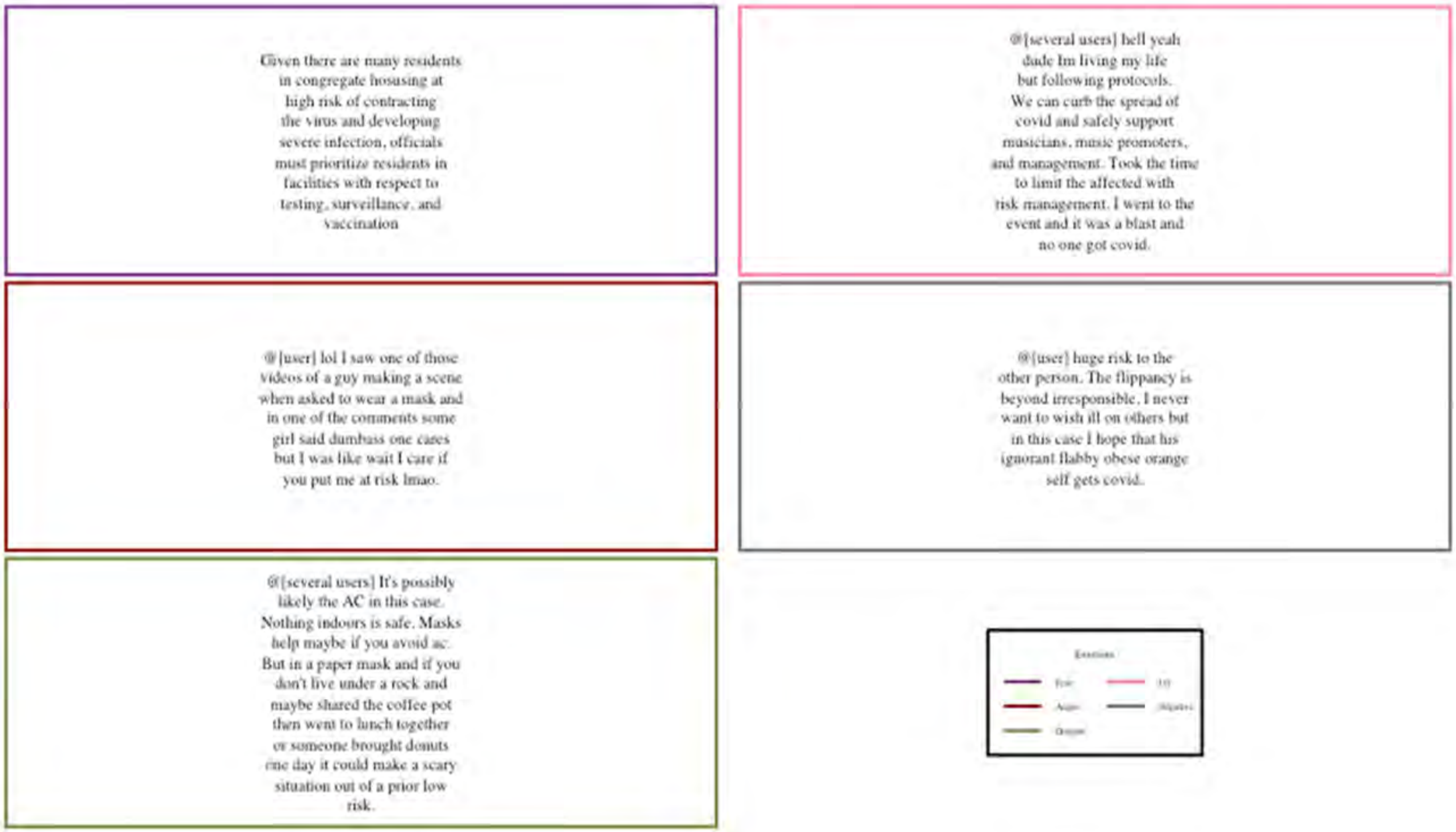


Figure 13.17b. Text Representative of 'Trusting' Tweets in Topic 91

No new cases of coronavirus today in PA's Delaware county. Officials say count remains at one case but there is now an emergency disaster declaration as the county releases additional funds @[news entity]	Officials at area colleges have contacted Sacramento county health officials, who say there is nothing to indicate that campus communities are at risk of exposure to the virus @[news entity]
Health officials confirm the first case of coronavirus in Fresno county. Health officials say there is no immediate threat to the general public, adding that people should continue practicing good public health hygiene.	The covid threat level in Harris county was reduced today from red to orange.

Figure 13.17c. Text Representative of ‘Fearful’, ‘Angry’, ‘Disgusted’, ‘Joyful’, and ‘Negative’ Tweets in Topic 91

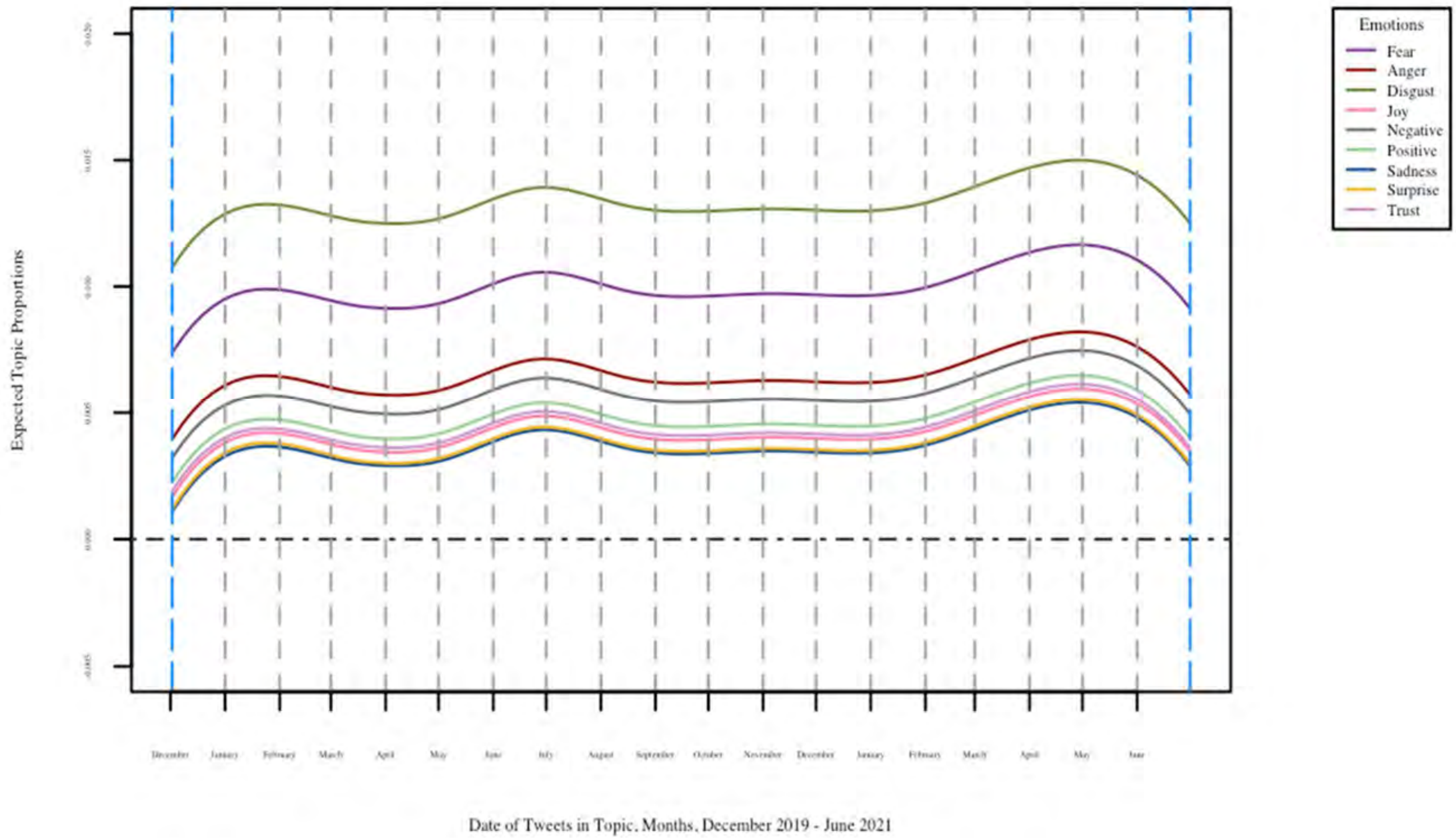


Some of these included contexts of “Joy” in topic91, like the proclamation that one was able to attend an event with mitigations in place and they were proud to report that “it was a blast and no one got COVID” (Figure 13.17c). Others provided less direct evidence by demonstrating feelings of “Anger,” “Disgust,” and “Negativity” over the prospect that risk was not gone when many claimed it was (Figure 13.17c).

Overall, topic 94 involved the broad idea of COVID exposure as it relates to risk of infection. Topic 94 tweets were predominantly “Disgusted,” suggesting a sense of “Disgust” over the information that the SARS-CoV-2 virus was spread primarily via aerosols (Figure 13.18a-b). Tweets in other emotional contexts like “Joy” highlight discussions of new tools like vaccines intended to mitigate the risk of infection when exposed, regardless of if the exposure was airborne or via contact with infectious surfaces (Figure 13.18c).

Many emotional contexts indicated an acceptance among Twitter users in the United States that COVID-19 could be transmitted through aerosols, that aerosols can linger in the air for hours after someone with COVID-19 leaves the room, that the risk of airborne exposure can be mitigated, not just with vaccines, but with non-pharmaceutical interventions (NPIs) like masks (Figure 13.3c), and that “the risk of coronavirus transmission is very high indoors” (Figure 13.3b). Relatedly, there were expressions of “Surprise” when government and public health officials announced measures that seemed counterintuitive for fighting the airborne spread of infectious disease, like when the Surgeon General suggested that they wanted “people to stop buying masks to prevent novel coronavirus” (Figure 13.18c).

Figure 13.18a. Estimated Change in Topic Prevalence over Time for Topic 94, Smoothed, by Emotions with Significant Effects on Tweet Content



Non-disgusted expressions also highlighted a sense of disagreement bordering disbelief over how the public and those in power handled the risk of COVID-19 infection, like “Sadness” over other people’s misunderstanding of the perseverance and collective effort required to foster participation in risk mitigating behavior. This is best demonstrated in the example “Sad” text for topic 94 tweets reading, “Harm reduction and risk mitigation earlier in my life was when AIDS activists handed out condoms and bleach kits for needles. Today infection control for corona virus means harm reduction and risk mitigation. This is everyone’s responsibility we can’t outsource it” (Figure 13.18c).

Tweets in topic 94 revealed some of the popular means of reducing the risk of airborne transmission of disease that emerged and/or became popularized during the pandemic. “Disgusted” tweets, for example, highlighted the increasing recognition of the importance of air filtration technologies, which could be used to filter out airborne virus particles in an enclosed space (Figure 13.18b). “Disgusted” tweets also highlighted the other, behavior-based, technologies used to mitigate the risk of inhaling virus particles. For instance, face masks provided individuals with a proximate filter that protected the nose and mouth (Figure 13.18b).

The significant increase in topic 94 prevalence over time is a good indication that the issue of airborne virus transmission became more important to discussions of COVID-19 risk as the pandemic endured into its second year (Figure 13.18a)

Topic 100 tweets were much more likely to contain “Angry” and “Negative” undertones than they were to hold expressions of other emotions (Figure 13.19a). The topic was characterized by conversations and personal testimony wherein Twitter users in the United States expressed their own views on the level of risk and whether they thought the response was proportionate and appropriate given such risk (Figure 13.19b-c).

Figure 13.18b. Text Representative of 'Disgusted' Tweets in Topic 94

Air filtration devices in classrooms in lieu of adequate HVAC reduces airborne contaminants but does not eliminate the risk of transmission.

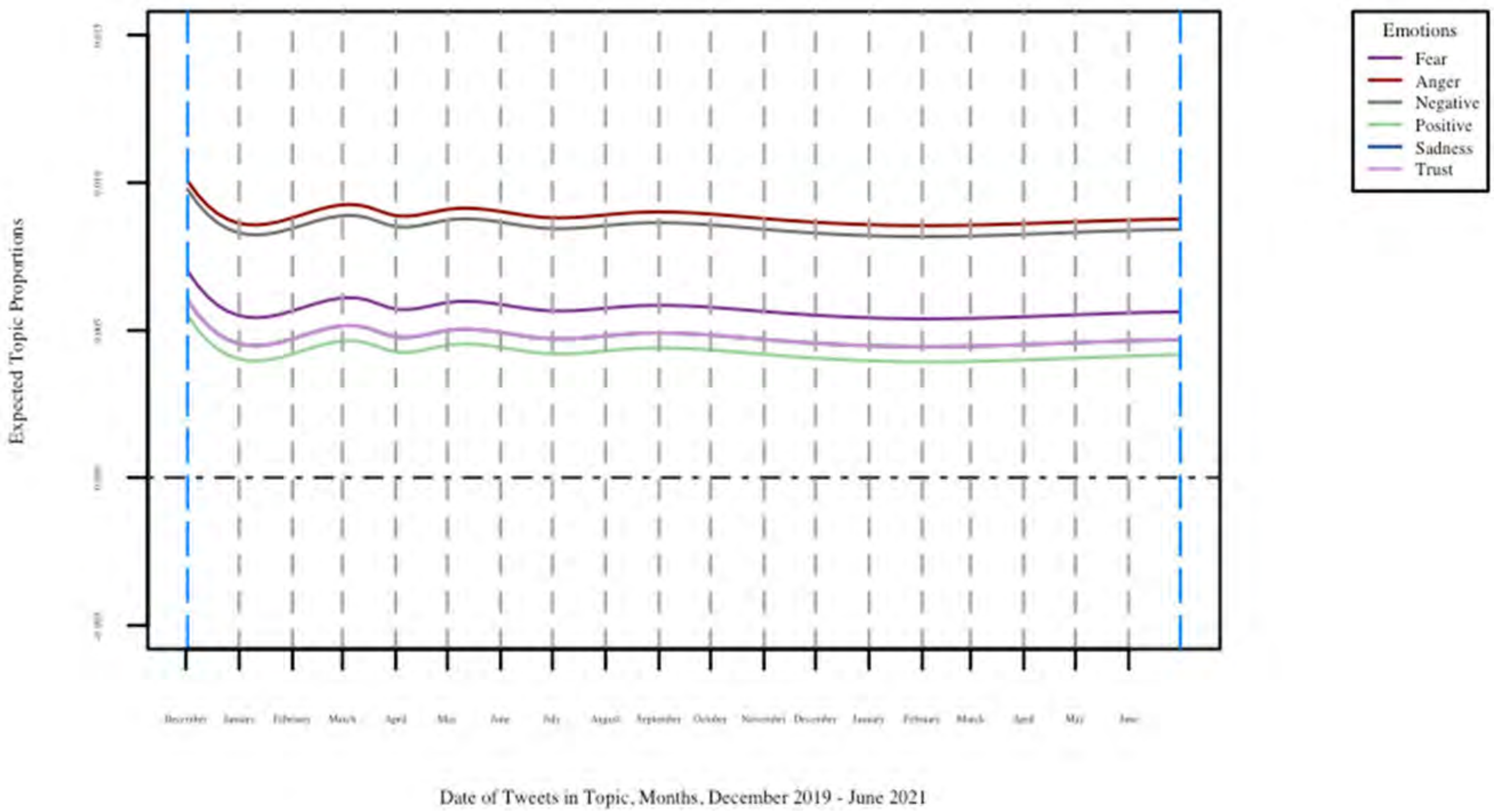
@[several users] the conclusion based on numerous studies from proven research groups says wearing a mask and distancing greatly reduces the risk of being infected, but I accept that we won't agree since we can't even agree on basic facts.

The potential spread through airborne transmission in the lingering air has been underplayed, a group of scientists has said.

The risk of coronavirus transmission is very high indoors.

Figure 13.18c. Text Representative of 'Fearful', 'Angry', 'Joyful', 'Negative', 'Positive', 'Sad', 'Surprised', and 'Trusting' Tweets in Topic 94

Figure 13.19a. Estimated Change in Topic Prevalence over Time for Topic 100, Smoothed, by Emotions with Significant Effects on Tweet Content



Topic 100 highlighted the contentiousness surrounding personal opinions about COVID-19 risk level and response. It was not simply that there was a lot of variation in opinions about risk and its mitigation—tweets in topic 100 suggest there were strong feelings of resentment over differences of opinion regarding COVID-19 risk and how/whether it should be reduced (Figure 13.19b-c). This echoes evidence from tweets in other topics suggesting arguments and the hailing of insults were common in discussions of specific behaviors used for COVID-19 risk mitigation, like the need for masks, or separately, vaccines.

Topic 100 alongside these other topics also shows that contention was consistently bi-directional, with provocation by both supporters of risk mitigation and those against it, regardless of how broad/specific the risk-related concern was. For example, “Angry” text in topic 100 tweets could include things like “Anger” towards others who “believe” others who did not perceive the novel coronavirus as a threat, but they also included “Anger” at others who insisted that COVID-19 was the most/only important emergency by pointing out other emergencies they felt were still more urgent than COVID-19, like “climate change” (Figure 13.19b).

Less heated tweets in context of emotions like “Trust” in topic 100 revealed an important nuance to the contentiousness of conversations about COVID-19 risk. Despite the high proportion of contentious tweets and tweets in context of emotions like “Anger,” “Fear,” “Disgust” and “Negativity” related to COVID-19 risk and its mitigation, there was still a significant proportion of people discussing their opinions on the issue to try to make sense of something that was, for many, an unimaginable scenario. That many of these discussions occurred in “Trusting” and “Positive” contexts suggests that people gained something useful from the non-contentious swapping of opinions and experiences with COVID-19 risk and mitigation (Figure 13.19c).

Figure 13.19b. Text Representative of 'Angry' Tweets in Topic 100

Dreamers who think baseball will still play really must believe the Trump reality that the virus isn't a threat and hasn't killed anyone in this country. The sad reality is that this could last the rest of the year and we dont know the future.	@[several news entities] unfortunately approx. half the population think covid is no big deal and take false comfort in thinking covid deaths are grossly inflated because misclassifications exist even though the covid danger is clear and present.
ya know with all this pandemic shit happening its easy to forget another existential threat to humanity. climate change is probably the single most important issue besides covid. don't forget this november to vote	Imma be honest when the first news about the virus broke in China I was like meh no big deal then I grew curious to see how big it would get. I have never seen a big national emergency like this since 9/11 so I was just really curious how far it will go to effect us.

Figure 13.19c. Text Representative of 'Fearful', 'Negative', 'Positive', 'Sad', and 'Trusting' Tweets in Topic 100

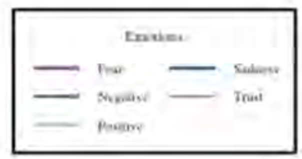
A common thread between anti-vax, climate change denial, and covid minimizing. It's preferring to deny any unpleasant reality instead of accepting the slight risk of discomfort to avoid a disastrous future.

I hope this hardship can help you see how nimble humans are that we quickly can learn new behaviors in a crisis. It is immensely important for the greater threat of climate change once the coronavirus dust settles. Please don't retreat keep fighting for humanity.

I'm a bartender and I think it depends on the current infection rate in your city and how much personal risk you are willing to take. If you wear a mask unless you are drinking or talking to the server and tip extremely well I am ok with it.

Amen! In an emergency it's important to see that you have got a crisis to identify what the crisis is. It's just that with the virus, to just recognize the crisis is already insufficient.

@[user] I think the concern is primarily the thinning capacity with unmitigated spread. There are not many ICU beds because covid patients who contracted it weeks ago r so bad. We have been running low for weeks and now it may spell big trouble.



Topic 109's discussions of risk framed the mitigation of COVID-19 risk in terms of a war, as something that required bravery and action but was ultimately something Americans could overcome with the right approach. Example text across emotional contexts for tweets in topic 109 was, relatedly, somewhat motivational, with many examples constituting calls to action (Figure 13.20b-c).

"Disgusted" sentiment was the most common among tweets in topic 109. However, "Disgust" in this topic did not seem to be "Disgust" over the "Disgusting," gross, nasty, etc., circumstance of being exposed to the virus, or "Disgust" that others did not find the virus "Disgusting." Instead, there is an implied expectation and sense of "Disgust" over people who did not heed the call to action, as if they were morally inferior or acting in a way that was unpatriotic if they did not embody the norm of bravery to express patriotism in the United States. Importantly, bravery seemed to be understood to include more than simple action. To be brave in the face of the threat of COVID-19, one must not only act, but act in a way that is rational, appropriate, and if available, aligned with some plan of action intended for most of the U.S. population. A good example of this is the "Disgusted" example text reading, "don't allow fatigue and exhaustion to win the current crisis in place. We have no space for greater risk. Stay vigilant by wearing a mask," calling users to persist in their actions but also implying that people who gave in were cowardly and/or not contributing to the fight (Figure 13.20b).

Figure 13.20a. Estimated Change in Topic Prevalence over Time for Topic 109, Smoothed, by Emotions with Significant Effects on Tweet Content

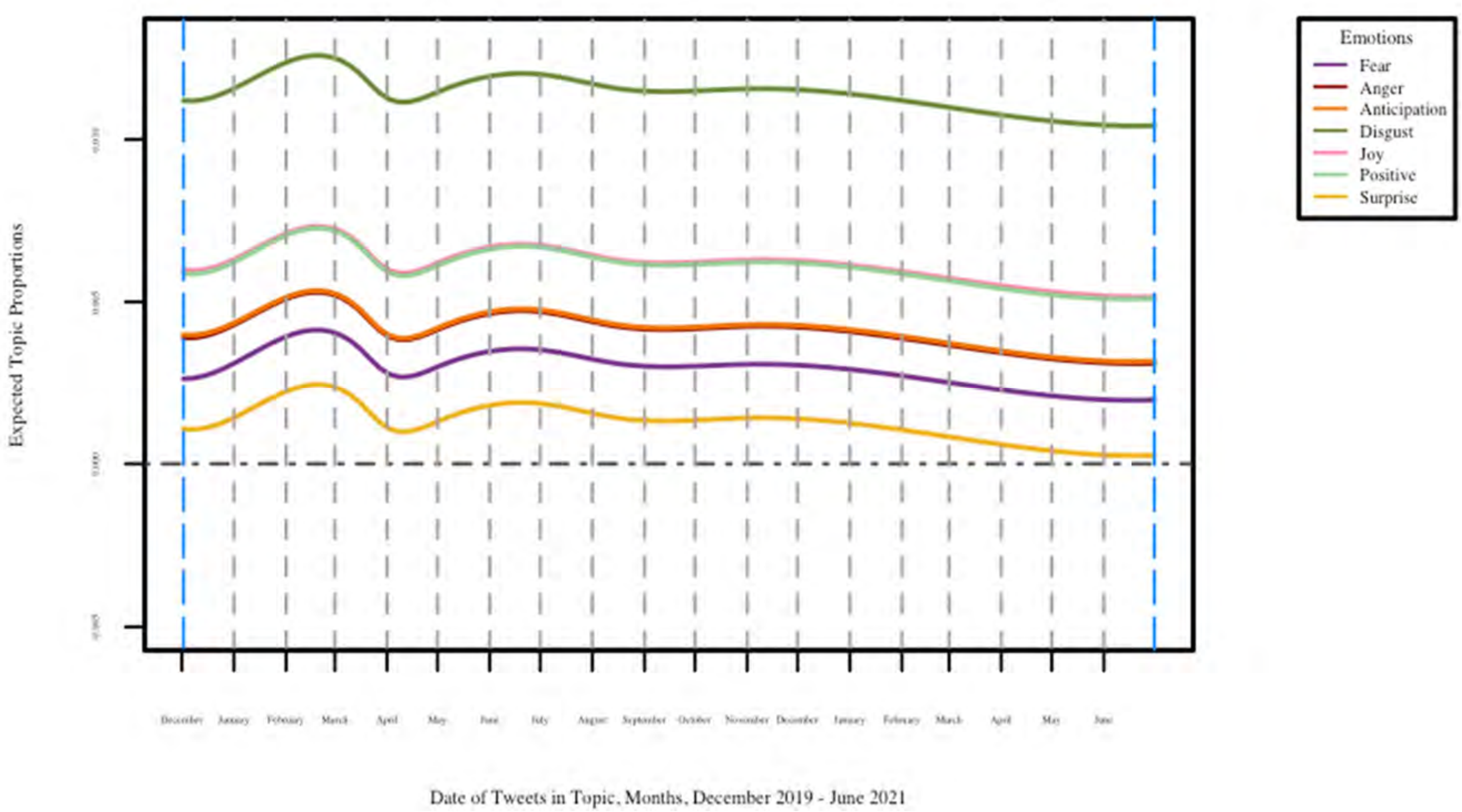


Figure 13.20b. Text Representative of 'Disgusted' Tweets in Topic 109

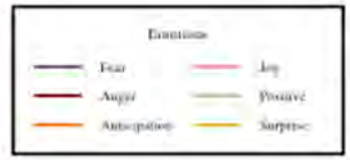
Don't allow fatigue and exhaustion to win the current crisis in place. We have no space for greater risk. Stay vigilant by wearing a mask, wash your hands, and stay 6ft away from others.	Literally just washing your hands controls so much. If your hands come into contact with the virus and you wash them it goes away. If you don't wash things and touch people and interact like there is no risk for hours or a long time you could be a carrier.
They have no concern for the publics health. This is not policitical. Wash your fucking hands, stay 6ft apart and wear a bloody mask.	The best way to combat corona-virus is by washing hands not ransacking the Costco emergency supplies lmfaoo dummies.

Figure 13.20c. Text Representative of 'Fearful', 'Angry', 'Anticipatory','Joyful', 'Positive', and 'Surprised' Tweets in Topic 109

I have really bad asthma and a heart condition so I am considered at risk even though I have type O blood, wash my hands, do not touch my face, practice good hygiene and wear my mask.

Worst case is we get a strain that mutates in a way so vaccines aren't effective and the people who felt safe aren't careful with masks and get tired of socially distancing. If so we will risk a huge wave will happen.

These are the everyday emergency workers who help keep us safe. Let's all help keep them safe by wearing our masks. It's the socially responsible thing to do.



@[user] thanks for the concern. What's crazy is the septum is just part of the nose. The mask goes over your nose and then it doesn't get stuck. Funny how things work huh.

@[several users] I totally understand. To keep family my safe I'm not willing to risk it. We'll mask and stay home. We will play our part to keep others safe.

I'm watching the coverage of Trump declaring a national emergency due to coronavirus and every single one of those are people shaking each others hands.

It would presumably also not be considered brave to ignore good hygiene in favor of hoarding goods, according to example "Disgusted" text from topic 109 tweets like "The best way to combat corona-virus is by washing hands not ransacking the Costco emergency supplies lmfaoo dummies" (Figure 13.20b). The acronym "lmfao" stands for "laughing my fucking ass off," and it is commonly used by members of the millennial generation (born ~1980—1996) to indicate that someone has done something ridiculous. The addition of extra letters at the end of the acronym (e.g., "lmfaoo") represents a common trend to express that a reaction does not just exist, but instead, to indicate that it is an unusually strong expression of the feeling. The use of an extra "o" at the end of "lmfao" would typically indicate that something is not just ridiculous, but *really* ridiculous.

Most of the tweets in topic 112 were directly related to the issue of funding for various aspects of the emergency response to COVID-19. The high proportion of "Surprise" in tweets about emergency funds indicates that many did not expect these funds to be authorized, either because they did not expect any funding or because the amount of funding authorized was much higher than expected (Figure 13.21a). For example, "Surprised" tweets touched on things like the state of California's authorization of "a billion-dollar emergency bill" and the federal response by the House of Representatives to pass a bill providing "a billion to the emergency rental assistance fund and a billion to the homeowners assistance fund" (Figure 13.21b).

Emotional contexts other than "Surprise" in topic 112 tweets highlighted things needing financial assistance that were either not receiving enough or had not been included among those eligible for existing financial assistance. For example, "Fearful" tweets expressed "Fears" that funding for research on other diseases like cancer was being ignored due to the shift in focus to COVID-19 (Figure 13.21c).

Figure 13.21a. Estimated Change in Topic Prevalence over Time for Topic 112, Smoothed, by Emotions with Significant Effects on Tweet Content

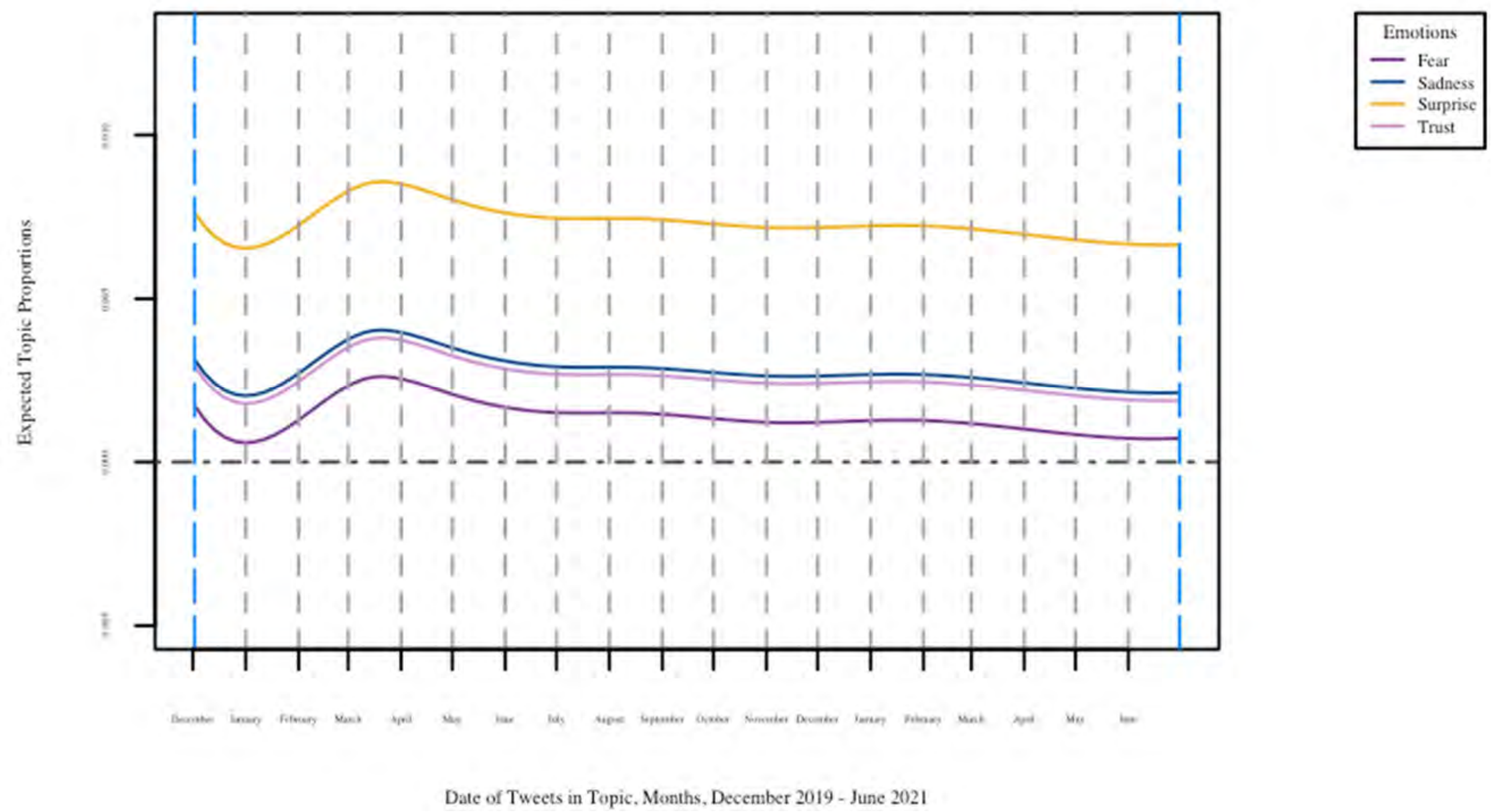


Figure 13.21b. Text Representative of 'Surprised' Tweets in Topic 112

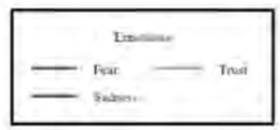
Under the Stafford Act the Trump emergency declaration provides funds and flexibility for state and local officials to deal with coronavirus.	Lawmakers urge that emergency funding for mental health must be in the next coronavirus stimulus package.
The House has passed the Emergency Housing Protec@[government official] and will provide a billion to the emergency rental assistance fund and a billion to the homeowners assistance fund.	California passes a billion dollar emergency bill for coronavirus funding, suspends all business capitol.

Figure 13.21c. Text Representative of 'Fearful', 'Sad', and 'Trusting' Tweets in Topic 112

The pandemic has devastated cancer research. The RISE act will provide emergency federal funding to help ensure biomedical research clinical trial networks can recover from the impact of covid but we still need to show our support.

They risk their lives cleaning hospitals, now they're getting vaccinated! @[news entity]

Surgeon general Dr. Jerome Adams wants people to stop buying facemasks to prevent novel coronavirus and warns there actually might be an increase in risk of infection if facemasks are not worn properly.



Topic 114 significantly increased over time, but the increase did not begin in earnest until about September 2020 (Figure 13.22a). Considering the topic involved vaccination, it makes sense that it would have become more prevalent towards the announcement and authorization of vaccines in the United States. Topic 114 was specifically focused on the risk versus effectiveness of vaccines, with the predominant sentiment being "Anticipation" related to the lacking effectiveness of vaccines for reducing COVID-19 transmission (Figure 13.22a-b). Many Americans felt "Anticipation" surrounding the denial[10] by the CDC and federal coronavirus task force that vaccinated individuals can still catch and transmit COVID-19 infection (Figure 13.22b).

Other emotional contexts point to the possibility of conflict over whether, and if so, how much, risk vaccinated people faced. Some tweets expressed "Anger" over the suggestion that the risk of COVID-19 would not be reduced enough for vaccinated people to safely stop wearing masks in public, like the example text declaring "If you want vaccinated people to wear a mask you are insane" (Figure 13.22c).

Regardless of disagreement about the risk posed to vaccinated people generally, topic 114 tweets draw attention to one point of consensus about risk after vaccination. There was little to no denial that vaccines would not entirely reduce risk for people who were medically vulnerable to complications and death from COVID-19 infection (Figure 13.22c). There was not necessarily consensus about what the ongoing risk to the medically vulnerable community would/should mean for other vaccinated people, though, shown in tweets defending the idea that most vaccinated people should continue to mask to protect the vulnerable (Figure 13.22c).

[10] The CDC reversed their stance on the effectiveness of COVID-19 vaccination for preventing transmission of the disease in late 2021, admitting that vaccinated individuals can, indeed, catch and transmit COVID-19

Figure 13.22a. Estimated Change in Topic Prevalence over Time for Topic 114, Smoothed, by Emotions with Significant Effects on Tweet Content

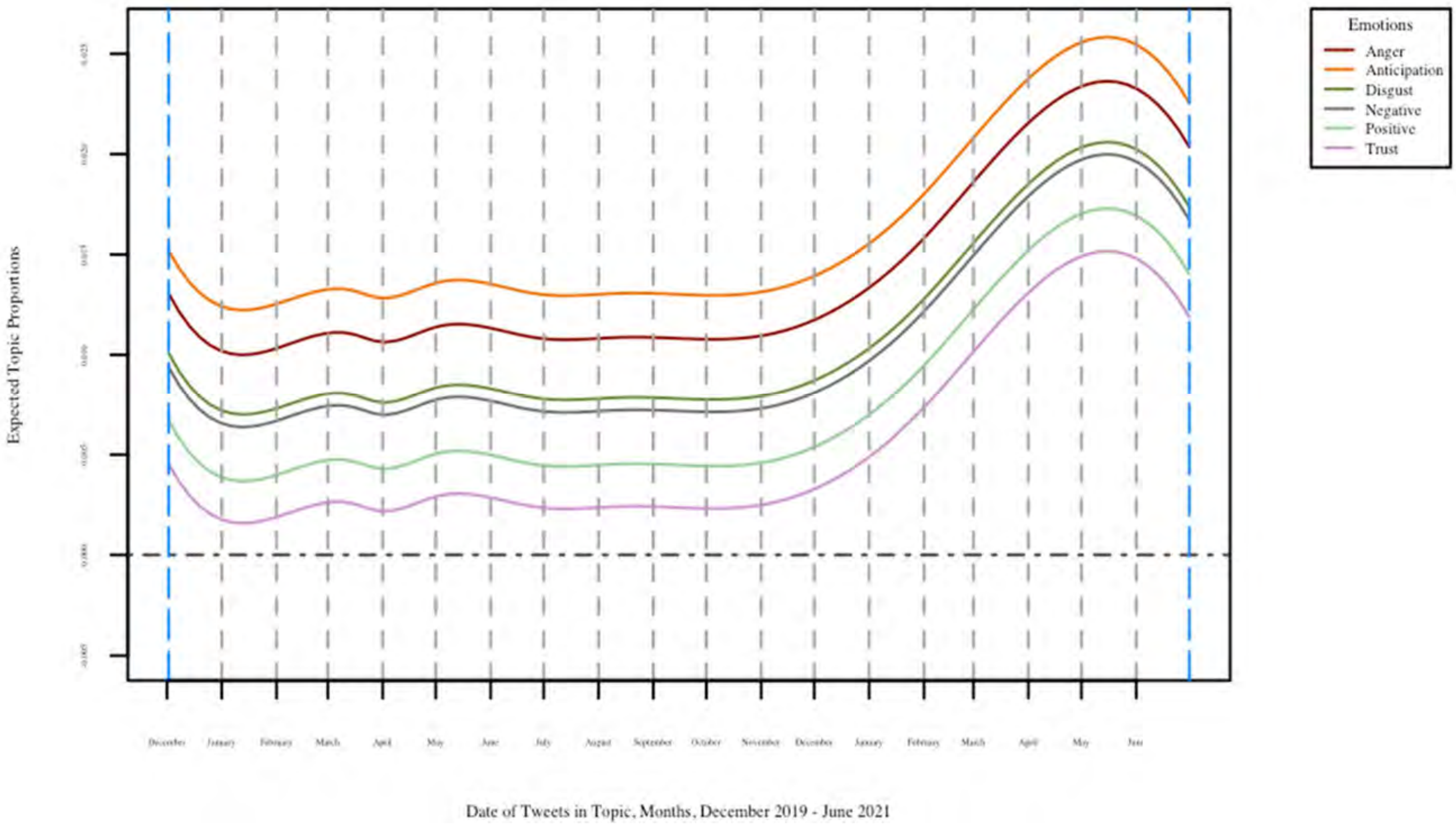


Figure 13.22b. Text Representative of 'Anticipatory' Tweets in Topic 114

There is a high probability that unvaccinated person will face high risk of death from covid of they interact with people. The probability is better for a vaccinated person. Stay safe from death from covid so you can interact with people. Currently the same regardless of variants.	I don't need to As a fully vaccinated individual I'm at zero risk of complications and xtremely low risk of catching and spreading. I have no problem with fully vaccinated people wearing masks that's their choice but I won't unless asked.
The CDC and Fauci admit that the vaccinated can catch, carry, and pass on covid, no different from the unvaccinated, but the vaccine may lessens severity of the virus if caught. Factually the unmasked vaccinated pose as much of a community threat as the unvaccinated since personal risk varies.	Maskless unvaccinated people are still the most risk to unvaccinated people. That's key.

Figure 13.22c. Text Representative of 'Angry', 'Disgusted','Negative', 'Positive', and 'Trusting' Tweets in Topic 114

The liberal elite in a one-on-one talking point. When they see this interview someone somewhere is going to be vaccinated and still think they need to wear mask when it is no concern or they are alone. If you want vaccinated people to wear masks you are insane.

We still need more protection because too many people are arrogant and stupid and aren't vaccinated. Like what is the threat to wear a mask for a few more months in a serious pandemic?

CDC says fully vaccinated Americans can travel, it is a low risk if you still wear masks social distance take covid test returning home

@[user] agreed, though vaccinated people not wearing masks when immersed in a soup of unvaccinated people is a recipe for selecting strains that can break vaccine protection, potentially putting us at risk again.

Donate so we can keep prioritizing hospitality workers who identify as BIPOC, LGBTQI, disabled, or are immunocompromised.

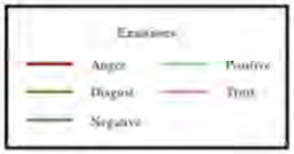


Figure 13.23a. Estimated Change in Topic Prevalence over Time for Topic 116, Smoothed, by Emotions with Significant Effects on Tweet Content

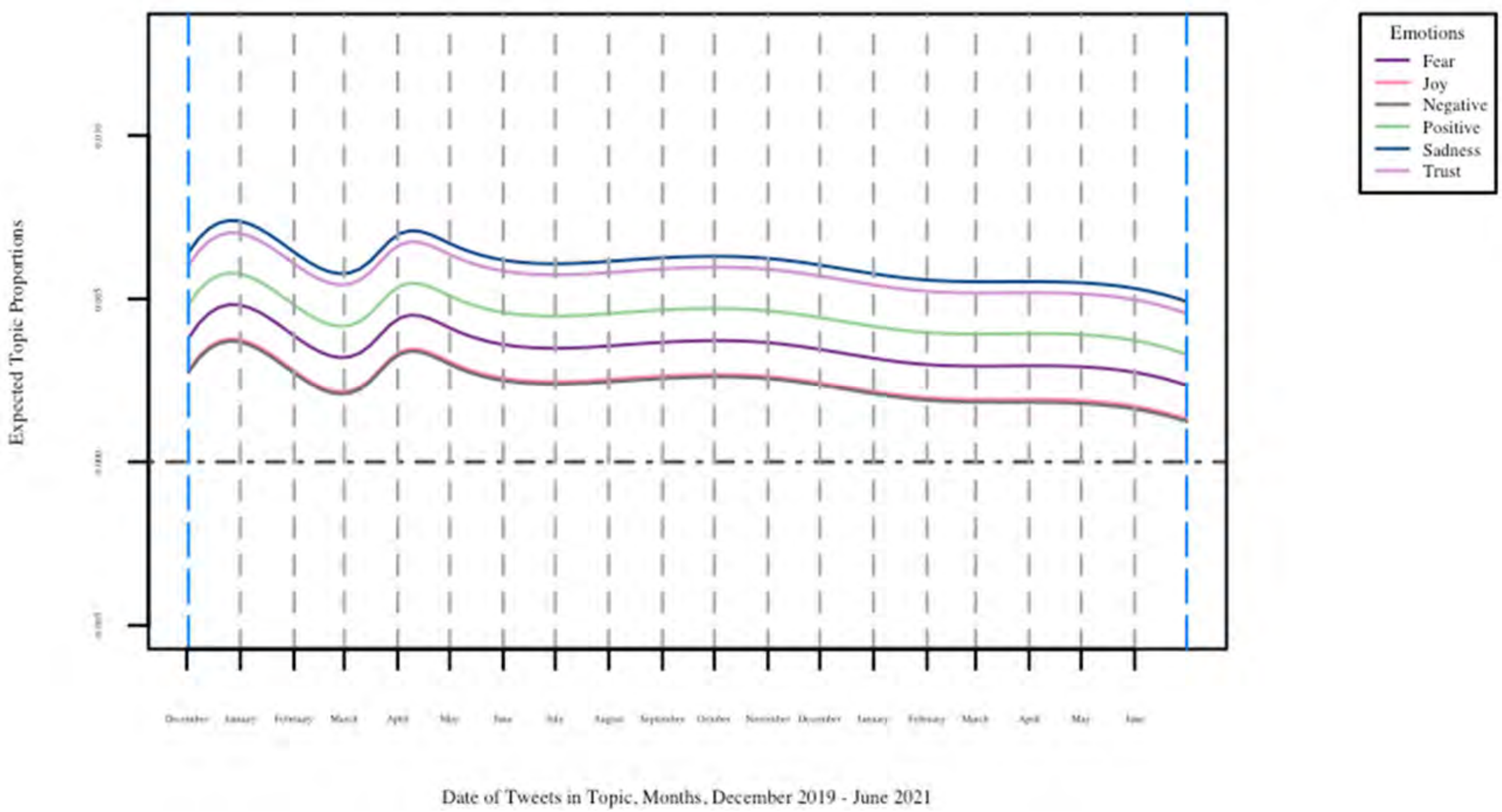


Figure 13.23b. Text Representative of 'Sad' Tweets in Topic 116

@[user] a Franklin Graham led group sent an entire field hospital to northern Italy, which led them to set up the emergency field tent in Central Park. Google is free, misinformation costly.

Today I saw the emergency field hospital going up in Central Park and passed an emergency morgue on the way back. At Bellevue I saw ambulances and so many cabs. I'm praying for all of NYC's sick, medical workers, and essential workers love solidarity

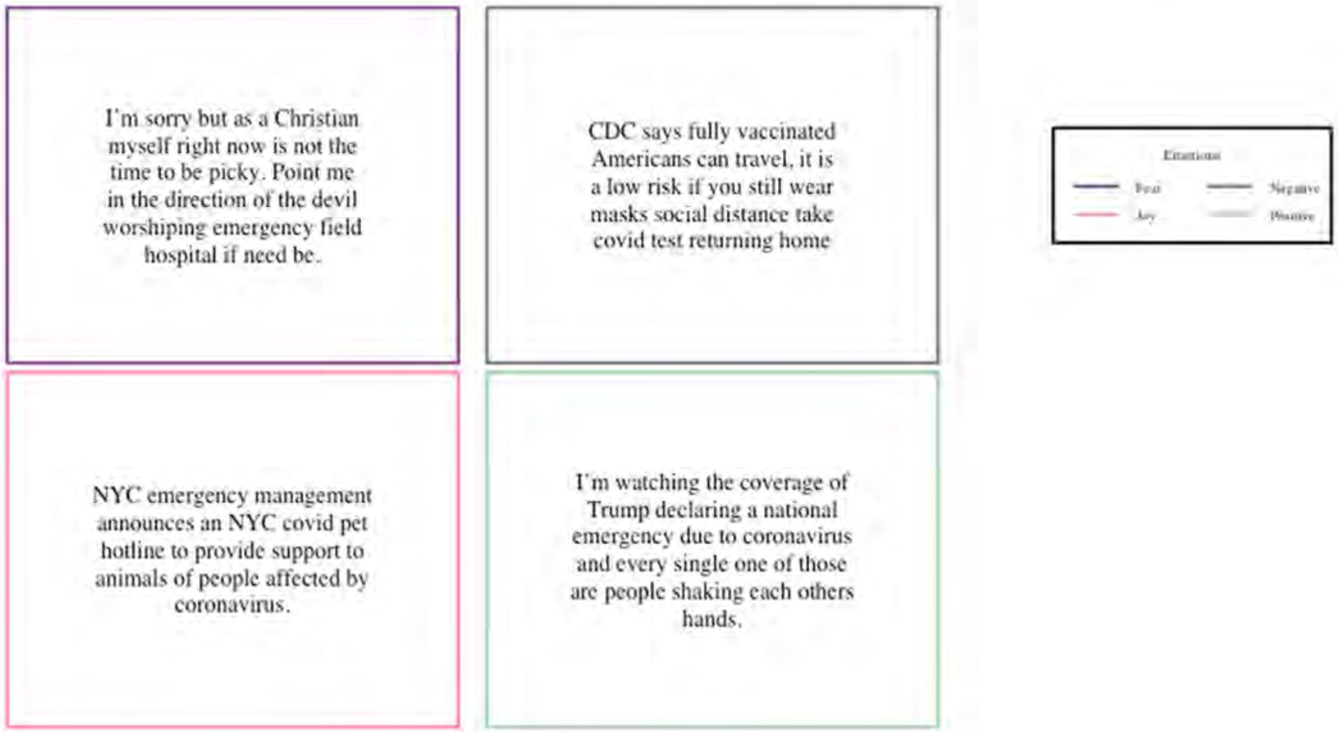
Construction begins today on an emergency field hospital in NYC's Central Park.

Arizona is now seeing a spike in cases. The ADPH director has sent a letter to hospitals recommending they prepare for crisis care.

Figure 13.23c. Text Representative of 'Trusting' Tweets in Topic 116

The covid pandemic presents a new opportunity for the city to help homeless residents. They have opened new emergency shelters St Andrews Park, Denker Recreation Park, will consider another addition.	As the coronavirus situation continues to unfold, @[local public health department] has set up a central command to share info, resources, and updates on the state of emergency. Our office will be sharing.
An emergency field hospital is now set up in Central Park to help with taking care of coronavirus patients, per a source.	My thinking about masks and covid is society can find ways to obtain additional revenues from those with unhealthy lifestyles to compensate for the additional risk without forcing the healthy to pay a premium.

Figure 13.23d. Text Representative of 'Fearful', 'Joyful', 'Negative', and 'Positive' Tweets in Topic 116



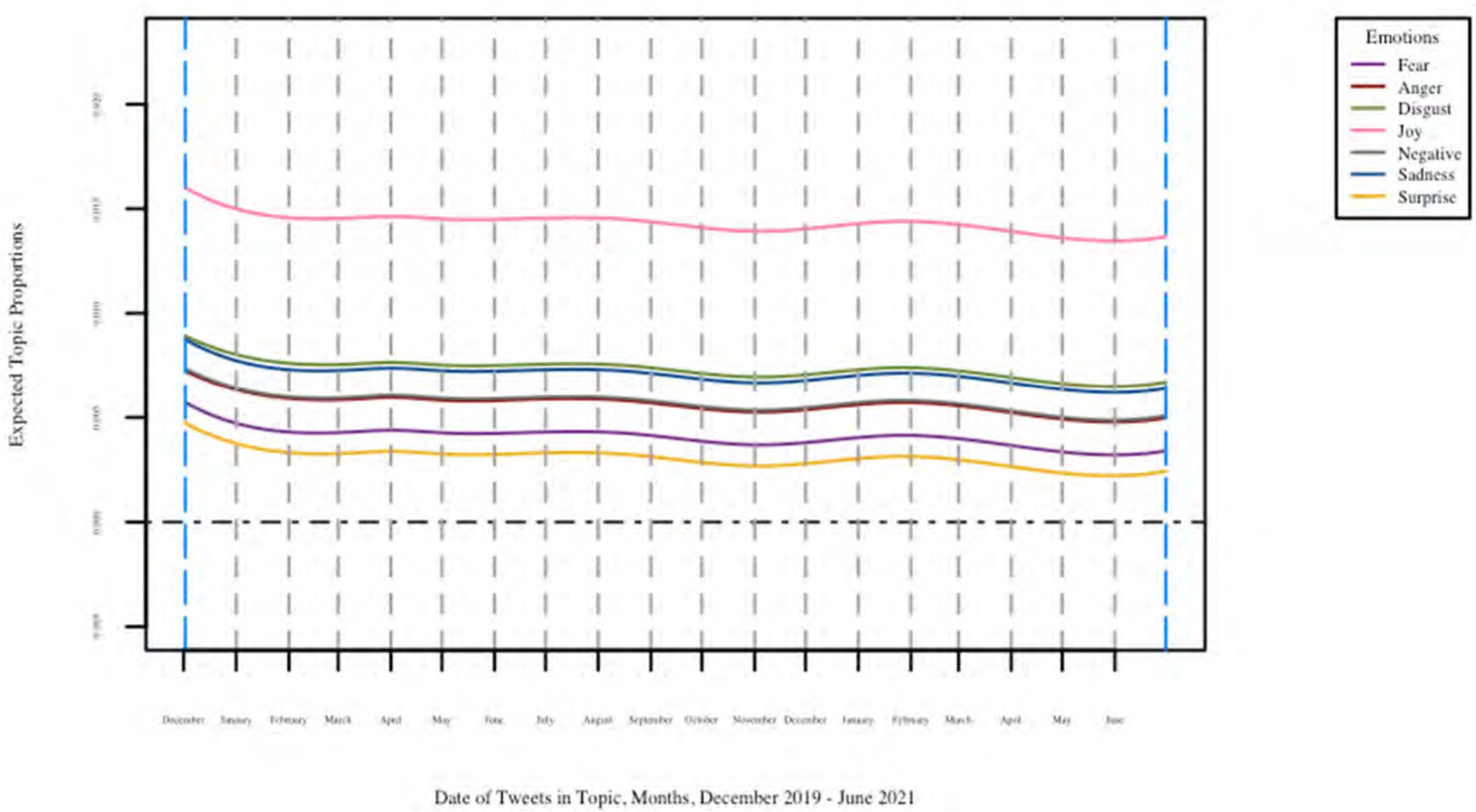
Topic 116 tweets shed light on some of the early conversations surrounding hospital capacity during the COVID-19 pandemic. These early conversations are characterized by things like “Sadness” over evidence that hospitals were overwhelmed, with many pointing out the emergence of field hospitals (Figure 13.23b). There was an almost equal proportion of “Trusting” tweets in topic 116, though, demonstrating that alongside the Sadness about hospitals were widespread feelings of collective efficacy and a desire to participate in collective action (Figure 13.23c). Given the prevalence of topic 116 significantly decreased over time, some people may have interpreted the issue of hospitals becoming overwhelmed from an influx of COVID-19 patients as diminished after shelter-in-place orders expired (Figure 13.23a).

This was also somewhat present in other emotional contexts like “Fear,” exemplified by the text “I’m sorry but as a Christian myself right now is not the time to be picky. Point me in the direction of the devil worshipping emergency field hospital if need be” (Figure 13.23d).

Topic 120 gave insight into what daily life was like for Americans during the initial days and months of the pandemic (Figure 13.24a). Across emotional contexts, topic 120 included reports about daily life activities and other things that characterized the abrupt disruption of normal life that took place for most people in the United States around March 2020 (Figure 13.24b-c). The various emotional contexts are useful for understanding how people felt about their new normal.

The “Joyful” tweets in topic 120 show how people adapted to cope with the changes to their everyday lives. Some people coped by building new routines, like scheduling a standing time for a daily video call with a close family member (Figure 13.24b). Others coped by sharing information with other twitter users, family members, and public officials (Figure 13.24b).

Figure 13.24a. Estimated Change in Topic Prevalence over Time for Topic 120, Smoothed, by Emotions with Significant Effects on Tweet Content



Tweets in other emotional contexts shed light on the many efforts by people to change their normal behaviors and routines only to fail or encounter an unexpected issue that renders one's efforts futile. Some people tried to make light of these situations, demonstrating one of the ways people used Twitter to try to alleviate feelings of frustration or despair when upsetting things happened. A good example is shown in the "Sad" text generated from topic 120 tweets where a user laments, "My wife decided yesterday that we needed emergency supplies for corona virus and goes and buys those individual pacs of ramen noodles and other weird things like a broth protein pack, pudding pack, and napkins," but follows it up by pointing to the bright side that, "At least she didn't go buy a ton of milk and bread" (Figure 13.24c).

Another popular response was found specifically among people who became infected with COVID-19. Prior to the development of pharmaceutical preventives and therapeutics for COVID-19, many people attempted to alleviate their symptoms with experimental and home remedies. Some tweets indicated "Surprise" that people used these treatments, like the remark, "I guess hydroxychloroquine and zinc taken as an early outpatient at the first sign didn't work, despite the known risk these were unproven claims. It must be a serious arrhythmia to go the ICU ventilator route" (Figure 13.24c). While this example mocked people who believed in and used experimental remedies to treat their COVID-19 symptoms, it also demonstrated that a seemingly irrational response could be more comforting than failing to respond.

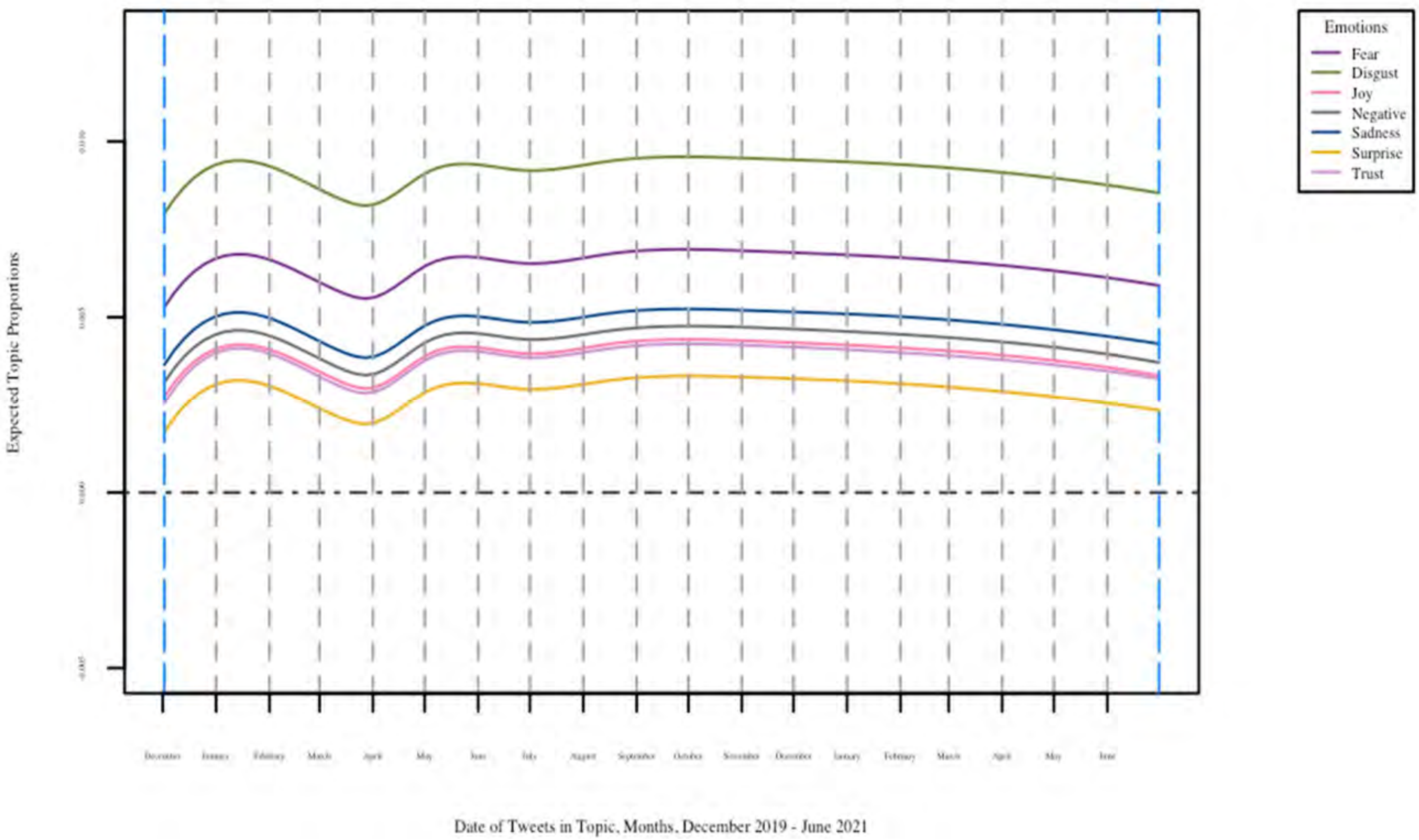
Other pandemic highlighted in topic 120 included avoiding healthcare unless infected and experiencing severe symptoms of COVID-19, transitioning restaurants from dine-in to take-away only, and wearing face masks in indoor public spaces (Figure 13.24b-c). Tweets about avoiding healthcare often contained "Fearful" undertones, like the example of a suggestion to another user, "Don't go to the hospital now you should wait to see if you get sick" (Figure 13.24c).

Figure 13.24b. Text Representative of 'Joyful' Tweets in Topic 120

I called my mom for our daily hour facetime call and she answered from the car in two masks saying I'm going to have to call you back I gotta make an emergency run and going now.	I really appreciate the honesty from @[government official] to call on Buckeyes to wear a mask in public. Great to hear him congratulate us on leading the world in the early days of the emergency and to remind us of our grit and ability beat this virus!
@[user] (laugh emoji) I appreciate your post. As a mom of three sometimes I am made to feel like I am overreacting. My daughter's pediatrician told me if it's an emergency don't wait for me to call back to go straight to the hospital.	Covid docs will be needed anywhere. Wherever you go you'll be putting your life at risk so it's good to go wherever is best for your family and that you are appropriately compensated for your hard work just like everyone else.

Figure 13.24c. Text Representative of ‘Fearful’, ‘Angry’, ‘Disgusted’, ‘Negative’, ‘Sad’, and ‘Surprised’ Tweets in Topic 120

Figure 13.25a. Estimated Change in Topic Prevalence over Time for Topic 125, Smoothed, by Emotions with Significant Effects on Tweet Content



Text like, “the argument isn’t that the government should not help people suffering so you can say fuck the risk of infection I wanna go to Golden Corral[11],” from “Negative” contexts reminded the general others of Twitter of the take-out norm for restaurant dining (Figure 13.24c). Other text criticizing people who did not wear masks in public, like the “Disgusted” example declaring that “if you think it’s wrong putting on a mask for a few minutes in the store you are selfish,” implying that there is no question about whether this behavior is selfish because that is a fact while also insisting that any questioning of this fact was opinion and irrelevant (Figure 13.24c).

Topic 125 tweets also concerned the new normal during the pandemic, but unlike tweets in topic 120, which touch on a variety of activities and behaviors, topic 125 focused specifically on the (1) new normal of wearing masks and (2) the attempts to revert from the new normal for other activities like take-away only restaurant patronage, not holding large social gatherings, working from home, and avoiding public transportation (Figure 13.25b-c).

There was a large proportion of “Disgusted” tweets surrounding the issue of what to do about face masks as the United States began its return to in-person activities (Figure 13.25a). They highlighted things like “the end of outside dining,” a nod to the phased return to in-person activities that began with those considered to have a low risk of virus exposure (Figure 13.25b). They also highlight the popular idea that activities with low risk of exposure to COVID-19 were any that could take place outdoors.

In addition to outdoor dining, “Disgusted” tweets in topic 125 provide examples of some of the other outdoor activities recommended as being safe, like “outdoor sporting events or camping” and “outdoor protests” (Figure 13.25b).

[11]Golden Corral is a popular, inexpensive, buffet-style, restaurant chain in the United States.

Figure 13.25b. Text Representative of 'Disgusted' Tweets in Topic 125

@[user] holding an indoor event without required masks is different than outdoor protests but the risk still exists obviously.	@[user] hmm yeah I've seen trouble with mask compliance but I usually try to switch to a different car. Thankfully the ventilation systems on rail and bus vehicles is way better than indoor spaces, and mask compliance on buses is better.
The Mayo Clinic lists outdoor dining as having low to moderate risk of covid spread, about the level of outdoor sporting events or camping.	Restaurants are a danger with winter coming. Just like the end of outside dining at night, king winter coming will kill restaurants. The newest mask mandate increases distrust in dining out as if it's on the verge of inside dining.

Figure 13.25c. Text Representative of 'Fearful', 'Joyful', 'Sad', 'Surprised', and 'Trusting' Tweets in Topic 125

Tweets in topic 125 went beyond simple identification of high-risk indoor versus lower risk outdoor activities, though. Other emotional contexts included commentary and the expression of personal reactions to discovering some activity was higher or lower risk than previously thought, like the "Joyful" context of saying "Wow. I'd assumed the risk of dining out was high," or the expression of "Sadness" that "eating out may be riskier than riding the bus in the COVID pandemic" and "Fear" that the "CDC says to avoid crows especially in poorly ventilated spaces to avoid risk of exposure to respiratory viruses like COVID, as it may increase in crowded close settings with little air circulation if people in the crowd are sick" (Figure 13.15c).

Topic 129 highlighted some of the changes to everyday life at the institutional level, with some emotional contexts also including the expression of opinions on those changes (Figure 13.26b-c). This suggests the changes were discussed less often as time wore on, which could be because the changes were already in place and therefore old news as time passed (Figure 13.26a). The predominant sentiment was "Surprise" over things like the minutiae of implementing emergency responses to COVID, for example, the text in a "Surprised" context discussing plans that "States are to set up emergency operations centers immediately," and "hospitals to activate emergency action plans" (Figure 13.26b).

Emotional contexts like "Trust" and "Anticipation" highlighted other institutional changes brought about during COVID-19, like "Trust" expressed in a tweet about the new norm for regular updates by public health officials , or "Anticipation" about a state pharmacy board meeting over emergency authorization to use a medication to treat COVID patients without having to go through a formal clinical trial specific to COVID-19 treatment, something that was common before COVID-specific treatments were created and tested (Figure 13.26c).

Figure 13.26a. Estimated Change in Topic Prevalence over Time for Topic 129 Smoothed, by Emotions with Significant Effects on Tweet Content

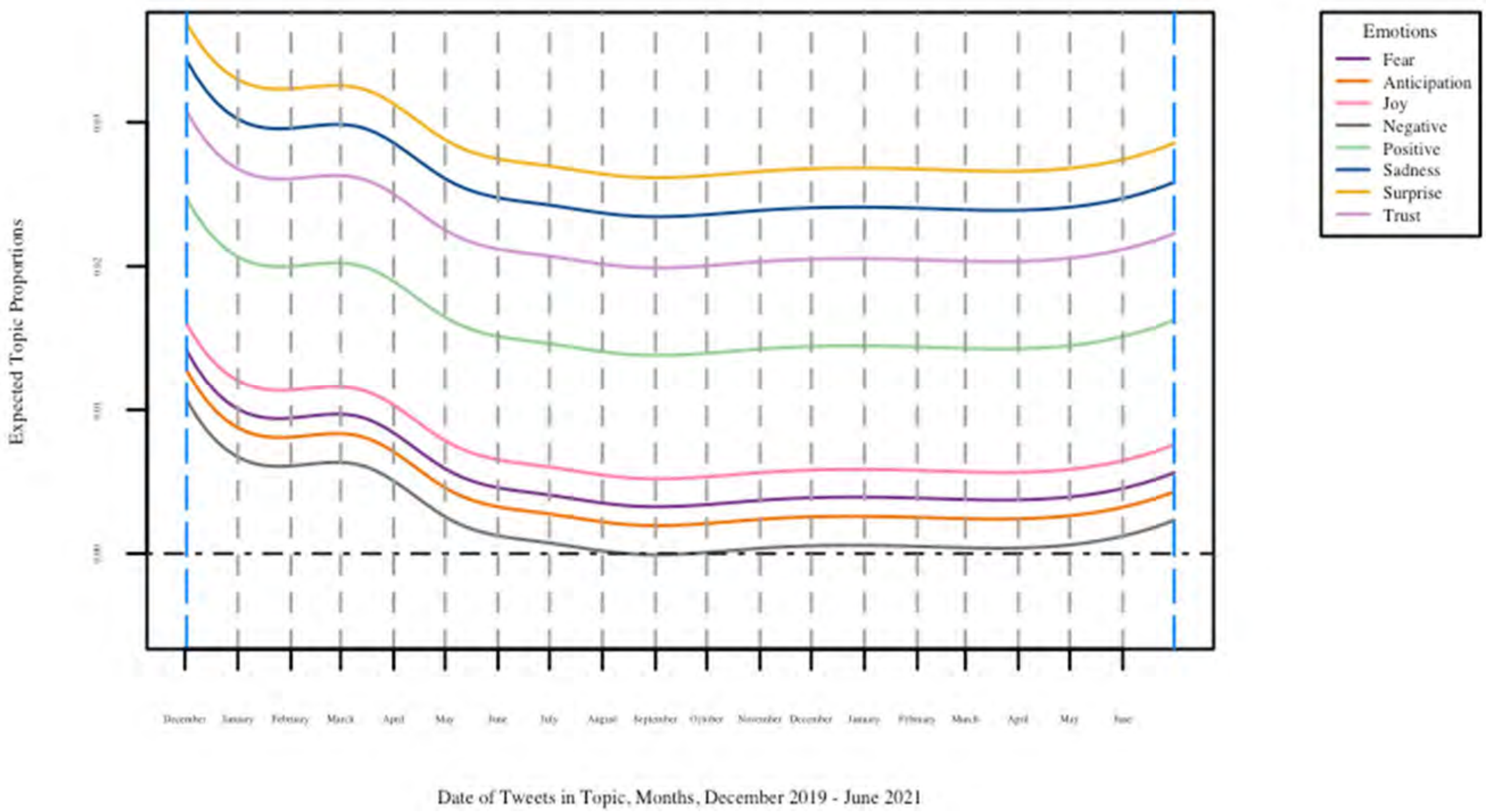


Figure 13.26b. Text Representative of 'Surprised' Tweets in Topic 129

@[government official] might convert idle cruise ships for emergency hospital use.

@[news entity] this is the aftermath of work in an emergency room hospital.

States are to set up emergency operations centers immediately, hospitals to activate emergency operations plans, announces POTUS.

So we can declare a national emergency due to the spread covid? Well what about white supremacy and gun violence? Declare war on domestic terrorism ala war on drugs and war on terror.

Figure 13.26c. Text Representative of ‘Fearful’, ‘Anticipatory’, ‘Joyful’, ‘Negative’, ‘Positive’, ‘Sad’, and ‘Trusting’ Tweets in Topic 129

Figure 13.27a. Estimated Change in Topic Prevalence over Time for Topic 132, Smoothed, by Emotions with Significant Effects on Tweet Content

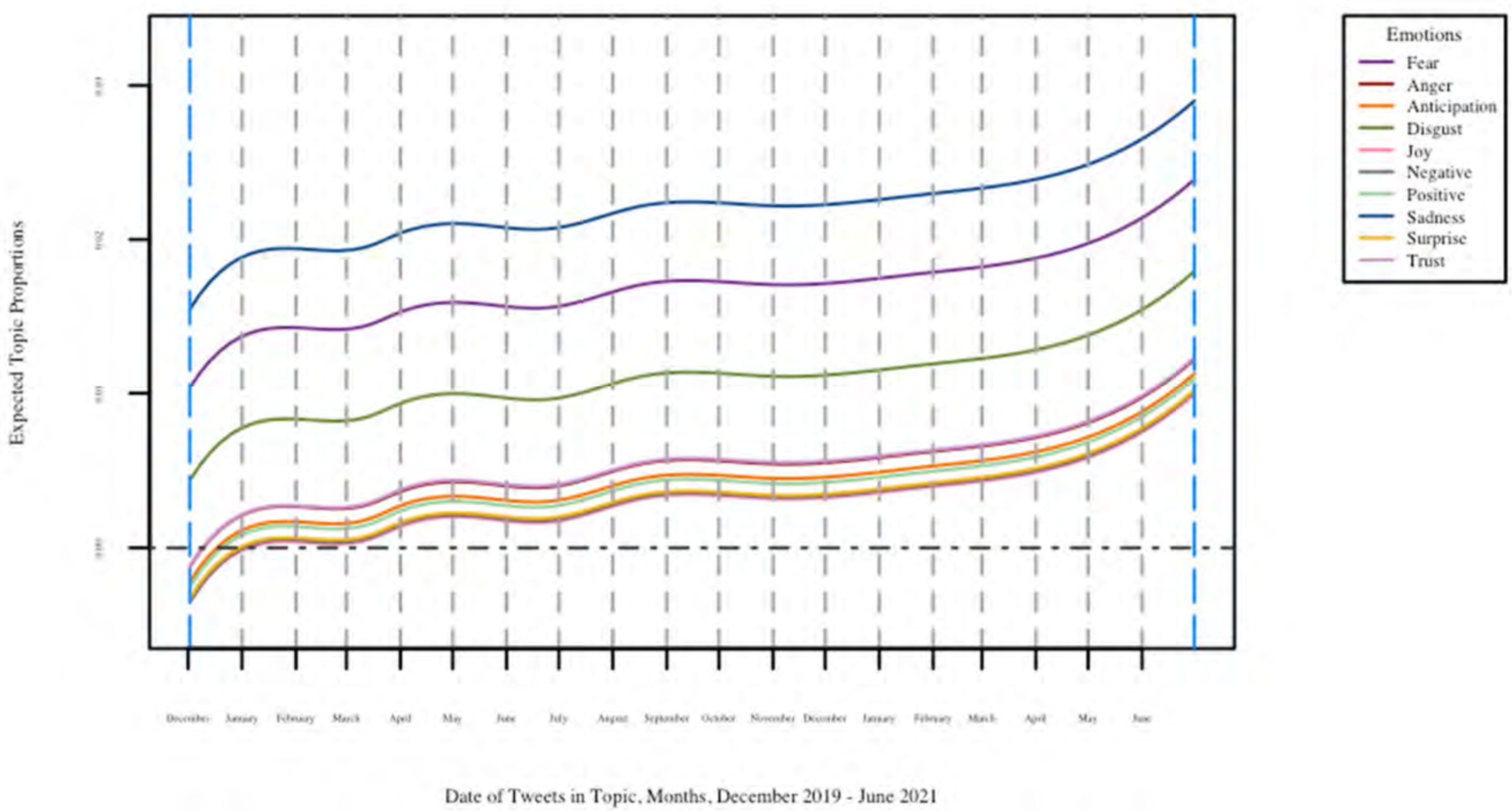


Figure 13.27b. Text Representative of 'Sad' Tweets in Topic 132

@[user] I agree on retesting covid pt when asymptomatic. However a pt covid dx one month ago with new onset hypoxia and elevated dimer? PE, isolate, treat empirically as covid as if it will pose high risk of transmission.	You know obesity raises individuals risk for severe covid outcomes? The preceding obesity epidemic exacerbated the covid pandemic.
The covid risk is sadly still rising with the caseload.	The covid risk is not the same for people who take different covid risks.

Figure 13.27c. Text Representative of 'Fearful', 'Angry', 'Anticipatory','Disgusted', 'Joyful', 'Negative', 'Positive', 'Surprised, and 'Trusting' Tweets in Topic 132

ACES can have adverse health outcomes that are risk factors for underlying conditions. Make sure that risk is part of what you are factoring for your chance of contracting and surviving covid.

How do we not understand that if we shove a bunch of people into a confined space like a cruise ship we expose everyone to covid and will have to quarantine the entire cruise ship. You may not care about the risk of death from covid but it is making the catastrophe worse.

We have been taking proactive steps to target poor disease outcomes resulting in long covid. We have been working since the start of the pandemic to accurately predict covid risk but we think it is important to keep up annual screenings and preventive care.

@[user] learning the hard way that coronaphobia was an intentionally instilled and serious mental illness. I don't know if it's reversible. Clearly by the comments it is not going away and that is never a reason to scare people. Covid risk is vastly overestimated.

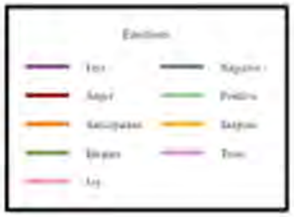
Guys times are uncertain right now so if you have a loved one with medical conditions go download this free printable to fill out that way if they go to the hospital the medical team can be well informed on their meds and conditions.

I think the point is that people and businesses have their livelihood tied to financially surviving that makes them willing to do it. My guess is Americans would risk getting covid if it gave them a chance save their business and retirement package.

When schools are reopened you say kids will be at low risk for severe infection. However, some kids will have underlying conditions that increase their risks and some teachers and staff will be high risk.

You say @[organization] is not downplaying anything with the event and don't forget the stats on other illnesses. They are a greater threat? That is a stupid point. None of those illnesses was as contagious and now covid will be the leading cause of death this year making your foolish point moot.

@[several users] gyms benefit people both their mental, physical, and emotional state, and pose no threat of spreading covid. I trust the data.



Topic 132 paints a picture of the emotional responses to the endurance of the COVID-19 pandemic, with “Sad” tweet content characterizing a large proportion of the tweets (Figure 13.27a). The significant and steady increase in the prevalence of topic 132 over time, when taken in context of the emotional undertones of tweet content, points to more heated responses to news of the pandemic’s continuation as time wore on (Figure 13.27a-c). “Sadness” expressed over things like “the covid risk is sadly still rising with the caseload” and “covid risk is not the same for people who take different risks” are good examples of this (Figure 13.27b). It is notable that tweets expressing “Sadness” “Fear,” and “Disgust” were visibly more prevalent than other emotions with a significant effect on the content of tweets in topic 132, as this suggests that the heightened response to the pandemic’s endurance was characterized primarily by becoming increasingly upset or frustrated that COVID-19 impeded their participation in desirable activities (Figure 13.27a).

Tweets in topic 150, which were significantly more prevalent by the end of June 2021 than they were in December 2019, give some indication that people became more “Trusting” of government actions to mitigate the risk of COVID-19 over time (Figure 13.28a-b). Examples of “Trusting” tweet text in topic 150 highlight not only “Trust” in governmental and institutional actions, but specifically “Trust” when the actions included firm parameters around time like, “a district-wide school closure from Friday March 7-Monday March 10” (Figure 13.28b). There seemed to be a strong sense of Trust related to officials providing a firm start and end date for changes resulting from an action. In contrast, example text from other emotional contexts hinted there was possibly a lack of “Trust” when guidance did not include a clear time frame.

Figure 13.28a. Estimated Change in Topic Prevalence over Time for Topic 150, Smoothed, by Emotions with Significant Effects on Tweet Content

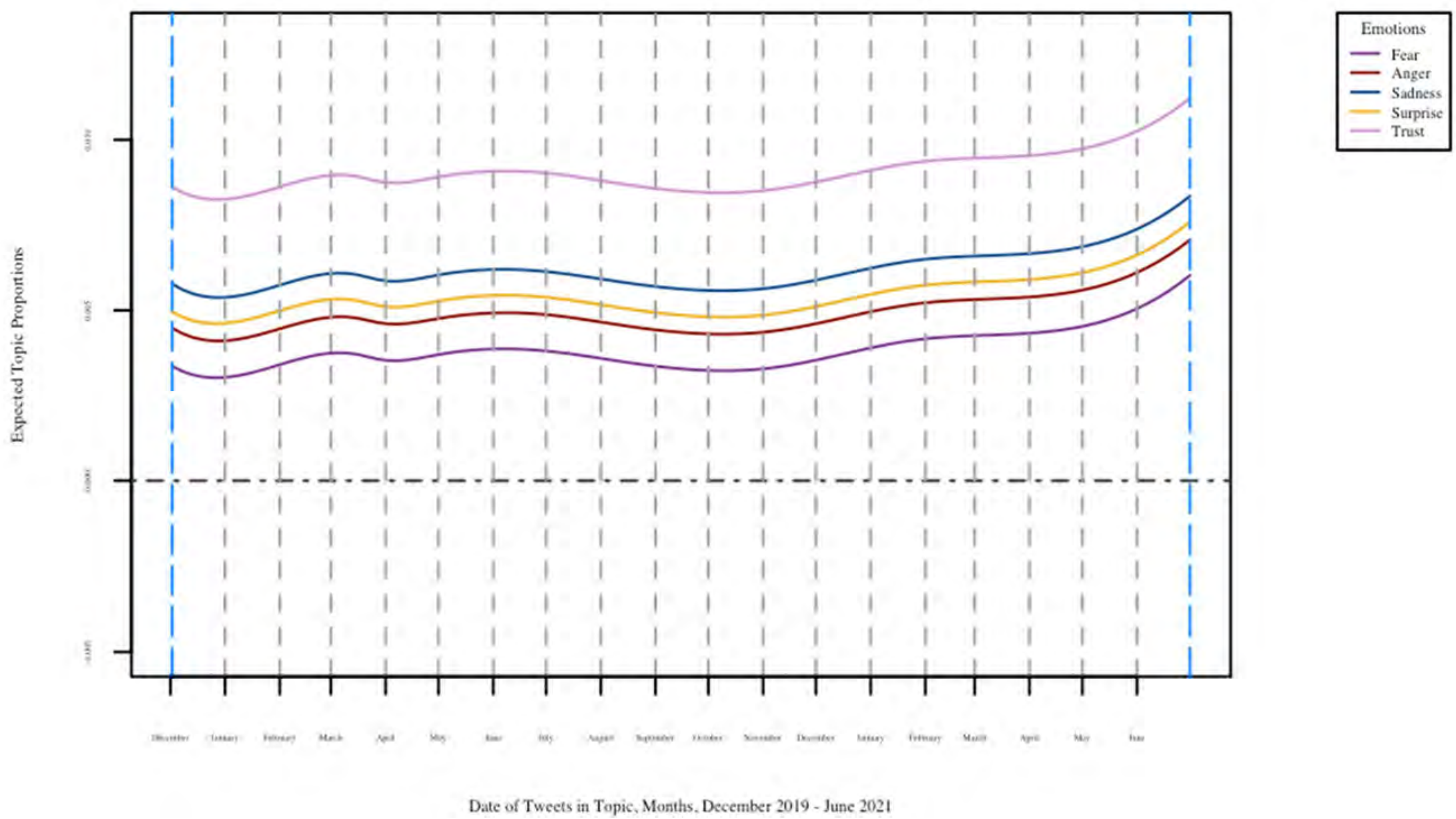


Figure 13.28b. Text Representative of 'Trusting' Tweets in Topic 150

@[government official] says he'll extend the state of emergency provision allowing county mask mandates that expires at the end of the month.

@[several suers] it's illegal in many states including Virginia for adults to wear face coverings in public but our law was suspended by the governor's declaration of the state of emergency. Declaration expires end of June.

FYI Governor Cooper extended North Carolina's state of emergency until the end of the month in response to covid so we can be ready if we need to order more restrictions in place.

the board of education held an emergency meeting to review and address the @[school district] coronavirus response. The governing board gave direction for a district-wide school closure from Friday March 7-Monday March 10.

Figure 13.28c. Text Representative of 'Fearful', 'Angry', 'Sad', and 'Surprised' Tweets in Topic 150

Instead of invoking “Trust,” closures and other measures that were characterized as indefinite or presented without time context invoked emotions like “Sadness,” “Fear,” “Anger,” and “Surprise” (Figure 13.28c). This was the case with the “Sad” example text announcing “Disneyland resort to close temporarily” without any evidence that a duration for the closure was included in the announcement by the theme park’s representatives (Figure 13.28c). It was also found in “Surprised” text about the FDA authorization of “a third one” in reference to the Johnson & Johnson COVID-19 vaccine, the third vaccine authorized for use in the United States (Figure 13.28c). In the “Surprised” context, the news was characterized as “a pretty good way to end the week,” implying a low expectation for good news at the end of the week given COVID-19 would still be a problem the following week (Figure 13.28c).

Topic 160 tweets, which increased significantly over time, focused on the perceived pros and cons of continuing to mitigate COVID-19 risk as the pandemic stretched on (Figure 13.29a). Most were in a “Fearful” context that suggested an increasing sense of “Fear” related to what many have begun to refer to as “pandemic fatigue” (Figure 13.29b). Some “Fears” were related to the potentially increased risk to children if adults gave into their feelings of burnout and ceased precautions like masking, seen in the “Fearful” tweet text pointing out that young children could not protect themselves with the example, “Masks for those under age 2 pose a high risk of suffocation” (Figure 13.29b). Others were related to the potential increased risk to frontline workers who could not avoid those who ceased risk mitigation in public and thus had a reduced ability to protect themselves even with precautions like masks. One example of “Fearful” tweet text, for instance, states that there is a “high risk of infection and even higher risk of shitty customers,” the suggestion being that customer behavior can serve to increase the risk faced by retail workers (Figure 13.29b).

Figure 13.29a. Estimated Change in Topic Prevalence over Time for Topic 160, Smoothed, by Emotions with Significant Effects on Tweet Content

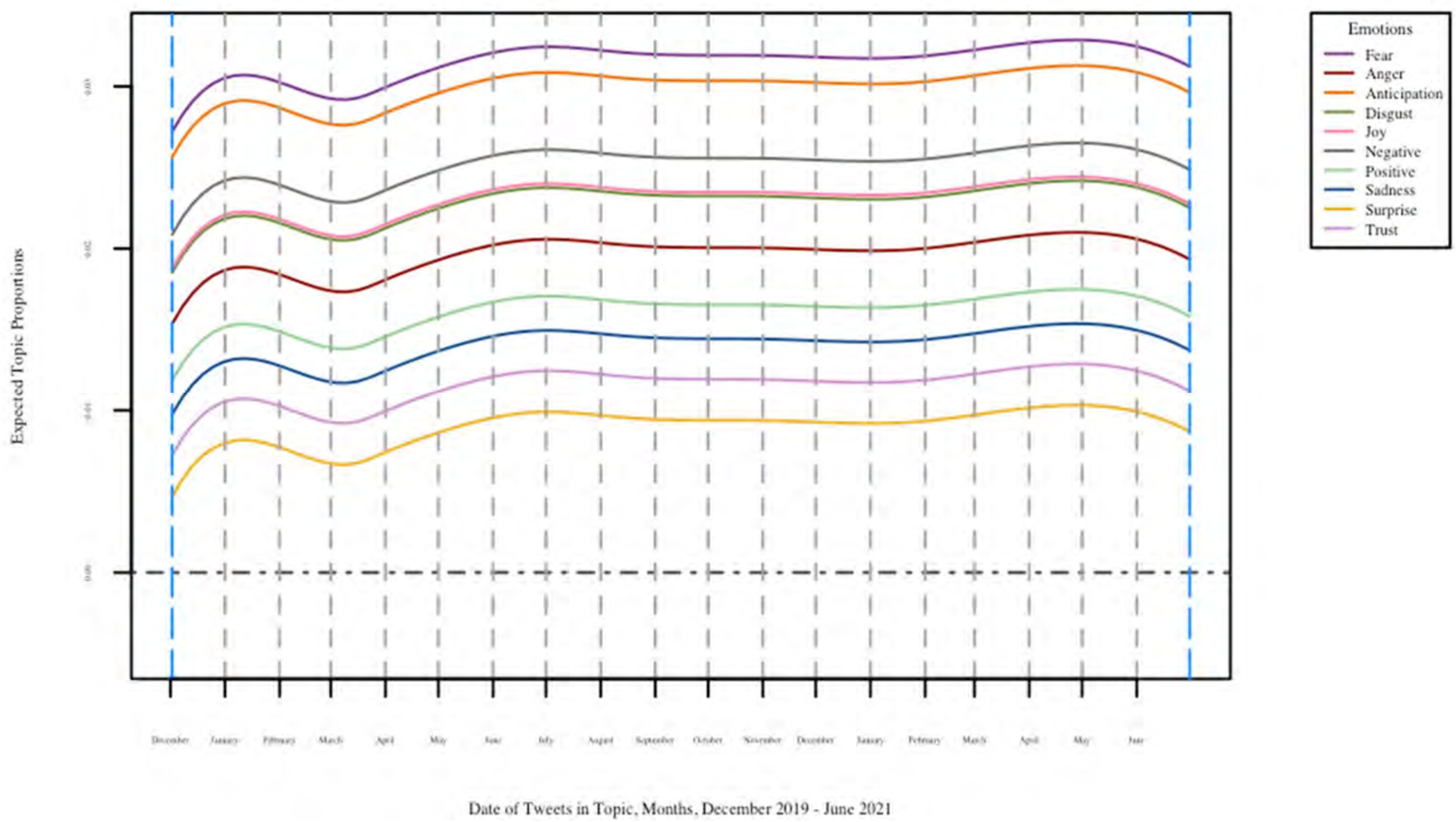


Figure 13.29b. Text Representative of 'Fearful' Tweets in Topic 160

Masks for those under age 2 pose a high risk of suffocation.	Almost all of the presidential candidates seem like a good combo for high age-related mortality risk and high exposure/infection risk o_o
@[user] obese people are high risk covid, if cases are that high why risk the stupidity?	High risk of infection and even higher risk of shitty customers. This is how US service workers spent the last year of the pandemic.

Figure 13.29c. Text Representative of ‘Angry’, ‘Anticipatory’, ‘Disgusted’, ‘Joyful’, ‘Negative’, ‘Positive’, ‘Sad’, ‘Surprised’, and ‘Trusting’ Tweets in Topic 160

Other emotional contexts like “Anger” pointed to other downsides of pandemic fatigue leading people to cease risk mitigation efforts, like the downside that “seating proximity is strongly associated with increased infection risk,” hinting that it was not optimal to be subject to exposure because you could not find a seat further away from someone in public places.

Spaces like restaurants, movie theaters and public transportation are all good examples of public spaces where someone may not have control over their proximity to others due to seating layouts and/or things like pre-assigned seating (Figure 13.29c).

Topics where Time had a Significant Effect on Topical Prevalence Only After Controlling for Emotional Sentiment

The final five topics for which time was a significant predictor of topical prevalence included topics 11, 123, 128, 140, and 151, all topics where the effect of time on topical prevalence was not significant *until* controlling for the emotional content of tweets in the topic (Table 3). In this case, the effect of time on topical prevalence can only be interpreted in context of the emotional undertones of the topic’s tweet content.

In topic 11, the largest proportion of tweets contained content with “Fearful” emotional undertones (Figure 14.1a). “Fearful” tweets in topic 11 decreased significantly over the course of the pandemic, peaking early in the pandemic during March 2020. The example text of “Fearful” tweets in topic 11 suggests that Twitter users in the United States were less likely to express “Fear” related to social groups at higher-than-average risk of severe disease and death from COVID-19 infection after March 2020 (Figure 14.1b).

Figure 14.1a. Estimated Change in Topic Prevalence over Time for Topic 11, Smoothed, by Emotions with Significant Effects on Tweet Content

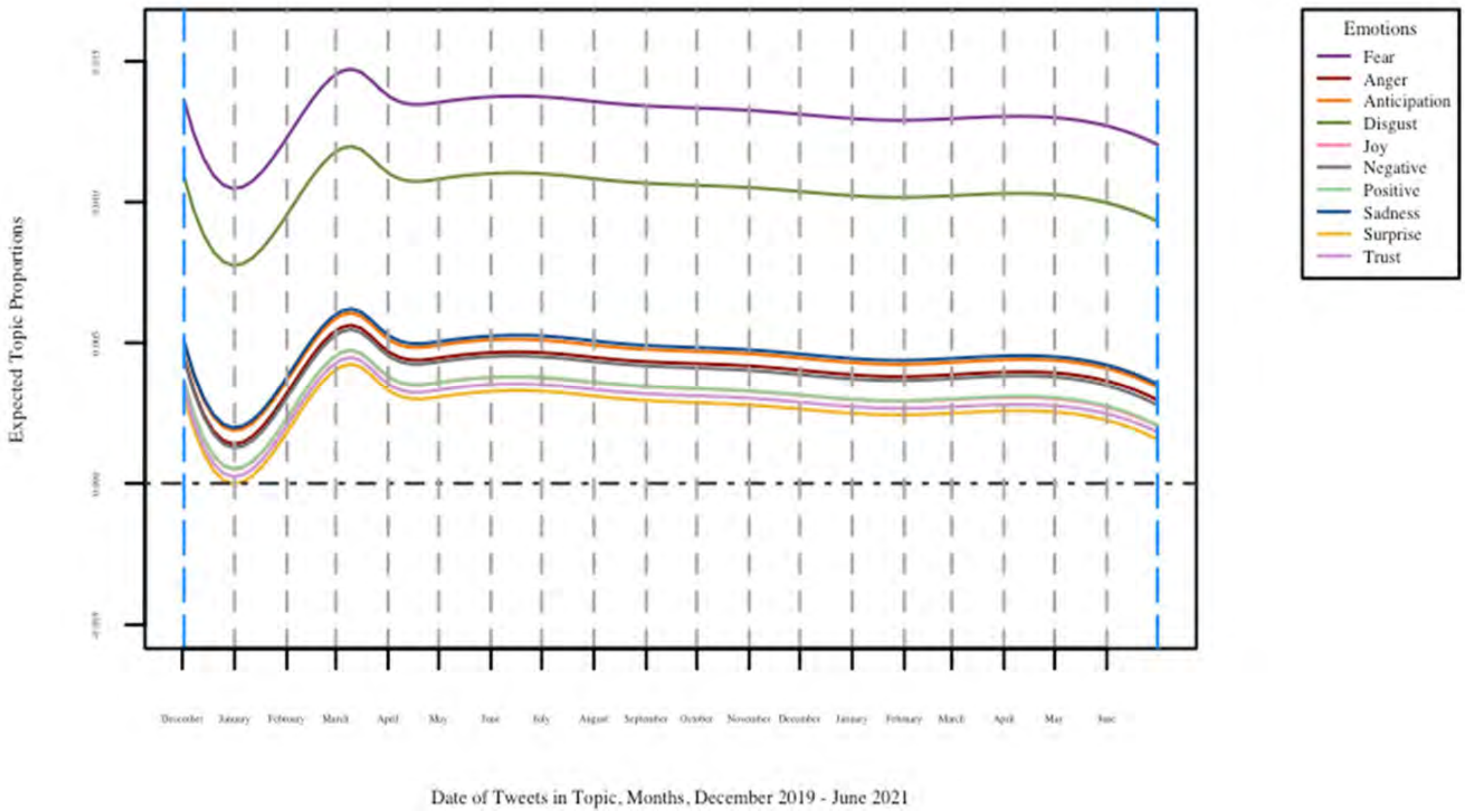


Figure 14.1b. Text Representative of 'Fearful' Tweets in Topic 11

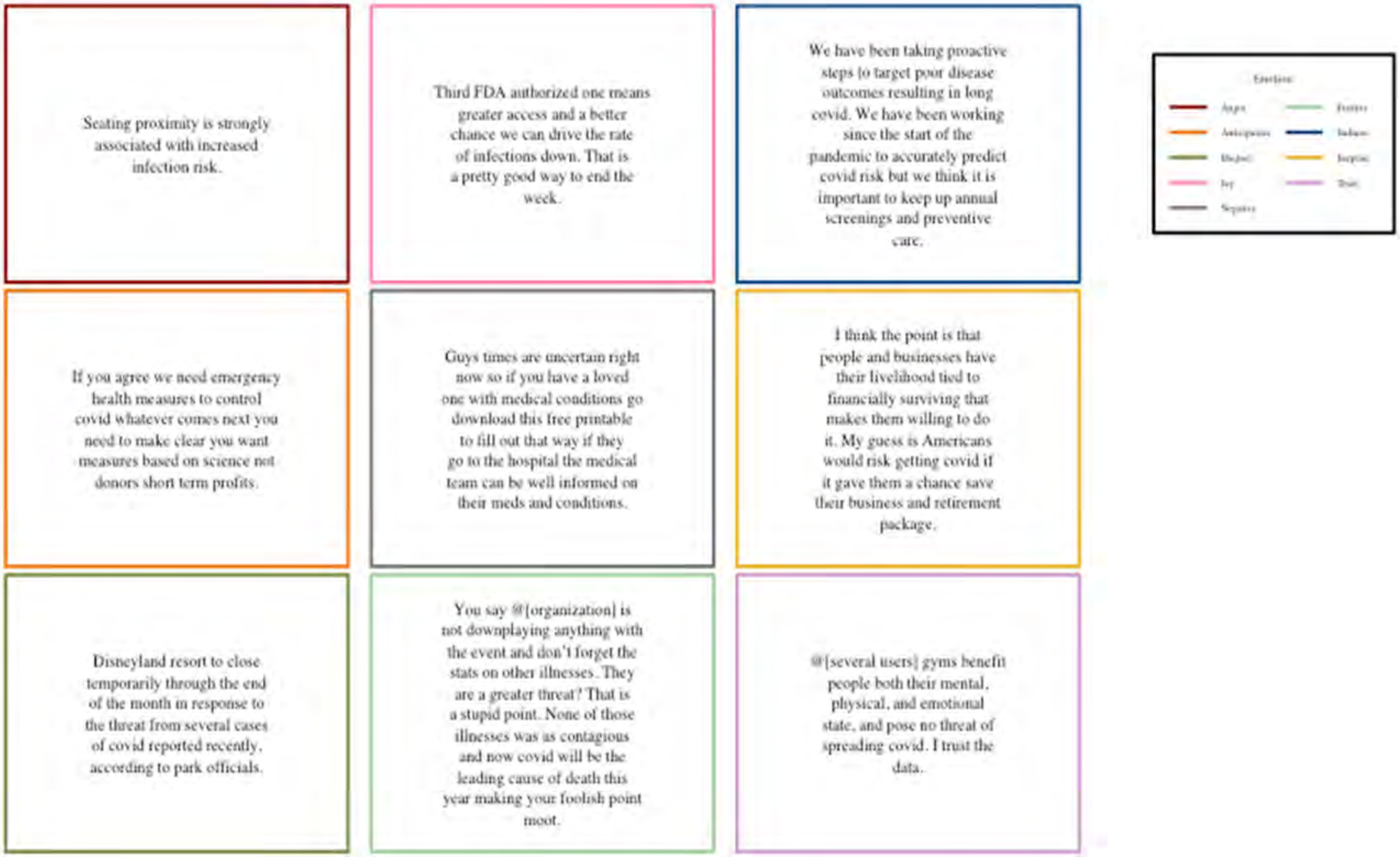
Apparently with MS I'm at higher risk for covid if I get it. Higher risk of severe symptoms largely depends on level disability, age, and weight

People at higher risk of illness from covid share their messages urging social distancing.

New CDC study says pregnant women face higher risk of severe illness from covid, via @[news entity]

@[medical doctor] but @[several other medical doctors] say the risk of blood clotting from covid is much, much, MUCH higher than the possibility of getting blood clotting from the vaccine.

Figure 14.1c. Text Representative of 'Angry', 'Anticipatory', 'Disgusted', 'Joyful', 'Negative', 'Positive', 'Sad', 'Surprised', and 'Trusting' Tweets in Topic 11



In context of the time trend for “Fearful” tweets, this suggests that expressions of “Fear” related to medical vulnerability did not see a resurgence of popularity after the initial peak of the pandemic in March 2020 (Figure 14.1a). This could indicate decreasing “Fears” about medical vulnerability, or alternatively, a decreasing interest in the risk to medically vulnerable individuals as the understanding that average risk of COVID-19 infection was low became more widespread among the non-disabled non-chronically ill U.S. population.

Tweets in other emotional contexts, which also peaked in March 2020 and decreased for the remainder of the 19 months through June 2021 (Figure 14.1a), give merit to the latter explanation, that people who identified as being of “average” risk from COVID-19 became less interested in the risk for more vulnerable people as they learned they may have much lower risk as a “healthy” person (Figure 14.1c). An example of “Anticipatory” tweet text in topic 11 points to early “Anticipation” that a science-based response to risk would be most appropriate, with “Anticipation” decreasing quite a bit after March 2020 (Figure 14.1c). Another useful example is found in “Negative” sentiments in topic 11 tweets urging people to get informed if they or someone they cared about was medically vulnerable (Figure 14.1c). This, in context of the significantly decreased prevalence by the end of June 2021, suggests that people felt less of a need to discuss protecting the vulnerable after the topic’s peak prevalence in March 2020 (Figure 14.1a).

The predominant emotional context for tweets in topic 123 was “Joy,” followed by “Disgust,” with the significant decrease over time indicating that the topic became less relevant to conversations about risk as time passed (Figure 14.2a). Example text generated from topic 123 tweets reveals that the implied opinion/understanding of COVID-19 risk as real and important is shared across emotional contexts (Figure 14.2b). The examples of “Joyful,” “Disgusted,” “Fearful,” “Trusting,” and “Surprised” tweets in topic 123 demonstrate the variety of approaches U.S. Twitter users employed to encourage others to adopt specific risk mitigating behaviors, and they are good representations of one recommended approach to public health involving a contextualized approach to the population in question (Figure 14.2b-c).

The most common approach to encouraging participation in risk mitigation was to use enthusiasm paired with concern, seen in “Joyful” contexts where users encouraged behavior while trying to remain nonchalant (Figure 14.2b). This approach could be useful for conveying that there is no judgement or ill thought behind the encouragement of a behavior, and to avoid the perception that one is “subtweeting” about another user or group of users. A “subtweet” is a tweet constructed to convey a passive aggressive response to something you noticed, in this case, what you perceive as bad behavior, without calling out the person who drew your attention to the behavior by name and instead framing your comment as being towards general others.

Subtweets can be used as tools to influence behavior, though, and we see this in the example of “Trusting” tweet text providing a humorous take on a situation in which former President Trump suggested that injecting people with bleach may be useful for combatting COVID-19 and was subsequently rebuffed by the host of a conservative talk show, among others (Forgey 2020) (Figure 14.2c). Feigning excitement over the response while hinting that the enthusiasm should be taken carefully because the bar for good behavior was low can be used to reach people who wish to separate themselves from behavior based in misinformation but who do not necessarily wish to avoid all behavior that others judge as bad or immoral.

Figure 14.2a. Estimated Change in Topic Prevalence over Time for Topic 123, Smoothed, by Emotions with Significant Effects on Tweet Content

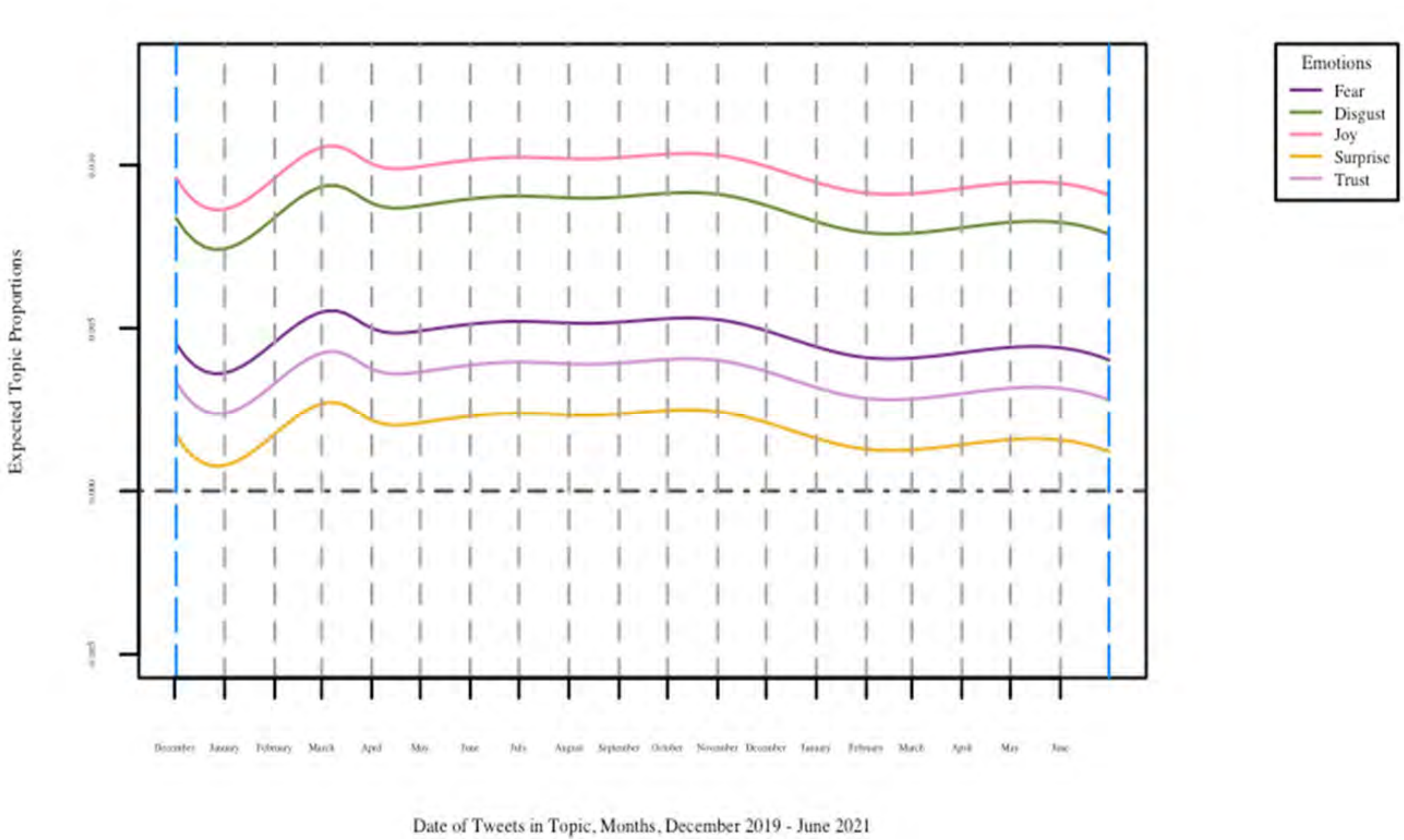
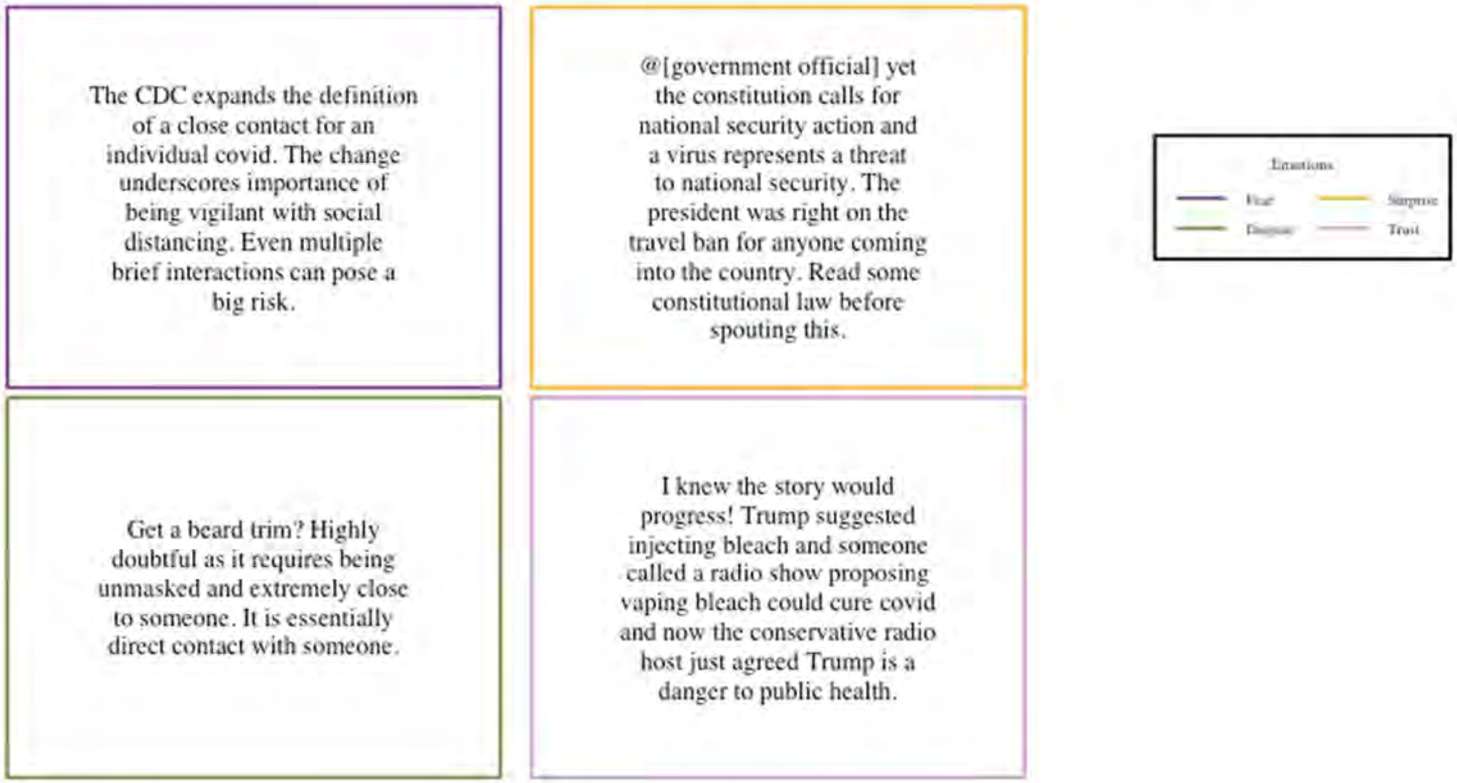


Figure 14.2b. Text Representative of 'Joyful' Tweets in Topic 123

This Sunday 6pm come and bring anyone to @[organization]'s outdoor pumpkin carving. Tools provided, you bring your own pumpkin and mask.	@[user] thank ya and I understand the concern and appreciate ya looking out for anyone who came. We said if you are sick don't come and checked everyones temperature when they walked in, had hand sanitizer all over the room and had anyone who came have a disinfected house.
@[several government officials] we are supposed to get tested if we have symptoms only if we somehow know we were exposed to someone infected. But someone at risk can't tell if someone within 6 feet has the rona.	Real talk folks it's no joke that those who are infected may not show symptoms and may be in a demographic that is at high risk for fatalities. It could be anyone you come into contact with. Please keep this in mind when you travel home. Please be careful and get home safe.

Figure 14.2c. Text Representative of 'Fearful', 'Disgusted', 'Surprised',and 'Trusting' Tweets in Topic 123



In some cases where one user answers another's question about a given risk during the COVID-era, some people used "Disgust" to bolster their recommendation with the additional disclaimer that one would personally behave in a certain way because behaving otherwise made one feel gross (Figure 14.2c). The emphasis was not on the idea that some behavior was "Disgusting," but instead on the sense that "Disgust" was highly personal. This could help invoke a sense of thought without blaming or shaming other users, the idea being that a cordial response could cause someone to pause and ponder whether they, too, find that thing "Disgusting." The technique is most useful when the person being influenced does not already have a strong opinion on the subject in question.

Other circumstances in topic 123 may have constituted unsolicited advice. For example, it is possible that the "Fearful" tweet text providing the newly expanded definition for a "close contact" during the pandemic was posted without encountering another Twitter user asking for details on the definition (Figure 14.2c).

A final technique for influencing the behavior of others in topic 123 is best characterized as the opposite of a subtweet. If a subtweet is passive-aggressive, tweets using this last technique were their aggressive counterpart. For example, "Surprised" tweets in topic 123 confronted other users for providing inaccurate or inappropriate information related to COVID-19, like the example text telling another user to "read some constitutional law before spouting this" in response to someone's alleged misunderstanding of whether the government could impose restrictions on the American public to combat a biohazard (Figure 14.2c).

Figure 14.3a. Estimated Change in Topic Prevalence over Time for Topic 128, Smoothed, by Emotions with Significant Effects on Tweet Content

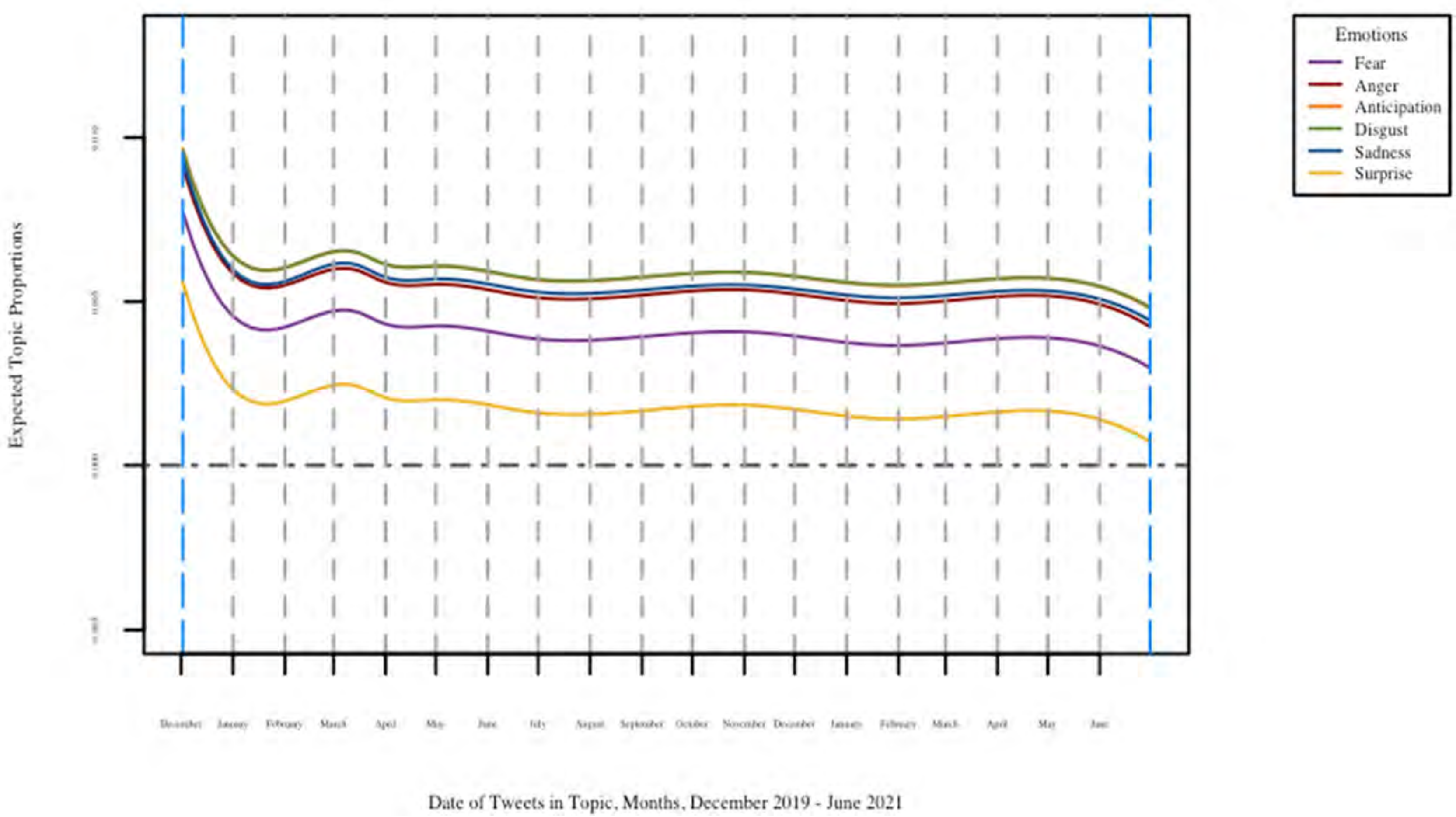


Figure 14.3b. Text Representative of 'Disgusted' Tweets in Topic 128

@[public heaalth official] I've been trying to find research on elevators. My family live in a multi-story building in lower Manhattan and I don't want them to touch anything in the elevator. If they are unlucky enough ride with someone contagious is that added risk factor?

@[user] the virus has rated R0 of 8. R0 of anything higher than R0 of 1 poses a risk of exponential infection. R0 2 is bad, R0 of under 1 unlikely. It wouldn't hurt to be prepared for a future hellscape.

On camera in my mask right now because it can't be contained unless I washed my hands every other moment. I never touch my mask from the moment I put it on to the moment I take it off. I don't want to put it away every time I touch something just to risk contamination.

I'd like to take a moment to thank the small portion of the medical on the field front line. From infectious disease to dialysis to nurses to techs who risk corona every time because it is not blood-born it is an air-borne very contagious disease.

Figure 14.3c. Text Representative of 'Fearful', 'Angry', 'Anticipatory', 'Sad', and 'Surprised' Tweets in Topic 128

A higher viral load means sicker people so healthcare professionals have increased risk. These are the lessons we learned from HIV. It is clear that when people have an undetectable viral load they tend to do much better than those with high viral titers.

I'd be curious to know the rider turnover rate per hour, per cubic meter of space, for elevators compared to subways. That will tell us the risk of infection with the virus in chambers because they are a smaller space like elevators. If it means heavier viral load per meter or faster turnover?

Coronavirus is responsible for developing a new form of kinky edge play by contacting sex workers as though you want to arrange an irl session to get the feeling of danger and then the thrill of dropping off halfway through negotiations bc jk actually too scared of covid to meet up.

The threat of violence is a great deterrent though. There are lots of anti mask motherfuckers who will not think twice before trying pass you like a former junior college O lineman. Not doing anything can be much better de escalation for the supermarket checker.

@[government official] we know better. Yes the threat may not have been strong at the time those data were compiled but it takes one asymptomatic individual to spread the virus around and weeks later the numbers of cases will climb.

Emotions
Fear
Anger
Anticipation
Sadness
Surprise

The significant decrease in “Disgusted” tweets about the infectiousness of COVID-19 and other viruses, the focus of topic 128, points to a diminished tendency to focus on infectiousness of COVID-19 both independently and compared to other viruses like HIV over time, particularly after April 2020 (Figure 14.3a-b). They also shed light on some of the concepts popularized during the pandemic that were previously unfamiliar to most people outside of science, public health, and health care, like “R0” (R_0[12], pronounced “R not”) (Figure 14.3b). Topic 128 provides evidence that people expressed less “Disgust” over COVID-19’s potential R_0 of 2+ after the initial peak case counts in March 2020 (Figure 14.3a).

Tweets in topic 140 were often reports about observations and experiences during COVID-19. They most often expressed “Disgust” over things witnessed in public, like the “mask refuser” who was alleged to be “having a tantrum inside the grocery store because they consider it a threat to their life,” or the observation that a grocery store cashier was shielded with a wall of plexiglass (Figure 14.4b). Not all emotional contexts involved observations in public spaces, though. For instance, the peak timing of tweets in topic 140 between March 2020 and May 2020 indicates that the “Joyful” context in which a user encourages others by providing cute animal footage from their time at home with their pets provides a report from the field (Figure 4.4c), which happened to be home for most people due to shelter-in-place orders in the United States that lasted for most of March, April, and May 2020 (Figure 14.4a).

[12] R_0 is a measure of how infectious a disease is based on the number of others predicted to be infected by a single infectious individual.

Figure 14.4a. Estimated Change in Topic Prevalence over Time for Topic 140, Smoothed, by Emotions with Significant Effects on Tweet Content

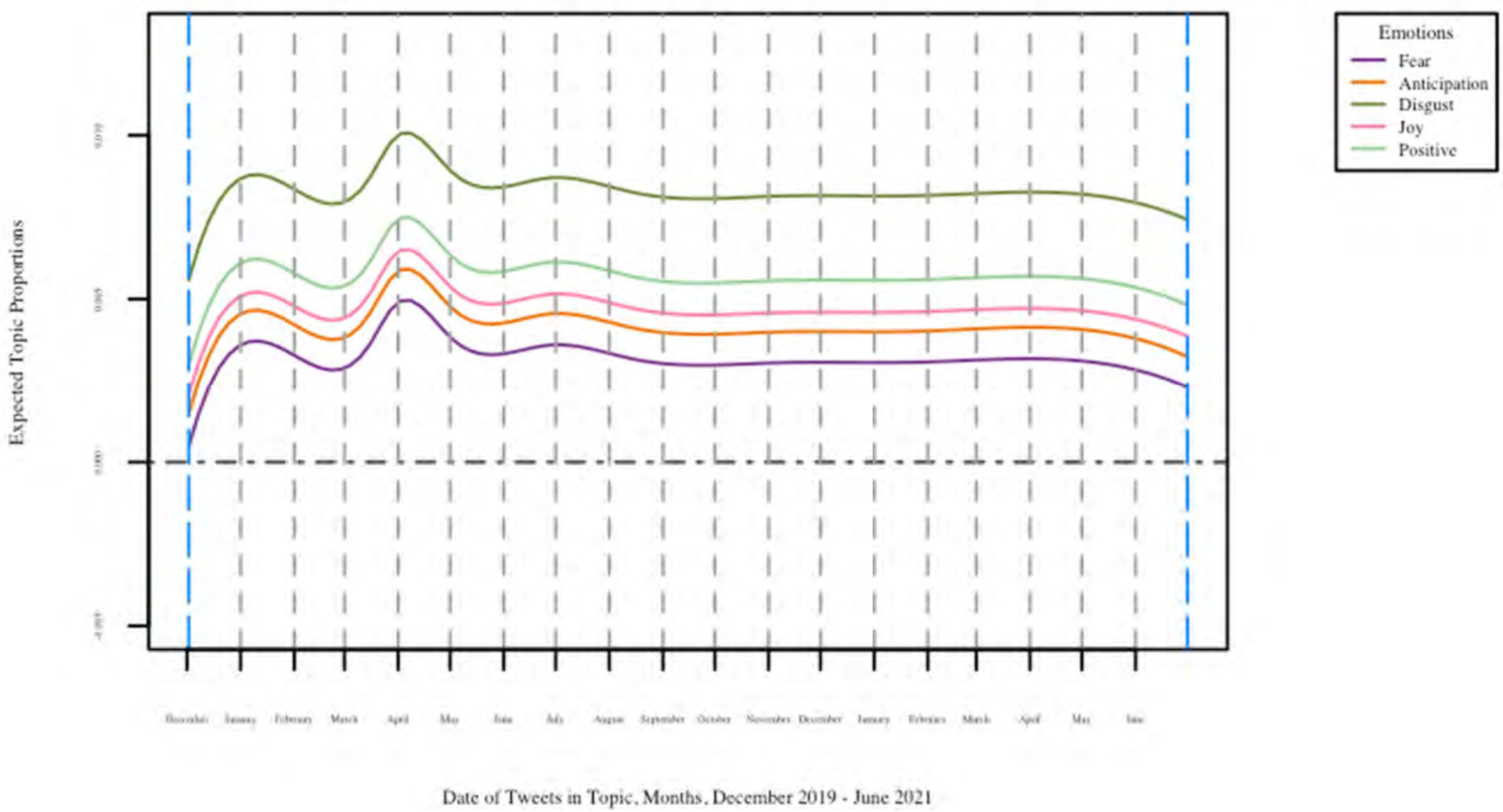


Figure 14.4b. Text Representative of 'Disgusted' Tweets in Topic 140

@[user] you need check out the @[shopping center] store near Kaiwah Island, SC. I was appalled by the lack concern covid associates aware social distancing protective gear plexi feel safe help

@[government official] I mean this with no disrespect-it's not safe enough to reopen the country. The governor of PA says it's still too dangerous outside. When we can go to the grocery store without a mask one will know it is safe to go. For now we are still in mortal danger

I want to re-calibrate my risk tolerance to drive to the grocery store in a combo mask-gloves. I feel that amongst walkers, cyclists, and kids easter parties in front yards, families shopping together at the store will show strong ranks on a local scale.

Wow. This mask refuser is having a tantrum inside the grocery store because they consider it a threat to their life.

Figure 14.4c. Text Representative of 'Fearful', 'Anticipatory', 'Joyful', and 'Positive' Tweets in Topic 140

Figure 14.5a. Estimated Change in Topic Prevalence over Time for Topic 151, Smoothed, by Emotions with Significant Effects on Tweet Content

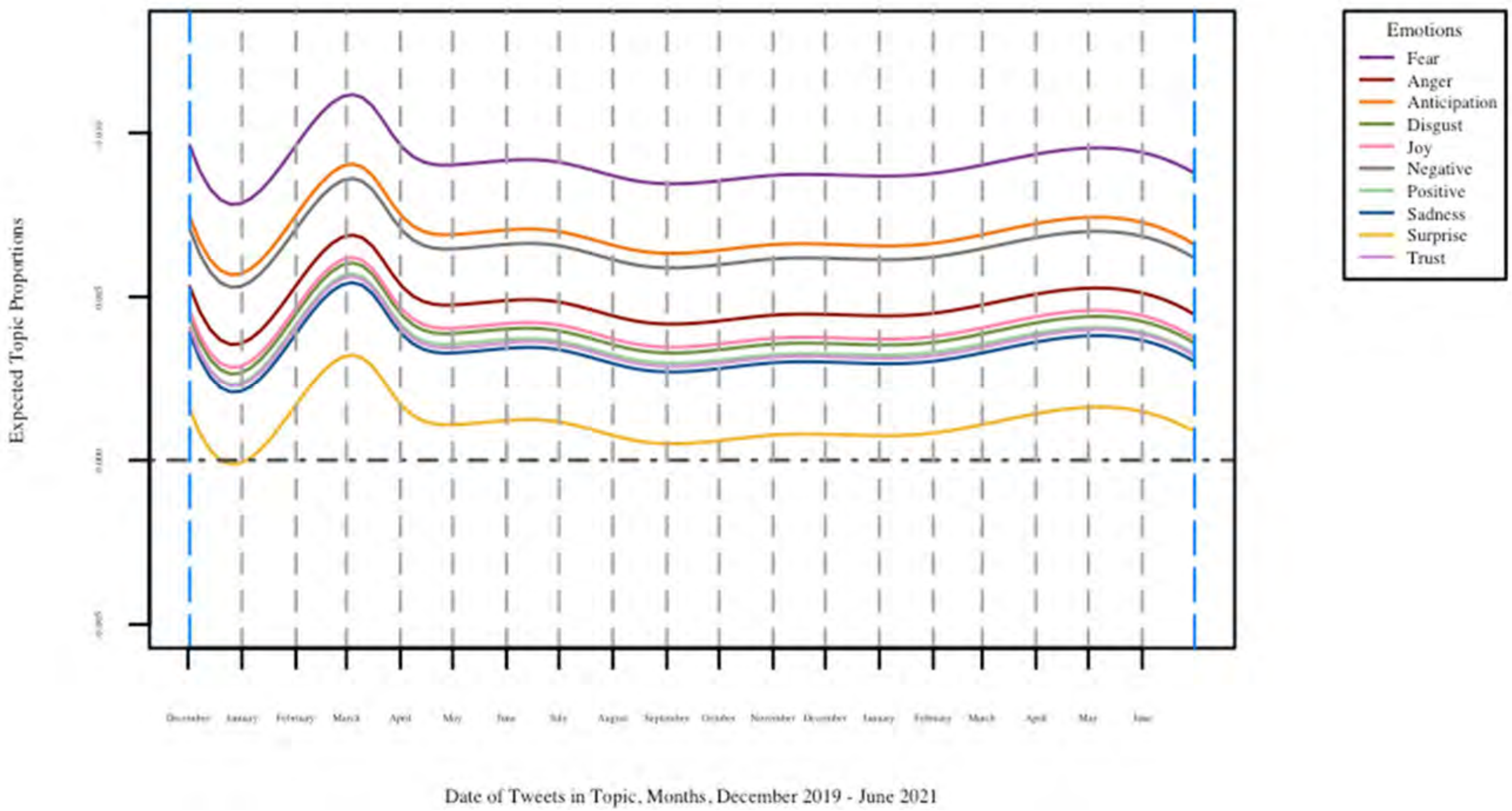
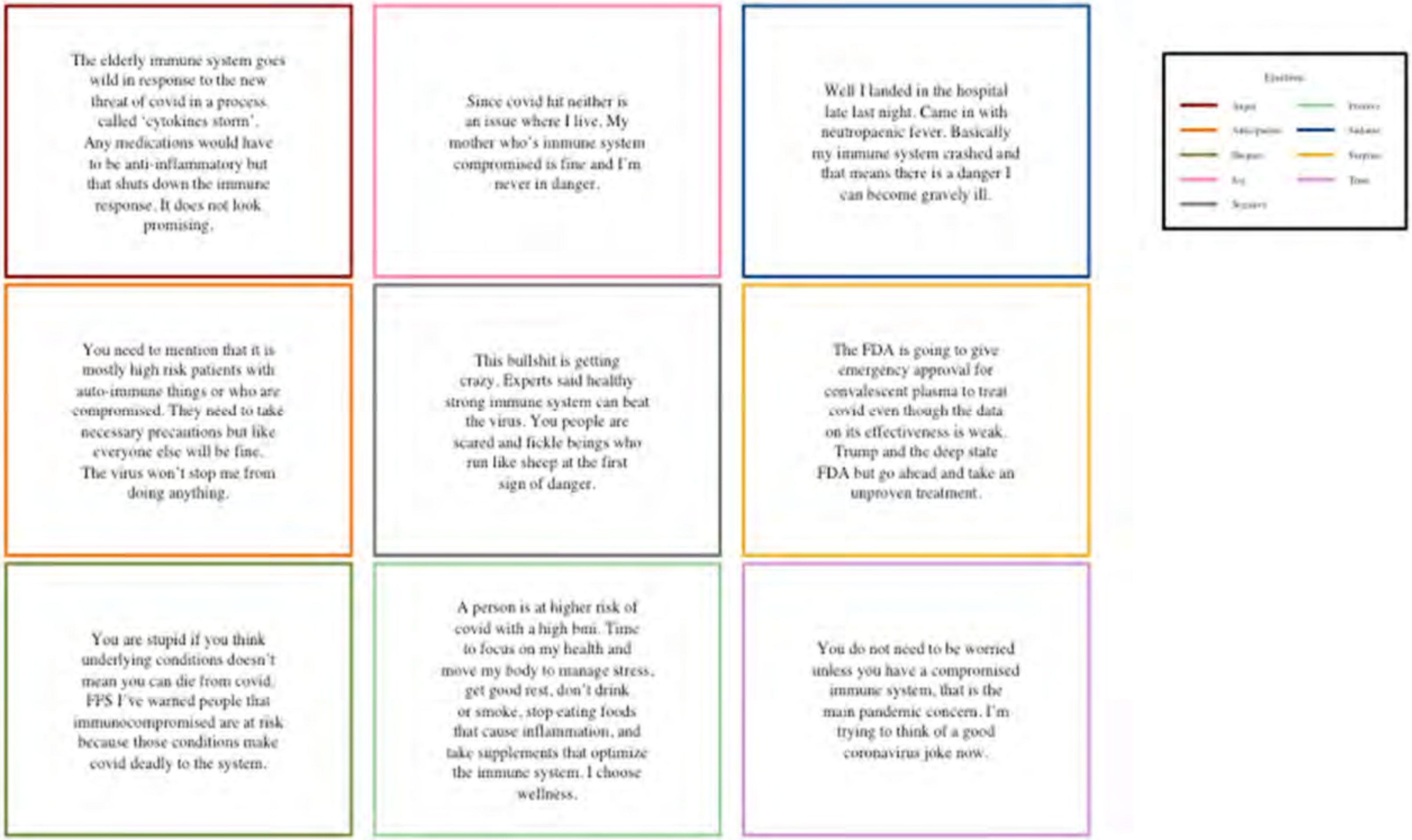


Figure 14.5b. Text Representative of 'Fearful' Tweets in Topic 151

@[user] unhealthy alcohol consumption may lower the immune system's defenses. It's well reported that covid is primarily attacking the respiratory system so smokers have the biggest risk.	Pneumonia happens when the infection is able to enter deeper into the lungs. How sick get from covid depends on how well the virus is able colonize. People with compromised lungs and immune systems are in danger be of that fact alone.
My sister had a heart transplant in October and we wear. a mask since she has a compromised immune system. Thanks for the concern.	Coronavirus isn't only affecting elderly people, it's all ages with compromised immune systems and other illnesses in the high-risk category. I'm disabled and immunosuppressed and I matter. The ill matter. The elderly matter. The healthy matter. HUMANS matter.

Figure 14.5c. Text Representative of 'Angry', 'Anticipatory', 'Disgusted', 'Joyful', 'Negative', 'Positive', 'Sad', 'Surprised', and 'Trusting' Tweets in Topic 151



The predominant emotional context of "Fear" in topic 151 given the significant decrease over time after an initial peak in prevalence between March—May 2020 is a good representation of just how frightened many people were at the beginning of the pandemic, but also of how quickly many members of the American public recovered from that "Fear." Topic 151 "Fearful" tweets suggesting things like "coronavirus isn't only affecting older people it's all ages with compromised immune systems" and discussing the biological process that occurs when someone has Pneumonia are evidence that many of these early Fears were related to uncertainty about the risk of COVID-19 (Figure 14.5b).

Tweets in other emotional contexts in topic 151 are a sign that, even when people did not feel frightened by the risk of COVID-19 in the earliest months of the pandemic, they felt some degree of disbelief and shock over the newly present risk.

Sometimes the disbelief was explicit and used profanity to indicate a heightened intensity of negative sentiment, like the example "negative" tweet where a user proclaims, "this bullshit is getting crazy" (Figure 14.5c). Other times it was more subtle, coming through in the need to report one's own discovery that the risk of COVID-19 existed and could be dangerous. For instance, an example of "Sad" tweet texts highlights the common circumstance of discovering how dangerous the virus was upon becoming "gravely ill" and hospitalized (Figure 14.5c).

TOPICS UNAFFECTED BY TIME

The prevalence of the remaining topics in the 180-topic model of general risk tweets was not significantly impacted by time in any model. These included topics 8, 68, 82, 98, 105, 106, 110, 113, and 141. However, at least one emotional sentiment was a significant predictor of content in all 9 topics unaffected by time, and at least one emotion per topic had a significantly different effect on topical prevalence than Fear. This is evidence that the content and prevalence of these topics was significantly shaped by emotion, and while it is possible that there are other covariates that interacted with emotional sentiment to shape prevalence and content of tweets in topics 8, 68, 82, 98, 105, 106, and 110, these results are a good indication that “time” can be eliminated from the list of potential covariates working alongside emotional sentiment to shape the prevalence and content of tweets about risk in these topics during the first 19 months of the COVID-19 pandemic. (Table 3-4)

CHAPTER 5

DISCUSSION, LIMITATIONS, AND CONCLUSIONS

While there has been much speculation as to what is said about COVID-19 risk, there has been no comprehensive compilation of the themes of COVID-19 risk ideology. This is a necessary first step to any comprehensive overview of the things said about COVID-19 risk because the context and therefore meaning of anything said about COVID-19 risk is, in part, shaped by the understanding of the social phenomena and/or social institutions to which an idea relates.

This study aimed to set parameters around the concepts of risk and risk mitigation during COVID-19 that captured the wide variety of ideas and emotions surrounding risk for people in the United States. I accomplished this for at least one segment of the United States population by analyzing personal accounts in the form of tweets, specifically those where Twitter users posted about their perceptions of risk and its mitigation. I also proposed a new approach to the structural topic model, which I call the "seeded structural topic model" (seeded stm), reflecting my use of seeded Latent Dirichlet Allocation (seeded LDA) to build training measures for use in structural topic modeling (stm). Time series and network analyses were used as postestimation techniques to aid with interpretation of the seeded structural topic model results.

One important takeaway from the network analyses is the importance of emotion for understanding the many different interpretations of and feelings about a single social fact. The analyses demonstrated that the various understandings of COVID-19 risk and risk mitigation among the U.S. public during the first 19 months of the COVID-19 pandemic were highly nuanced. While they can be characterized as generally relating to several broad social issues during the COVID-19 pandemic, there are a variety of factors understood as relevant to each issue, and several emotionally driven perceptions of these factors as they relate to each issue. This includes multiple viewpoints expressing a single emotional context of the same factor relating to an issue.

Many have tried to neatly categorize perceptions of COVID-19 risk, including those about risk mitigating behaviors, into two opposite views of "pro" versus "anti" risk and "pro" versus "anti" behavior. Furthermore, those who are "pro" risk are often framed as "anti" behavior, while those who are "anti" risk have been characterized as "pro" behavior, effectively lumping people into two camps of risk ideology based on their acceptance of risk mitigating behavior. The results of this study expose a major flaw in reducing risk ideology to two categories based on perceptions of risk mitigating behavior. In doing so, we ignore that health behaviors to mitigate risk are not a monolith, and that there were several risk mitigating health behaviors identified by scientists as potentially important for mitigating the specific risk of the SARS-CoV-2 virus.

The lumping of risk ideology, perception of risk mitigating vs. risky health behavior, and participation in risk mitigating vs. risky health behaviors also conceals the importance of other factors for determining participation in a risk mitigating behavior, independent of ideological views about risk and behavior. Most importantly, resistance to risk-mitigating behavior is not synonymous with engagement in risky behavior, but engagement with risky behavior may be tied to certain "pro-risk" ideologies.

Below, I provide an overview of the "social facts" of COVID-19 risk as identified in tweets about risk posted by Twitter users in the United States between December 2019-June

2021, or what I label the "initial phase" of COVID-19. Next, using the Health Belief Model and The Risk Society theories as frameworks, I explain the possible connection between these three dimensions of COVID-19 risk ideology and behavior to mitigate the risk of COVID-19, given the "social facts" of COVID-19 risk (Beck 1996; Becker 1974). I end with a discussion of the limitations of this study, recommendations for future research in sociology, and recommendations for public health policy to increase engagement with risk mitigation in face of new recombinant variants from the omicron lineage like XBB.1.5 as we mark the fourth year of life with SARS-CoV-2.

SETTING THE [SOCIAL] FACTS STRAIGHT ABOUT RISK IDEOLOGY AND COVID-19

Ideological views about risk are multi-dimensional and best characterized as operating along a spectrum within and between dimensions. I identify three main aspects of the "social facts" informing "risk ideology" during COVID-19 which may work alongside other social characteristics like race, gender, socioeconomic status, education, religious affiliation, political ideology, and disability status to shape whether and how someone engages with a health behavior to mitigate the risk of COVID-19. I argue that the many dimensions of COVID-19 risk ideology can be understood in terms of three main aspects, all relevant to the "social fact":

1) the understanding of a social fact
2) the emotion surrounding one's viewpoint of a social fact
3) the understanding of the social fact's relation to larger social phenomena or social institutions

At the lowest level (most specific) were emotions embedded in facts. There were many instances where there was consensus that something was a fact, and consensus that the fact was related to a broad theme like politics, but different emotional sentiments attached to those facts indicating that the interpretation of the fact varied. These interpretations largely related to whether something “should” be fact, or the interpretation of a fact as inherently right or wrong, good or bad, harmful or harmless, etc. For example, it was a fact that COVID-19 risk was more severe for disabled and elderly people, but depending on the emotional sentiment, this was interpreted as meaning three different things: COVID-19 was harmless, COVID-19 was not severe for healthy people, or COVID-19 was severe for everyone and even worse for the medically vulnerable.

The Focus of the Facts: Social Phenomena and Institutions

Tweets about general risk during the early phase of the COVID-19 pandemic reveal at least 10 important themes of COVID-19 risk ideology, constituting the highest (most general) level of the multi-dimensional ideology. These are the broad social phenomena to which the social facts of risk relate, and their importance is not in any objective tie to a set group of social facts, but in the presence of a perceived tie between the phenomenon and fact:

1) Politics

2) Social Media

3) Mandates and Guidelines

4) Risk Mitigating Health Behavior

5) Medically Vulnerable Social Groups

6) Frontline Workers

7) Other Potentially Vulnerable Groups

8) Profane Expressions

9) Life and Death

10) Sickness and Symptoms of Illness

The 180 topics of discussion in the final model tended to relate to these themes, but there was overlap, with some topics falling into more than one category. Top words and example text generated from tweets included in a topic indicate that there are several "social facts" about each topic. These facts and their grouping within a topic provide information about which social phenomena the users tweeting on that topic might have perceived as relevant to it. For example, the "social facts" of risk during COVID-19 included that there were declarations of emergency, and more specifically that there were declarations of emergency at the local, state, and federal levels, and outside of the United States.

The Social Facts as Defined by Twitter Users in the U.S.

The "social facts" of COVID-19 risk, as defined by Twitter users in the United States, include emotionally driven variations of facts about the 10 social phenomena/institutions outlined in the previous section.

Political Facts.

Political facts dealt with defining COVID-19 risk as being defined by some social institution. In this case, the social institution was politics. At the most general level, then, the facts of COVID-19 risk included:

1) COVID-19 risk is political
2) COVID-19 risk mitigation is political

Political facts of COVID-19 risk were also attached to specific political institutions spanning many levels of government from local to federal. They also included facts about specific political actors within these institutions. Facts stemming from the ideas that COVID-19 risk, and risk mitigation, are political included:

1) COVID-19 risk is a public health emergency

2) COVID-19 risk is a national security threat
3) COVID-19 risk is a foreign, not home-grown, threat
4) COVID-19 risk is severe enough to require mitigations in the State of California
5) COVID-19 risk is not bad enough to implement long-term requirements for its mitigation in the states of Alabama, Florida, Georgia, and Texas.
6) COVID-19 risk varies a lot at the local level in the states of Georgia and Texas
7) COVID-19 risk is bad enough to allow mandated mitigations at the local level in certain large cities and counties in the states of Texas and Georgia, like Houston, TX, and Fulton County, GA.
8) COVID-19 risk is a legal matter to be settled by the courts
9) COVID-19 risk existed during President Donald Trump's time in office
10) COVID-19 risk was eradicated by President Donald Trump's actions, including "Operation Warp Speed."
11) COVID-19 risk was a lie/hoax spread by deep government actors, including Drs. Anthony Fauci and Deborah Birx.
12) COVID-19 risk did not exist during President Donald Trump's time in office
13) COVID-19 risk was a means for Speaker of the House Nancy Pelosi to seize power
14) COVID-19 risk was much lower during President Joe Biden's time in office than in President Donald Trump's time in office
15) COVID-19 risk was the product of the Biden administration taking over in 2021
16) COVID-19 risk remained about the same under both the Trump and Biden administrations

17) COVID-19 risk was a distraction from the real risk that the government was using 5G to spy on Americans
18) COVID-19 risk was the result of an experiment-gone-wrong and being defined as zoonotic to coverup the actions of the Chinese and/or U.S. governments
19) COVID-19 risk was much worse than the U.S. and other countries' governments were willing to admit

The final two political facts about COVID-19 risk, as defined by Twitter users in the United States, alleged that the construction of COVID-19 risk was a technique to distract from other risks. These included things like racism and climate change:

20) COVID-19 risk was overblown by the federal government to keep people from protesting racism and associated police violence against Black people
21) COVID-19 risk was overblown to protect corporate lobbyists' interests like ignoring climate change.

COVID-19 facts stemming from the idea that risk mitigation is political related to facts about risk severity and the necessity for risk mitigation. They included the following:

1) COVID-19 risk mitigation is necessary when it is required by government mandate
2) COVID-19 risk mitigation is unnecessary
3) COVID-19 risk mitigation is a personal decision, regardless of government mandate
4) COVID-19 risk mitigation, specifically sheltering-in-place and masking, should only be required for the medically vulnerable

5) COVID-19 risk mitigation can only be effective protection for the vulnerable with a government mandate in place to ensure majority compliance
6) COVID-19 risk mitigation was important, warranting government mandates at the beginning of the pandemic, but less so after vaccines became available
7) The removal of risk mitigation mandates was an intentional act by the federal, state, and local governments to reduce the population of disabled people (some went as far as to term this "eugenics")

Social Facts related to Social Media.

There were far fewer facts about some of the other institutions and phenomena than there were about politics. This included facts about social media, of which there were only a handful:

1) Facebook was a hub for misinformation about COVID-19 risk
2) Facebook was the preferred platform for finding news about risk among social groups like members of the "Baby Boomer" (i.e. "Boomer") generation of people born prior to the year 1965, and supporters of former President Donald Trump
3) Social media was not a valid source of information about COVID-19 risk
4) Twitter, specifically #COVIDIsAirborne Twitter, were possibly the only valid source of information about COVID-19 risk

The final social fact of risk related to social media demonstrated the technology's importance as a tool for assessing risk. This was one of few points of widespread agreement about risk, even among those who felt information about how to handle risk and the biological aspects of risk should come from elsewhere. Social media provided a glimpse of other people's behavior surrounding risk mitigation, including risk mitigating behavior, but also behaviors to resist mitigation.

1) Social media should be consulted to assess whether and where people were mitigating risk in public, and to assess where one might encounter other risks like violence from people who strongly detest risk mitigation

Social media could provide information about the location of a super spreader event, for example. Sometimes people posted their own footage while attending the event, and this was used as an indication that the person was "unsafe" for those looking to avoid COVID-19 risk. Other times people used social media as a tool to shame and "doxx[13]" others engaging in risky behavior by making a spectacle of their behavior, often without their knowledge.

The most important finding related to social media, though, did not come in the form of "social facts." That so many conversations about assessing risk revolved around social media's role in influencing risk mitigating behavior gives credit to the use of social media testimony like tweets to explore COVID-19 risk ideology. Even among those who did not agree that social media was a valid source of information about risk, there was consensus that many people in the United States still used social media platforms like Facebook and Twitter as a primary news source. It appears that social media testimony represented AND influenced COVID-19 risk ideology, including ideology about and participation in risk mitigating behaviors.

Social Facts Involving Mandates and Guidelines for Risk Mitigation.

Many of the social facts about mandates/guidelines were also political facts, outlined above. However, not all could be characterized as political. Most notably, there were several social facts about mandates and guidelines that were distinctly not political, with some even emphasizing the importance of private institutions over political ones for implementing mandates

[13] "doxxing" is the practice of finding and publishing private information about other people to a public location on the internet, often as an intentional means to inflict harm on that person

and guidelines for behavior. Social facts about mandates and guidelines that were not political included:

1) Implementing risk mitigating behavior mandates can be bad for business
2) Implementing mandates for behavior is a crucial step for employers invested in the safety of their employees
3) COVID-19 risk was severe enough that most people should work from home to help curb the spread
4) COVID-19 risk was an excuse for employees to avoid engagement with their jobs
5) Businesses are not accessible to disabled and elderly people during COVID-19 without mandates for risk mitigating behavior

There were also facts related to how effective mandates and guidelines were for mitigating the risk of COVID-19. As with many of the social facts of COVID-19 risk, they included two opposing views:

1) Mandates and guidelines are an effective tool for encouraging participation in risk mitigating behavior because they indicate that there is a risk severe enough to be mitigated
2) Mandates and guidelines are useless because people have made up their minds to either face the risk or avoid it.

The Social Facts of Risk Mitigating Behavior.

Facts about health behavior to mitigate risk tended to involve how effective a behavior was, how necessary a behavior was, and for whom a behavior was necessary. Facts about behavioral effectiveness varied, and they were highly sensitive to time. Coincidentally, this is the first social fact pertaining to risk mitigating behavior:

1) The scientific understanding of the severity of COVID-19 risk changed as we became more familiar with the virus

Relatedly, as the scientific understanding of that risk changed, the understanding of whether and how to mitigate it changed, too:

2) At the beginning of the pandemic, fomites were a main vector of COVID-19 risk that should be mitigated with hand washing, frequent disinfecting of high-touch surfaces like door knobs and point-of-sale stations, and by wearing gloves.
3) By mid-March 2020, it was clear that aerosols were a main vector of COVID-19 risk that should be mitigated with masks, preferably N95 respirators

The facts demonstrated many degrees of scientific consensus and disagreement about COVID-19 risk and risk mitigation. For example, just as the scientific understanding that COVID-19 is airborne emerged, resistance to this fact grew alongside it. This meant the existence of facts like the following:

4) Handwashing is the most important tool for mitigating the risk of COVID-19

For many experts in medicine and public health, the revelation that COVID-19 was airborne did not change their understanding of the social facts specific to risk mitigation. These experts did not necessarily reject that COVID-19 was airborne, but many rejected the idea that masks were the best solution to mitigate the risk even if it were airborne. They provided a variety of reasons for rejecting masks:

1) Masks are not effective tools for mitigating the spread of COVID-19
2) Masks could be effective tools for mitigating risks only if people use them consistently and correctly

3) People without medical training are unlikely to use masks correctly, even if they use them consistently
4) Masks do not mitigate the spread of COVID-19, but N95, N100, and P100 respirators do mitigate the spread of COVID-19

Some provided alternative ideal mitigations for airborne disease. For example, many compared masks to other risk mitigation tools, presenting as fact that the alternatives were quite useful:

1) Mitigating the risk of COVID-19 requires improving air quality indoors
2) The risk of airborne spread of COVID-19 can be effectively mitigated with HEPA filtration and ventilation to ensure indoor air is replaced rather than recycled
3) HEPA filtration does not require a high-end air purifier, it can be accomplished by attaching HEPA-grade furnace filters to box fans using the Corsi-Rosenthal design (Dal Porto et al. 2022; Rosenthal 2020).
4) UV-C and Far-UV technology kills the SARS-CoV-2 virus, effectively eradicating its risk

There were also facts asserting that none of these technologies was sufficient on its own, and thus, it was a fact that:

5) Risk mitigation during COVID-19 requires a layered approach combining masks, HEPA filtration, ventilation, UV technologies, and avoiding indoor spaces

Risk mitigation also involved place, evidenced by the previous fact highlighting that avoiding indoor spaces should be part of a layered approach to risk mitigation for COVID-19. It was widely accepted as fact that:

1) There is little to no risk of COVID-19 transmission outdoors

Not everyone agreed, though. Others strongly felt that:

2) COVID-19 risk is omnipresent

This fact was tied to an acceptance of the need for a layered approach to mitigation as fact. The items included in a layered approach were sensitive to time, though, and just as there was an understanding that a layered approach should incorporate masks, HEPA filtration, ventilation, UV technology, and the avoidance of indoor (poorly ventilated) spaces, after vaccines became widely available in 2021, there were two distinct understandings of the layered approach to risk mitigation:

1) Vaccines eliminated the need for a layered approach to risk mitigation
2) Vaccines were an additional tool to add to the still necessary layered approach to risk mitigation

These related to the last important set of facts about risk mitigating behavior during COVID-19. There were several different understandings of which social groups were at risk of COVID-19 complications like hospitalization and death, some of which were sensitive to time and the vaccine rollout in 2021. They included the understanding that:

1) Everyone needs to participate in risk mitigation because everyone is at risk of complications of COVID-19

In this case, the variation in risk is ignored in the fact that everyone is at risk, the implication being that the risk ranges from bad to extremely bad. This was distinct from other views focusing on degrees of vulnerability:

2) COVID-19 is most severe for people with chronic illnesses and elderly people

3) COVID-19 is only severe for immunocompromised people, people with asthma, people with diabetes, obese people, and people over the age of 65 who are not “active” and “healthy”
4) COVID-19 was a severe risk at the beginning of the pandemic, but the risk was later eliminated for the “healthy” vaccinated
5) COVID-19 risk after the introduction of vaccines was highest for unvaccinated people

Like social facts of COVID-19 risk suggesting that there were varying degrees of vulnerability to COVID-19, there was an understanding of who needed to mitigate risk and how they should do so:

1) It was necessary for everyone to participate in risk mitigation early in the pandemic because the risk was widespread
2) Mitigating the risk of COVID-19 requires widespread vaccination
3) After the introduction of vaccines, unvaccinated and immunocompromised people should wear a mask to mitigate their risk
4) After the introduction of vaccines, vaccinated people no longer needed to mask to protect themselves
5) After the introduction of vaccines, participation in non-pharmaceutical interventions like masking was optional but recommended around unvaccinated and immunocompromised people
6) After the introduction of vaccines, engaging in risk mitigation was a personal choice, and not doing so was seen as an active choice to confront risk rather than avoid it

7) After the introduction of vaccines, risk behaviors like virtual schooling and working from home were harmful, not helpful

Facts about Vulnerable and Potentially Vulnerable Groups.

Three of the broad themes characterizing the "social facts" of COVID-19 risk involved vulnerable social groups, each focusing on a different set of groups. The facts suggest that the reasons these groups were considered vulnerable varied. Vulnerable and potentially vulnerable groups during COVID-19 included the following:

1) Disabled People
2) Elderly People
3) Frontline Workers
4) Adolescents
5) Young Adults
6) Athletes

There were a variety of takes as to whom these groups included. For example, some people referred simply to the "disabled community" or "vulnerable folk," indicating the social fact that:

1) Any person with a disability or chronic illness qualifies as highly vulnerable to complications and death from COVID-19 infection

Others highlighted specific disabilities and chronic illnesses. These eventually included illnesses that resulted from a COVID-19 infection:

2) People with diabetes are more vulnerable to COVID-19 risk
3) People with asthma are more vulnerable to COVID-19 risk
4) People undergoing chemotherapy are more vulnerable to COVID-19 risk

5) People on immunosuppressants are more vulnerable to COVID-19 risk
6) People with long-COVID are more vulnerable to COVID-19 risk
7) Anyone who has been infected with COVID-19 can be considered among the most vulnerable due to the immune dysregulation and micro clots shown to appear in upwards of 80% of people previously infected with the disease

In the case of elderly and disabled people, vulnerability was tied to medical vulnerability. For the other groups, vulnerability was tied to the social fact that certain groups had a high and somewhat unavoidable risk of catching COVID-19. This included the inability to avoid infection due to employment as a frontline worker:

1) Healthcare workers have a high risk of exposure to COVID-19 that is unavoidable because they are frontline workers
2) People who work in grocery stores have a high risk of exposure to COVID-19 that is unavoidable because they are frontline workers
3) Police, fire fighters, and emergency medical services (EMS) workers have a high risk of exposure to COVID-19 that is unavoidable because they are frontline workers

There was somewhat of a consensus that frontline workers, the elderly, and disabled people had increased vulnerability to COVID-19 risk. There was less agreement on other facts of vulnerability during COVID-19. The facts of risk surrounding other social groups included:

1) There is little risk of COVID-19 infection in schools, adolescents are not similarly vulnerable to catching COVID-19 as frontline workers

2) There is little risk of COVID-19 infection in schools because adolescents are less medically vulnerable than other age groups and therefore less likely to spread the disease both in and outside of school
3) Adolescents remain at extreme risk to COVID-19 infection when they attend in-person school without risk mitigation like masks
4) Adolescents remain at extreme risk to COVID-19 infection when they attend in-person school, regardless of risk mitigation.
5) The risk to adolescents is specific to children with pre-existing medical conditions, and thus, a risk related to medical vulnerability and not age

For athletes and young adults, concerns about vulnerability were tied to communal settings and other risky behaviors like drinking. Just as with children, there were facts opposing the idea that these groups were at heightened risk alongside ones arguing heightened vulnerability. The following facts about young adults and athletes were evident in the tweets about risk during the first 19 months of the COVID-19 pandemic:

1) Athletes have a high risk of exposure to COVID-19 due to travel and contact with players on other teams
2) Athletes are among the healthiest people in the U.S. population and are therefore at much lower risk despite their contact with communal settings
3) Young adults have a high risk of exposure if they live with roommates or in larger communal settings like college dormitories.
4) Young adults are at the prime of their life in terms of health and fitness, unless they have a pre-existing medical condition, they have much lower vulnerability than others in the United States regardless of communal living

5) Young adults engage in risky behaviors related to drinking that increase their risk of exposure to COVID-19, including contact with crowded indoor settings like bars and house parties and contact with other people by sharing beverages, intimate touching, and sexual intercourse.

Profanity as Social Fact.

Profane tweets provided information about some of the perceptions of other social facts. The expressions of these perceptions through the use of profanity could be considered social facts in their own right. These included the widely understood facts that:

1) COVID-19 is “bullshit”
2) COVID-19 risk mitigation is a “fucking” waste of time
3) COVID-19 risk mitigation is extremely “fucking” annoying
4) It is “bullshit” that there are so many people who deny COVID-19 risk
5) If you care about vulnerable people, you will put your “damn” mask on
6) Pointing out other people’s lack of risk mitigation by saying they were endangering others made you an “asshole”
7) Refusing to engage in risk mitigating behavior when asked made you an “asshole”
8) Refusing to engage in risk mitigating behavior to protect vulnerable people unless it was required made you a “shitty” person
9) People who thought COVID-19 was a risk were “scare little bitches”
10) People who thought COVID-19 was not a risk were “stupid motherfuckers”
11) People who acknowledged COVID-19 was a risk but ignored risk mitigating behavior were “dumb asses” and “idiots”

These facts demonstrate an important aspect of varying COVID-19 risk ideology—that differences in this ideology could lead to conflict ranging from more benign name-calling to extremes involving violent altercations.

Facts about COVID-19 Symptoms, and Life/Death during COVID-19.

The final set of social facts related to COVID-19 risk and risk mitigation included facts about COVID-19 symptoms. These included their severity, the issue of death from and during COVID-19, and the issue of quality of life during COVID-19. These were also highly sensitive to time, with important transitions after the "lockdown" phase of the pandemic between March and May 2020, and again when vaccines became available to most U.S. adults in early 2021. Additionally, the discussions of symptoms themselves was sensitive to time, not just because of vaccines, but because of actual changes in symptomology between the alpha and beta variants.

These changes are incredibly important, as the symptomology and severity of COVID-19 symptoms were alleged to have changed even further with the introduction of the "Delta," "Omicron," and most recently, the omicron recombinant "XBB.1.5" variant in late 2022 and early 2023. These findings give merit to the allegations by demonstrating that even allegedly minor changes in symptomology and severity were important influences on the social facts of risk during COVID-19 over time. They also point to an important potential focus for future research interested specifically in perceptions of COVID-19 symptoms and severity, indicating that any future research in this area should account for changes over time that may have continued beyond June 2021 as new variants of COVID-19 emerged through the third year of the pandemic. The facts of COVID-19 symptoms and their severity included:

1) Symptoms of COVID-19 are "mild" for most people

2) Symptoms of COVID-19 can become moderate to severe, in which case they may lead to hospitalization and/or death
3) A hallmark symptom of COVID-19 infection with the alpha and beta variants was the loss of smell and taste.
4) For "healthy" people, symptoms of COVID-19 were similar to the flu
5) For "healthy" people, symptoms of COVID-19 felt like a bad cold
6) For "healthy" people, symptoms of COVID-19 were comparable to seasonal allergies
7) Severe symptoms of COVID-19 required a ventilator, primarily involving the lungs
8) A common symptom of "long COVID," or persisting symptoms after a COVID-19 infection, was "brain fog"
9) Fatigue was a symptom of COVID-19 that could range from mild to severe
10) After "brain fog," another common symptom of "long COVID" included persistent fatigue made worse by exercise
11) Symptoms of "long COVID" were psychiatric
12) Symptoms of COVID-19 were only severe for elderly and disabled people
13) Symptoms of COVID-19 were no longer severe for "healthy" vaccinated people
14) Later in the pandemic, the majority of people with severe symptoms were unvaccinated
15) Children do not get severe symptoms of COVID-19 unless they have an underlying medical condition

16) Everyone is at risk of COVID-19 symptoms becoming severe, including young people and "healthy" people
17) Symptoms of COVID-19 were especially severe for people with asthma because they involved the lungs
18) Symptoms of COVID-19 were worse for people who qualified as being obese
19) One could reduce their risk of COVID-19 symptoms becoming severe by eating a lot of fruits and vegetables
20) Vitamin C reduces the symptom severity during COVID-19 infection
21) Zinc reduces the severity of COVID-19 symptoms

Another sickness-related issue surrounding death from COVID-19 included conflicting facts about the level of sickness and death in the United States. Some of the change over the course of the pandemic can be attributed to the information available from state and local governments and departments of health in the United States. For instance, early in the pandemic from December 2019 to about the middle of March 2020, facts about COVID-19 risk included the following, emerging in order, leading up to emergency declarations in the United States:

1) There are no COVID-19 cases in the United States
2) There are COVID-19 cases only in China
3) There are only COVID-19 cases in China and Italy
4) There are COVID-19 cases in the United States, but they are clustered in specific big cities like Los Angeles, Seattle, and New York City
5) There are no COVID-19 cases in rural towns

6) The only COVID-19 cases in the United States are among those who recently traveled to China or Italy and those on one of the cruise ships needing to evacuate passengers due to outbreaks onboard
7) There are no deaths from COVID-19 in the United States
8) The University of Washington has identified many cases of COVID-19 in recent samples collected for an ongoing study of the flu.
9) There are many more COVID-19 cases in the state of Florida than originally thought
10) Every resident of New York City should assume they have been exposed to COVID-19
11) There is no way of knowing how many cases of COVID-19 exist in the United States because testing is limited
12) There is no way of knowing how many cases of COVID-19 exist because healthcare is overburdened with patients and can only manage the most severe cases
13) There are several clusters of cases within long-term care homes for the elderly
14) There are a high number of cases in most location in the United States, too many for the health care system to manage.
15) There have been so many deaths in New York City that the morgues are full and there are ice trucks outside of the hospitals
16) The majority of deaths from COVID-19 were among elderly and immunocompromised people
17) No children have died from COVID-19 infection

18) A small number of children are dying from a secondary infection called MIS-C that develops after a COVID-19 infection

19) Death by suicide has increased as a result of pandemic chaos

After the initial lockdown phase, the facts still included the "fact" that:

20) no (or, "hardly any") COVID-19 cases or deaths existed.

They also included other social facts:

21) There are many more cases of COVID-19 in the United States than most people will admit

22) There are many more deaths from COVID-19 in the United States than are being reported.

23) Cases of COVID-19 in the United States are undercounted due to rapid-antigen testing performed at home

Finally, the facts of living with COVID-19 during the first 19-months of the pandemic included new norms for behavior and the popularization of previously niche hobbies. Life during the "lockdown phase" of the pandemic through about May 2020 was characterized by the following social facts:

1) Video conferencing was a primary means of communication for both work and checking in with significant others

2) Life during lockdown was isolating

3) Life was less isolating during lockdown if you could implement a routine, including routine social interaction with significant others

4) Restaurants were take-out only, or they were not open

5) New laws were put in place in some cities to allow for alcohol delivery, including with take-away food orders
6) School from Kindergarten through Higher Education transitioned to virtual learning
7) There was no childcare
8) Health care for non-COVID issues was put on hold
9) People turned to binge-watching television and movies through streaming services like Netflix to pass the time during lockdown
10) Many people adopted pets during lockdown
11) 'Everyone' is making bread
12) There were some displays of collective efficacy during the lockdown, like cheering health care workers from balconies at a set time every evening to offer support

The norms of daily life began to change around the same time mandates to shelter-in-place expired for most people in most locations in the United States, but this timing coincided with other incidents not directly related to the pandemic, particularly incidents of police violence. When George Floyd was killed by Minnesota police on May 25, 2020, there were mass protests in response. The date fell on the weekend of a major federal holiday in the United States, Memorial Day. Tweets about daily life mentioning things specific to the holiday weekend and/or death of George Floyd suggest that the following facts existed in late May-early June 2020:

1) Memorial Day weekend was the unofficial return to some semblance of normal, marking the end of "lockdowns"

2) The summer of 2020 was nicknamed "hot girl summer[14]" to mark the unofficial return to some semblance of normal
3) "Hot Girl Summer" activities included a return to in-person dining and in-person socialization, but doing so primarily in outdoor settings
4) People began to travel again during "Hot Girl Summer" but stuck to outdoor vacations, like camping, and locations they could reach by motor vehicle, thus avoiding the airport.
5) Widespread protests occurred throughout the Summer of 2020 and continued through the rest of the period studied in June 2021.

After this first summer of the pandemic in 2020, the facts of COVID-19 risk indicate a shift back towards the "lockdown phase" norms:

1) COVID-19 is not done with "us" (People in the United States)
2) Some schooling was virtual, some returned to in-person, and a new "hybrid" style of learning combining virtual and in-person learning emerged
3) Some schools mitigated the risk of COVID-19 by mandating masks for in-person learning

Not all the facts suggested a heightened sense of risk persisting into the latter months of 2020, though. There were also facts suggesting a refusal to return to "lockdown" phase norms. For instance, the following facts emerged around Summer 2020 with no information indicating they had changed by the end of the study period in June 2021:

1) The State of Georgia is fully reopened and welcomes visitors
2) The states of Florida and Texas will not allow mask mandates in schools

[14] "Hot Girl Summer" references a song of the same name released by Megan Thee Stallion (Megan Pete) in 2019 (Pete et al. 2019)

3) Major League Baseball (MLB) is back.
4) The National Football League (NFL) will not be cancelling the season due to COVID-19 risks
5) The NFL will allow fans to attend games
6) The NCAA conferences disagreed about whether changes should be made to the Fall 2020 college sports schedules to account for COVID-19 risk
7) The Southeastern Conference (SEC) will not cancel Fall 2020 sports due to COVID-19
8) The SEC will allow fans to attend football games at a limited capacity for the Fall 2020 season
9) The SEC will require fans to wear masks when not in their assigned seats for the Fall 2020 season
10) No NCAA conferences canceled the Fall 2020 sports season
11) The National Basketball League (NBA) will implement a bubble for the remainder of the 2020 season
12) Athletes across professional and college sports were given the option to opt out of participating in 2020 with no penalty

Finally, there were facts emerging towards the end of the study period indicating widespread celebration over the CDC's announcement that vaccinated people were safe to take off their masks. The announcement set up for the social fact, playing on the previous summer's nickname while referencing the key to freedom, vaccines:

1) Summer 2021 was known as "hot vaxx summer"

The Emotions attached to Social Facts of COVID-19 Risk and Risk Mitigation

The emotional context of tweet content can give some insight about the meaning of the above social facts for behavior during the pandemic. While the emotional contexts are not sufficient explanation for varied behavioral responses during the pandemic, they can provide useful information, particularly for understanding the extremes. Contexts of “Fear” provide additional information about why someone may choose to engage in a behavior, while contexts of “Anger” may be useful for the context of vehement resistance to risk mitigating behavior.

All emotional contexts provide useful information about COVID-19 risk ideology, but contexts of “Fear” and “Anger” may have an additional benefit of helping understand engagement with risk behavior in terms of “pro” and “anti” risk/behavior. This can be important for understanding the circumstances in which other risks are likely to arise from an encounter involving risk and/or risk mitigation for COVID-19. These included important circumstances like conflict, particularly violent conflict that was likely to arise in confrontations about mandated risk mitigating behavior.

The most common emotions attached to social facts rarely included contexts of “Joy” and “Positive” sentiment, and while slightly more frequent, there were also few contexts for which “Trust” was the dominant emotion. This is not necessarily an indication of widespread ill feelings about COVID-19 risk and its mitigation, but it *is* an indication that there were not widespread feelings of happiness, contentment, or optimism regarding the social facts of COVID-19 risk between December 2019 and June 2021.

Of emotions characterizing a largest proportion of content in a topic, “Anger,” “Anticipation,” and “Sadness,” were as uncommonly dominant as “Joy.” Three emotional contexts stood out as characterizing the largest proportion of a topic for the greatest number of topics. “Disgust” was the most commonly dominant, followed by “Surprise,” then “Fear.”

Prior research on the connection between emotion, perception of risk, and participation in risky versus risk mitigating behavior, has suggested that "Fear" may be attached to risk aversion and participation in behaviors to avoid risk. This would suggest that when "Fear" was a dominant emotion attached to a social fact, people were risk-aversive and "pro" risk mitigating health behavior. Importantly, the proportion was highest in the earliest months of the pandemic for most topics for which "Fear" was the dominant emotion.

The lone exception was a topic involving the risks of wearing masks versus the benefit of wearing masks for mitigating risks, where it would seem "Fear" was attached to two social facts, the fact that masking was an effective tool for mitigating the risk of COVID-19, and the fact that risk mitigating behaviors (in this case, masking) could cause more harm than good. This demonstrates something "crucial" about "Fear" and "risk" as they relate to risk mitigating behavior during COVID-19. If it truly is the case that "Fear" is linked with risk aversion during the COVID-19 pandemic as it has been shown in pre-COVID contexts, these findings point to different definitions of "the risk," the idea that many social facts about risk exist at any given time, as a crucial factor in determining participation in risk mitigating health behavior during COVID-19.

The connection between "Fear" and participation in risk mitigation during COVID-19 may be more complex than prior investigations of "Fear" and "risk" would suggest. In the case of COVID-19, it was not simply the "fact" that COVID-19 posed a risk and an associated "Fear" of the recognized risk. Instead, "Fears" about other risks relative to COVID-19 were important. In this case, someone may have "Feared" the risk of COVID-19 and endorsed the facts that it existed and was severe, but they may have avoided a specific mitigatory behavior like "masking" if they also believe the behavior to pose a risk. They may opt for another behavior, or they may decide to endorse the "fact" that COVID-19 risk mitigation was not worth the effort considering other, greater, risks. The clustering of "Fear" towards the beginning of the pandemic regarding other facts, though, was aligned with expectations based on existing research on emotion, risk, and behavior. The changing facts of risk may be linked to a lower presence of "Fear" surrounding that risk over time.

Also extremely important was the absence of "Anger" among the highest proportion emotions for most topics. Just as the presence of "Fear" alongside risk aversion was an expectation outlined by previous research on emotion, risk, and behavior, "Anger" alongside risk enthusiasm was an expectation outlined by previous research as a potential influence on health behavior. If this had been the case, the "Angry" example text should have indicated endorsement that a risk exists but a refusal to avoid it. Instead, Anger was often used alongside presenting, as fact, that COVID-19 risk does not exist, or that the risk is not severe enough to be worthy of special attention. In fact, the behavior of agentic risk-taking did not seem to really become popular until after the introduction of vaccines, and many of the risk-takers were people who had already taken actions to prevent risk, suggesting they were not as risk-enthusiastic as other research has found people expressing "Anger" to be.

The most common dominant emotions attached to facts, "Disgust" and "Surprise," were useful added context for understanding the social facts of risk. Given the wide variety of social facts attached to each emotion, and considering that within this variety were things like "Disgust" over partaking in but also over ignoring risk mitigation measures, "Surprise" that risk mitigation was necessary but also at people who actually participated in risk mitigating health behavior, and "Disgust" of the virus related to a "Fear" of its severity but also the opposite, "Disgust" that people were "hysterical" with "Fear" over something not understood as severe, this study provided evidence that emotion could not neatly explain the variation in risk behavior adoption during COVID-19 as a 1:1 behavior to emotion ratio.

Together, the social facts of COVID-19 risk, the social phenomena and institutions they involve, and the variety of emotions attached to each fact, provide important information about health behavior that is useful for understanding the varying degrees and methods of engagement with risk mitigating health behavior during the first 19 months of the COVID-19 pandemic among people in the United States. This is true for social facts about risk mitigating behavior related to COVID-19, but also of social facts about COVID-19 risk independent of mitigation. While emotions attached to social facts of risk during COVID-19 provide useful context for fine-tuning the understanding of how the facts themselves vary, they may not be the best predictors of engagement in versus avoidance of risk mitigating health behavior during COVID-19.

The Importance of Time/Date for Social Facts about COVID-19 Risk

The time series analyses point to another important aspect of variation in the facts of COVID-19 risk, specifically that they were sensitive to time. As varied as the social facts of COVID-19 risk were overall, they also changed quite a bit over the 19 months between December 2019 and June 2021. For example, the social fact that COVID-19 is airborne did not gain traction until well into 2020, while the social fact that COVID-19 is spread via droplets existed at the start of the pandemic and has persisted even with the emergence of conflicting social (and scientific) facts that the disease is airborne.

Changing perceptions of COVID-19 risk over time have been attributed to an objectively lower biological risk with the rollout of vaccines and vaccine boosters, with some going as far as to assert that the emerging variants have been less pathogenic despite being more transmissible. However, these “facts” do not match the true scientific facts demonstrating that the biological risk of COVID-19 remains, that risk being the proven high likelihood of immune dysregulation, micro clots, inflammation of the brain, and other symptoms attributed to “long COVID” developing in between 10-20% of people infected with COVID-19 (Bowe, Xie and Al-Aly 2022; Davis et al. 2023; Smith 2022).

Regardless of the scientific findings that COVID-19 is airborne, and other findings about the biological mechanisms of the disease and the physics surrounding aerosols, the social facts, including the ones that are seemingly irrational or have been characterized as “wrong” for being counter to science, will remain of utmost importance to health behavior if there are people who endorse them as fact. It is in this regard that public health measures in the United States have been so misguided. People behave according to what they believe, not what has been scientifically proven, and sometimes those two things are the same, but often they aren’t. While it may seem useful to point out to others that they are mistaken of the facts or that their behavior is irrational or in defiance of logic, a true understanding of behavior requires accepting that the person enacting the behavior may not agree with the “fact” that the behavior is irrational.

APPLYING SOCIOLOGICAL THEORY TO EXPLAIN THE MEANING OF THE ‘SOCIAL FACTS’ OF COVID-19 RISK FOR RISK MITIGATING HEALTH BEHAVIOR

Two theories from medical sociology provide especially useful frameworks for understanding the link between health behavior, both risky and risk-mitigating, and health beliefs about risk, during the initial phase of the COVID-19 pandemic in the United States. They frame health behavior and health beliefs as related to social inequality and technocratic society (Beck 1996; Becker 1974). Ulrich Beck’s theory of The Risk Society explains that certain health beliefs, like the understanding of risk as normal/unavoidable, are characteristic of capitalist societies (1992; 1996). The Health Belief Model (HBM) is a useful complement to Beck’s theory of The Risk Society, accounting for two of its major limitations (Beck 1992; 1996; Becker 1974).

While The Risk Society suggests that people will engage in risky behavior and ignore risk mitigating behavior when a risk is seen as normal/unavoidable, it does not elaborate on the circumstances underlying the conclusion that a risk is unavoidable. The HBM provides a link between risky/risk mitigating health behavior and the belief that risk is normal/unavoidable. It highlights specific mechanisms influencing behavior that account for other characteristics of capitalist society like extreme social inequality, and characteristics of the Digital Era like unfettered access to information (Becker 1974). The HBM also accounts for the possibility that some people in capitalist societies may reject the idea that risk is normal/unavoidable while expanding to provide additional possibilities for how members of capitalist society may respond to risk beyond an avoidance/seeking dichotomy (Beck 1992; 1996; Becker 1974).

In addition to accounting for those who do not prescribe to the idea that risk is normal/avoidable, the HBM allows for other ideological views of risk beyond whether it is normal or inevitable (Becker 1974). Other facets of risk ideology include whether a risk *should* be mitigated, regardless of whether it is avoidable. This addresses the important limitation of The Risk Society, its focus on a single health belief that risk is normal/unavoidable (Beck 1992; 1996).

COVID-19 as a "Toxic Agent" in a Global Risk Society

The process of redefining the risk of COVID-19 as scientifically less severe in the face of information proving otherwise (Smith 2022) constitutes a process of normalizing risk that is characteristic of western capitalist societies. Understanding behavior later in the pandemic when the "scientific" facts of COVID-19 risks changed requires understanding *why* the facts changed, and why they were presented as scientific fact despite their opposition to the scientific findings that existed at the time. In other words, understanding the behavior of the public, which is influenced by experts, requires an understanding of the behavior and beliefs of experts as normal members of the population in Western Capitalist countries socialized into the same norms as their non-credentialed peers.

The patterns of variation among responses to the pandemic make sense when examined as responses to a 'toxic agent' in 'The Risk Society' (Beck 1992, 1996; Beck, Bonss, and Lau 2003). Western industrialized nations' tendency to favor normalizing the risk of COVID-19 over mitigating it's spread is a perfect example of how modern risks are characterized as inevitable, despite their resulting from preventable human actions (Berghs 2022; Fitzgerald 2021; Krzyzanowski and Krzyzanowska 2022). The theory of the Global Risk Society (Beck 2012) offers a worthy explanation for why the social "facts" about COVID-19 risk in the United States included the eventual normalization of COVID-19 risk, endorsing the understanding of risk as a normal and expected feature of living in the United States in present-day. It also explains why these same people would be expected to view risk-mitigation as "futile," here the idea being risks are unavoidable, so they cannot effectively be mitigated anyways. The understanding of risk-mitigation as "futile" is one possible explanation for resistance to behaviors intended to mitigate the risk of COVID-19.

Ulrich Beck described "The Risk Society" as characterizing postmodern society, which was risky due to the increased presence of toxic agents that could harm health and/or cause illness/disability (1992). Toxic agents are suggested to be the result of an over-reliance on technology, and technology is so central to the development of postmodern society that over-reliance is considered inevitable (Beck 1996). Once society has become over-reliant on technology and toxic agent exposure comes to be seen as inevitable, people become disillusioned by the constant exposure to risk (Beck 1996). The idea is that people will attempt to re-define risk rather than mitigate it when mitigation would involve becoming less reliant on technology they are unwilling to relinquish.

The initial risk posed by the SARS-CoV-2 virus highlighted the potentially deadly threat posed by interaction with many of the familiar technological innovations of the 21st century, like central heating and cooling systems (Gu et al. 2023). Reducing the risk of air recirculation when the air contains a novel airborne pathogen can be costly, though (Dal Porto et al. 2022; Rosenthal 2020). The United States has historically neglected to invest in infrastructure in favor of reduced corporate tax burden (Schaper 2021). Addressing the risk of recirculated air would involve confronting decades of decisions to favor funding innovation in information technology instead of allocating funds to maintain infrastructure technology.

While some have suggested that the American public's reduced interest in COVID-19 risk mitigation did not become widespread until the availability of vaccines, it still would make sense to eventually see the push to normalize COVID-19 risk even without the introduction of vaccines. Along these lines, "hot girl summer" (Pete et al. 2019) taking place in Summer 2020 is evidence that the push did occur without the introduction of vaccines. It is possible, then, that the introduction of vaccines simply accelerated an ongoing process of normalization characteristic of the Risk Society by providing additional social groups an excuse to cease risk mitigating health behavior when "hot girl summer" (Pete et al. 2019) did not immediately lead to widespread acceptance of the fact that COVID-19 infection posed little risk to most people.

There are important ways of framing "risk" versus "danger" in postmodern society that make it easier to redefine risk instead of relinquish technology. "Risk" is divorced from "danger" in postmodern industrial societies in the sense that outcomes like injury, illness, disability, and death can be inherent and expected if the source of the threat is something that exists in nature. In industrialized societies some threats are highly uncertain because they emerge from human actions. The uncertainty of modern "risks" allows industrial societies to frame them as "uncontrollable," shifting any duty of risk mitigation to the individual. (Beck 2002, 2011). In contrast, the natural "danger" is easily identifiable because these dangers tend to trigger the "fight or flight" response, meaning they give off signs and signals that we can identify socially but also, and more importantly, somatically. For example, most people are socialized to recognize smoke as a sign of a fire, but there are also signs that a fire is a threat when you react to the smell of smoke, cough due to inhaling smoke, and when smoke inhibits vision. You can exercise agency and decide to evade natural danger, but agency is not necessary—if rational thought becomes difficult, your body will still try to invoke a response that leads to you avoiding the threat.

Modern risks are uncertain and constantly evolving, and addressing them is not reflexive, instead *requiring* agentic action (Beck 1996, 2002, 2011). For example, the risk of dying while not wearing a seat belt is not inherent or easily identifiable, and most of the time, the consequence of death will not come to fruition if you forego the seatbelt. To protect yourself from the risk of death in your vehicle, you must first decide that the seatbelt will alleviate the risk of death, then you must take action to fasten the seatbelt based on your assessment of the risk.

The framing of modern risk as uncontrollable is further reinforced by the proximity of actual risk, or really, the lack thereof. You must assess modern risk in absence of a truly risky situation, an assessment based on hypotheticals. Whereas the risk of fire is proximate (i.e., I smell smoke, I see fire, I run away), the risk of dying from not wearing your seatbelt is much more distant, being predicated on some adverse event while driving (i.e., you experience an automobile accident, you may or may not have chosen to wear your seatbelt). This is consistent with the assertion that perceptions of the future are increasingly important sociological context (Beckert and Suckert 2020).

The threat of COVID-19 was extremely distal, especially after the understanding that it was transmitted via aerosols became widespread among scientists (Gu et al. 2023). Additionally, there is some evidence emerging that long COVID may increase the risk of death for at least 6-12 months post-acute COVID-19 infection (Davis et al. 2023), meaning the prospect of death from COVID-19 was difficult for many people to perceive. Like imagining the risk of dying in a future car crash and deciding to mitigate it using a seat belt, imagining the risk of death from COVID-19 infection required the recognition of an invisible risk whose consequences could take several years to emerge. If people could not conceptualize the true risk of COVID-19 because it did not become obvious until the proximate "risk" of infection had long passed, it would make sense that they may resist mitigating the risk. After all, people resisted seatbelts as useful for many years, with many Americans only adopting the behavior when it was codified into law and some still resisting the behavior (Roos 2020).

The same was true for other behaviors important to public health, like smoking tobacco. Tobacco is a useful example when trying to understand risks related to air quality, like the risk of an airborne disease, and risks that bring pleasure, like using drugs or, in the case of COVID-19, socializing in crowds. The push to reduce Americans' cigarette use did not start to see success until the early 2000s, several decades after the widespread dissemination of scientific evidence that there were long-term health risks of tobacco use like lung cancer (USDDS 2014). Like seatbelts, the risk of lung cancer was not inevitable, and the effect of smoking on health was even less proximate than the danger of a hypothetical automobile accident, which was uncertain but would have immediate effects if it occurred. While injury from an automobile accident, seatbelt or not, was likely to be discovered within a few hours of the dangerous event and could occur with a single risky encounter, lung cancer was something that often took decades to develop and was not always discovered immediately upon its development (USDDS 2014). Lung cancer was also unlikely to occur with a single risky encounter (e.g., your first and only cigarette), meaning it often took many encounters with tobacco over time for the risk to have the long-term effect on health (USDDS 2014). The same could be said of long COVID, which only has a rate of around 10-25% for people experiencing a single COVID-19 infection (Davis et al. 2023) but becomes more likely with each subsequent infection (i.e., encounter with risk) (Bowe et al. 2022; Brazil 2023; Goodman 2022) and may not be discovered until years after the initial infection (Davis et al. 2023).

One other caveat to COVID-19 risk that makes mitigation even more difficult than the straightforward example of seatbelts is shared by tobacco. Unlike seatbelts, tobacco use presented the additional hurdles of being pleasurable and a common means of socializing with others. Even when people were able to ignore the physical cravings for nicotine to cease smoking, many still engaged in "social smoking," a behavior that typically involves he simultaneous use of other substances like alcohol (Villanti et al. 2017). Avoiding COVID-19 infection, and thus, long COVID, meant maintaining a degree of isolation from one's peers and avoiding many of the activities Americans depend on for socialization. For example, "brunch" is an important weekend bonding activity that involves dining at restaurants, often with alcoholic beverages available (Petertil 2018). It is also considered a major status symbol for American elites (Ternikar 2014). Adhering to the new COVID-19 norm to mitigate risk by ordering take-away instead of dining out at restaurants meant foregoing this important bonding activity, and for some, it meant foregoing an activity that was important for maintaining a powerful position in society. This could be one of the things contributing to social facts of COVID-19 risk that combined approaches to risk mitigation that seemed to oppose each other, like the "social fact" that COVID-19 risk mitigation meant masking in public spaces unless eating or drinking.

The similarities between seatbelt use, tobacco use, and COVID-19 risk mitigation are also important for understanding the future of COVID-19 risk mitigation is not futile. People did eventually adopt seatbelts and wearing them was eventually required by law (Roos 2020). It is much less common to smoke tobacco in the United States than it was twenty years ago, and the CDC estimated an approximately 67% reduction in the number of U.S. adults who smoke cigarettes between 1967—2017 (Wang et al. 2017). Many states now have their own anti-tobacco campaigns, and it is no longer legal to smoke tobacco in most non-residential indoor spaces in the United States (USDDS 2014). These are just two of many successful public health campaigns. Given adoption of new behaviors upon the release of new information about a public health risk often takes years to become widespread, it is quite possible that widespread acceptance and adoption of risk mitigation for COVID-19 as normal will be achieved in the future, albeit the distant future.

One last issue contributing to the uncertainty surrounding threats in Western Capitalist society is that modern risks are global. The global network of risk societies and their shared risks comprises The World Risk Society (Beck 1996). The threats in The World Risk Society have a global impact, but participation in the creation of risk versus victimization from risk are not equally distributed given the high levels of social inequality found in and resulting from the interference of capitalist societies (Beck 1996, 2011, 2012). The global distribution of risk burden is shaped by different manifestations of conflict, including ecological conflict, global financial conflict, and global terror networks.

Modern global crises like the September 11, 2001, attack on the World Trade Center in New York City have previously been examined as examples of The World Risk Society in action, framing the emergence of global terror networks as a uniquely modern risk. (Beck 2002, 2011). The COVID-19 pandemic may be another uniquely modern risk, and it could be understood as an ecological conflict that had residual economic effects leading to global financial conflict. The COVID-19 pandemic provides a new context within which to look at the complex interplay between ecological conflict and global financial conflict in the world risk society. The context relates to the United States' disproportionate contribution to the global burden of COVID-19 disease risk and normalization of COVID-19 risk as inevitable because of global industry despite the likelihood that COVID-19 was the result of a zoonotic spillover event.

Many infectious diseases emerge naturally via a phenomenon called "zoonotic spillover." Zoonotic spillover occurs when a pathogen not previously known to infect humans is transmitted from a non-human animal host to a human host (Ellwanger and Chies 2021). There is evidence that technological innovation could shape one's exposure to infectious disease. For example, indoor plumbing was a technological innovation related to industrialization that contributed to the spread of cholera (Pyle 1966). It is also the case that industrialization may shape zoonotic spillover, but importantly, zoonotic spillover does not require those conditions and absolutely occurred prior to modern industrialization.

Like cholera, technology can increase or decrease the amount of contact one has with SARS-CoV-2 (Brown and Zinn 2021). The leading theory on the emergence of SARS-CoV-2 is zoonotic spillover, though (Ruiz-Aravena et al. 2022). Additionally, SARS-CoV-2 is airborne, meaning it is spread by aerosolized particles in the air (Centers for Disease Control and Prevention 2021; Gu et al. 2023). While the virus poses inherent biological risks to humans and can spread in absence of industry, much of the response to SARS-CoV-2 has framed the threat almost exclusively as a modern "risk," dismissing the natural "dangers" posed by the virus (Hancock and Garner 2021). Together, the existing information about SARS-CoV-2 suggests that it is a prime candidate for exploring the possibility that toxic agents in The Risk Society could involve a complex interplay between technological "risks" and natural "dangers" (Beck 1992, 1996, 2012; Beck et al. 2003).

Medical sociologists employing "The Risk Society" theory have emphasized the importance of "toxic agents," which are potentially harmful but whose harm may not be obviously/clearly the byproduct of a technological innovation like factory manufacturing (Brown 2016). Despite some research into the spread of disease as an environmental health risk of modernity, most of the research on environmental risks and health using a World Risk Society frame focuses on toxic agents that are tangible products of industry, like pollution and waste (Altman et al. 2008; Barrett 2008; Benz 2017; Cable, Shriver, and Mix 2008; Carrera and Brown 2020; Chen, Tu, and Zheng 2017; Fitzgerald and Rubin 2010; Moors 2019). For example, de Graaff and Bröer examined the potential establishment of electromagnetic fields as risks to health (2012), and similar research examined nuclear waste as a risk to workers employed at nuclear plants (Cable et al. 2008).

Studies that do examine viral pathogens as "toxic agents" have focused on HIV (Rangel and Crath 2021), Zika virus (Laurent-Simpson and Lo 2019), and influenza (Lohm et al. 2015), and not in context of pollution. This could be because pollution and waste can impact the epidemiological trajectory of an infectious disease outbreak, but they are not necessary prerequisites for the emergence and spread of infectious disease. Novel disease can be linked to pollution, but it can also emerge due to other phenomena, independent of pollution. Novel disease is also not typically framed as a pollutant in its own right, but COVID-19's high infectiousness and airborne mode of transmission have shown that the risk of aerosolized infectious virus poses a similar, if not worse, detriment to human lung and cardiovascular health than commonly targeted air pollutants like cigarette smoke and smog.

The emergence of an airborne pathogen and the subsequent pandemic from its uncontrolled spread has brought renewed attention to the idea that "toxic agents" of "the risk society" could include and/or involve infectious disease. The "uncontrollable" narrative surrounding COVID-19 is a compelling example of "The Risk Society" in action (Beck et al. 2003). SARS-CoV-2 is a good example of how the "risks" of modern society are not so easily divorced from the natural "dangers" that pose a threat to humans independent of technology.

It also is questionable whether people living in postmodern industrial societies, which emerged in the Digital Era, truly have agency because participation in individualism is expected and unavoidable as a highly valued societal norm (Bauman 2000). This could be critical to understanding the rationalization of seemingly irrational health behavior during the COVID-19 pandemic. It is possible that the near-certain risk of being "othered" by society for promoting something deviating from societal norms outweighed the potential risks of hospitalization and death from COVID-19. In this case, health behavior would also be shaped by the "liquefaction of modern life," where social bonds are increasingly fragile but also necessary (Bauman 2000).

Additional theory may serve to complement the theory of the Global Risk Society (Beck 2012) by providing insight as to what beliefs other than the normalization and/or minimization of COVID-19 might be expected and relevant to the understanding of Americans' resistance to engagement in risk-mitigation during COVID-19. It is also important for understanding why some people in the United States have been able to resist social pressure to normalize COVID-19 risk as inevitable and unmitigable. The theory of the Risk Society is not sufficient for explaining the continued adherence to risk-mitigation by some Americans due to continued endorsement of the social fact that COVID-19 risk exists and is severe.

Health Beliefs, Health Behavior, and Health Beliefs about Behavior

Beliefs about the risk-mitigating health behaviors themselves are another important factor linking health beliefs to health behavior. This includes the assessment of a risk mitigating behavior's benefit versus the cost of engagement. The Health Belief Model (HBM) frames health behavior in context of (1) whether there is a belief that a serious risk exists and (2) whether the behavior necessary to mitigate the risk is feasible and worthwhile (Becker 1974).

The Health Belief Model (HBM) provides a more nuanced explanation as to why Americans resisted risk-mitigation during COVID-19, accounting for beliefs about risk alongside beliefs about and access to risk-mitigating health behaviors. Access to the tools necessary to participate in risk-mitigating behaviors may prove important, independent of beliefs about those behaviors, in the U.S. context of extreme inequality. According to the HBM, an individual will engage in a risk-mitigating behavior and/or avoid a risk to their health if the following four conditions are met (Becker 1974):

(1) They believe themselves to be at risk

(2) They believe the risk to be serious

(3) They believe the benefit of the mitigation effort to be worth the cost

(4) They do not have any major barriers to accessing tools to engage in mitigation/avoidance

In the case that some, but not all, of these conditions are met, an individual may resist a risk mitigating behavior and/or fail to avoid a known health risk, like COVID-19.

While the theory of the Global Risk Society (Beck 2012; Beck et al. 2003) indicates that Americans are predisposed to violate conditions 1 and 2 of the HBM (Becker 1974), neither theory would suggest that the predisposition precludes all Americans to deny that they are at risk and/or believe the risk to be minimal (i.e., not serious). Thus, it is to be expected that some Americans would believe themselves to be at risk and believe the risk to be serious.

The theory of the world risk society does not provide an explanation for failing to mitigate risk when one believes the risk exists and is serious, focusing solely on the beliefs that risk is minimal but also a normal and therefore unavoidable facet of modern/post-modern, or "cosmopolitan," society (Beck 1996). It also does not provide an explanation for mitigating risk when one believes the risk exists and is serious.

Research on health behavior during the pandemic has applied the Health Belief Model to explain the connection between health beliefs and health behavior, identifying the model as useful for understanding behavior in this context (Bechard et al. 2021; Becher et al. 2021; de Vries et al. 2022). This study adds to that growing literature by providing evidence that the theory is applicable to the social facts of COVID-19 risk as they were defined by Twitter users in the United States between December 2019 and June 2021.

The results of this study went beyond simply demonstrating that the HBM is applicable in context of COVID-19 beliefs about health risk and engagement in behaviors to mitigate the risk of COVID-19. The results of this study reveal different barriers to engagement with different health behaviors, even among people with shared beliefs about risk. For instance, there is evidence that it was often the case that people had a shared understanding that COVID-19 poses a real risk but differing engagement with specific health behaviors based on their understanding of how effective those behaviors would be.

Two people may agree that COVID-19 risk exists, but the social facts of risk taken in context of the social facts of risk mitigation found here highlights several instances where people agreeing that COVID-19 risk exists disagreed about its mitigation, including a different understanding of the effectiveness of lockdowns, social distancing, vaccines, and wearing masks. In each of these instances, engagement versus resistance to risk mitigating behavior can be explained by the HBM proposition involving the cost versus benefit of a behavior (proposition 3). If the risk mitigating behavior is seen as futile the HBM suggests it is unlikely someone will engage. These results indicate that many people saw behaviors including wearing masks, lockdowns, social distancing, and vaccination as futile, and not because they had normalized COVID-19 risk or reframed it as non-serious.

The results provide insight as to the various reasons for perceiving the behaviors as futile when COVID-19 risk was accepted to exist and be serious. Take the example of masks. Many felt masking was futile because they endorsed the competing social fact about the importance of face covering type. The social fact that only N95, N100, and P100 respirators mitigate the risk of COVID-19 meant that many people who endorsed the behavior of covering one's face did not actually endorse wearing face masks, because surgical and cloth masks are not "respirators" used to protect the wearer from airborne toxins. Others felt masking was futile because people outside of health care would not mask well enough to filter COVID-19 out of the air. These people endorsed the idea that masks could work but rejected the notion that their benefit outweighs their cost for the general American public faced with COVID-19.

Time played a role here, too, as there were some who endorsed masks until the introduction of vaccines, at which point, they took the stance that unvaccinated and medically vulnerable people should mask. This was tied to an understanding of whom masks offered protection to, in this case, the wearer. People with this view did not perceive the effectiveness of personal mask wearing as being better when other people also wore masks. People who did not share this understanding, instead, endorsed the fact that everyone wearing masks was an effective means of filtering the air, especially in absence of other filtration technology like HEPA filters.

The results of this study also reveal that another proposition of the HBM constituted a major barrier to risk mitigating behavior, one with potentially increasing relevance further into the pandemic. Proposition 2 of the HBM suggests that one must believe themselves to be seriously at risk, not just believe the risk exists, to engage in risk mitigating health behavior. One of the most enduring and widely endorsed social facts of COVID-19 risk was the fact that COVID-19 risk is only severe for disabled and elderly people, meaning people who were already medically vulnerable without COVID-19 infection. It could be the case that vaccinations becoming available only served to widen the endorsement of this social fact. Considering these points, the widespread health belief about risk suggesting that COVID-19 was not a risk for "normal," "healthy," and "young" people may have constituted the one of the most widespread and enduring barriers to participation in risk mitigation. The results only point to one other barrier as being similarly widespread and enduring.

The final proposition of the health belief model asserts that people will not avoid risk if there are no means of avoidance and/or substantial barriers to avoidance. Tweets about risk during COVID-19 point to a substantial barrier to risk avoidance that relates to the larger issue of social inequality in the United States.

Financial status proved to be a substantial barrier to acquiring the supplies necessary to participate in risk mitigating behaviors, both because goods like masks could be pricey, but also because of the hoarding that took place in response to supply shortages that were worst in 2020 but have persisted into the pandemic's fourth year. People who could not afford to buy in bulk were left to pick over the scraps left by those who could and used that privilege to hoard goods. Sometimes shelves were empty, leaving no options for risk mitigation because the goods did not exist. Other times, the only option left would be too pricey, leaving no viable options for acquiring goods necessary to mitigate risk.

Compounding the issue was the imbalance of unavoidable exposure versus who had access to the tools necessary to mitigate risk. Often, it was wealthy, white-collar workers and their families with access to the tools for risk mitigation. With many in this population working from home during the pandemic, this allowed for a circumstance in which the people with the least risk of unavoidable exposure, in addition to having the best financial resources for acquiring tools to mitigate risk, also had the least immediate need to access them. This left frontline workers, especially those in health care, extremely vulnerable to risk, and the tweets about risk posted between December 2019 and June 2021 include evidence that these risks had tangible consequences.

Consequences included infection with COVID-19 ranging from mild to severe, hospitalization and/or death due to COVID-19 infection, the exacerbation of existing or emergence of new symptoms of chronic illnesses like diabetes and heart disease, the exacerbation of existing or emergence of new symptoms of mental illness like Depression, Anxiety, and ADHD, overwhelming guilt over passing an infection to a vulnerable significant other, the passed infection resulting in the hospitalization and/or death of a significant other, burnout so severe that leaving the profession was the only viable option, and death by suicide (Al-Aly 2023; Bowe et al. 2022; Davis et al. 2023; Fedorowski and Sutton 2023; Giacca and Shah 2022; Merza et al. 2023; Smith 2022). The circumstance of the wealthy having access to risk mitigation tools at the expense of the working poor was an important factor in both risk exposure and participation in risk mitigating behavior in the United States.

SEEDED STRUCTURAL TOPIC MODELING AS A QUANTITATIVE CONTENT ANALYSIS METHOD FOR SOCIOLOGICAL RESEARCH

For this study, I combined several approaches to quantitative text analysis to accomplish an automated approach to identifying seed words that accounts for the context of word use, effectively overcoming some of the greatest limitations of existing contextual models used for quantitative text analysis. This approach provides an effective means of making inferences about the meaning of written personal testimony using emotional, syntactical, and when information about time is available, historical context.

In addition to the benefit of outlining a new approach to quantitative content analysis, my use of this method with text data representing personal testimony related to a specific topic demonstrates the importance of the internet as a source of data for sociological investigations of culture, emotion, and social interaction. Beyond the data themselves, techniques like data mining could be a crucial tool for sociologists to overcome issues with validity, reliability, and generalizability in similar research using other data collection methods. They may also allow sociologists better access to personal testimony by vulnerable or hard-to-reach populations like disabled people. The "Information Age" has changed norms of social interaction, making it increasingly important that sociologists not ignore the relevance of personal testimony on the internet as a valid and informative source of information about social life.

LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

One of the main limitations of the study is the timeframe ending in June 2021. Though this study includes tweets posted during the first year and a half of the pandemic, at the time of data collection it was not clear that the pandemic would persist beyond these dates, and it was especially unclear that its persistence would mean any further changes to risk ideology or behavior. In 2023, the fourth year of the pandemic, we now have information that the pandemic indeed persisted, and a lot of evidence that circumstances surrounding risk and risk mitigating behavior have continued to evolve. Further research examining the remainder of the second year of the pandemic (2021) and the third year of the pandemic (2022) is necessary to understand the full scope of COVID-19 risk ideology in the United States and its relation to behavior beyond the first 19 months of the pandemic.

Other limitations include the focus on testimony in the form of microblogging, specifically microblogging on Twitter, and the focus on Twitter users in the United States. To overcome the limitation of a U.S. focus and better understand the connection between risk ideology and western capitalist societies more broadly, an expanded focus including testimony from Twitter users in other Western Capitalist nations is necessary, at minimum. A more robust study may choose to execute a comparison of Twitter users in Western Capitalist nations versus

Twitter users elsewhere, or alternatively, a comparison of Twitter users in these contexts to testimony to other social media platforms like Facebook, and in other formats like the increasingly popular video testimony seen on Tik Tok, Snapchat, and Instagram. More importantly, Twitter was privatized in a sale to Elon Musk in late 2022, leading to drastic and ongoing changes to the platform that may limit researchers' ability to freely access Tweets in the future (Conger, Isaac, Mac and Hsu 2022). Most recently, the platform announced that beginning on February 9, 2023, the Twitter API would no longer be available for free and public use and would instead become part of their new paid "Twitter Blue" plan (Mehta and Singh 2023).

Tweets about risk posted by Twitter users in the United States between December 2019 and June 2021 are evidence that perceptions about COVID-19 risk and risk mitigation cannot be described as a simple dichotomy within a group of people with a single shared interest, like the internet or a single social media website. On the one hand, people who use Twitter are distinct from people who refuse to engage with the internet, and Twitter users do not necessarily include all internet or social media users. On the other hand, Twitter users are not comprised exclusively of people from one social group. Instead, the collectivity of Twitter users includes people from most social groups in the United States, thus also providing a representative sample of the U.S. population in terms of other important shared characteristics like race, gender, socioeconomic status, education, religious affiliation, political ideology, and disability status.

This means that, in addition to demonstrating a wide variety of viewpoints among people with a single shared characteristic through their engagement with Twitter, the tweets examined in this study also represent the viewpoints of people belonging to a variety of social groups in contexts outside of Twitter. To this extent, they are not generalizable to the entire United States population, but they do provide some insight as to what viewpoints exist that could be useful for establishing parameters for future studies exploring ideological views about risk in the United States. Even if Twitter users are somehow distinct from people in their social groups who do not use Twitter, the vast representation across many social groups among Twitter users would suggest these results are conservative. If such variety exists among people who use Twitter, the variety of viewpoints in the total population could be even more expansive if Twitter users from each of these social groups have differing views from their counterparts remaining off the platform. Additionally, because this study did not incorporate external information about the people tweeting, instead opting to focus only on the characteristics of the tweets, these findings provide a template for additional within-group, as well as between-group, comparisons exploring similarities in COVID-19 risk ideology and risk mitigating behavior among people of different social groups.

The other main limitations dealt with computational power and the issue of timeliness. Structural topic models (stm) employ a heavy computing process. Executing a process of the magnitude required for the structural topic model can take minutes at best, but at worst, it could take days. The time to execute the topic model increases with the number of topics and number of documents modeled, which for social media testimony often goes well into the tens of thousands. This means analyses of data mined from social media, especially over any extended period, can easily take several days. Adding to the issue is that there is no robust method for identifying the number of topics to model, meaning all analyses must test multiple models to identify the best number of topics to fit the documents modeled.

The issue of expediency is important considering many of the subjects researched using the combination of text mining and topic modeling involve crises, meaning time is of the essence and delays can be costly in terms of damage. This is particularly true for new concerns about the spread of misinformation about crises. Being able to identify misinformation expediently and accurately in a crisis is vital for proactive efforts to eliminate its impact, as a delay could render efforts useless if reactive to a threat that has already gotten too far out of hand.

CONCLUDING REMARKS

This study set out to develop a more nuanced understanding of the social facts of COVID-19 risk and risk mitigation extending beyond the popular dichotomy of “pro” versus “anti” risk and behavior. I accomplished this goal by with evidence from personal testimony in the form of tweets about risk by Twitter users in the United States in the initial year and a half of the pandemic. Emotional sentiment was suspected to play a role in the variation of things understood as “fact,” and the findings suggest that there was a high proportion of three emotions in tweets about COVID-19 risk: Disgust, Surprise, and Fear. While prior research had pointed to the possibility of emotion as an important factor linking risk ideology and participation in risk mitigating behavior, these findings suggest that other factors are more applicable in context of COVID-19 risk and its mitigation. I identify the normalization of risk during COVID, the widespread understanding that COVID-19 risk was specific to medically vulnerable populations like elderly and disabled people, the belief that risk mitigating behaviors including masks and social (physical) distancing are ineffective and/or futile, and extreme socioeconomic inequality in the United States, as primary explanations for the patterns of adherence and resistance to risk mitigating behavior during the first 19 months of the COVID-19 pandemic.

This study demonstrates the importance of social facts for behavior, which I believe may be the most important takeaway for public health policy aimed at encouraging participation in risk mitigating behavior. While there has been much speculation as to why many behaved in ways that were seemingly counter to scientific facts, and why many believed misinformation even after being presented with scientific facts countering its accuracy, few have taken "social facts" that are malign with scientific facts seriously. This is evidenced even early in the pandemic, shown here in tweets mocking and belittling people who believed misinformation. It would seem that the combined minimization of social facts as relevant and ill treatment of people who shaped their behaviors on their beliefs instead of information presented to them by scientists only served to exacerbate tensions over COVID-19 risk and its mitigation. These issues may serve as an important focus for future retrospective works covering risk ideology and participation in risk mitigating behavior during the COVID-19 pandemic, however long it may last.

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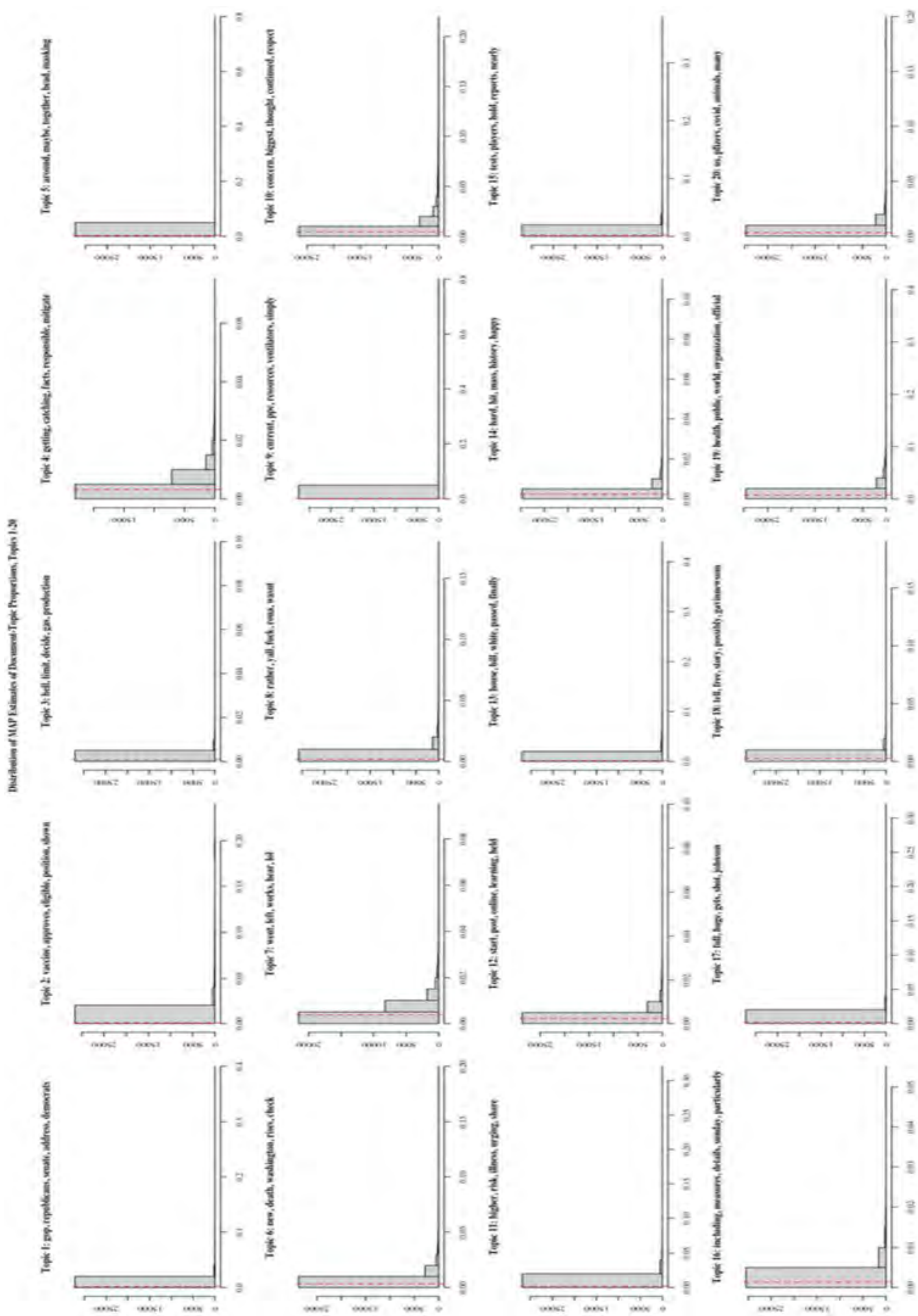
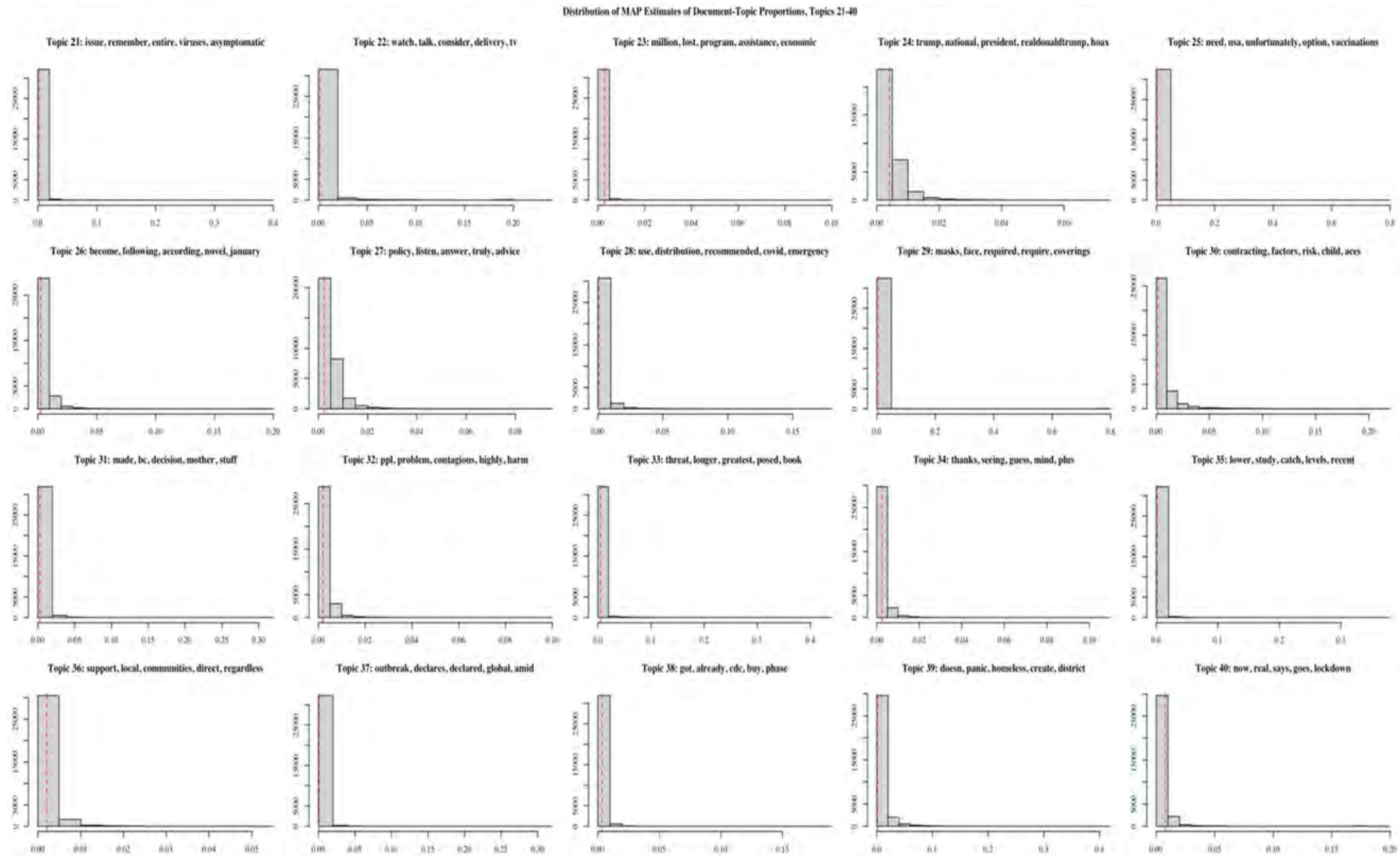
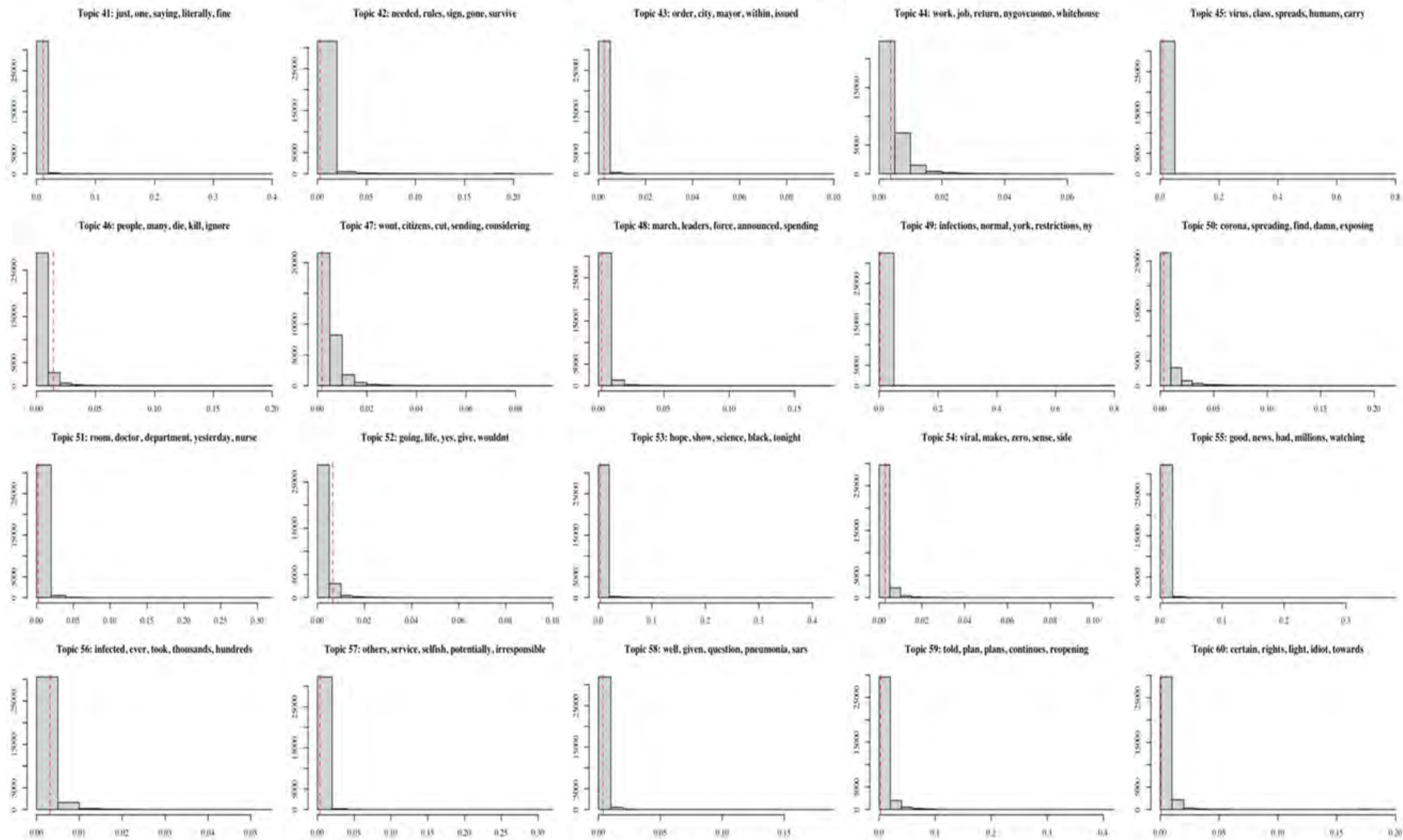
APPENDIX A

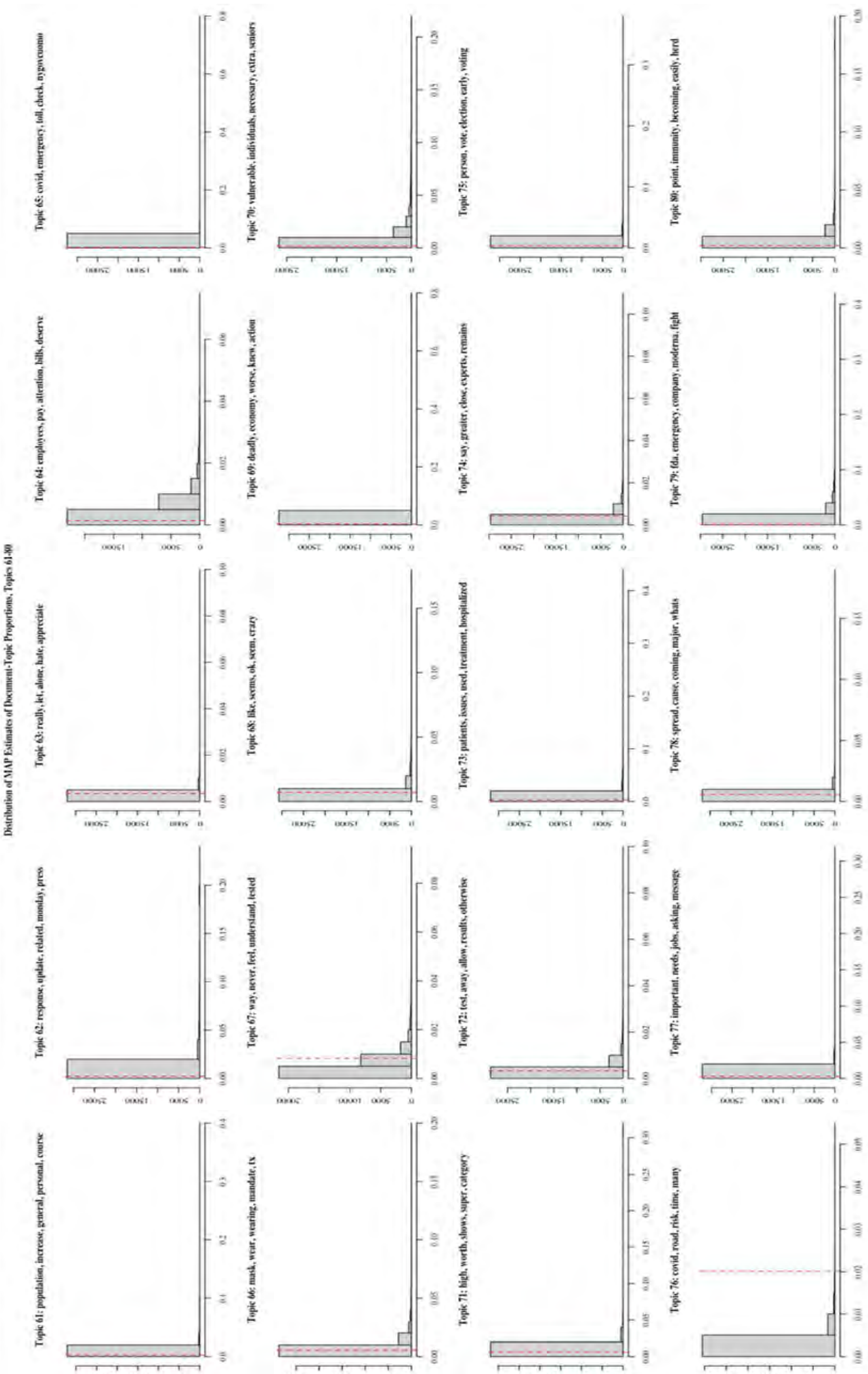
DISTRIBUTION OF MAP ESTIMATES BY TOPIC

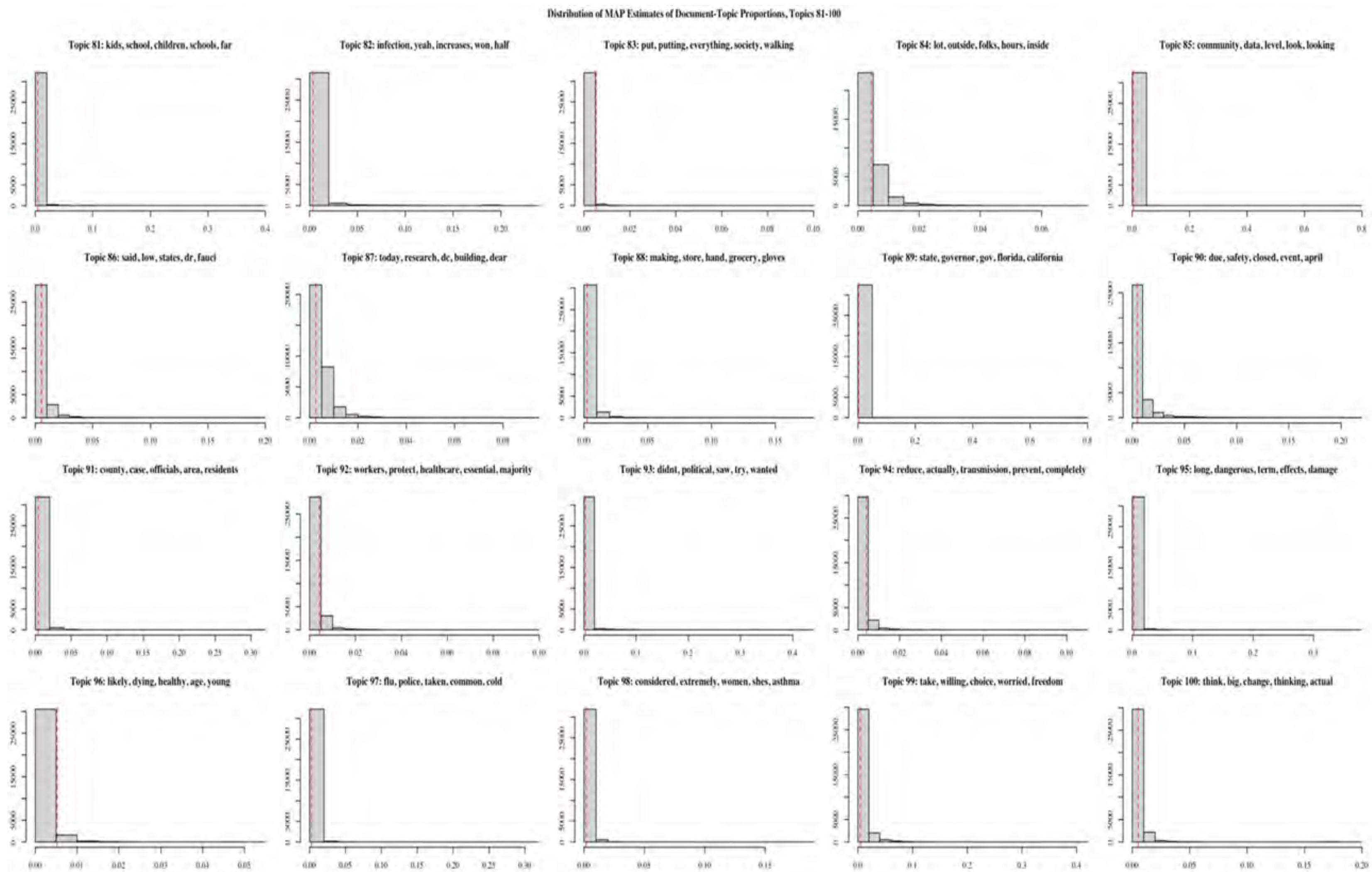


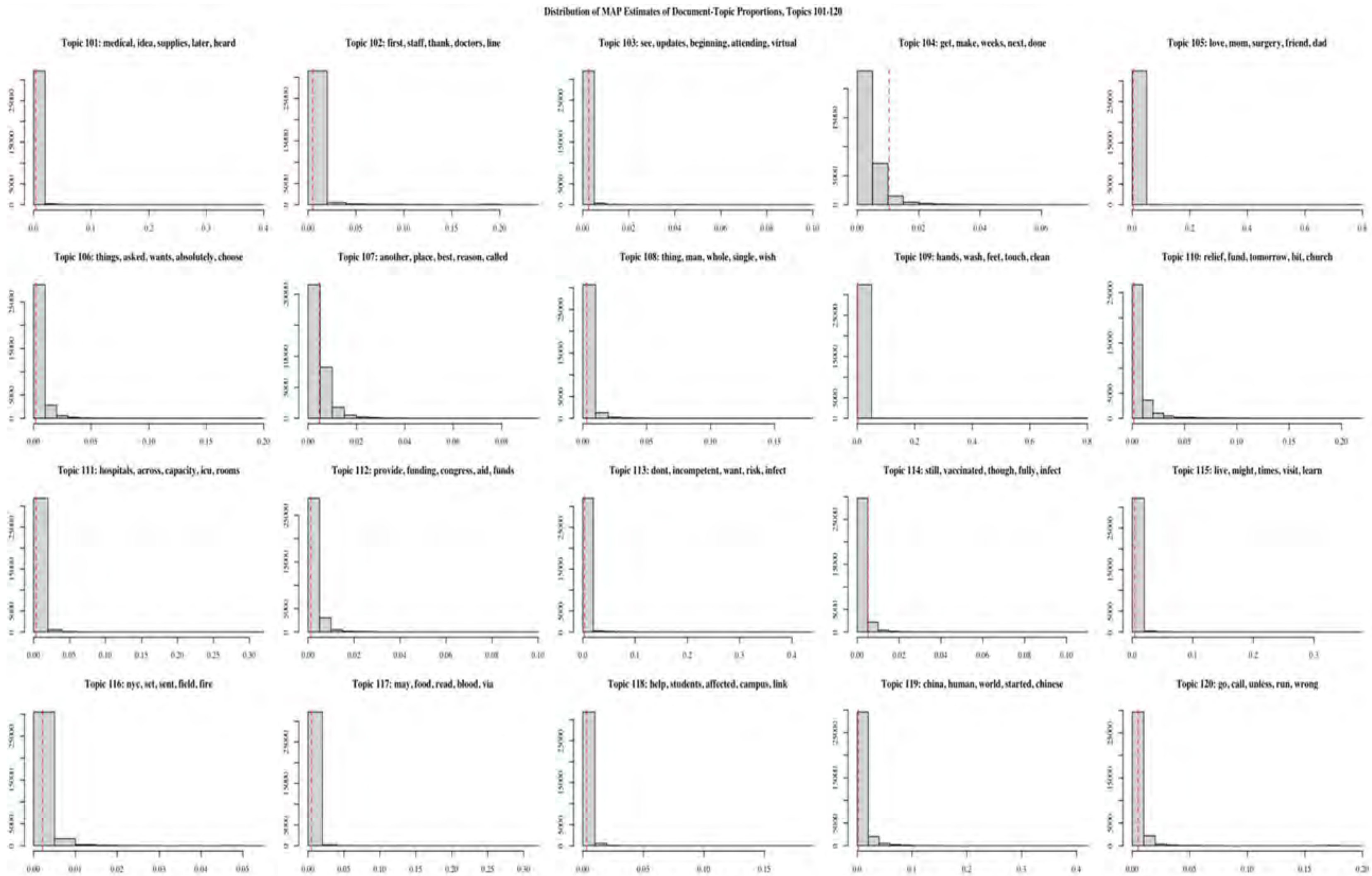

Distribution of MAP Estimates of Document-Topic Proportions, Topics 21-40
Topic 21: issue, remember, entire, viruses, asymptomatic
Topic 22: watch, talk, consider, delivery, tv
Topic 23: million, lost, program, assistance, economic
Topic 24: trump, national, president, realdonaldtrump, hoax
Topic 25: need, usa, unfortunately, option, vaccinations
Topic 26: become, following, according, novel, january
Topic 27: policy, listen, answer, truly, advice
Topic 28: use, distribution, recommended, covid, emergency
Topic 29: masks, face, required, require, coverings
Topic 30: contracting, factors, risk, child, aces
Topic 31: made, bc, decision, mother, stuff
Topic 32: ppl, problem, contagious, highly, harm
Topic 33: threat, longer, greatest, posed, book
Topic 34: thanks, seeing, guess, mind, plus
Topic 35: lower, study, catch, levels, recent
Topic 36: support, local, communities, direct, regardless
Topic 37: outbreak, declares, declared, global, amid
Topic 38: got, already, cdc, buy, phase
Topic 39: doesn, panic, homeless, create, district
Topic 40: now, real, says, goes, lockdown

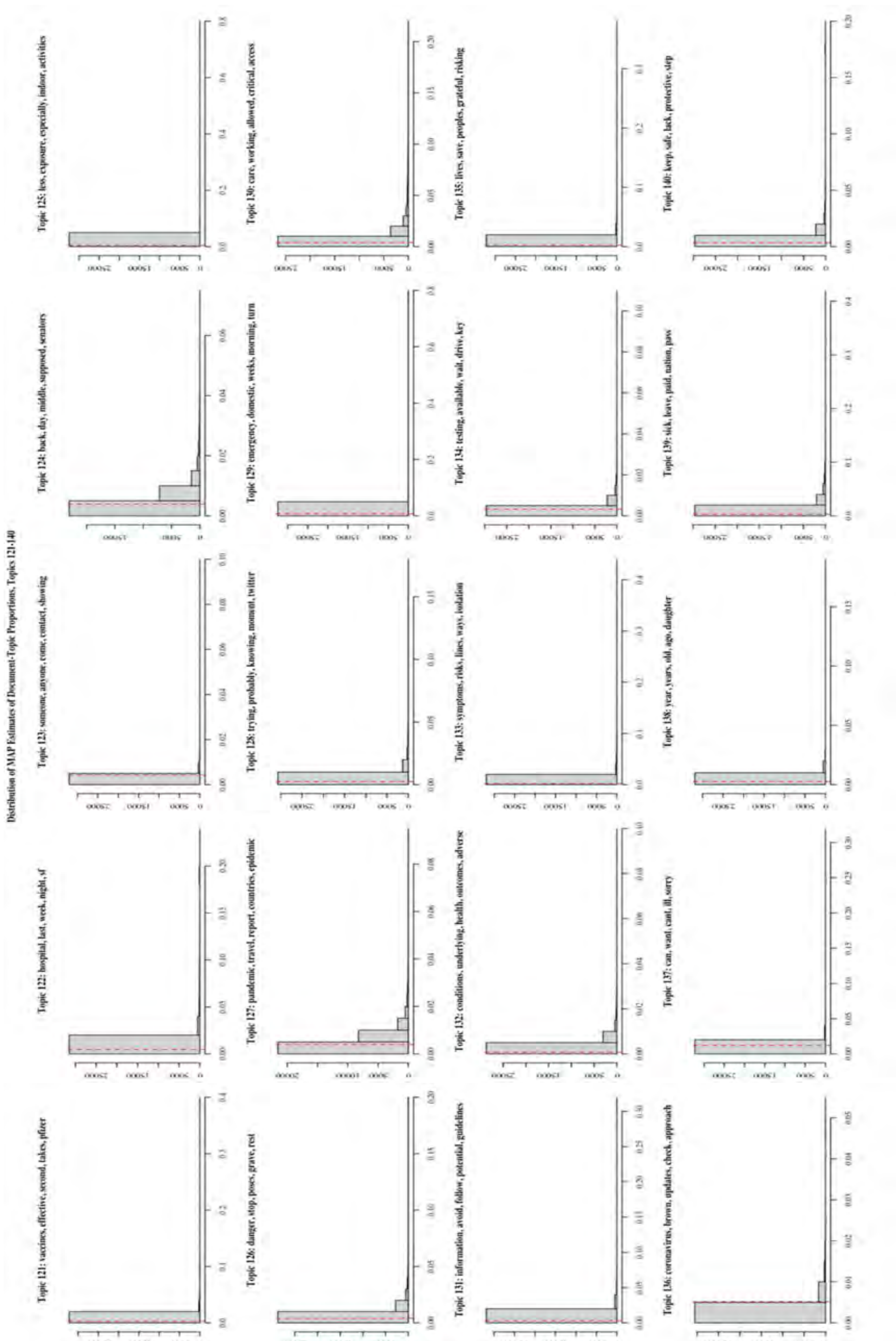
Distribution of MAP Estimates of Document-Topic Proportions, Topics 41-60

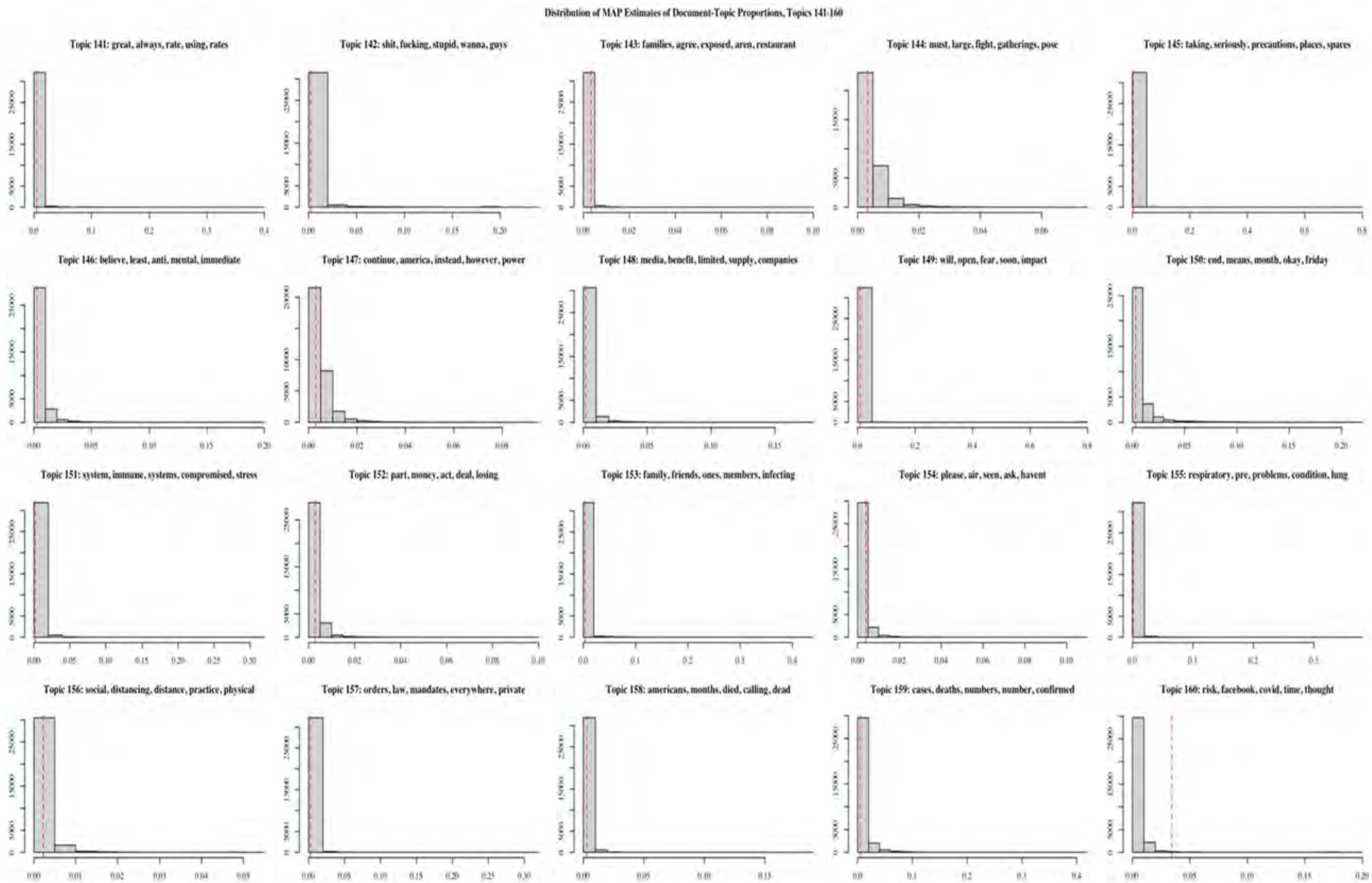


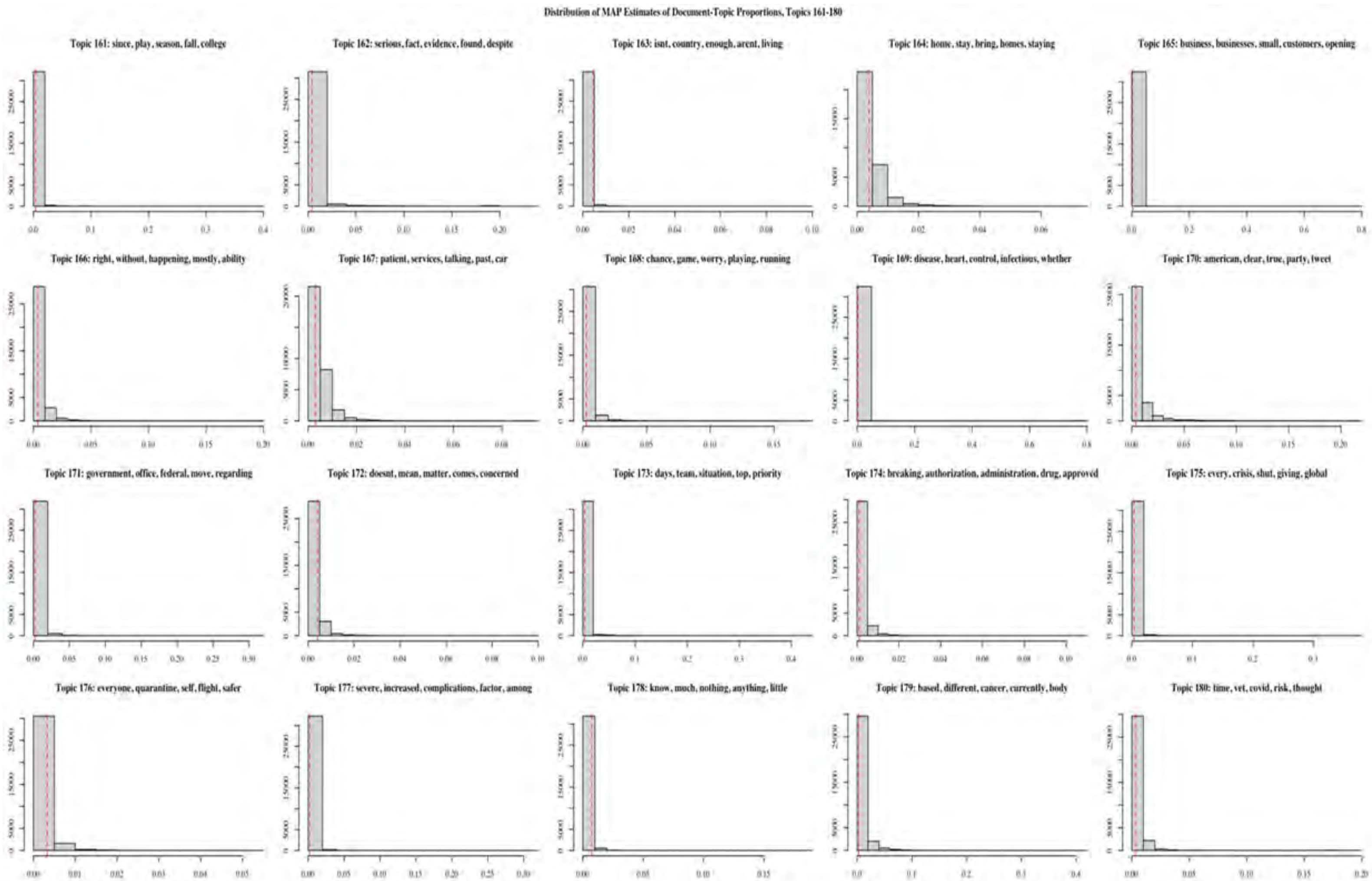

Distribution of MAP Estimates of Document-Topic Proportions, Topics 61-80
Topic 61: population, increase, general, personal, course
Topic 62: response, update, related, monday, press
Topic 63: really, let, alone, hate, appreciate
Topic 64: employees, pay, attention, bills, deserve
Topic 65: covid, emergency, toll, check, nygovcuomo
Topic 66: mask, wear, wearing, mandate, tx
Topic 67: way, never, feel, understand, tested
Topic 68: like, seems, ok, seem, crazy
Topic 69: deadly, economy, worse, knew, action
Topic 70: vulnerable, individuals, necessary, extra, seniors
Topic 71: high, worth, shows, super, category
Topic 72: test, away, allow, results, otherwise
Topic 73: patients, issues, used, treatment, hospitalized
Topic 74: say, greater, close, experts, remains
Topic 75: person, vote, election, early, voting
Topic 76: covid, road, risk, time, many
Topic 77: important, needs, jobs, asking, message
Topic 78: spread, cause, coming, major, whats
Topic 79: fda, emergency, company, moderna, fight
Topic 80: point, immunity, becoming, easily, herd


Distribution of MAP Estimates of Document-Topic Proportions, Topics 81-100
Topic 81: kids, school, children, schools, far
Topic 82: infection, yeah, increases, won, half
Topic 83: put, putting, everything, society, walking
Topic 84: lot, outside, folks, hours, inside
Topic 85: community, data, level, look, looking
Topic 86: said, low, states, dr, fauci
Topic 87: today, research, dc, building, dear
Topic 88: making, store, hand, grocery, gloves
Topic 89: state, governor, gov, florida, california
Topic 90: due, safety, closed, event, april
Topic 91: county, case, officials, area, residents
Topic 92: workers, protect, healthcare, essential, majority
Topic 93: didnt, political, saw, try, wanted
Topic 94: reduce, actually, transmission, prevent, completely
Topic 95: long, dangerous, term, effects, damage
Topic 96: likely, dying, healthy, age, young
Topic 97: flu, police, taken, common, cold
Topic 98: considered, extremely, women, shes, asthma
Topic 99: take, willing, choice, worried, freedom
Topic 100: think, big, change, thinking, actual


Distribution of MAP Estimates of Document-Topic Proportions, Topics 101-120
Topic 101: medical, idea, supplies, later, heard
Topic 102: first, staff, thank, doctors, line
Topic 103: see, updates, beginning, attending, virtual
Topic 104: get, make, weeks, next, done
Topic 105: love, mom, surgery, friend, dad
Topic 106: things, asked, wants, absolutely, choose
Topic 107: another, place, best, reason, called
Topic 108: thing, man, whole, single, wish
Topic 109: hands, wash, feet, touch, clean
Topic 110: relief, fund, tomorrow, bit, church
Topic 111: hospitals, across, capacity, icu, rooms
Topic 112: provide, funding, congress, aid, funds
Topic 113: dont, incompetent, want, risk, infect
Topic 114: still, vaccinated, though, fully, infect
Topic 115: live, might, times, visit, learn
Topic 116: nyc, set, sent, field, fire
Topic 117: may, food, read, blood, via
Topic 118: help, students, affected, campus, link
Topic 119: china, human, world, started, chinese
Topic 120: go, call, unless, run, wrong

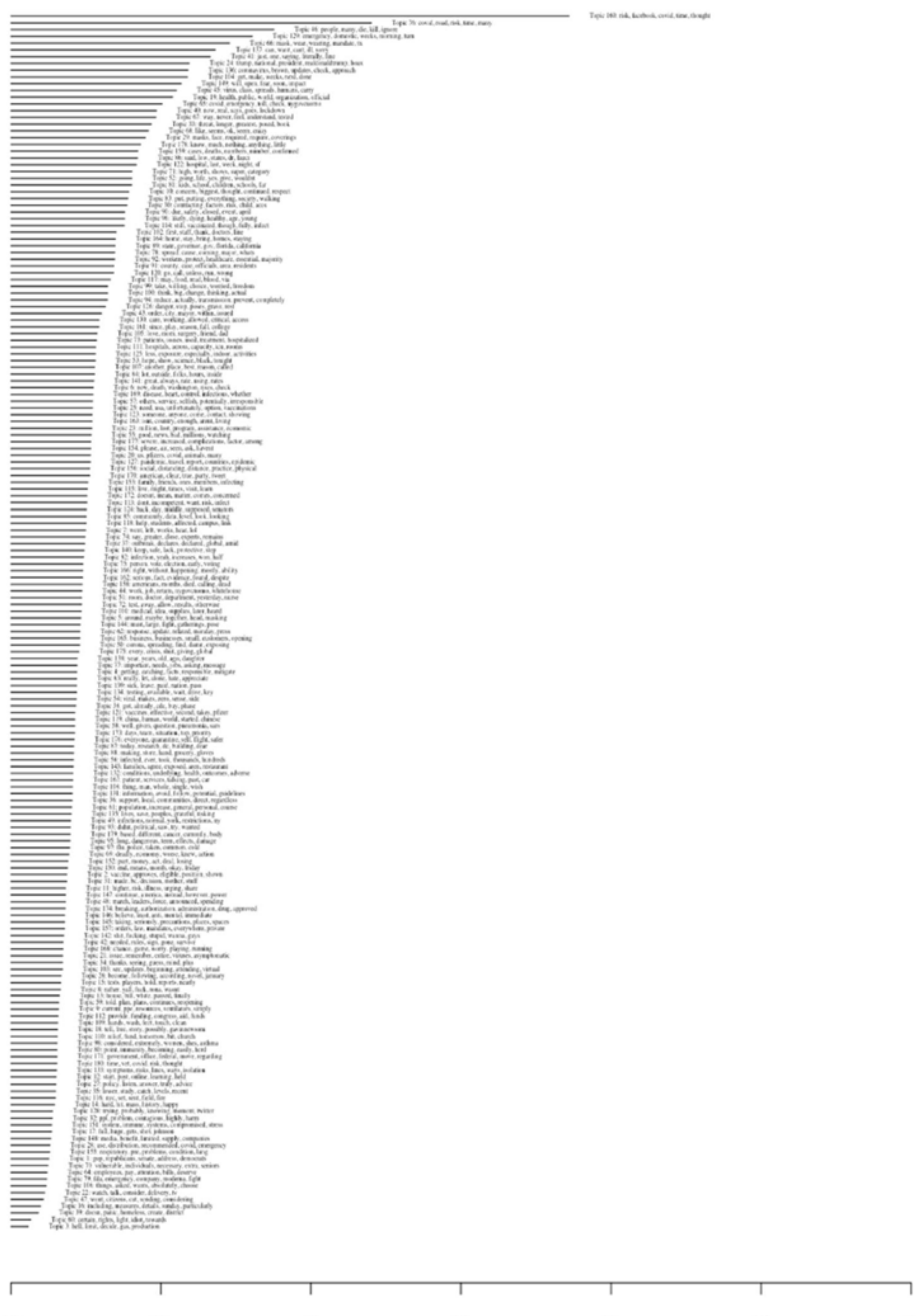

Distribution of MAP Estimates of Document-Topic Proportions, Topics 121-140
Topic 121: vaccines, effective, second, takes, pfizer
Topic 122: hospital, last, week, night, sf
Topic 123: someone, anyone, come, contact, showing
Topic 124: back, day, middle, supposed, senators
Topic 125: less, exposure, especially, indoor, activities
Topic 126: danger, stop, poses, grave, rest
Topic 127: pandemic, travel, report, countries, epidemic
Topic 128: trying, probably, knowing, moment, twitter
Topic 129: emergency, domestic, weeks, morning, turn
Topic 130: care, working, allowed, critical, access
Topic 131: information, avoid, follow, potential, guidelines
Topic 132: conditions, underlying, health, outcomes, adverse
Topic 133: symptoms, risks, lines, ways, isolation
Topic 134: testing, available, wait, drive, key
Topic 135: lives, save, peoples, grateful, risking
Topic 136: coronavirus, brown, updates, check, approach
Topic 137: can, want, cant, ill, sorry
Topic 138: year, years, old, ago, daughter
Topic 139: sick, leave, paid, nation, pass
Topic 140: keep, safe, lack, protective, step


Distribution of MAP Estimates of Document-Topic Proportions, Topics 141-160
Topic 141: great, always, rate, using, rates
Topic 142: shit, fucking, stupid, wanna, guys
Topic 143: families, agree, exposed, aren, restaurant
Topic 144: must, large, fight, gatherings, pose
Topic 145: taking, seriously, precautions, places, spaces
Topic 146: believe, least, anti, mental, immediate
Topic 147: continue, america, instead, however, power
Topic 148: media, benefit, limited, supply, companies
Topic 149: will, open, fear, soon, impact
Topic 150: end, means, month, okay, friday
Topic 151: system, immune, systems, compromised, stress
Topic 152: part, money, act, deal, losing
Topic 153: family, friends, ones, members, infecting
Topic 154: please, air, seen, ask, havent
Topic 155: respiratory, pre, problems, condition, lung
Topic 156: social, distancing, distance, practice, physical
Topic 157: orders, law, mandates, everywhere, private
Topic 158: americans, months, died, calling, dead
Topic 159: cases, deaths, numbers, number, confirmed
Topic 160: risk, facebook, covid, time, thought


Distribution of MAP Estimates of Document-Topic Proportions, Topics 161-180
Topic 161: since, play, season, fall, college
Topic 162: serious, fact, evidence, found, despite
Topic 163: isnt, country, enough, arent, living
Topic 164: home, stay, bring, homes, staying
Topic 165: business, businesses, small, customers, opening
Topic 166: right, without, happening, mostly, ability
Topic 167: patient, services, talking, past, car
Topic 168: chance, game, worry, playing, running
Topic 169: disease, heart, control, infectious, whether
Topic 170: american, clear, true, party, tweet
Topic 171: government, office, federal, move, regarding
Topic 172: doesnt, mean, matter, comes, concerned
Topic 173: days, team, situation, top, priority
Topic 174: breaking, authorization, administration, drug, approved
Topic 175: every, crisis, shut, giving, global
Topic 176: everyone, quarantine, self, flight, safer
Topic 177: severe, increased, complications, factor, among
Topic 178: know, much, nothing, anything, little
Topic 179: based, different, cancer, currently, body
Topic 180: time, vet, covid, risk, thought

APPENDIX B

EXPECTED PREVALENCE FOR ALL 180 TOPICS MODELED



APPENDIX C

LIST OF ABBREVIATIONS

Abbrev.	Term
HCPs	health care providers
CDC	Centers for Disease Control and Prevention
WHO	World Health Organization
RT	retweet / reply tweet
QT	quote tweet
LDA	Latent Dirichlet Allocation
SNA	Social Network Analysis
HRG/HRGM	Hierarchical Random Graph Model
NPI	Non-Pharmaceutical Intervention
STM	Structural Topic Model
DM	Direct Message
NLP	Natural Language Processing

APPENDIX D

GLOSSARY OF KEY TERMS

Term	Definition
node	An actor in a network; nodes can represent many units of analysis, including individuals, organizations, ideologies, and geographic location.
tie	A connection between actors in a network, also called an “edge”
edge	A connection between nodes in a network, also called a “tie”
bipartite	A network with two types of nodes
edge list	A list of ties in a network; an alternative format for a network data frame object in R that allows for analysis of very large networks more efficiently than with adjacency matrices
data frame	A container in R for datasets, edge lists, and network matrices
vector	A container in R for a single variable or subset of variables
tidy format	A data format available in R that allows for easier analysis of complex data, particularly string format data
professional medical experts	Twitter users who identify themselves as members of the medical and/or public health professions
experiential medical experts	Twitter users who identify themselves as disabled and/or as having some chronic illness
non-experts	Twitter users who do not identify themselves as either disabled or affiliated with the medical/public health professions
health risk ideology	Ideological views about the health risks and risk mitigating health behaviors associated with COVID-19
lockdown-phase	March 2020—May 2020
initial phase	The first 19 months of the COVID-19 pandemic, December 2019—June 2021
Twitter	An online social media platform that allows for efficient communication with many other users
tweet	A post by a Twitter user
retweet	Simple re-posting of another user’s tweet
quote tweet	Re-posting another user’s tweet with additional commentary

Term	Definition
hashtag (#)	A user identifies the topic of their tweet using "#" to link the tweet to a searchable topic.
cold call (@)	A user identifies another user in their tweet by tagging them using "@" followed by the other user's screen name
twitterverse	The network of regular Twitter users
trend	When a large portion of Twitter users engage with a hashtag, it is designated and promoted by Twitter as a trending topic, increasing the topic visibility even further
thread	A user reply to their own tweet, as follow-up
SARS-CoV-2	A novel coronavirus discovered in late 2019
COVID-19	The illness caused by the SARS-CoV-2 virus
R	A programming language and statistical software
doxx	Publishing personal information about someone else maliciously on the internet without their permission
Karen	A slang term for a privileged white woman who exercises privilege at the expense of others, often by playing the victim