SOCIAL MEDIA USE IN PUBLIC HEALTH AND POLICY STUDY

by

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ABSTRACT

JINGJING GAO. Social Media Use in Public Health and Policy Study. (Under the direction of Dr. JASON WINDETT)

The Internet plays a significant role in health information searching, sharing, and emotional support. Chapter 1 explores complementary and substitute value of online health information from diseases, especially chronic diseases, health insurance, barriers to health resources, and their interaction effects with income. Furthermore, social networks such as Twitter enable people to interact with each other and share health-related concerns and emotions in an effective and novel way, as evidenced during the COVID-19 pandemic when in-person communication became more inconvenient under the stay-at-home policy. Public emotions from these social network data have increasingly attracted scholars' attention because of their significant value in predicting public behaviors and public opinions. Chapter 2 examines 1) the spatial-temporal clustering trends of negative emotions (or spillover effects); 2) whether health policies such as stay-at-home policy and political ideology are associated with spatiotemporal emotion patterns towards COVID-19.

During COVID-19, public mobility experienced a significant reduction as many people's work environment shifted from workplace to home or offline to online, especially under policies like the stay-at-home policy (Wen, Sheng, & Sharp, 2021). However, little has been done to examine the relationships between public emotions mined from social networks and the public behavioral responses to the COVID-19 crisis, especially considering the interaction effects between public emotions and public policy and political leaders' political ideology. Chapter 3 fills these gaps by examining the relationships between public emotions and working modes, and

the interaction effects between public emotion, public policy, and political leaders' political ideology on working modes.

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DEDICATION

To my father Zhan Gao, my brother Fei Gao, and my best friend Honeybee, for their unconditionally love and emotional support always.

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ARTICLE 1: THE COMPLEMENTARY AND SUBSTITUTIVE VALUE OF ONLINE HEALTH INFORMATION

Abstract: The Internet plays a significant role in health information searching, sharing, and emotional support. However, scholars have devoted little attention to the complementary and substitute value of online health information from diseases, especially chronic diseases, health insurance, barriers to health resources, and their interaction effects with income. This research utilizes data from the 2020 Health Information National Trends Survey (HINTS 2020), the latest HINTS survey that includes seeking online health information questions critical to this research. This paper proposes that the factors contributing to seeking online health information can be categorized into two modalities – complementary and substitutive. Concerning the complementary value, I argue that individuals with certain health conditions use online health information as a complementary health resource in addition to traditional health resources such as doctors to understand their health issues better. Online health information also functions as substitute information sources for individuals who have experienced more barriers to typical health information resources.

Keywords: Online Health Information, Chronic Disease, Health Insurance

What is known about this topic?

- Online health information brings various benefits to the public's health (Levac & O'Sullivan, 2016, p. 51). Still, scholars have devoted little attention to the complementary and substitutive value of online health information from diseases, health insurance, barriers to health resources, and their interaction effects with income.

What does this paper add?

- Online health information provides complementary value for individuals with certain conditions like depression while not for other health conditions like heart disease and cancer. Online health information' substitutive values are more significant for vulnerable communities such as individuals who have more barriers to acquiring typical health information resources.

Introduction

In 2020, Health Information National Trends Survey reported that 69.97% of Americans use the Internet to seek health or medical information for themselves. From an economic perspective, two products are complementary goods if used together, while they are substitute goods if one good can be used in place of another (Sanders, 2011). In addition to the typical health resources such as doctors and healthcare services, online health information can function as complementary and substitute goods. Although online health information is becoming more frequent (Prestin, Vieux, & Chou, 2015), the factors motivating individuals' behavior in seeking online health information have not been thoroughly examined from their complementary and substitute value in addition to typical health resources. Numerous studies suggested that Internet-based search engines and social media data provide complementary sources for understanding epidemiologic diseases and traditional information sources such as doctors. Examples of this include infectious eye diseases (Bernard et al., 2018; Deiner, Lietman, McLeod, Chodosh, & Porco, 2016), Dengue fever (X. Y. Ye, Li, Yang, & Qin, 2016), Cholera (Chunara, Andrews, & Brownstein, 2012), mosquito-borne diseases (Jain & Kumar, 2018) and COVID-19 (P. L. Liu, 2020). This research evaluates the complementary and substitutive value of seeking online health information for people with chronic diseases (diabetes, high blood pressure, heart disease, cancer, lung disease, depression, and obesity risk). The substitute value of seeking online health information happens when individuals have more barriers to health resources, forcing them to seek online health information as a substitute.

I argue that financial status interplays with an individual's health condition, health insurance, and the barriers to typical health resources when seeking online health information. To test these relationships, I use the data from the 2020 Health Information National Trends

Survey (HINTS 2020). I control for the influence of demographic variables such as income, age, education, gender, and race on the behavior of seeking online health information. Additionally, income is one of the most significant economic factors, and it is consistently and positively associated with seeking online health information (W. Jacobs, Amuta, & Jeon, 2017). This study will further examine the interaction effects between income and seeking online health information's complimentary and substitutive values. I show that as income increases, the probability of seeking online health information increases more for individuals who have certain health conditions and have more barriers to typical health information resources. These results indicate that online health information works as a more valuable substitute and complementary health resource for these most vulnerable individuals. Future health policy should consider improving health information equality on the Internet.

Seeking Online Health Information

With the exponential growth in information processing, storage, and communication capabilities, information costs rapidly decrease (Altman, Nagle, & Tushman, 2015). The constraints associated with the costs are also disappearing (Altman et al., 2015). Health-related information on the Internet has been widely used for multiple health-related purposes such as self-care (Jamal et al., 2015), primary disease diagnosing (Kuehn, 2013; Walsh, Hyde, Hamilton, & White, 2012), and health education (Beaunoyer, Arsenault, Lomanowska, & Guitton, 2017; Kuehn, 2013). Researchers in many countries have explored and analyzed online health information-seeking behavior. For example, in the United States (Bhandari, Shi, & Jung, 2014), China (Chen & Zhu, 2016), Scotland (Harbour & Chowdhury, 2007), Egypt (Ghweeba et al., 2017), France (Renahy, Parizot, & Chauvin, 2010) and Switzerland (Caiata-Zufferey, Abraham, Sommerhalder, & Schulz, 2010).

In 2013, more than 33% of United States individuals used the Internet for health diagnosis (Kuehn, 2013). The population seeking online health information is constantly increasing in the U.S. By 2017, about 38.5% of U.S. adults were using online health information without frustration (Finney Rutten et al., 2019). The percentage of individuals using online health information is exceptionally high among young individuals. For instance, survey research found that 67.7% of university students use the Internet for health purposes (Osei Asibey, Agyemang, & Boakye Dankwah, 2017). Smartphones further enable individuals to seek online health information virtually anytime and anywhere, significantly increasing the convenience of searching for health information on the Internet.

Online health information brings a variety of benefits to individuals. Health communication tools like websites provide customized responses to individuals' specific needs and situations (Kreps, 2017). Research indicates that social media can function as a tool for health promotion (Korda & Itani, 2013; Kruse & Beane, 2018). For instance, scholars find that social media positively influences health by "increasing accessibility, interaction, engagement, empowerment and customization" (Levac & O'Sullivan, 2016, p. 51). Online health information-seeking behavior positively influences individuals' fruit and vegetable consumption and physical activity (Lee, Boden-Albala, Jia, Wilcox, & Bakken, 2015). Additional research on adolescents finds that exposure to credible online health sources such as MedlinePlus® is positively associated with higher eHealth literacy scores and the higher likelihood of having adequate health literacy (Ghaddar, Valerio, Garcia, & Hansen, 2012). In addition to other health resources, online health information's values could be divided into two categories - complementary and substitute based on individual's health conditions (this study focuses on chronic diseases including depression), health insurance status, and other barriers to health information resources.

Chronic Diseases

There are benefits associated with seeking online health information as a complementary health resource, especially for specific health conditions. For example, to gain acknowledgment, perspective, and reduce uncertainty (Caiata-Zufferey et al., 2010). The information available on the Internet could help individuals make critical decisions for severe health issues such as mental health (Chen & Zhu, 2016; Lal, Nguyen, & Theriault, 2018) and cancer (Xiao, Sharman, Rao, & Upadhyaya, 2014) to complement the information from their doctors. Individuals feel that online health information can influence their health-related decisions and improve communications with their physicians (Sillence, Briggs, Harris, & Fishwick, 2007).

Greiner, Chatton, and Khazaal (2017) found that online health information-seeking activities of different diseases share similarities. Patients have common goals such as seeking support and education, making friends, and providing support to others on the Internet. Patients also like their health professionals to offer some help via the Internet, suggesting that policymakers and health institutions consider extending healthcare services beyond the hospital settings to the Internet (R. Jacobs, Boyd, Brennan, Sinha, & Giuliani, 2016). During the COVID-19 pandemic, many health professionals used social media as an essential way to communicate with their patients because of the social distancing policy. The pandemic makes online health information more critical for individuals with certain health conditions.

The severity of a disease is an influential factor in using online health information (W. Jacobs et al., 2017). Individuals with severe conditions such as cancer still tend to use health professionals as their primary source of health information and use the Internet as a secondary source of information (W. Jacobs et al., 2017). This study proposes that online health information works as a complementary information source for patients with chronic diseases such as diabetes, high blood pressure, heart disease, cancer, lung disease, depression, and obesity risk (measured by BMI), leading to the first hypothesis:

Hypothesis H_1 (Chronic Diseases): Individuals with health issues (diabetes, high blood pressure, heart disease, cancer, lung disease, depression, and obesity risk) are more likely to seek online health information.

Health Insurance

Other than working as a complementary health resource, online health information functions as a substitute health resource for individuals with insurance with higher deductibles, especially when using the Internet for self-diagnosis. Using the Internet for self-diagnosis can reduce healthcare costs associated with less severe disorders such as colds and many other healthcare issues. The Affordable Care Act (ACA) extends health insurance coverage to individuals who lack access to affordable health resources (Garfield, Damico, Cox, Claxton, & Levitt, 2016). In California, there were about 2.764 million uninsured individuals in 2016: 868 thousand individuals (31%) are Medicaid or other public assistance eligible, and 1.494 million (54%) are ineligible for financial aid due to income, ESI offer, or Citizenship. (Garfield et al., 2016).

For individuals with Medicare, which has relatively lower deductibles, online health information is not always the best choice for various reasons, such as limited health literacy or online health information's reliability and quality issues. This study proposes that online health information is a substitute for individuals with health insurance with relatively higher deductibles. Hence, individuals with insurance such as Medicare and Medicaid are less likely to seek online health information, and individuals with employer-based insurances are more likely to seek online health information.

Hypothesis H_2 (Health Insurance): Individuals with health insurance like employer-based insurances *are more likely to use online health information.*

Barriers to Health Information Resources

Online health information also functions as a substitute for individuals with more barriers to acquiring typical health resources. Tustin (2010) found that online health information can be convenient if patients feel dissatisfied with their physicians. About 31% of the patients felt that they did not receive enough support from their healthcare system and turned to seek help from the Internet (R. Jacobs et al., 2016). Research shows that online health information is negatively associated with the frequency of visiting doctors, and dissatisfied patients in patient-provider interaction tend to seek and trust the information from the Internet (Tustin, 2010). In addition to dissatisfaction with physicians, individuals have other barriers such as “difficulty getting timely appointments with doctors, and conflicts in scheduling during clinic hours” could also use online health information as a substitute health resource (Bhandari et al., 2014, p. 1113). This study proposes that the need for online health information increases as individuals’ barriers to typical health resources increase, such as dissatisfaction in communication with their doctors.

Hypothesis H_3 (Barriers): Individuals with more barriers to health information from doctors, nurses, or other health professionals *are more likely to use online health information.*

Socioeconomic Factors

Demographic characteristics such as age, gender, income, and education also contribute to widespread Internet use and online health information-seeking behaviors (Cotten & Gupta, 2004; Ghweeba et al., 2017; W. Jacobs et al., 2017; Miller & Bell, 2012; Myrick & Willoughby, 2017; Paek & Hove, 2014; Rowley, Johnson, & Sbaffi, 2017). Female and college-educated individuals are more likely to seek online health information (Myrick & Willoughby, 2017). Compared to Whites, Blacks, Hispanic, and other races have lower rates of seeking online health information (Fareed, Swoboda, Jonnalagadda, Walker, & Huerta, 2021). In U.S. adults, younger and higher socioeconomic status (SES) populations are more likely to use online health information (W. Jacobs et al., 2017; Massey, 2016).

Among these SES factors, individuals' financial status is one the most significant factors impacting individuals seeking online health information (W. Jacobs et al., 2017). As income increases, individuals' probability of seeking online health information increases. This study further examines how income interplays with individuals' health conditions, especially mental health, insurances, barriers to health resources when seeking online health information. The associated hypotheses are as below:

Hypothesis H_{4a} (Diseases and Income): individuals with depression are more likely to seek online health information as income increases. In contrast, individuals without depression will not change their behavior as much.

Hypothesis H_{4b} (Health Insurance and Income): Individuals with employer-based health insurance are more likely to seek online health information when their income increases. Individuals without employer-based health insurance have a relatively lower probability of seeking online health information as their income increases.

Hypothesis H_{4c} (Barriers' Index and Income): Individuals with a higher barrier index are more likely to seek online health information than individuals with lower barriers' index as income increases.

Data and Methods

Data

This study utilizes the 2020 Health Information National Trends Survey (HINTS 2020) to test the hypotheses above. It is a single-mode mail survey using the Next Birthday Method for respondent selection. The sample design of this study consisted of two stages: 1) an equal-probability sample of addresses was selected from within each explicit sampling stratum, and 2) one adult was selected within each sampled household. The survey has 3,865 respondents, whose ages are 18 and older. The HINTS 2020 survey covered questions such as health conditions, health behaviors, and health insurance coverage. Table 1 below provides some basic descriptive information of the HINTS 2020 survey data.

Table 1: Descriptive Information of the HINTS5 2020

Gender	Male	1,552 (41.60%)
	Female	2,179 (55.40%)
Diseases	Diabetes	817 (21.74%)
	High Blood Pressure	1,675 (44.44%)
	Heart Disease	402 (10.67%)
	Cancer	615 (16.36%)
	Lung Disease	548 (14.56%)
	Depression	901(23.91%)
Insurance	Medicare	1,416 (37.82%)
	Medicaid	583 (15.78%)
	Employer-based	1,889 (50.59%)
	Private Insurances	586 (15.87%)

	Other	1,027 (26.83%)
Insurances		
	Uninsured	176 (4.60%)

Measures

The primary dependent variable measures respondents' *seeking online health information* behavior. Concerning the dependent variable, respondents answered the question, "In the past 12 months, have you used a computer, smartphone, or other electronic means to look for health or medical information for yourself?" Multiple studies have used similar information to measure respondents' seeking online health information (Nguyen, Mosadeghi, & Almario, 2017; Yoon, Jang, Vaughan, & Garcia, 2020). The variable is coded 1 for YES and 0 for NO. About 76.59% of respondents in my study sample (N=2648) used the Internet for health or medical information.[1]

The key independent variables in my research are chronic diseases, health insurance, and the index of barriers to formal health information resources. Respondents answered several questions about chronic diseases, including diabetes, high blood pressure, heart disease, cancer, lung disease, depression, and obesity risk. These diseases were chosen because they are among the predominant diseases in America, and they represent varying degrees of severity. Table 2 provides variable measures associated with the diseases (diabetes, high blood pressure, heart disease, cancer, lung disease, and depression). All the disease variables are coded 1 for YES and

[1] Table 2 provides detailed information about the dependent variable and independent variables.

0 for NO. For insurance, the data were recoded into several categories –Medicare, Medicaid, employer-based insurance, private insurance, and other insurances.

Table 2. Diseases Variable Measures

Has a doctor or other health professional ever told you that you had any of the following medical conditions:

Diabetes	"Diabetes or high blood sugar?"
High Blood Pressure	"High blood pressure or hypertension?"
Heart disease	"A heart condition such as heart attack, angina, or congestive heart failure?"
Lung Disease	"Chronic lung disease, asthma, emphysema, or chronic bronchitis?"
Depression	"Depression or anxiety disorder?"
Cancer	"Have you ever been diagnosed as having cancer?"

This study considers seven barriers to accessing health information from doctors, nurses, or other health professionals during the past 12 months; Does your healthcare provider: 1) Give you the chance to ask all the health-related questions you had; 2) Give the attention you needed to your feelings and emotions; 3) Involve you in decisions about your health care as much as you wanted; 4) Make sure you understood the things you needed to do to take care of your health; 5) Explain things in a way you could understand; 6) Spend enough time with you; 7) Help you deal with feelings of uncertainty about your health or health care. With these seven barriers, this study created a new variable- Barrier Index, which measures the total number of barriers a respondent has experienced out of these seven items. Demographic information (age, sex, and race) is controlled since previous studies had implied their significance (Bhandari et al., 2014; Dobransky & Hargittai, 2012). The descriptive information of variables used for the models is presented in Table 3.

Table 3. Descriptive Information of Variables in the Model

Variable	Count	Percentage (%)	Mean	Std. Dev.	Min	Max
Seeking Online Health Information:						
Yes	2,028	76.59				
No	620	23.41				
Diabetes:						
Yes	554	20.92				
No	2,094	79.08				
High Blood Pressure:						
Yes	1,191	44.98				
No	1,457	55.02				
Heart Disease:						
Yes	279	10.54				
No	2,369	89.46				
Cancer:						
Yes	459	17.33				
No	2,189	82.67				
Lung Disease						
Yes	416	15.71				
No	2,232	84.29				
Depression						
Yes	685	25.87				
No	1,963	74.13				
BMI			27.24	5.67	13.86	77.69
Insurance:						
Uninsured	136	1.99				
Medicare	935	35.31				
Medicaid	377	14.24				
Employer-based	1,456	54.98				
Private Insurances	403	15.22				
Other Insurances	617	23.30				
Sex:						
Male	1,086	41.01				
Female	1,562	58.99				
Race:						
White	1,695	64.01				
African American	343	12.95				
Hispanic	407	15.37				
Asian	108	4.08				
Other Races	95	3.59				
Education:						
High School and Below	1,353	51.10				
College Degree	736	27.79				
Graduate Degree	559	21.11				
Barrier Index:	2,648		11.04	4.43	7	28
Income	2,648		10.59	5.416294	1	19
Age	2,648		55.72	16.478	18	104

Note: Total observation number is 2,648. This table only includes respondents that were included in the regression models for this paper and not all respondents. N refers to the total number of individuals, and the percentages are not weighted.[2]

[2] Gender is coded 0 for males and 1 for females. White is coded as 0, while African American, Hispanic, Asian, and Other Races are coded in order from 1 to 4. Income is coded as an ordinal variable from 1 to 20 as 1 represents "less than 10,000" dollars annual income while 20 represents "over 200,000" dollars annual income.

Data Analysis

The dependent variable capturing the respondent *seeking online health information* is dichotomous, so this study estimates a logistic regression to examine the factors associated with the dependent variable. As logistic regression coefficients are not easily interpreted, the full models can be found in Appendix 1, with predicted probabilities generated from these models below. The initial model examines the direct effects of the disease, insurance, barriers to health resources, and demographic variables on the dependent variable – *Seeking Online Health Information*.

Results

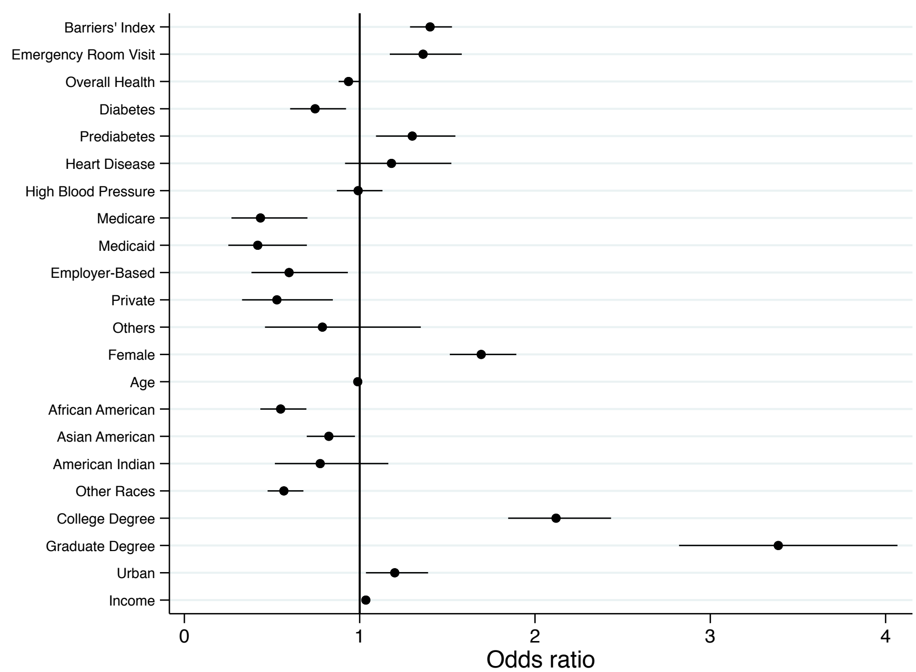

Figure 1. Factors Associated with Seeking Online Health Information
Note: This Figure is based on the results from Model 1 in Appendix 1.

Figure 1 presents the results with the points representing odds ratios and 95% confidence intervals based on Model 1 in Appendix 1. Figure 1 shows the odds ratios of diseases, health insurance, barriers to health resources, and demographic factors on using online health information. Being female, younger, and respondents with higher income have a higher predicted probability of using online health information.

I expected to see individuals with diseases (Hypothesis H_1) or more barriers to health resources (Hypothesis H_3) have a higher predicted probability of using online health information. On the other hand, I expected respondents who have employer-based health insurance (Hypothesis H_2) to have a higher predicted probability of using online health information. In Model 1, *diabetes, high blood pressure, heart disease, cancer, and lung disease* are not statistically significantly related to seeking online health information. Interestingly, depression increases the probability of seeking online health information significantly, which confirms the previous research by W. Jacobs et al. (2017) that patients with severe diseases like cancer tend to rely on more reliable health information such as information from doctors rather than the Internet.

Additionally, having a higher risk of obesity (measured by BMI) decreases the predicted probability of seeking online health information, confirming the previous research that patients with obesity have issues using online health information. The low probability of using online health information among patients with obesity is associated with low health literacy (Mayberry, Kripalani, Rothman, & Osborn, 2011), lack of motivation, passiveness, inconsistency of information, generality, or loss of information (Milewski & Chen, 2010). This result potentially implies why general research is more likely to examine the behavior of seeking online health information for a specific disease. Concerning Hypothesis H_3, dissatisfaction in communication with the doctors, nurses, or other health professionals contributes to the higher probability of using online health information. These results support the hypothesis that online health information functions as a substitute health information source when individuals have more barriers to traditional health information resources.

Model 1 in Appendix 1 also shows that individuals with employer-based insurance have a higher predicted probability of using online health information than others. This result does support Hypothesis 2 that individuals with employer-based health insurance are more likely to seek online health information than others. However, having other insurances such as Medicare, Medicaid, private insurance, and other insurance is not significantly associated with using online health information. This phenomenon could be caused by the higher out-of-pocket cost of employer-based insurance.

Additionally, I examine the interaction effect between income and depression, employer-based insurance, and barriers index using online health information. Based on hypothesis H_{4a}, I expected to see individuals with depression have a higher predicted probability than individuals without depression as income increases. Model 2 of Appendix 1 tests the interaction effect for hypothesis H_{4a}. Model 2 does not detect a statistically significant interaction between prediabetes and income using online health information.

However, Figure 2 represents more nuanced information regarding the interaction effect between income and depression on seeking online health information. In Figures 2-4, the horizontal axis represents the income from $10,000 to more than $200,000, while the vertical axis represents the predicted probability of seeking online health information. As income increases, the likelihood of using online health information increases. However, individuals with depression are statistically significantly more likely to use online health information than individuals without depression when the income is under 150,000 in Figure 2, supporting the trend of Hypothesis H_{4a}.

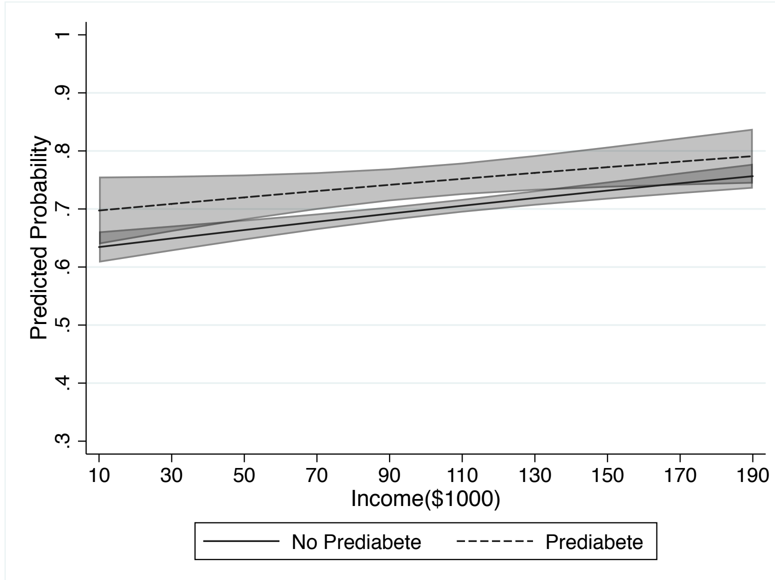

Figure 2. The Effect of Prediabetes and Income on Seeking Online Health Information
Note: Based on Appendix 1- Model 2, Figure 2 is used to test H_{4a}.
Shaded region=95% confidence interval.

To clarify the effects of income and insurance on using online health information, Figure 3 displays the interaction effects of these two variables. The top line represents respondents with Medicare, and the bottom line represents others. Figure 3 indicates that insurance does not significantly interact with income in using online health information.

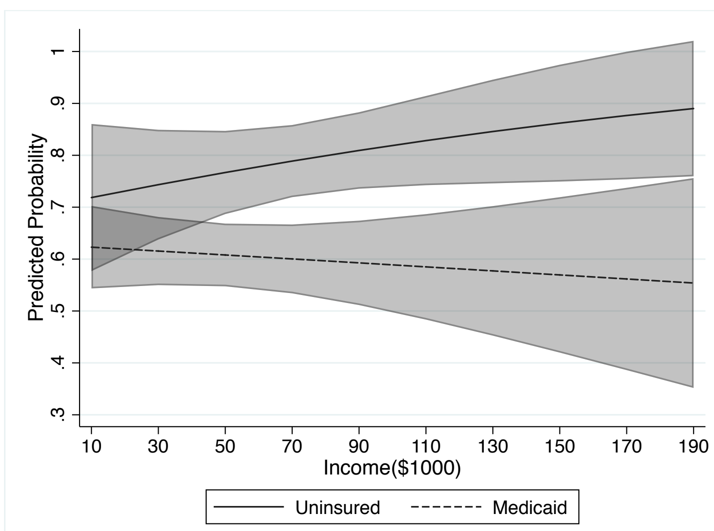

Figure 3. The Effect of Insurances and Income on Seeking Online Health Information
Note: Based on Appendix 1- Model 3, Figure is used to test H_{4b}.
Shaded region=95% confidence interval.

Figure 4 shows the interaction effect between barrier index and income on seeking online health information. As income increases, the predicted probability of seeking online health information is significantly lower for individuals with fewer barriers to health resources than individuals with more barriers, indicating that online health information is critical for individuals with more difficulties acquiring health information resources.

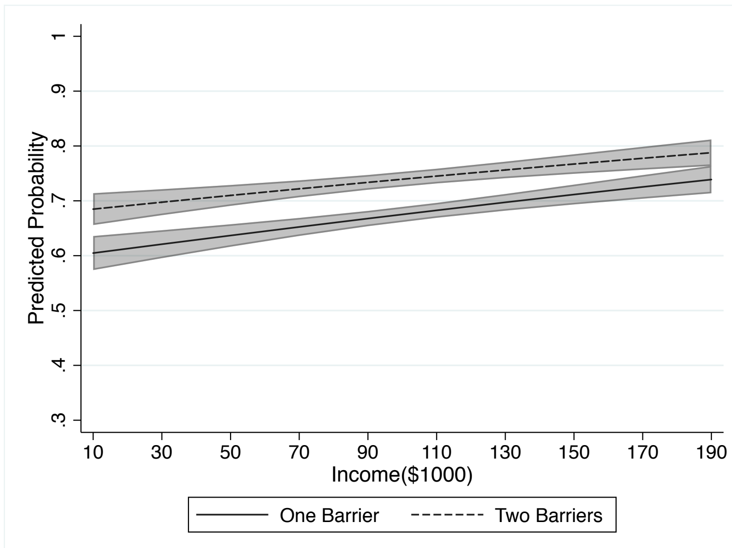

Figure 4. The Effect of Barriers and Income on Seeking Online Health Information
Note: Based on Appendix 1- Model 4, Figure is used to test H_{4c}.
Shaded region=95% confidence interval.

Discussion and Conclusions

This paper found that online health information can function as complementary resources for individuals with certain conditions like depression while not for individuals with heart diseases or high blood pressure, which partially supports my hypothesis H_1 that: Individuals with health issues are more likely to seek online health information. These results confirm previous research showing that disease severity matters regarding the value of online health information (Brophy et al., 2004; W. Jacobs et al., 2017; Peppa, Edmunds, & Funk, 2017; Sassenberg & Greving, 2016; Zhang, Guo, Lai, & Yi, 2019). Further research about the importance of online health information for different diseases is necessary since online health information's complementary value is only valid for specific conditions such as mental health.

Interestingly, online health information is essential for individuals with employer-based insurance, which suggests that individuals who pay more out of pocket are more likely to use online health information. Additionally, online health information is important for vulnerable individuals who have more barriers to health information resources, such as dissatisfaction in communication with doctors, which supports my hypothesis H_3 that individuals with more barriers to health resources are more likely to use online health information. This result confirms previous studies that vulnerable communities are more likely to use online health information (Bhandari et al., 2014, p. 1113; Furtado, Kaphingst, Perkins, & Politi, 2016; Jabson, Patterson, & Kamen, 2017; R. Jacobs et al., 2016; Tustin, 2010; Zimmerman, 2018), and subsequently supports the theory proposed by this study that online health information has substitutive value for vulnerable communities. The interaction effects between income and various factors, including depression and barriers to health resources, reinforce complementary and alternative values, especially among low-income communities.

This study finds that females, younger individuals, and those with higher income are more likely to use online health information. These results confirm a substantiative body of research with similar findings (I & Gupta, 2004; Ghweeba et al., 2017; W. Jacobs et al., 2017; Miller & Bell, 2012; Myrick & Willoughby, 2017; Paek & Hove, 2014; Rowley et al., 2017).

Additionally, prior work has shown that online health information has problems concerning accuracy and completeness (Risk & Petersen, 2002), health information reliability (Garfinkle et al., 2019), issues associated with individuals' limited health literacy (Meppelink, Smit, Diviani, & Van Weert, 2016). These potential threats indicate the importance and necessity of improving the quality of online health information and individuals' ability to use online health information. These findings suggest that government and private health-related institutions would be well served by improving the public's quality of online health information.

Concerning the COVID-19 pandemic, online health information is crucial in educating, supporting, and helping individuals slow the spread of the virus and get their vaccine (Q. Ye, Zhou, & Wu, 2020). Noticeably, online health information is essential for people with depression, which needs further research as depression increased significantly during the COVID-19 pandemic (Ettman et al., 2020, 2021; Hawes, Szenczy, Klein, Hajcak, & Nelson, 2021; C. H. Liu, Zhang, Wong, & Hyun, 2020). Additionally, seniors and individuals who have some disease such as obesity tend to be left out by the knowledge available on the Internet.

As the diseases are discussed separately in this study, more research is needed to examine how people with multiple health conditions use online health information. Additionally, new research with updated data is necessary as the health policies have changed a lot over the past several years. The research presented in this paper does not confirm a correlation between having health insurance and online health information searching behaviors. Furthermore, this study suggests that 1) online health information have two important economic values – complementary and alternative for the public, and 2) barriers to accessing online health information should be removed so that the people who need access to this information the most can obtain it to maximin the economic value bring by the Interest.

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Appendix 1: Seeking for Online Health Information[3]

VARIABLES	(1) Model 1 (Initial Model)	(2) Model 2 (Depression *Income)	(3) Model 3 (Employer Insurance*Income)	(4) Model 4 (Insurance* Barrier Index)	(5) Model 5 (Full Model)
Barrier Index	0.0259*	0.0260*	0.0259*	0.0184	0.0186
	(0.0119)	(0.0119)	(0.0119)	(0.0184)	(0.0184)
Diabetes	0.0215	0.0238	0.0209	0.0233	0.0250
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
High Blood Pressure	-0.160	-0.160	-0.160	-0.158	-0.158
	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)
Heart Disease	0.266	0.268	0.267	0.266	0.267
	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)
Cancer	0.245	0.243	0.244	0.245	0.242
	(0.134)	(0.134)	(0.134)	(0.134)	(0.134)
Lung Disease	0.0261	0.0269	0.0263	0.0286	0.0295
	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)
Depression	0.680***	0.601**	0.681***	0.682***	0.605**
	(0.134)	(0.197)	(0.134)	(0.134)	(0.198)
BMI	-0.0172*	-0.0172*	-0.0172*	-0.0174*	-0.0174*
	(0.00801)	(0.00801)	(0.00801)	(0.00801)	(0.00802)
Medicare	0.0963	0.100	0.0958	0.0953	0.0988
	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)
Medicaid	-0.129	-0.120	-0.126	-0.128	-0.116
	(0.155)	(0.156)	(0.157)	(0.155)	(0.158)
Employer-based	0.294*	0.291*	0.313	0.294*	0.306
	(0.129)	(0.129)	(0.193)	(0.129)	(0.193)
Private Insurances	0.155	0.153	0.154	0.153	0.150
	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)
Other Insurances	0.0709	0.0697	0.0699	0.0706	0.0686
	(0.118)	(0.118)	(0.119)	(0.118)	(0.119)
Birth Gender	0.391***	0.392***	0.391***	0.390***	0.391***
	(0.104)	(0.105)	(0.105)	(0.105)	(0.105)
Age	-0.0401***	-0.0401***	-0.0401***	-0.0400***	-0.0401***
	(0.00498)	(0.00498)	(0.00499)	(0.00498)	(0.00499)
African American	-0.124	-0.124	-0.124	-0.126	-0.127
	(0.151)	(0.150)	(0.151)	(0.151)	(0.150)
Hispanic	-0.193	-0.194	-0.194	-0.190	-0.192
	(0.146)	(0.146)	(0.146)	(0.146)	(0.146)
Asian	-0.129	-0.130	-0.130	-0.127	-0.128
	(0.274)	(0.274)	(0.274)	(0.274)	(0.274)
Other Races	0.146	0.146	0.145	0.153	0.152
	(0.319)	(0.319)	(0.319)	(0.319)	(0.320)
College Degree	0.594***	0.595***	0.594***	0.595***	0.596***
	(0.134)	(0.134)	(0.134)	(0.134)	(0.134)
Graduate Degree	0.823***	0.827***	0.823***	0.827***	0.830***
	(0.161)	(0.162)	(0.161)	(0.162)	(0.162)
Income	0.00671***	0.00650***	0.00688***	0.00534	0.00528
	(0.00120)	(0.00126)	(0.00176)	(0.00282)	(0.00314)

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05

[3] The values in the table are odds ratios.

ARTICLE 2: IMPACT OF HEALTH POLICIES AND LOCAL POLITICAL IDEOLOGY ON SPATIAL-TEMPORAL PATTERN OF PUBLIC EMOTION TOWARDS COVID-19

Abstract: Social networks such as Twitter enable people to interact with each other and share health-related concerns and emotions in an effective and novel way, as evidenced during the COVID-19 pandemic when in-person communication became more inconvenient under the stay-at-home policy. Public emotions from these social network data have increasingly attracted scholars' attention because of their significant value in predicting public behaviors and public opinions. However, little attention has been paid to the impacts of health policy and local political ideology on the trends of spatiotemporal emotions related to COVID-19. This study examines 1) the spatial-temporal clustering trends of negative emotions (or spillover effects); 2) whether health policies such as stay-at-home policy and political ideology are associated with spatiotemporal emotion patterns towards COVID-19. This article finds that: COVID-19-related negative emotions detected by social media have spillover effects and that counties with stay-at-home policy or counties that are predominantly democratic exhibit a higher observed number of negative emotions toward COVID-19. These results suggest that scholars and policymakers may want to consider the impacts of interventions caused by public policy and political polarization on spatial-temporal emotions detected by social media.

Keywords: Social Media, COVID-19, Twitter, Health Policy

Introduction

Infodemiology combines information and epidemiology to analyze diseases' geography patterns to help make health policies (Eysenbach, 2009, p. 2). During the COVID-19 pandemic, social networks could function as a tool to analyze the spatial-temporal pattern of public emotions. Analyzing people's activities on social networks is one of many infodemiology applications; however, little research explores the impacts of public policies on public emotions in COVID-19, especially in a polarized political environment. Regarding health policies, this study mainly evaluates the impacts of the stay-at-home policy, restaurant/bar/entertainment-related business closures, bans on significant events, and closures of public schools on the spatiotemporal patterns of COVID-19 emotion patterns of COVID-19 during the early stages of the pandemic. Additionally, my research further explores these relationships while considering the spillover effect of public emotions from a geography perspective.

Furthermore, political polarization in the U.S. has been a severe issue as the public and policymakers tend to disregard information that contradicts their political ideology, which leads to a less efficient situation in policymaking and policy implementation (Fiorina & Abrams, 2008; Rekker, 2021; West, Gao, & Jang, 2021). The polarization in political ideology triggers deep conflicts in resolving public issues, and the conflicts are rooted in emotions from the public narratives (Aureli & Smucny, 2000; Baker, 2018; Brigg, 2008; Cobb, 2013; Funk & Said, 2004; Halperin, 2014; Retzinger & Scheff, 2000; Simmons, 2020). Emotions have increasingly attracted attention from scholars studying conflict studies (Gupta, Bhattacharya, & Gopalan, 2021; Halperin, 2015; Halperin & Tagar, 2017; Hurtado-Parrado et al., 2019; Kupatadze & Zeitzoff, 2021; Susanu & Nicolae, 2019). However, public's emotions in a divided political environment have received little attention considering the interventions from public policies

(Nair, 2008). My study is going to fill this gap by examining whether political ideology is associated with public emotions in a conflicted situation like COVID-19.

I also control for socioeconomic conditions such as education, population size, and per capita income to determine their influence. I focus on the following research questions: 1) Is there a spillover effect of public emotions detected by Twitter data? And 2) What are the relationships between various COVID-19 health policies, political ideology, and the spatial-temporal emotion patterns of the public?

Review of the Literature

Social Media Use on Policy Issues

Studying public emotions in a global crisis is essential. It could provide a snapshot of how the public reacts under multiple policies, potentially offering some guidelines for policymakers (Feng & Kirkley, 2021). However, literature on public emotional response under multiple policy interventions is scarce, especially considering the polarized political environment. This study will use social media as a tool to measure the public's collective emotions, which multiple scholars have used in studying policy response (Burnap & Williams, 2015; Feng & Kirkley, 2021; Syaifudin & Puspitasari, 2017).

Social media data has been increasingly applied in social sciences (Bartlett, Lewis, Reyes-Galindo, & Stephens, 2018). Scientists used Twitter data to measure public activities, such as the Black Lives Matter protest in this pandemic (Zhang et al., 2020). Social sharing through social networks is essential for the diffusion of health information (Nielsen & Schrøder, 2014; Purcell, Rainie, Mitchell, Rosenstiel, & Olmstead, 2010; Sharma, Yadav, Yadav, & Ferdinand, 2017). With the increasing influence of social media, the public could conveniently and in a timely way express their concerns, experiences, and emotions toward a public crisis on a large platform. This information on social networks can be used as data to analyze the dynamics of public emotions. Health information on social networks, in part, helps policymakers better understand the emerging health crisis (King et al., 2013; Schillinger, Chittamuru, & Ramírez, 2020; Sharma et al., 2017).

Twitter provides access to millions of short, geographically localized messages. Emotions detected in a timely manner by social networks such as Twitter are especially valuable in the management of health crises (Chunara, Andrews, & Brownstein, 2012; Valdez, Ten Thij, Bathina, Rutter, & Bollen, 2020). During infectious disease outbreaks, near-real-time data from social networks can provide an earlier estimate of emotion dynamics for policymakers and health institutions than what is traditionally available. There are several advantages in using social networks to detect public emotions: 1) social networks data are cost-effective (Cao et al., 2018); 2) social networks data are timely and 3) social networks can be monitored both locally and globally (Al-Surimi, Khalifa, Bahkali, EL-Metwally, & Househ, 2017). Social media data has been helpful in predicting public health opinions and behaviors (Xiaolei Huang et al., 2017). For instance, the use of Twitter data could also alleviate the problems of underrepresentation of the minority population and low sensitivity to new emerging public health issues.

Social media use as an informational tool to assist in disease management and prevention has grown significantly in recent years (Xiao Huang, Li, Jiang, Li, & Porter, 2020; Santoro, Castelnuovo, Zoppis, Mauri, & Sicurello, 2015; Schillinger et al., 2020; Stellefson, Paige, Chaney, & Chaney, 2020). Social media data have been frequently used to study the spatial patterns of many types of diseases: 1) influenza-like illnesses such as COVID-19 (Bisanzio, Kraemer, Brewer, Brownstein, & Reithinger, 2020; Xiao Huang et al., 2020); 2) chronic diseases (Reich et al., 2019; Szeto et al., 2018); 3) noncommunicable diseases (Islam et al., 2019); and 4) rare diseases (Pemmaraju, Utengen, Gupta, Thompson, & Lane, 2018; Pohlig et al., 2017) which subsequently formed an interdisciplinary field – infodemiology. However, many studies fail to consider spatial dependence of the information detected through social networks, which means "the propensity for nearby locations to influence each other and to possess similar attributes" (Goodchild, 1992, p. 33). Spatial dependence is widely studied in social science, including the economy (Chegut, Eichholtz, & Rodrigues, 2015; Hall & Ahmad, 2012; Patacchini & Zenou, 2007), public health (Leroux, Lei, & Breslow, 2000), and public policy (Neumayer & Plümper, 2012). Tobler proposed the first law of geography, Tobler's first law (TFL), which states that 'everything is related to everything else, but near things are more related than distant things' (Tobler, 1970). Spatial dependence is sometimes called spillover effect. In the economic field, it means institutions in a country lead to improvement in economic growth in its own country, and it also consequently generates spillover effect on economic growth in neighboring countries (Hall & Ahmad, 2012).

My research extends the use of social media in public emotion detection uniquely by considering the spatial dependence across the U.S. at the county level. For example, if the total number of deaths or the total infected from COVID-19 is relatively high in county A, the negative emotional reaction, such as fear, is strong in county A and its neighboring counties. Understanding this spatial dependence is critical to comprehend public emotions detected by social networks such as Twitter, especially in a health crisis like COVID-19.

Twitter Use in COVID-19

Social media like Twitter provides multiple benefits in the COVID-19 pandemic: 1) One of the crucial positive roles of Twitter in defeating COVID-19 is uniting people by spreading courageous stories of health workers; 2) Twitter has policies to filter out misinformation; and 3)

Twitter research results can be published rapidly, which is a considerable advantage over the traditional approach of releasing information through peer-reviewed journals (Rosenberg, Syed, & Rezaie, 2020). Health professionals also use social networks to send early alarms of a health crisis to attract the attention of international organizations (Alasaad, 2013). For example, a Chinese doctor - Li, Wenliang - had used social networks to signal the early outbreak of Coronavirus in 2019.

Due to its convenience, many scholars used Twitter data to detect the spatial-temporal dynamics of public emotions in COVID-19. Twitter data can capture the online collective public's emotions, which helps capture the mental well-being of the population, perception of public risk in health crises related to COVID-19 (Arora, Chakraborty, Bhatia, & Mittal, 2020; Dyer & Kolic, 2020). COVID-19 Twitter data could highlight the spatial-temporal trend of public attention and emotion (Medford, Saleh, Sumarsono, Perl, & Lehmann, 2020). This study proposes that emotion patterns on Twitter follow TFL; counties hit hardest by COVID-19 may have more negative emotions, and these negative emotions will influence their neighboring counties (termed spillover effects) with emotions like anger, fear, sadness, and surprise. Furthermore, this study also evaluates the temporal trend of public emotions. Considering the benefits of using social media data and Tobler's first law, I will test the spillover effects of negative emotions; and the relationships between the number of confirmed cases of COVID-19 per county and emotions in this pandemic. I propose counties with more negative emotions have spillover effects and counties with hot spots of COVID-19 activity in the early stages of the pandemic tend to have more negative emotions such as anger, surprise, sadness, and fear.

Using social media to Study Impacts of Policies on Emotions

With the tremendous cost of lives, loss of jobs, and the economy's slowdown, governments within the United States at the local, state, and federal levels adopted multiple health policies to control the COVID-19 pandemic. During the early stage of the COVID-19 pandemic, the U.S. State governments adopted various health policies, including shelter-in-place orders, closures of restaurants/bars/entertainment-related businesses, bans on large events, and closures of public schools.

The effectiveness of these policies was widely studied by scholars (C. Courtemanche, J. Garuccio, A. Le, J. Pinkston, & A. Yelowitz, 2020; C. J. Courtemanche, J. Garuccio, A. Le, J. C. Pinkston, & A. Yelowitz, 2020; Dave, Friedson, Matsuzawa, & Sabia, 2020; Friedson, McNichols, Sabia, & Dave, 2020). For instance, the stay-at-home policy is more effective in decreasing mobility among Democratic-leaning counties (Gao & Radford, 2021). However, no studies have evaluated the influence of these policies on public emotions towards COVID-19 on social networks. Since infodemiology suggests that social media data can reflect the disease pattern, my research further examines whether government interventions such as health policies could affect spatial-temporal patterns of emotions on social media.

Using social media to Study Impact of Political Ideology on Emotions

Conflict extension means Republicans have become more consistently conservative on policy dimensions while Democrats have grown more consistently liberal (Layman & Carsey, 2002a, 2002b). Increasing political polarization between Democratic and Republican provoke mass policy attitudes response under public policies (Layman & Carsey, 2002a, 2002b). Political polarization makes public policies less efficient, especially in policymaking and implementation (Brady, Ferejohn, & Harbridge, 2008; Jesuit & Williams, 2017; Weber et al., 2021). Examples of political polarization in the policymaking process include welfare, education, energy, and environmental policies (Dar & Spence, 2011; Hart, Stedman, & Clarke, 2021; McCright, Xiao, & Dunlap, 2014; Weber et al., 2021). Regarding policy implementation, political ideology dominates the public's health reactions towards the COVID-19 pandemic, including policy preferences, mask use, social distancing, and public mobility under this polarized political environment (Bruine de Bruin, Saw, & Goldman, 2020; Gao & Radford, 2021). This study is going to further explore whether conflict extension or political ideology polarization impacts the public emotion response under several health policies.

As COVID-19 is contagious, the way to contend with its spread is to take protective actions, such as washing hands more frequently and wearing the mask. Unlike some countries adopting much stricter policies such as a lockdown of a whole city. Most policies in America, such as stay-at-home policies or social-distancing policies, are mostly executed depending on the individual's self-protection cognition. Furthermore, the then president's opinion on controlling this pandemic is initially significantly different from that of health experts, leading to a division in public emotional reactions to this crisis. Previous studies confirmed that political ideology influences attitudes (van Holm, Monaghan, Shahar, Messina, & Surprenant, 2020; Zaller, 1992). Subsequent studies also found that political ideology affected individuals' health protection actions (Gao & Radford, 2021; West et al., 2021). This study further examines the relationship between political ideology and public emotional reactions to COVID-19, especially in this divided political environment.

Demographic Information of Counties

Social media data have a representative bias (Ruths & Pfeffer, 2014). For example, educated adults are more likely to use social networks to express their health concerns. This study controls the level of education at the county level to alleviate bias. Furthermore, many studies using Twitter data did not consider the background information of the tweets, such as the population and the community's economic status. To alleviate the above biases, I control the counties' education, population size, and income.

Hypothesis H_1 (infected number): Counties with more infected people will experience a higher number of negative emotions from COVID-19.

Hypothesis H_2 (health policy): Counties with more days of stay-at-home policy will experience a higher number of negative emotions from COVID-19.

Hypothesis H_3 (political ideology): Counties with higher Trump support rates will experience a higher number of negative emotions from COVID-19.

Hypothesis H_4 (education): counties with a higher percentage of the population with colleague degrees, including college and graduate degrees, will experience a higher number of negative emotions weekly COVID tweets.

Hypothesis H_5 (income): counties with a higher per capita income will experience a higher number of negative emotion rate.

Methodology

Data: My research utilizes composite data from several data sources to test these hypotheses. I use Twitter data from Data Science School at the University of North Carolina at Charlotte from February 11, 2020, to April 9, 2020. Given the importance of geographical location, I only include geotagged tweets. Typically, Twitter data concerning health topics only has 2.02% to 2.70% of tweets with GPS information (Burton, Tanner, Giraud-Carrier, West, & Barnes, 2012). The Python package Test2emotion detected five emotions (angry, fear, sad, surprise, and happy) from each tweet. Test2emotion[4] is a Python package to extract emotions from the content. Scholars have increasingly used Test2emotion in the public health field to detect public sentiments (Di Sotto & Viviani, 2022; Kumar, Reji, & Singh, 2022; Ramírez-Sáyago). The raw count of deaths and confirmed cases per county is from Johns Hopkins University. The 2016 U.S. county-level presidential result measures political ideology. Population, income, and education data come from the U.S. Census Bureau. This study excludes the data from Alaska and Hawaii as lots of information regarding these two states are lost.

Dependent variable: my dependent variable is the aggregated total count number of negative emotions, including anger, fear, sadness, and surprise per county per week.

Independent variables: My key independent variables are all measured at the county level. The duration of the policy is measured by the days of implementation of each policy, including the stay-at-home policy by April 9. Political ideology is measured by the Biden support rate at the county level.

Control variables: my research controls the socioeconomic characteristics of counties to alleviate the representative bias of Twitter data. These control variables are education, income, and population. Education is measured by the percentage of the population with bachelor's or higher degree per county; income is measured by per capita income per county; the population is measured by the log of the population size by county.

Statistical Methods:

[4] https://pypi.org/project/text2emotion/

I use Python for data preprocessing, ArcGIS Pro for spatial visualization, and STATA for running models. I use multiple spatial statistic methods: 1) Moran's I[5] to test the spillover effect or the spatial cluster of emotions; 2) Zero-Inflated Poisson (ZIP) regression for initial analysis because 82.23% of the dependent variables' values is zero and ZIP regression was designed for count data with excess zeros (Cameron & Trivedi, 2010; Lambert, 1992; Long & Freese, 2006; Long & Long, 1997), 3) Additionally, the data is panel data, so this study will use the random-effects model to reinforce the results by considering the temporal trend; 4) Furthermore, one of the spatial autoregression (SAR) models - generalized spatial two-stage least squares (GS2SLS) was adopted to analyze the association relationships while considering the spatial components (Kelejian & Prucha, 1998, 1999, 2010). Various spatial-temporal models, such as the fixed effects model and the random-effects model with spatial weight matrix are available in multiple software such as Geoda, R, Python, and Stata, are available to analyze spatial data (Belotti, Hughes, & Mortari, 2017; Elhorst, 2014; StataCorp, 2017). However, the results from these models are complex to explain, and the data size of this study is too large to use these models to process, so this study will mainly use the ZIP, random-effects model, and GS2SLS to examine the association relationships.

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[5] Moran's I is a test for spatial autocorrelation developed for spatial data (Moran, 1950). Here it is used to test the spatial cluster trend of public emotion detected by Twitter. Moran's I is defined as $I=\frac{N}{W}\frac{\sum_i\sum_j w_{ij}(x_i-x_j)(x_j-\bar{x})}{\sum_i(x_i-\bar{x})^2}$. Here N is the number of spatial unites and this study is the number of counties; Here i and j the spatial unit's index from the horizontal and vertical perspective; $\bar{x}$ is the mean of x; w_{ij} is a matrix of spatial weight (Cliff & Ord, 1981; Getis, 1995; Goodchild, 1986; Li, Calder, & Cressie, 2007; Mitchel, 2005). The null hypothesis is Error terms are independent and identically distributed (i.i.d). If Moran's I test rejected the null hypothesis here, it means there is spatial clustering trend of the data or the emotion in this study is not randomly distributed and the further regression needs to consider the spatial weight matrix into the regression formula.

Results

Emotions

Table 1a provides the temporal statistics of five emotions (angry, surprised, sad, fearful, and happy) of COVID-19. The number in the table is the total number of each kind of emotion per week. The total number of COVID-19 tweets with happiness jumped from 49 in the week of February 11 to its peak of 8935 on March 17. The number then slowly decreased to 4709 by April 9. Negative emotions (angry, surprised, sad, and fearful) follow a similar pattern that jumps sharply after March 10. Figure 1 shows the daily temporal trends of emotions. It confirms that negative emotions dominate during the COVID-19 pandemic (Lwin et al., 2020). Furthermore, Figure 1 shows that fear is the most significant emotion out of all the five emotions, and the first peak of the emotion appeared one day after public school closure and two days before stay-at-home policies were issued. Since the three most dominant emotions (*anger, sadness, and surprise*) are all negative emotions, so the following analyzes use the aggregated number of all negative emotions at the county level as a dependent variable.

Table 1a Temporal statistics of emotions.

Time (2020)		Happy	Angry	Surprise	Sad	Fear
February 11						
	Sum	49	25	101	102	165
	Min	0	0	0	0	0
	Max					
February 18						
	Sum	71	39	143	161	276
	Min	0	0	0	0	0
	Max	13	8	36	22	55
February 25						
	Sum	492	214	900	839	1269
	Min	0	0	0	0	0
	Max	48	21	107	82	125
March 3						
	Sum	1103	499	1917	1857	2800
	Min	0	0	0	0	0
	Max	62	33	117	116	169
March 10rd						
	Sum	5836	2176	8314	8374	11685
	Min	0	0	0	0	0
	Max	367	113	494	471	670
March 17rd						
	Sum	8935	3622	11786	12419	18023
	Min	0	0	0	0	0
	Max	510	238	731	726	1054
March 24rd						
	Sum	7796	3474	11517	11697	16232
	Min	0	0	0	0	0
	Max	463	198	692	733	932
April 2						
	Sum	6208	2622	8836	9320	12292
	Min	0	0	0	0	0
	Max	333	164	479	571	736
April 9						
	Sum	4709	1889	6714	6934	9508
	Min	0	0	0	0	0
	Max	303	110	518	502	673
Total						
	Sum	35199	14560	50228	51703	72250
	Min	0	0	0	0	0
	Max	510	238	731	733	1054

Figure 2a and Figure 2b show the spatial distributions of all negative emotions and surprise, respectively. These two figures show that negative emotions and surprise were primarily distributed on the east coast and the west coast of the U.S. This phenomenon corresponds with the fact that these coastal areas were hit most at the early outbreak of the pandemic in the U.S.

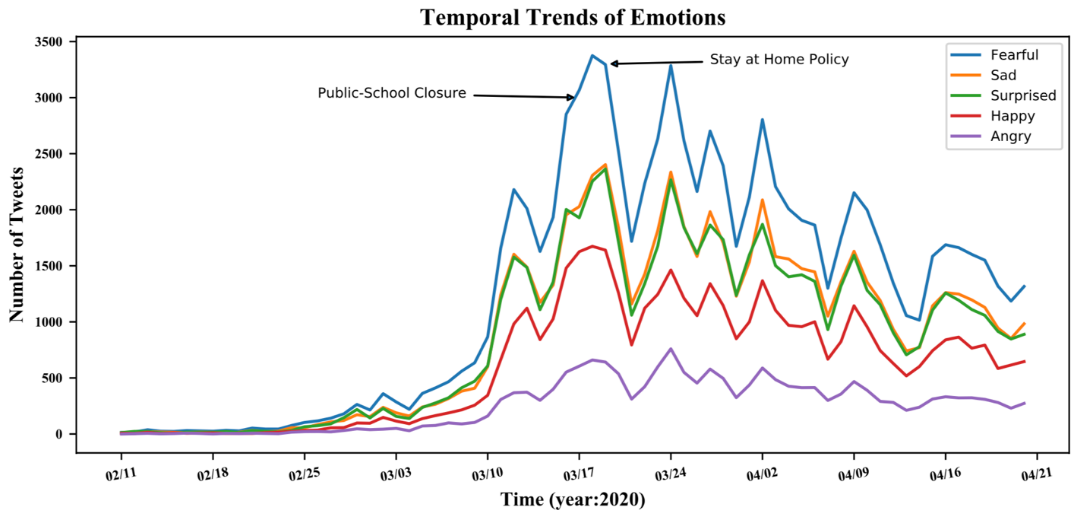

Figure 1. Temporal Trends of Emotions

Note: The lines represent the total number of emotions (anger, happiness, surprise, sadness, and fear) by time in the U.S. The X-axis represents time, while Y-axis represents the total number of each emotion. 02/11 represents February 11th, and 02/18 represents February 18th, etc.

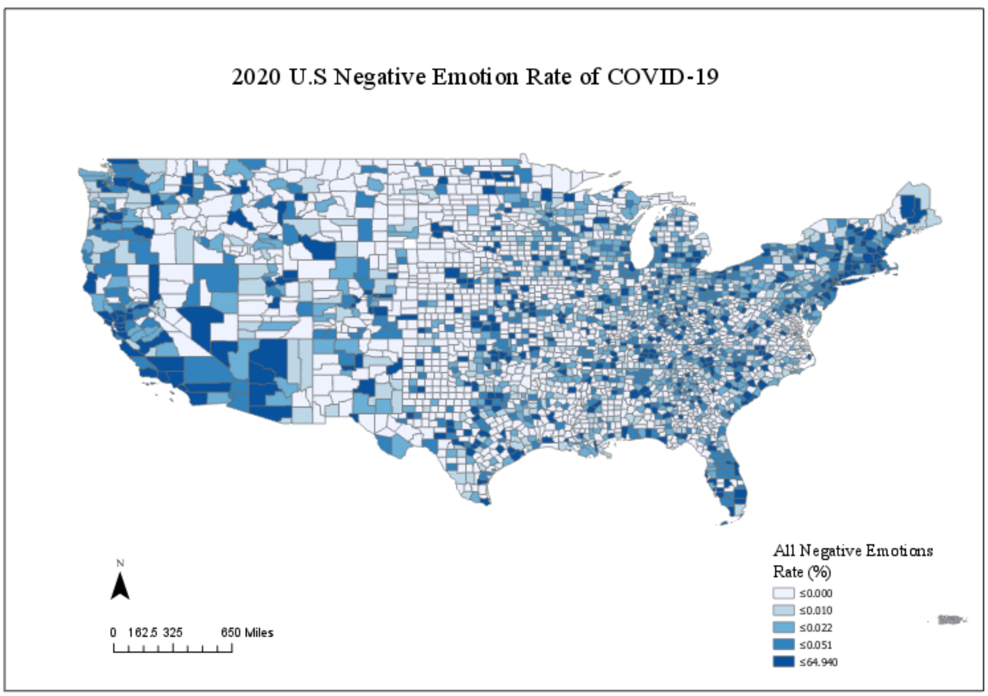

Figure 2a. Spatial Distribution of All Negative Emotions

Note: All negative emotions include anger, surprise, sadness, and fear. The map is normalized by population size.

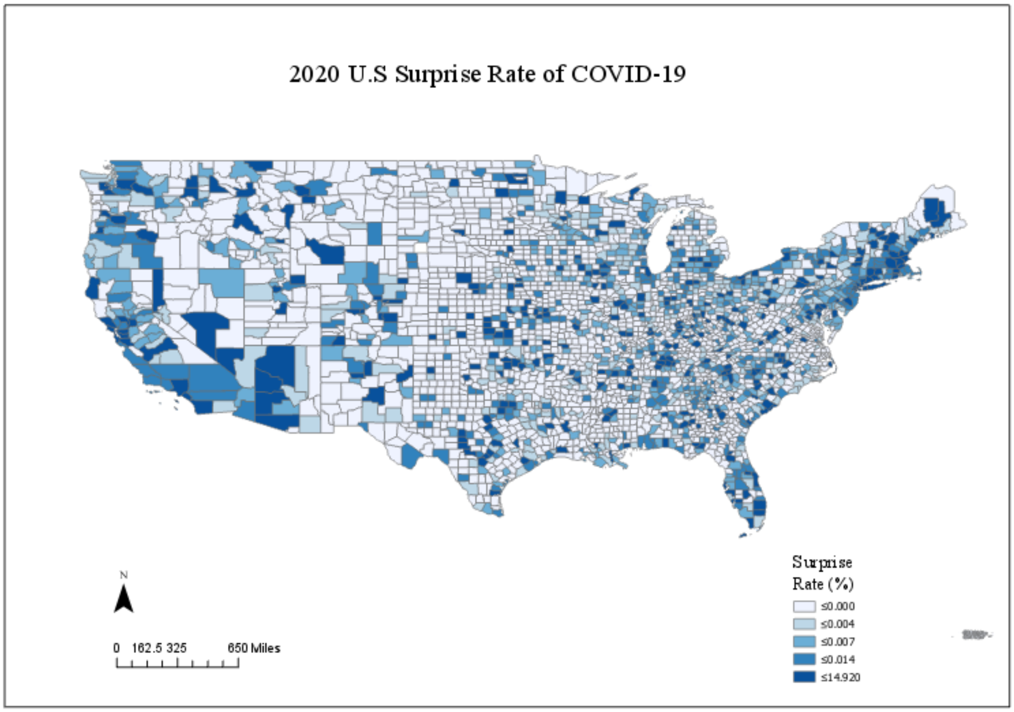

Figure 2b. Spatial Distribution of Emotion Surprise
Note: The map is normalized by population size.

The spatial statistical method-Moran I was applied to test the spatial clustering trend. Table 1b shows the results of the Moran I test: 1) at the week of February 11, Moran's I test failed to reject the null hypotheses that the residuals of the models are independent and identically distributed (i.i.d.), which means that the emotion tweets are not statistically spatially clustered together in the early stage of the pandemic in the U.S.; 2) however, as time went on, Moran's I test rejected the i.i.d. hypotheses of emotions at the week of April 9, which confirms that there are spatial clusters (or spillover effects) of emotions on Twitter, which confirms the visual appraisal of the emotion trend at Figure 2a and 2b. Furthermore, the change in Moran's I test results over time indicates that this study should use panel models to analyze the data because time plays an essential role in affecting the spatial distribution of emotions. These two results also suggest using the spatial autoregressive model (SAR) as the panel data analysis method.

Table 1b Statistical tests of spatial autocorrelation by Moran's I.

Time (2020)	Happy	Angry	Surprise	Sad	Fear
February 11	3.28	0.10	0.06	0.00	0.02
February 18	8.67**	0.27	0.03	0.00	2.16
February 25	51.48***	46.30***	35.96***	78.68***	81.18***
March 3rd	97.97***	49.18***	67.71***	68.49***	87.91***
March 10	91.05***	91.18***	76.32***	80.21***	79.75***
March 17	114.33***	83.57***	87.00***	96.21***	105.64***
March 24	102.92***	109.13***	97.51***	96.54***	98.50***
April 2	130.50***	80.19***	133.22***	113.24***	120.64***
April 9th	113.42***	103.77***	84.57***	84.80***	106.81***

Note: *, **, and *** indicate significance at 0.05, 0.01, and 0.001 levels, respectively. The null hypotheses are no spatial autocorrelation.

Public Policies

California is the first state that announced the stay-at-home policy on March 19, 2020. By Mach 24th, 2020, there were 14 States in total that issued the stay-at-home policy, and there were 17 more States (including Alaska and Hawaii) issued this policy by April 2, 2020. However, there are 10 States that never implement the stay-at-home policy, and these States are mostly located in the middle of the U.S. Figure 3a provides detailed information on the spatial-temporal pattern of stay-at-home policy.

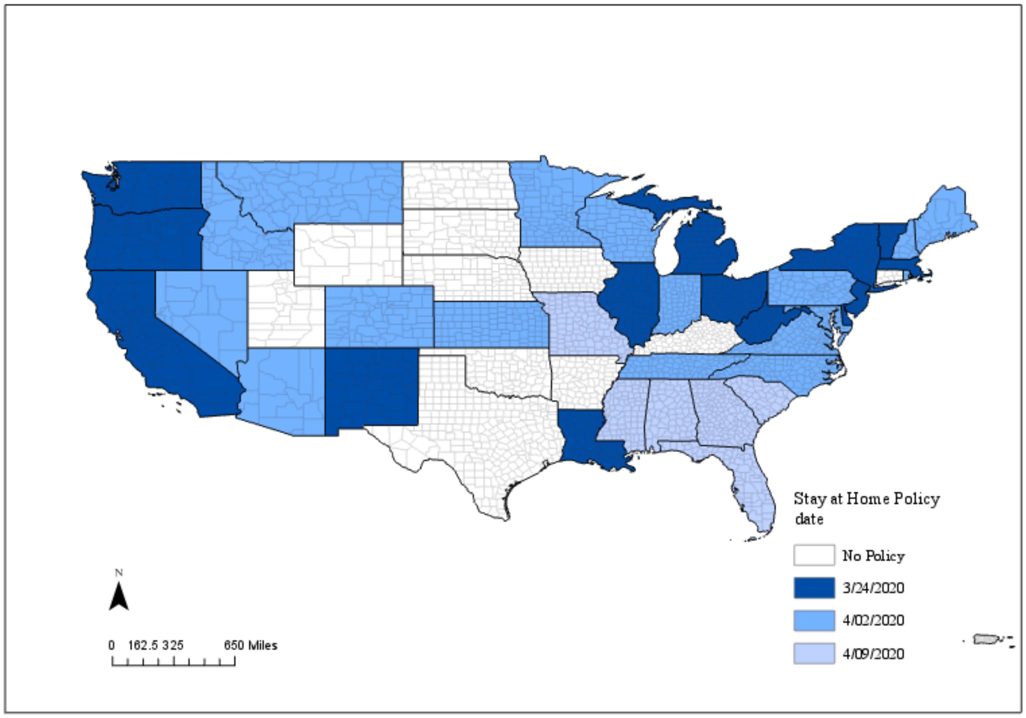

Figure 3a. Implementation Date of Public Policies

Note: White color represents no policy in this State; Dark blue color represents implementing the policy on and before March 24, 2020; Medium blue color represents implementing the policy on and before April 2, 2020; and Light blue color represents implementing the policy on and before April 9, 2020.

As to the entertainment facility and gym closure, this policy was implemented between March 16, 2020, and April 3, 2020. South Dakota was the only state that did not implement the closing gym policy. More information about the spatial-temporal distribution of the gym closure can be found in Figure 3b. Regarding public school closure, all the States in the U.S. had implemented this policy between March 16, 2020, and April 3, 2020. On March 16, 2020, the very first day of public-school closure, there were 20 States issued this policy (including Alaska and Hawaii). Detailed information about the spatial-temporal distribution of public-school closure can be found in Figure 3c.

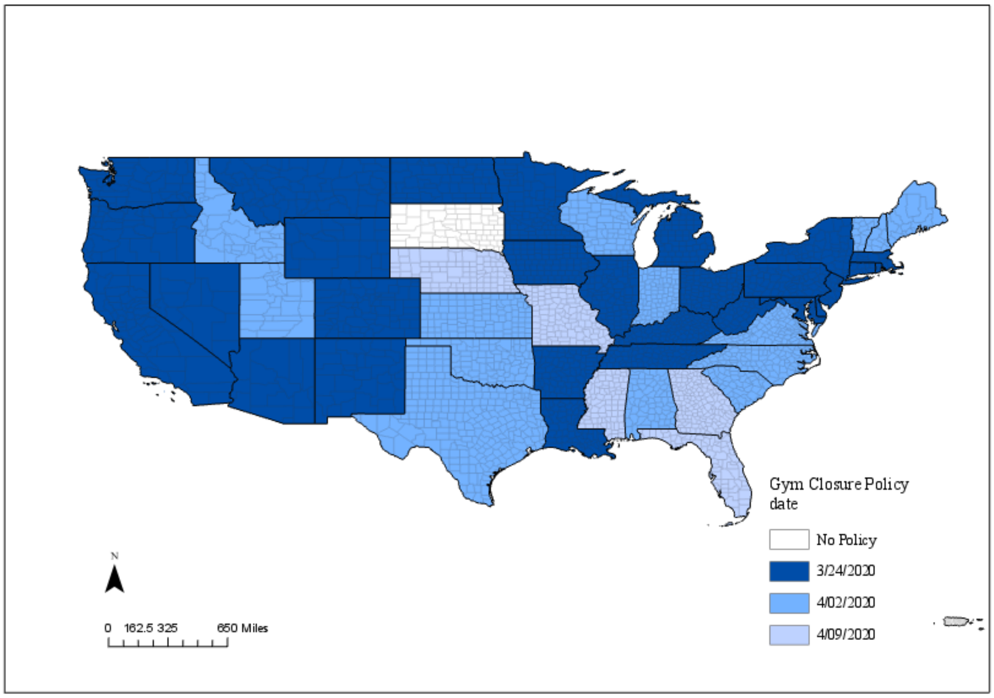

Figure 3b. Implementation Date of Public Policies

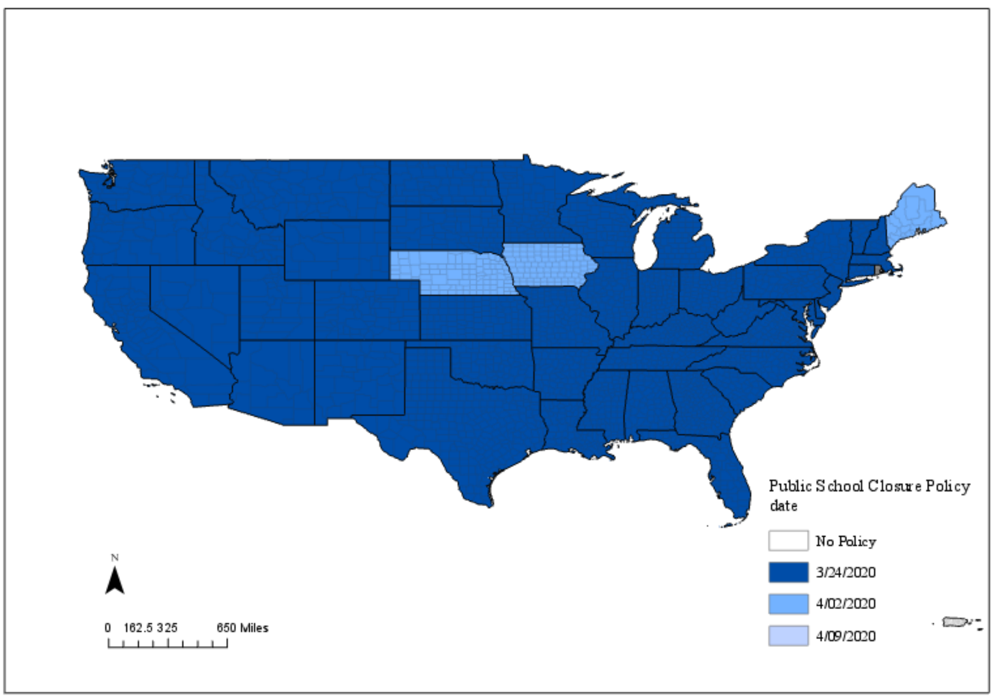

Figure 3c. Implementation Date of Public Policies

Political Ideology

Rather than using the maps from political science that indicate the final winning or loss in the 2020 presidential election, this map uses more detailed information to explore the relationship between political ideology and public health behavior. Figure 4a shows the geographic distribution of the Trump support rate in the 2016 presidential election. Figure 4a shows that Trump's support level was high in the middle of the U.S. The political map did not change significantly four years later. Figure 4b shows the spatial distribution of Biden support level in the 2020 presidential election. Figure 4b visually shows that shows Biden supporters are mostly clustered on the east and west coasts. Similarly, Republicans are distributed in the middle of the U.S. while Democratic are distributed at the coat lines.

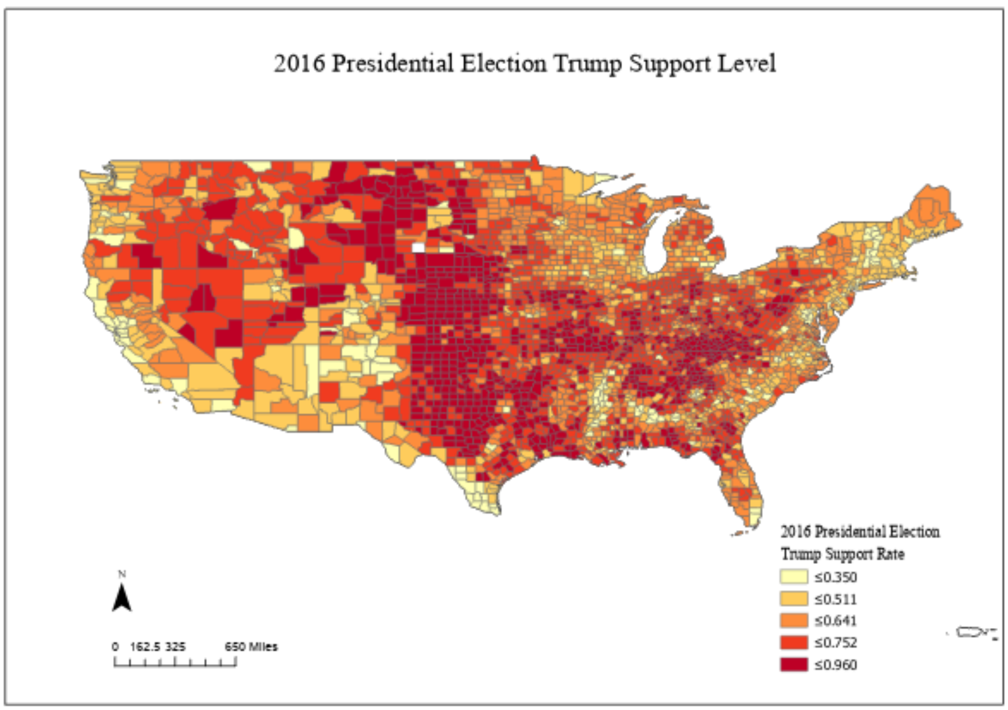

Figure 4a. Spatial Distribution of Trump Support Rate at 2016 Presidential Election
Note: The intervals are produced by using the method of Natural Breaks (Jenks).

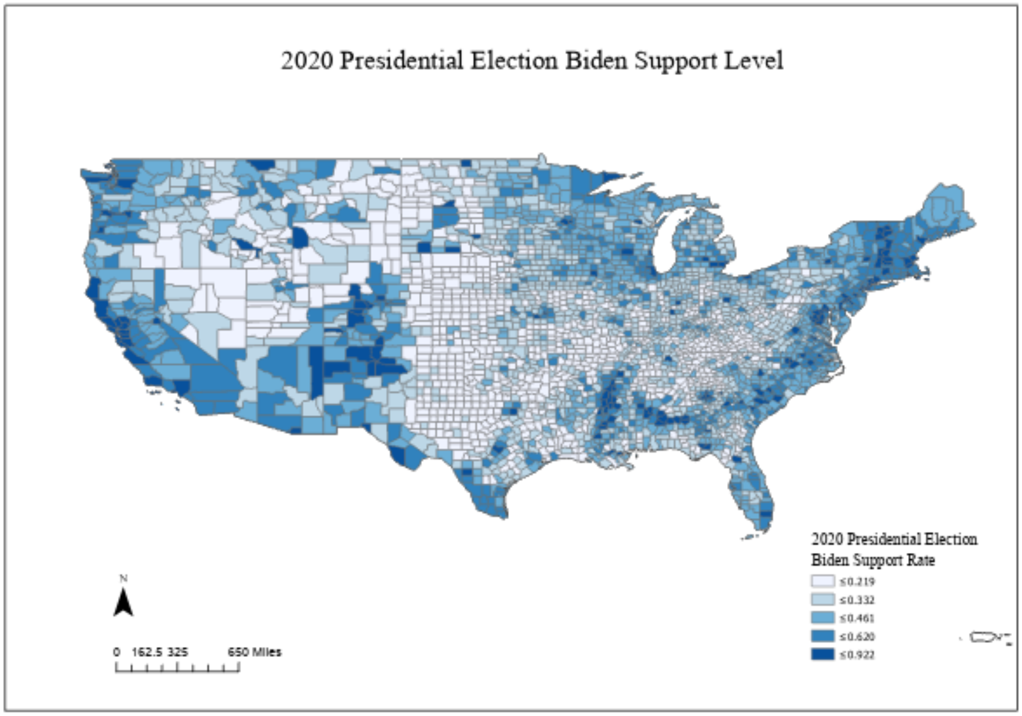

Figure 4b. Spatial Distribution of Biden Support Rate at 2020 Presidential Election

Public Policies, Political Ideology, and Public Emotions

I used a balanced panel sample of 3,233 US counties over nine weeks from February 11 to April 9. Considering the temporal trend of emotions, Table 2 shows the impacts of the total number of COVID-19 infections, the 2016 Trump support rate, and health policies on the negative emotion count detected by Twitter per week per county. As expected, counties with more total infected cases tend to have higher negative emotion rates detected from Twitter, which confirms hypothesis H_1. This result is consistent across three models: ZIP, Random Effects, and SAR. This shows that counties with more infected cases have a higher negative emotion rate, which indicates that Twitter data could reflect the public emotion concerns based on the spatial-temporal seriousness of the health crisis.

Regarding stay-at-home policy, the results are consistent across three models, the longer the counties had been impacted by the stay-at-home policy in implementation, the more negative emotions the counties had been clouded by. These results support my hypothesis H_2. However, regarding the political ideology's impact on public emotion, the results are not consistent across these models. Furthermore, to better understand the relationships between stay-at-home policy, Trump support rate, and negative emotions, I examine the interaction effect between the duration of the stay-at-home policy and Trump support level on negative emotions. The interaction effect results are shown in figure 5. Interestingly, as the days that the counties impacted by the state policy-stay-at-home increase, the predicted number of negative emotions of Democratic-leaning counties with Trump support level at 10% in the 2016 presidential election increases from 0 to 30 per county per week; however, the predicted number of Republican-leaning counties with Trump support level at 90% in 2016 presidential election decreases from 20 to 0. This shows how the public's emotion changes during the first month under the implementation of stay-at-home policy for counties with different political ideologies.

Table 2. Pooled OLS, fixed-effects, and random-effects models.

Variables	(1) zip	(1) zip	(2) Random effects	(3) SAR (April 9)
Infected	5.24e-05***	-3.59e-05	0.0107***	0.0130***
	(1.23e-05)	(0.000103)	(0.000553)	(0.000911)
Trump 2016 rate	2.432***	-0.198	67.82***	-7.744
	(0.586)	(0.187)	(9.981)	(9.910)
Per capita income	-4.08e-06	3.94e-05***	0.000365*	0.000752*
	(6.88e-06)	(5.45e-06)	(0.000181)	(0.000309)
65 years old population rate	1.217	-0.915	9.003	1.614
	(1.589)	(0.536)	(15.52)	(23.98)
College degree rate	0.0176**	-0.0473***	0.0906	-0.00689
	(0.00589)	(0.00369)	(0.128)	(0.207)
People of color rate	0.786*	1.228***	25.54***	20.34*
	(0.315)	(0.173)	(5.566)	(8.789)
Log population	0.624***	-0.993***	6.154***	9.645***
	(0.0589)	(0.0207)	(0.553)	(0.996)
Stay-at-home policy	0.121***	-0.00484	4.922***	0.736**
	(0.0214)	(0.00436)	(0.479)	(0.280)
Social gathering ban	-0.00600	0.000866	-0.191	-0.0781
	(0.00810)	(0.00442)	(0.133)	(0.277)
Public-school closure	-0.00704	0.00889	-0.531**	-1.715***
	(0.0128)	(0.00618)	(0.202)	(0.442)
Restaurant closure	-0.0127	-0.0133*	-0.00194	0.0840
	(0.0117)	(0.00653)	(0.204)	(0.442)
Gym closure	-0.00659	0.0109**	-0.126	-0.195
	(0.00930)	(0.00420)	(0.144)	(0.247)
Stay-at-home policy* Trump 2016 rate	-0.208***		-7.077***	0.0130***
	(0.0414)		(0.727)	(0.000911)
Constant	-5.947***	12.18***	-105.3***	-7.744
	(0.925)	(0.336)	(11.38)	(9.910)
Weight (DV: Negative)				-0.493***
				(0.117)
Observations	28,017	28,017	28,017	2,624
Number of counties			3,113	

Note: Standard errors are in parentheses, *** p<0.001, ** p<0.01, * p<0.05

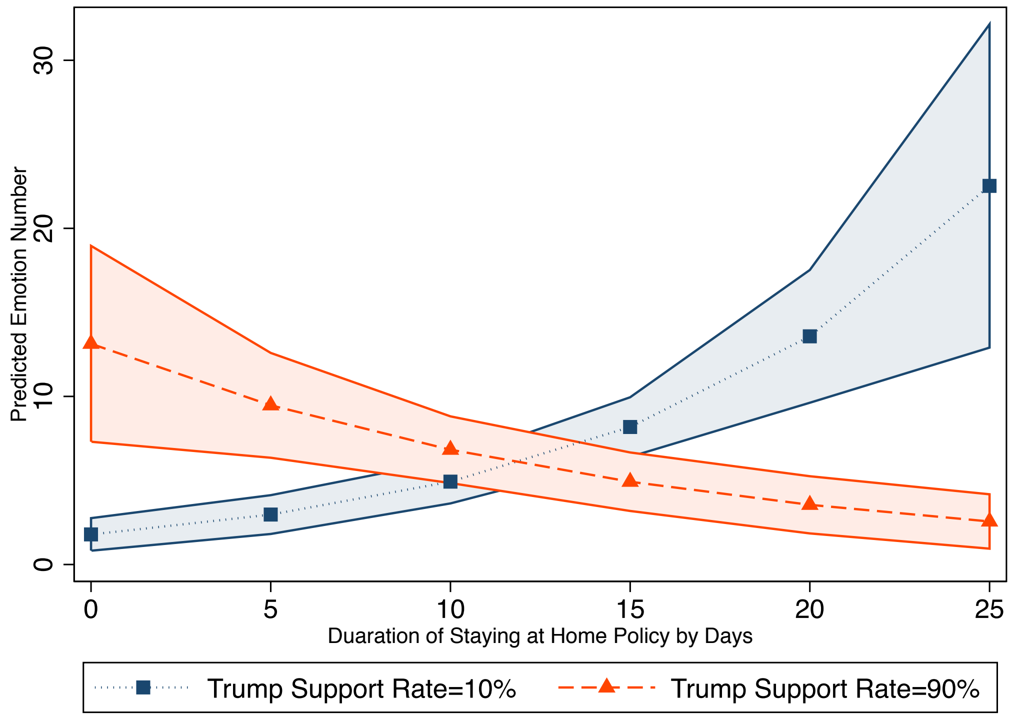

Figure 5. Interaction Effect of Stay-at-Home Policy and Trump Support Rate
Note: The orange area and the green area are the 95% confidence intervals.

The results are not consistent regarding other policies, including social gathering ban, public-school closure, restaurant closure, and gym closure. The random-effects model and SAR model for public school closure show that as the days those counties under this policy increase, the public's negative emotions decrease, which indicates that the public emotionally supports public school closure at the beginning of this pandemic. Policies like social gathering ban, restaurant closure, and gym closure are not significantly associated with the public's emotions based on panel data and spatial data analysis methods.

Regarding the socioeconomic status of the counties: 1) the higher per capita income the county had, the more negative emotions the county experienced.; and 2) the higher percentage of people of color per county had, the more negative emotions the county experienced, which potentially indicates that people of color in this pandemic were unproportionally impacted the negative emotions were heavily clouded around the communities with more people of color.

Discussion and Conclusion

In general, at the beginning of the COVID-19 outbreak, the negative emotions of the public on social media do not have a trend of social clustering (or spillover effects). However, these emotions began to show social dependence or spillover effects by the end of February, confirming that Tobler's first law applies the public's emotion on social media. The spillover effect of public emotions towards COVID-19 means that public emotions are affected by their close neighbors. Furthermore, the change of spillover effects also confirms a study by Dredze, Osborne, and Kambadur (2016) that timing matters in analyzing Twitter data with geolocation. Additionally, counties with more infected cases of COVID-19 have significantly higher negative emotions, which indicates that the public emotions detected from the social network could reflect the public's emotional footprint as the public's health situation was being threatened by a new health crisis (Arora et al., 2020; Dyer & Kolic, 2020).

Health policies such as the stay-at-home policy affect the number of negative emotions in a county. As the days counties under stay-at-home policy get longer, the public's negative emotions increase. This result indicates that future studies regarding using social network data for emotion studies should consider the policy interventions' impacts. Furthermore, political ideology affects county-level emotional reactions. Counties with low support rate for Trump have stronger negative emotions towards COVID-19. This confirms that conflict extension or political polarization impacts public's emotion reaction towards a health crisis. Regarding the impacts of counties' socioeconomic characteristics on the public' emotions, this study also found that counties with a higher percentage of people of color population with a college degree or counties with higher per capita income have a higher rate of negative emotions towards COVID-19.

There are several limitations to this study. First, causal relationships cannot be confirmed by this research and the time range in this study need to be extended in the future. Second, even representative issues of using Twitter are alleviated by controlling education, population size, and income; however, Twitter data still suffer from technical problems. Social media data were created for direct business purposes, so they are vulnerable to companies' modification of data collection algorithms to increase profits (Titiunik, 2015). Apart from these biases, the accuracy of the Twitter surveillance system decreases with 'chatter messages', which is caused by media attention (Broniatowski, Paul, & Dredze, 2013).

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ARTICLE 3: PUBLIC EMOTIONS AND PUBLIC WORKING MODES IN COVID-19: MODERATOR ROLES OF PUBLIC POLICY AND GOVERNORS' POLITICAL IDEOLOGY

Abstract: Studies of emotions have a long history before COVID-19 because emotions are essential indicators of public behaviors. During COVID-19, public mobility experienced a significant reduction as many people's work environment shifted from workplace to home or offline to online, especially under policies like the stay-at-home policy (Wen, Sheng, & Sharp, 2021). However, little has been done to examine the relationships between public emotions mined from social networks and the public behavioral responses to the COVID-19 crisis, especially considering the interaction effects between public emotions and public policy and political leaders' political ideology. This study fills these gaps by examining the relationships between public emotions and working modes, and the interaction effects between public emotion, public policy, and political leaders' political ideology on working modes. My research confirms that public emotions are associated with regional public mobility or working modes: counties with a higher number of negative emotions tend to have 1) more people staying at home, 2) fewer people working part-time, and 3) fewer people having delivering behaviors. Interaction effects show that: 1) For counties that are impacted by the state health policies, as the public's negative emotions increase, the risk-avoiding behaviors such as staying at home increase more significantly than in counties that were not affected by health policies; and 2) For counties under a Democratic governor, as the public's negative emotions increase, the risk-avoiding behaviors such as staying at home increase much more significantly than counties that are under a Republican governor.

Keywords: Social Media, COVID-19, Twitter, Health Policy

Introduction

In the early stages of COVID-19, there was no vaccine or effective medicines to prevent or cure the symptoms caused by the new virus, resulting in increased mortality rates. An onslaught of COVID-19 related stressors precipitated negative psychological reactions in U.S. citizens (Copeland et al., 2021; Pfefferbaum & North, 2020). These psychological reactions, including anger, fear, and other feelings, were captured by scholars through social network data mining (Banda et al., 2021; Lwin et al., 2020; Xue et al., 2020). The emotions captured from these social networks are valuable for studying public behaviors because emotions have long been studied as essential indicators of individuals' tendencies to take risks (Druckman & McDermott, 2008). In the case of COVID-19, no study has examined the relationship between the communities' emotions and their tendency of risk-taking like working from home during this pandemic.

Furthermore, many states issued various policies to ease the socioeconomic burdens caused by the virus, including the social distance policy, public school closure, small business closure especially restaurants, entertainment facilities and gym closure. However, little is known about how the policies interact with communities' emotions on public mobility or working modes. This study further investigates how the public policies interact with group-based public emotions in shaping their working choice, including working from home, working part-time, and working full-time. Other than that, previous studies have confirmed that political leaders' political ideology has played a significant role in moderating public behaviors (Cannonier & Burke, 2019; Neelon, Mutiso, Mueller, Pearce, & Benjamin-Neelon, 2021). However, no study has examined the interaction effect between political leaders' political ideology and public emotions on public behaviors.

This study fills these gaps by examining the relationships between the total number of negative emotions, including anger, fear, sadness, and surprise towards COVID-19 detected by Twitter and the public's mobility or working modes, including working from home, working part-time, and delivering behavior and further examine the interaction effects between public emotion, public policy and political leaders' political ideology on public mobility or working modes.

Literature Review

Emotions on Social Media

Emotion was defined as "organized cognitive-motivational-relational configurations whose status changes with changes in the person-environment relationship as this is perceived and evaluated (appraisal)" (Lazarus & Lazarus, 1991, p. 31). Emotion is a critical stimulus in a crisis (Jin, Pang, & Cameron, 2010), and scholars identified four dominant negative emotions, including anger, anxiety, and sadness (Coombs & Holladay, 2005; PANG, 2010). With the development of modern communication technologies, the public increasingly uses social media during a crisis to deliberate their emotions (Jin, Liu, & Austin, 2014; Johansen, Johansen, & Weckesser, 2016; Oh, Lee, & Han, 2021; Vignal Lambret & Barki, 2018).

Public psychological reactions, such as anger and fear, play significant roles in social movement (Cullen, Gulati, & Kelly, 2020; Della Porta & Giugni, 2013; Sjöberg, 2007). Emotions, especially intense emotions, are critical in shaping social behaviors and social decision-making (Andrade & Ariely, 2009; Buck, 1999; Clore, Schwarz, & Conway, 1994; Haselton & Ketelaar, 2006; So et al., 2015; Sołtys, Sowińska-Gługiewicz, Chęć, & Tyburski, 2017). Numerous scholars indicate that emotions are instrumental in driving real-life actions (Kuppens & Yzerbyt, 2012; Teper, Zhong, & Inzlicht, 2015; Zahn-Waxler, Friedman, & Cummings, 1983). Studies show that public emotions are associated with their behaviors, and "emotion interacts with cognition in determining an individual's behavior" (Della Porta & Giugni, 2013, p. 123). Emotions' significant role in shaping public behaviors is mainly because of their considerable influence on individuals' tendencies to take risks (Druckman & McDermott, 2008, p. 297).

Furthermore, emotions are essential in health-related decisions (Ferrer, Klein, Lerner, Reyna, & Keltner, 2016). Negative emotions such as fear, worry, and regret are strongly associated with preventative health behaviors such as following the health policies' guidance and taking vaccines (Chapman & Coups, 2006; Mou & Lin, 2014). People with positive emotions tend to have a high level of physical activities and mobility (Castillo, 2013). In a public crisis, tense emotions are mostly stirred by perceived risk or perceived vulnerability, which means the judgment of the magnitude and probability of potential adverse outcomes caused by an action (Ellen, Boyer, Tschann, & Shafer, 1996; Gough, 1990; Perloff & Fetzer, 1986; Van der Pligt, 1996). In the case of COVID-19, the negative emotions came from the actual risk, such as economic loss (losing jobs) and the contagious virus' damage to the human body with symptoms such as fever and cough (Carlos, Dela Cruz, Cao, Pasnick, & Jamil, 2020; Chen et al., 2020; Chung et al., 2020; Shi, Han, & Zheng, 2020; Song et al., 2020; D. Wang et al., 2020; W. Wang, Tang, & Wei, 2020).

Large datasets produced by social networks enable scholars to detect public emotions regarding various health topics. Before COVID-19, Social networks were proved to be complementary sources for understanding the spatiotemporal patterns of epidemiologic diseases (Bernard et al., 2018; Chunara, Andrews, & Brownstein, 2012; Deiner, Lietman, McLeod, Chodosh, & Porco, 2016; Jain & Kumar, 2018; Ye, Li, Yang, & Qin, 2016). Additionally, scholars increasingly use social network data to measure the public's emotional reactions toward health topics. For example, scholars use social media, especially Twitter, to capture the public's emotions, such as fear of health issues like cancer (J. Wang & Wei, 2020) and mental health (Seabrook, Kern, Fulcher, & Rickard, 2018; Valdez, Ten Thij, Bathina, Rutter, & Bollen, 2020).

During COVID-19 Pandemic, scholars confirmed that geolocated social network data are valid in describing the mobility dynamics of COVID-19 worldwide (Bisanzio, Kraemer, Brewer, Brownstein, & Reithinger, 2020; Huang, Li, Jiang, Li, & Porter, 2020). Furthermore, Twitter data were widely used to detect spatiotemporal dynamics of public emotions. Various public emotions associated with COVID-19 were captured from the social networks, such as fear of the virus (Arora, Chakraborty, Bhatia, & Mittal, 2021; Dyer & Kolic, 2020; Lwin et al., 2020), and positive emotions towards vaccination (Lyu, Le Han, & Luli, 2021).

As behavioral prevention of disease is critical in decreasing mortality and improving quality of life, understanding the public's health-related choices is increasingly vital in communities' health management (Ford, Zhao, Tsai, & Li, 2011; Hannan, Kringle, Hwang, & Laddu, 2021; Khaw et al., 2008; Krist et al., 2020; O'Connor, Evans, Rushkin, Redmond, & Lin, 2020). I argue that public emotions mined from social networks are essential indicators of behavioral changes such as working from home, working part-time, and providing delivery services. COVID-19 is a perfect scenario to study how emotions predict the public's behavioral choices – staying at home, working part-time, and providing delivery services at the community level-county level. The first research question of this study is: are emotions detected through social networks associated with regional public mobility or working modes? In this study, I mainly test whether negative emotion (including anger, fear, sadness, and surprise) is associated with preventative health behaviors such as staying at home, working part-time, and providing delivery behavior at the county level.

Public Policy, Governors' Political Ideology, and Working from Home

Emotions mined from social networks are a precious asset for policy studies because emotions are significant indicators of public behaviors. Emotions "significantly influence individuals' tendencies to take risks" (Druckman & McDermott, 2008, p. 297). However, using these emotions mined from social networks received little attention in public policies studies, so this study is going to fill this gap by evaluating the relationship between the public's emotions towards COVID-19 and public mobility at the beginning of the outbreak of COVID-19 by mining the data from Twitter while considering the impacts from multiple public policies.

After the outbreak of COVID-19 in early 2020, multiple policies were adopted by many states across the United States to curb the spread of the virus. These policies include shelter-in-place orders[6], closures of restaurants/bars/entertainment-related businesses, bans on significant events, and closures of public schools. Studies found that these policies significantly affect mobility behaviors, the interventions of public policies, especially stay-at-home policies, cause the mobility to decline significantly in urban areas (Armstrong, Lebo, & Lucas, 2020; Jacobsen & Jacobsen, 2020; Praharaj, King, Pettit, & Wentz, 2020; Vannoni, McKee, Semenza, Bonell, & Stuckler, 2020). Research indicates that emotions interact with situational factors in making health-related decisions (Ferrer et al., 2016). This is very important to know how policy interacts with the public's emotions on mobility because study found that psychological characteristics interreact with the policies on people's behaviors (Sumaedi et al., 2020). I argue that the interaction effects between public policies and public emotion are statistically significant on risk avoiding behavior – working from home. To put it another way: with the same level of negative emotions,

[6]also known as stay-at-home order

policies intervention could cause people's willingness to work from home to get stronger in the case of COVID-19.

The political division makes the policy less effective because the escalated disagreement in public policy priorities leads to bipartisan compromise less and less possible (Dixit & Weibull, 2007; Fiorina & Abrams, 2008). Furthermore, the notorious red-blue presidential election map of the United States became geographically more apparent since the 2000 election (Fiorina & Abrams, 2008). These side effects of political polarization have attracted tremendous attention from academia in studying public policy (de Bruin, Saw, & Goldman, 2020; Gao & Radford, 2021; Makridis & Rothwell, 2020; Weber et al., 2021; West, Gao, & Jang, 2021).

Facing the same crisis, some individuals may overestimate their risk, while others may underestimate their risk (Sjöberg, Holm, Ullén, & Brandberg, 2004; Weinstein, 1987). The uncertainties of COVID-19 in the early stage make some individuals underestimate the risks significantly, especially when President Trump downplayed the seriousness of this pandemic. The role of the public's political ideology has been well studied in COVID-19, and the public's political ideology plays a significant role in public health behaviors during the COVID-19 (Agarwal et al., 2021; Gao & Radford, 2021; Kerr, Panagopoulos, & van der Linden, 2021; van Holm, Monaghan, Shahar, Messina, & Surprenant, 2020). Republicans were: more likely to believe in and push conspiracy theories; less likely to engage in health-protective behaviors like wearing face masks; less likely to get the COVID-19 vaccine (Agarwal et al., 2021; Havey, 2020; Kerr et al., 2021; Killgore, Cloonan, Taylor, & Dailey, 2021). From the policy perspective, Conservatives were more likely to downplay their health risks and consequently less likely to follow social distancing protocols (Rothgerber et al., 2020). A few previous studies investigated political leaders' significant role in moderating public behaviors (Cannonier & Burke, 2019;

Neelon et al., 2021). However, the governor's political ideology has not received enough attention in its' impact on policies outcomes. My study fills this gap by proposing that: Governor whose political ideology is consistent with the president who favors the policies could make the policy more effective.

Other Socioeconomic Factors

Additionally, based on previous literatures, public mobility or working modes was also impact by multiple other socioeconomic factors such as age, education, and income (Haustein, 2012; Hunecke, Haustein, Böhler, & Grischkat, 2010; Hunecke, Haustein, Grischkat, & Böhler, 2007). Racial disparity in death and infected cases caused by COVID-19 across the U.S. is confirmed by multiple studies (Carethers, 2021; McLaren, 2021; Shah, Sachdeva, & Dodiuk-Gad, 2020). My study controls local communities' older population size, education, income, and racial proportion in evaluating the relationships between public emotion, public policy, governor political ideology, and public working modes at the county level.

The corresponding hypotheses are:

Hypothesis H_{1a} (stay-at-home): Counties with a higher rate of negative emotions experience more people staying at home.

Hypothesis H_{1b} (working part-time): Counties with a higher rate of negative emotions experience fewer people working part-time.

Hypothesis H_{1c} (delivering behavior): Counties with a higher rate of negative emotions experience more people with delivery behavior.

*Hypothesis H_2 (policies*emotion): As the negative emotion number increase, counties with COVID-19 policies experience a significantly higher number of people staying at home than counties without policies.*

*Hypothesis H_3 (governor*policies): As the negative emotion increases, counties with a Democratic governor experience significantly fewer people staying at home than counties with a Republican governor.*

Methodology

Data: This study adopts composite data from multiple sources to test the hypotheses. The public's emotions were detected by using Twitter data from the Data Science School at the University of North Carolina at Charlotte from February 11st, 2020, to April 9th, 2020. I only include geotagged tweets because the geographic location is the crucial information in this study as the study unit is the community - county. To measure social distancing behavior (SDB), I use the Social Distancing Metrics data provided by SAFEGRAPH, which includes information about people's working types based on mobile device telemetry. I use Kaiser Family Foundation (KFF)[7] for the political leaders' party identity. The raw count of deaths and confirmed cases per county is from Johns Hopkins University. The 2016 U.S. county-level presidential result measures political ideology[8]. I use Python for data preprocessing, ArcGIS for spatial visualization, and Python for temporal visualization. I use Python package Test2emotion[9] to detect five emotions (angry, fear, happy, sad, and surprise) from each tweet. The population, income, and education data come from the United States Census Bureau.

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[7] https://www.kff.org/other/state-indicator/state-political-parties/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D

[8] The data is collected by Tony McGovern from Fox News, Politico, and the New York Times and shared through Github (https://github.com/tonmcg/US_County_Level_Election_Results_08-20).

[9] https://towardsdatascience.com/text2emotion-python-package-to-detect-emotions-from-textual-data-b2e7b7ce1153

Dependent Variables: My research will aggregate the data at the county level to test the hypotheses. My study uses three dependent variables to measure the working modes: 1) staying at home; 2) working part-time; 3) providing delivery services. Staying at home is measured by the total number of people staying at home per county; working part-time is measured by the total number of people working part-time per day per county; 3) providing delivery services is measured by the total amount of people providing delivery service.

Key Independent Variables: My key independent variables include negative public emotion, public health policies, and governors' political ideology. Public emotion was measured by the total number of negative emotions, including anger, fear, sadness, and surprise per county per day. Public policies were measured by how many days the policy had been in implementation by April 9^{th}. The policies in this study include 1) stay-at-home policy; 2) social gathering ban policy; 3) public school close policy; 4) restaurant closure policy; and 5) entertainment facility and gym. Governors' political ideology was measured by the governor's political ideology in office in 2020. Governors' political ideology is coded as one of the counties had a Republican governor in office in 2020, while it is coded as zero of the counties had a Democratic governor in office. Additionally, the public's political ideology is measured by the rate of people voting for Trump by county in the 2016 presidential election in the U.S.

Control Variables: Income is measured by the per capita income of the county; education is measured by the percentage of the population in the county with bachelor's degrees and/or graduate degrees; race is measured by the percentage by people of color in the county.

Statistical Methods:

Various models, such as the fixed effects model and random-effects model on software such as Stata, SPSS, R, Python, and even some spatial statistical software like Geoda, are available to analyze panel data (Belotti, Hughes, & Mortari, 2017; Elhorst, 2014; StataCorp, 2017). Scholars suggested that the random effects model should naturally be preferred because it could address a wider range of research questions (Clarke, Crawford, Steele, & Vignoles, 2010; Riley, Higgins, & Deeks, 2011), so I chose to use the random-effects model to test my hypotheses for my panel data analysis.

Results

Table 1a provides the descriptive weekly temporal statistics of working modes. Figure 1a visually shows the daily total number of people staying at home. The total number increased dramatically after March 10th and reached a peak at the beginning of April and then dropped a little bit around April 10th and kept stable. Figures 1b visually shows the daily temporal trend of working part-time. The total number of people working part-time at the workplace dropped dramatically after March 10th and kept stable after that. The lower points represent the weekends when most people stay at home rather than stay at the workplace. In addition, the total number of people with delivery behavior and the total number of active devices dropped after March 10th based on Figures 1c and 1d. The results from these graphs indicate that the COVID-19 pandemic shifted the public’s activities from offline to online.

Table 1a. Temporal statistics of mobility and COVID-19 death and infected number.

Time (2020)		Home	Part-time	Full time	Delivery	Death	Infected
February 11th	Sum	4440548	2746062	2042946	577972	0	15
	Min	2	1	1	1	0	0
	Max	92701	50854	33533	15226	0	2
	Mean	1377.77	852.02	633.87	179.33	0	0
	Median	376	235	168	46	0	0
February 18th	Sum	3830313	2441677	1754461	532464	0	13
	Min	1	1	1	1	0	0
	Max	79447	48951	29621	14906	0	2
	Mean	1188.43	757.58	544.36	165.21	0	0
	Median	335	217	150	42	0	0
February 25th	Sum	7556409	1766759	1014283	475033	0	15
	Min	2	1	1	1	0	0
	Max	137449	30198	18699	9365	0	2
	Mean	2345.25	548.34	314.80	147.43	0	0
	Median	649.5	148	79	37	0	0
March 3rd	Sum	4586555	2900922	2012239	646992	7	72
	Min	1	1	1	1	0	0
	Max	90725	51427	32012	15448	6	21
	Mean	1422.19	899.51	623.95	200.62	0	0
	Median	377	251	167	51	0	0
March 10rd	Sum	3727247	2445440	1658622	613217	28	707
	Min	1	1	1	1	0	0
	Max	82302	47985	30183	13982	21	116
	Mean	1155.74	758.28	514.30	190.15	0	0
	Median	293	213	140	49	0	0
March 17rd	Sum	5853870	1551551	989024	483453	126	5888
	Min	3	1	1	1	0	0
	Max	137342	29003	21612	11294	46	569
	Mean	1815.15	481.10	306.67	149.91	0	2
	Median	423	155	87	43	0	0
March 24rd	Sum	7020755	1128373	732379	390423	867	52678
	Min	3	1	1	1	0	0
	Max	154271	21601	16158	10674	126	4465
	Mean	2176.98	349.88	227.09	121.06	0	17
	Median	497	117	69	35	0	0
April 2nd	Sum	8574597	1192801	733300	453345	6923	236227
	Min	4	1	1	1	0	0
	Max	186382	23810	17371	12042	966	16268
	Mean	2661.27	370.21	227.59	140.70	2	75
	Median	615.5	126	68	40	0	3
April 9th	Sum	8104804	1045763	634617	404352	18164	457696
	Min	4	1	1	1	0	0
	Max	186837	18732	15074	9898	2182	27752
	Mean	2515.46	324.57	196.96	125.50	6	146
	Median	591.5	113	61	39	0	6
Total	Sum	5.37E+07	1.72E+07	1.16E+07	4577251	26115	753311
	Min	1	1	1	1	0	0
	Max	186837	51427	33533	15448	2182	27752
	Mean	1850.79	593.53	398.87	157.77	1	27
	Median	448	165	102	42	0	0

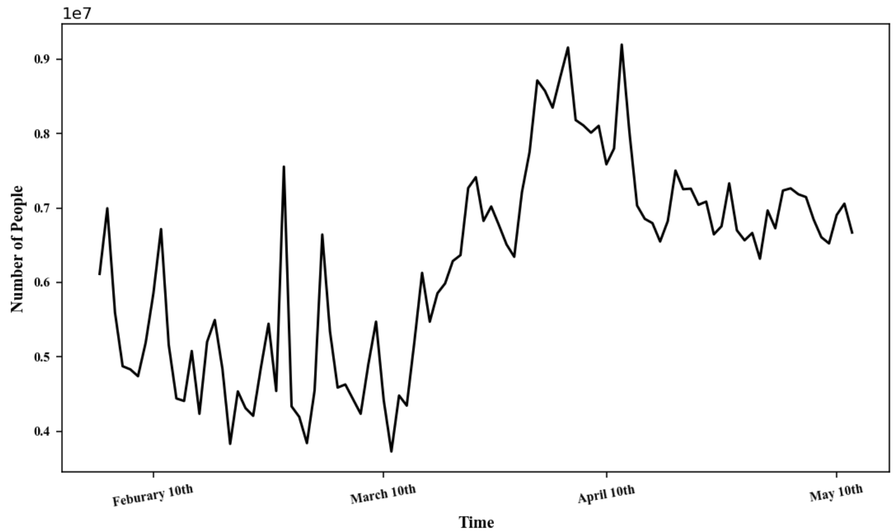

Figure 1a. The Temporal Trend of People Staying at Home

Note: The figure above shows the total number of people staying at home from February 1st to May 12th. The X-axis represents time, while the Y-axis represents the total number of devices that imply the population's size staying at home. Here le7 is a standard scientific notion. For instance, 0.9 on the Y-axis indicates 0.9*le7=0.9*10^7=9,000,000.

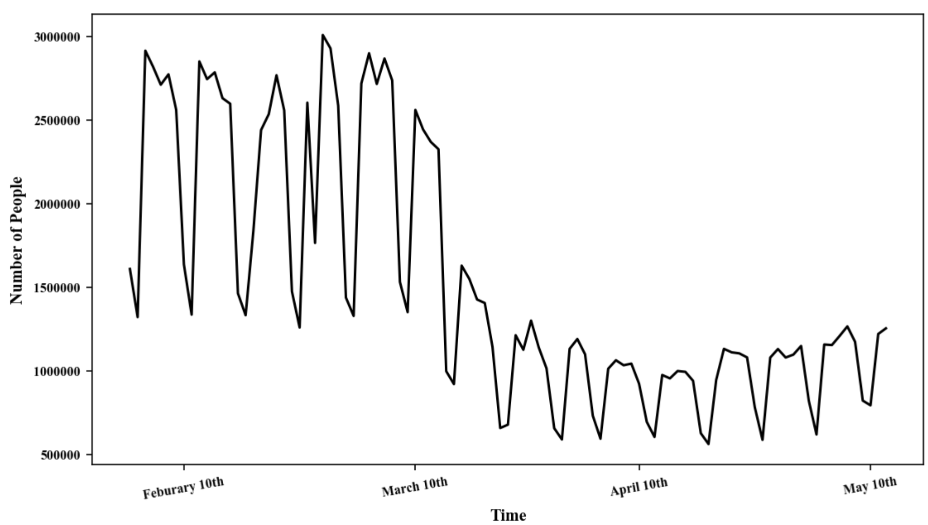

Figure 1b. The Temporal Trend of People Working Part-time

Note: The figure above shows the total number of people staying part-time at the workplace from February 1st to May 12th.

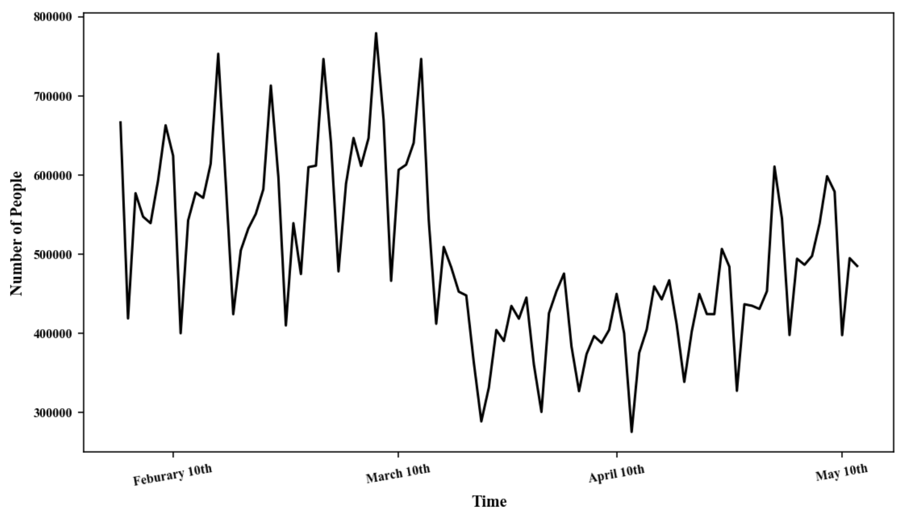

Figure 1c. The Temporal Trend of People with Delivery Behavior

Note: The figure above shows that the total number of people have delivery behavior from February 1st to May 12th.

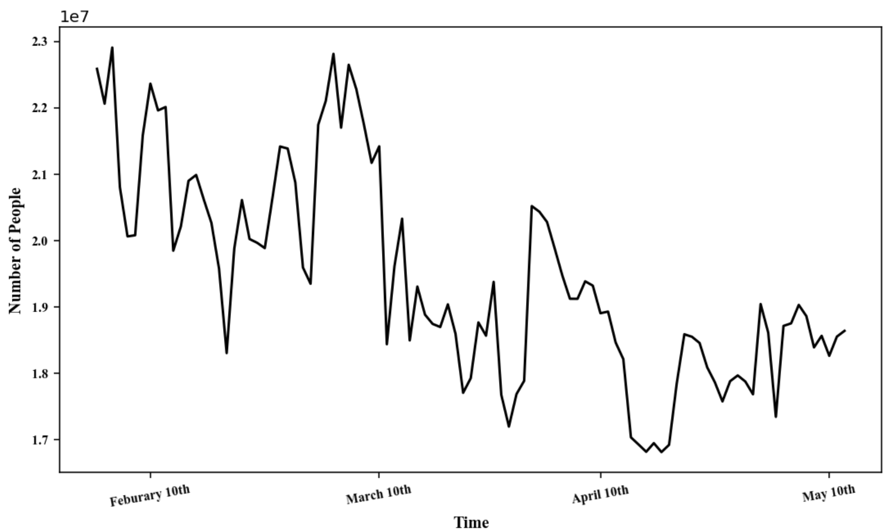

Figure 1d. The Temporal Trend of Total Active Devices

Note: The figure above shows the total number of active devices from February 1st to May 12th.

Table 1b shows the results of random effects models of public emotion and public mobility. The negative emotions count is significantly associated with the total number of people staying at home *($p<0.05$)*, working part-time *($p<0.05$)*, and delivery behavior *($p<0.05$)*. This indicates that if the public has an overall higher percentage of negative emotions towards the health crisis, they are more likely to stay at home and less likely to work part-time in their workplace or provide delivery services.

Regarding public policies' impact on the public working modes, my study finds that: 1) the earlier the county has been impacted by the stay-at-home policy, the more people working from home, working part-time, or providing delivering services; 2) the earlier the county has been impacted by the policies including public school closure, restaurant dine-in closure, and entertainment facility and gym closure, on the other hand, they are going to have significantly fewer people working from home, working part-time, or providing delivering services.

Table 1b. Public Emotion and Public Mobility

Variables	(1) (DV=Total number staying at home)	(2) (DV=Total number working part-time)	(4) (DV=Total number providing delivering service)
Negative emotions	18.83***	-6.632***	-0.863***
	(0.307)	(0.119)	(0.0190)
Infected	1.888***	-0.477***	-0.0826***
	(0.0277)	(0.0108)	(0.00170)
Trump 2016 rate	-196.6	352.0	-102.5
	(592.4)	(192.0)	(56.58)
Per capita income	0.104***	0.0376***	0.0102***
	(0.0162)	(0.00526)	(0.00155)
65 years old rate	-2,385	-940.8*	-82.29
	(1,412)	(457.7)	(134.9)
College degree rate	-14.64	0.730	-3.152**
	(11.65)	(3.777)	(1.113)
People of color rate	2,607***	1,265***	289.2***
	(505.9)	(163.9)	(48.31)
Log population	1,817***	681.4***	185.1***
	(50.48)	(16.37)	(4.819)
Stay at home	70.47***	25.12***	7.259***
	(14.68)	(4.758)	(1.402)
50 gathering ban	-14.01	-3.831	-1.367
	(12.03)	(3.900)	(1.149)
Public schools	-67.77***	-32.89***	-8.483***
	(19.29)	(6.252)	(1.843)
Restaurants dine in	-72.37***	-24.10***	-8.468***
	(18.42)	(5.971)	(1.760)
Entertainment gym	-16.55	-9.894*	-2.216
	(13.52)	(4.381)	(1.291)
Republican Governor	478.7**	182.5***	46.42**
	(157.0)	(50.86)	(14.99)
Constant	-16,588***	-6,440***	-1,563***
	(960.6)	(311.3)	(91.73)
Observations	27,989	27,989	27,989
Number of Counties	3,110	3,110	3,110

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Regarding the political ideology, the Trump support rate in the county is not significantly associated with the number of people working from home, working part-time, or providing delivery services. Additionally, the more people are infected with COVID-19 in a county, the more people work from home, and fewer people work part-time and provide delivery services at this county.

Figure 2a and Figure 2b visually and geographically explain the relationship between political ideology and social distancing behavior. Figure 2a shows the presidential election result of 2016. The Trump supporters are mostly clustered in the middle, and the South of the U.S. Additionally, the states without the stay-at-home policy mainly were geographically distributed in areas with a high Trump support rate in the 2016 presidential election. Figure 2b geographically shows the relationship between communities' political ideology and public health risk-avoiding behaviors – staying at home. In Figure 2b, the pink areas represent the counties with high Trump support rates and low staying-at-home rates, and most of these counties are geographically distributed in the Midwest and South of the U.S.; the white areas represent counties with low Trump support rates and low staying-at-home rate, and the geographic distribution of these counties in the South match the "Black Belt Region" which means regions that with "crescent-shaped region of prairies and dark soil that is 25 to 30 miles wide across central Alabama and northern Mississippi and their residents are predominately black with a high prevalence of diabetes, hypertension, stroke, and obesity" (Barone, 2005; Robinson, Wadsworth, Webster, & Bassett Jr, 2014, p. S73). The dark blue areas represent counties with high Trump support rates and high staying-at-home rates, and most of these counties are distributed in states like Idaho and Wyoming. The light blue areas represent counties with low Trump rates and high staying-at-home rates, and most of these areas distribute on the west coast and the northeast. This phenomenon indicates that most Republican counties are less likely to follow the staying-at-home policy. This map shows that the public's staying-at-home health behavior is polarized based on communities' political ideology.

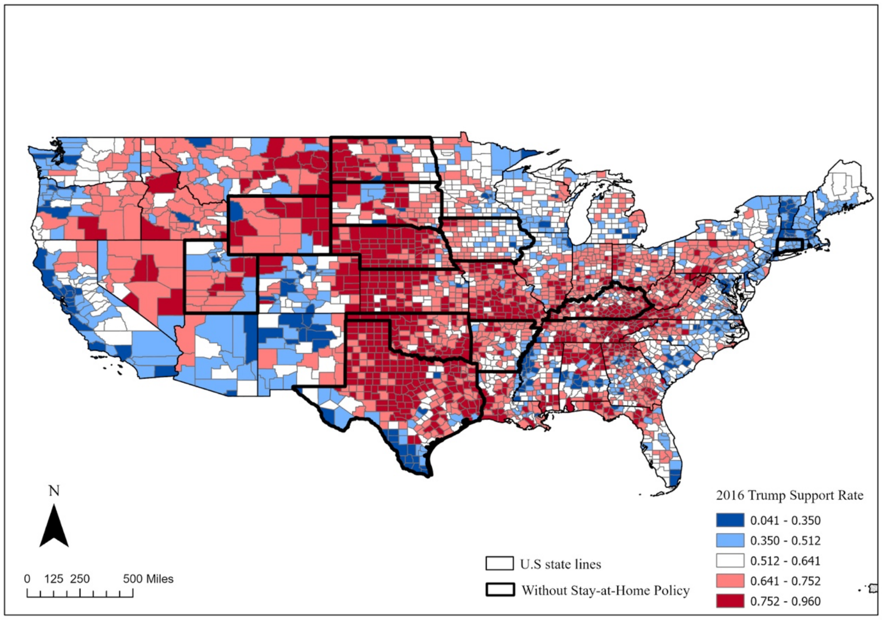

Figure 2a. Trump Support Rate at 2016 Presidential Election

Note: This map shows the geographic distribution of the Trump support rate in the 2016 presidential election. Rather than using the maps from political science that indicate the final winning or loss in the 2016 presidential election, this map uses more detailed information to explore the relationship between political ideology and public health behavior. The cut points of Trump support rate and stay at the home rate on April 9th across the 48 states of the U.S. are based on Natural Breaks (Jenks) method[10].

[10] "Numerical values of ranked data are examined to account for non-uniform distributions, giving an unequal class width with varying frequency of observations per class" (based on ArcGIS Pro)

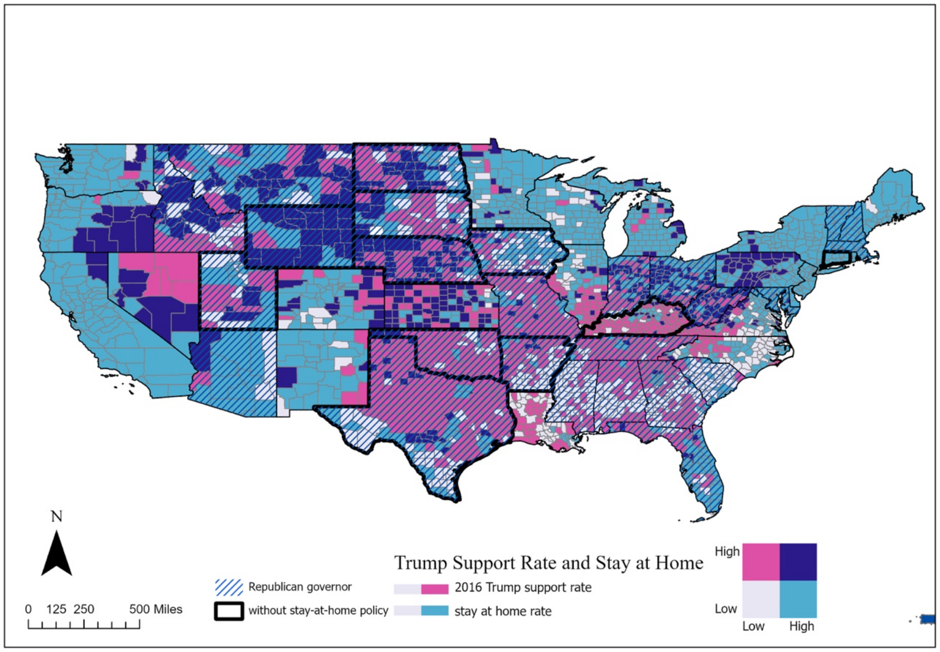

Figure 2b. 2016 Presidential Election Trump Support Rate and Staying at Home Rate
Note: The cut points of Trump support rate and stay at the home rate on April 9th across the 48 states of the U.S. are based on the Quantile method[11].

Income is significantly associated with the public's working modes: the higher per capita income is positively (*p<0.05*) associated with the total amount of people working from home, working part-time, and providing delivery services. There is also a racial disparity in the choosing work styles – the percentage of people of color per county is significantly (*p<0.05*) associated with the working modes. The rate of people of color per county is positively associated with the total number of people working from home, working part-time, and providing delivery services. Additionally, my study does not find local communities' education level is associated with the total number of people working from home, working part-time, and providing delivery services.

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[11] Quantile method means all the observations are equally distributes across the class interval. Each class has the same frequency of observations but the class withs are not necessarily the same.

Table 2. Interaction Effects between Public Emotion and Public Policy on Public Mobility

Variables (DV=Total number staying at home)	(1) home* emotion	(2) school* emotion	(3) restaurant* emotion	(4) entertainment* emotion
Negative emotions	4.874***	39.52***	-13.06***	-5.605**
	(1.100)	(3.290)	(3.060)	(1.965)
Infected	1.879***	1.892***	1.879***	1.876***
	(0.0277)	(0.0277)	(0.0277)	(0.0277)
Trump 2016 rate	-177.0	-234.8	-173.1	-154.7
	(586.1)	(592.4)	(589.1)	(587.5)
Per capita income	0.102***	0.105***	0.103***	0.103***
	(0.0160)	(0.0162)	(0.0161)	(0.0161)
65 years old rate	-2,402	-2,270	-2,350	-2,347
	(1,397)	(1,412)	(1,404)	(1,401)
College degree rate	-12.48	-15.02	-13.25	-13.09
	(11.53)	(11.65)	(11.59)	(11.56)
People of color rate	2,570***	2,573***	2,598***	2,613***
	(500.5)	(505.9)	(503.0)	(501.7)
Log population	1,824***	1,818***	1,824***	1,823***
	(49.94)	(50.48)	(50.20)	(50.07)
Stay at home	66.03***	68.93***	69.86***	70.16***
	(14.53)	(14.68)	(14.60)	(14.56)
50 gathering ban	-13.10	-13.54	-14.30	-13.64
	(11.90)	(12.03)	(11.97)	(11.93)
Public schools	-64.85***	-63.88***	-67.13***	-67.39***
	(19.09)	(19.30)	(19.18)	(19.13)
Restaurants dine in	-72.24***	-72.03***	-76.60***	-71.44***
	(18.23)	(18.42)	(18.33)	(18.27)
Entertainment gym	-15.30	-16.25	-15.68	-19.65
	(13.37)	(13.52)	(13.44)	(13.41)
Republican Governor	491.5**	476.1**	490.2**	490.8**
	(155.3)	(156.9)	(156.1)	(155.7)
Stay at home *emotion	0.819***			
	(0.0618)			
Public schools *emotion		-0.959***		
		(0.152)		
Restaurants dine-in *emotion			1.384***	
			(0.132)	
Entertainment gym *emotion				1.083***
				(0.0859)
Constant	-16,716***	-16,696***	-16,616***	-16,650***
	(950.4)	(960.7)	(955.2)	(952.7)
Observations	27,989	27,989	27,989	27,989

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
Note: the dependent variable is the total number of people working from home or staying

at home all day.

Table 2 shows the interaction effects between COVID-19 policies and negative public emotion on the total number of people staying at home by county. Molde1 shows the interaction effect between the duration of the stay-at-home policy and the negative emotion on the total number of people working from home. The interaction effect between policies and days of stay-at-home policy and public emotion is statistically significant, and Figure 3a visually illustrates the interactions on the total number of people working from home per county. Figure 3a shows that as negative emotions increase, the predicted number of people staying at home increases. However, in counties that have been impacted by the state level stay-at-home policy earlier, the slope of predicated number of people staying at home is sharper. In counties without a stay-at-home policy, the predicated number of people staying at home increased from 0 to 21,000 as the number of negative emotions increased from 0 to 3,000. However, in counties that have been under the stay-at-home policy for 20 days by April 9^{th}, the predicted number of people working from home increased from 0 to 69,000 as negative emotions increased from 0 to 3,000. Figure 3a indicates that the public's negative emotions are statistically positively associated with the public's behavior of working from home. However, the stay-at-home policy plays a dramatic moderator in regulating the association relationship between public emotions and public mobility. Figure 3b confirms this interaction effects geographically: On both the west coast and northeast coast, the public's negative emotion rate and stay at home rate are high; the southern part of the U.S., except Florida, experienced both low negative emotion rate and stay at home rate; the public experienced a higher rate of negative emotions and a lower rate of staying at home at the middle of the U.S. However, most counties within the states that did not issue the stay-at-home policy experienced both low negative emotions and stay-at-home rates. Figure 3c shows the similarities regarding negative emotion rate, stay-at-home policy, and working part-time rate. Most counties in states without a stay-at-home policy experienced both low negative emotion rate and low work part-time rate.

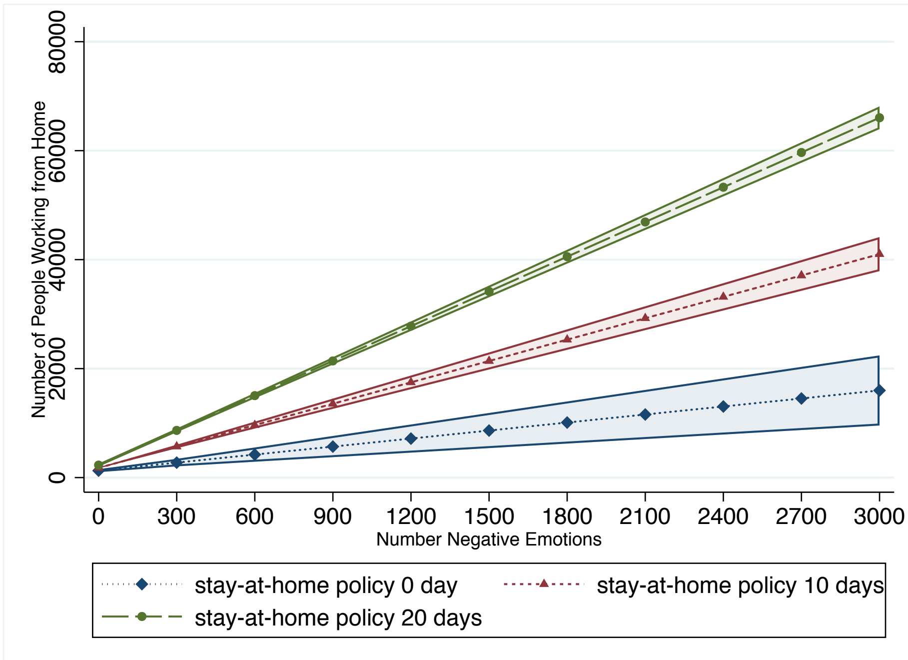
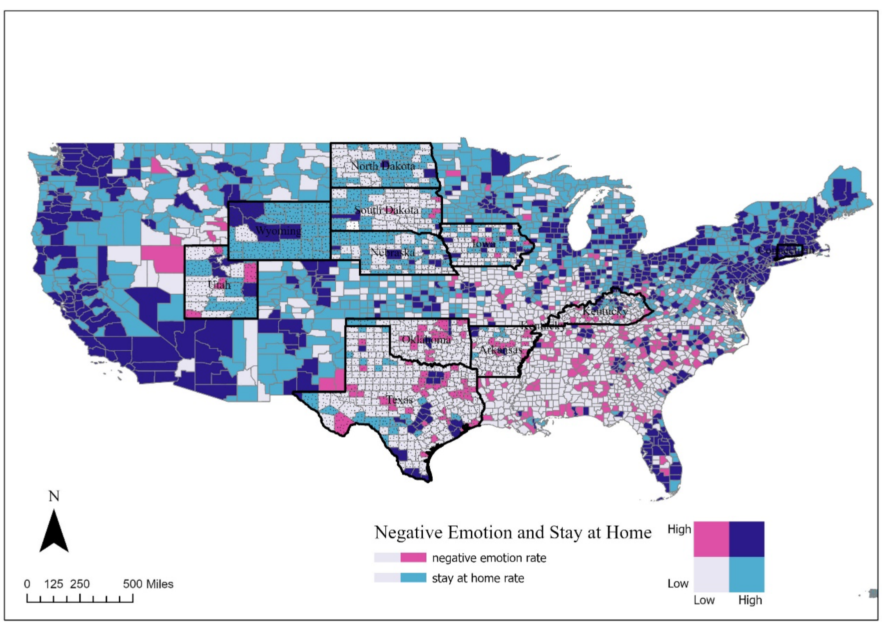


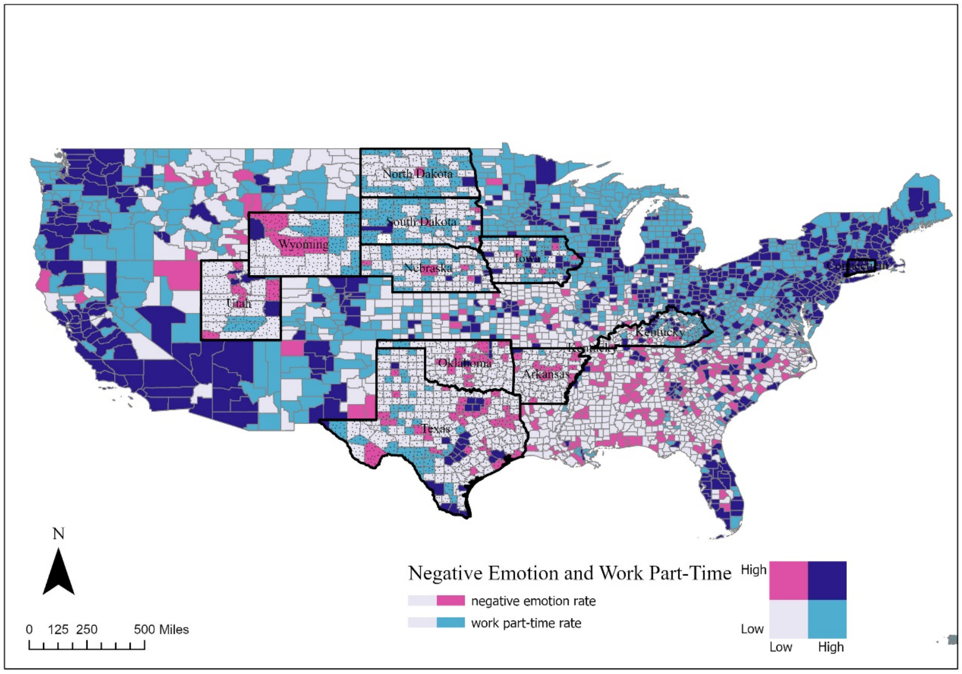
Figure 3a. Interaction effect between stay-at-home policy and public emotion on public mobility

Note: The X-axis represents the total number of negative emotions detected by Twitter related to COVID-19. The Y-axis represents the predicated total number of devices that imply the population's size staying at home. The X-axis and Y-axis in Figures 8 to 10 represent the same meaning under different policies.



Map 3b. Negative Emotion Rate and Stay at Home Rate

Note: This map adopts the bivariate colors to visually show the relationship between negative emotion and staying at home. The cut points of negative emotion rate and stay at the home rate on April 9th across the 48 states of the U.S. are based on the Quantile method. States with Black bolder did not issue the stay-at-home policy.



Map 3c. Negative Emotion Rate and Working Part-Time

Note: This map adopts the bivariate colors to visually show the relationship between negative emotion and staying at home. The cut points of negative emotion rate and work part-time rate on April 9th across the 48 states of the U.S. are based on the Quantile method.

Figure 3d shows the interaction effect between public emotions and public-school closure based on model 2 in table 2. Interestingly, counties that have been impacted by the state-level public school closure earlier had experienced a significantly lower amount of people staying at home than others as negative emotions increased. This potentially can be explained by the fact that public-school closure caused young people to remain inside hours decreased because they are not required to stay in class anymore.

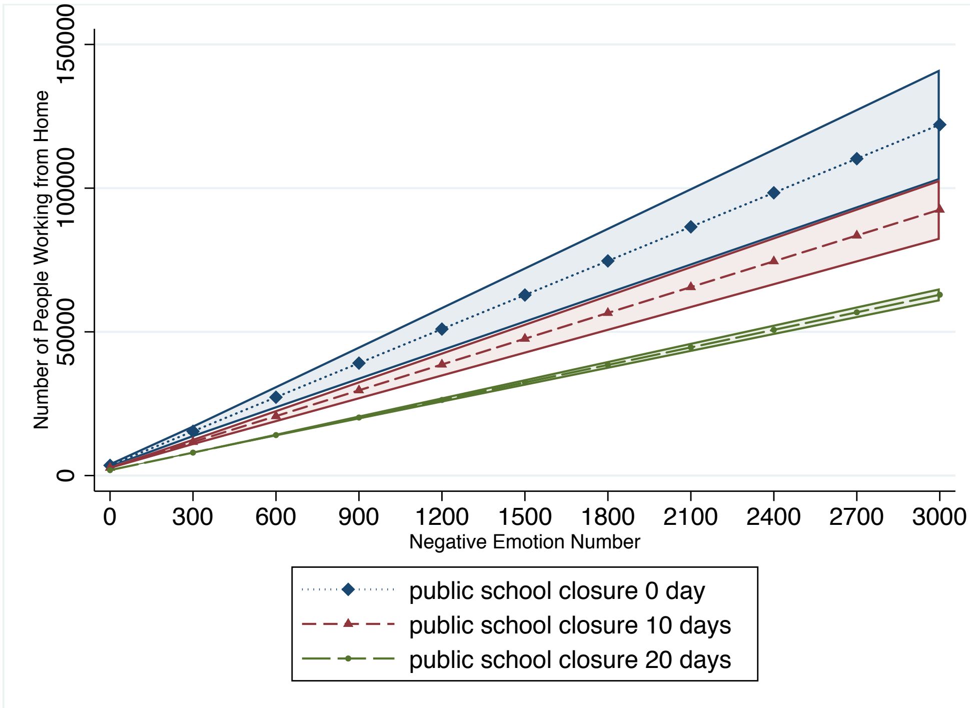


Figure 3d. Interaction effect between public school closure policy and public emotion on public mobility

Figure 3e shows the interaction effect between public emotions and restaurant closure order based on model 3 in table 2. For counties without restaurant closure for ten days, as the public's negative emotions increase, the predicted number of people staying at home or working from home increases marginally. However, in counties under restaurant closure order for 20 days, as the public's negative emotions increased, the predicted number of people staying at home or working from home increased significantly from 3,000 to 48,000.

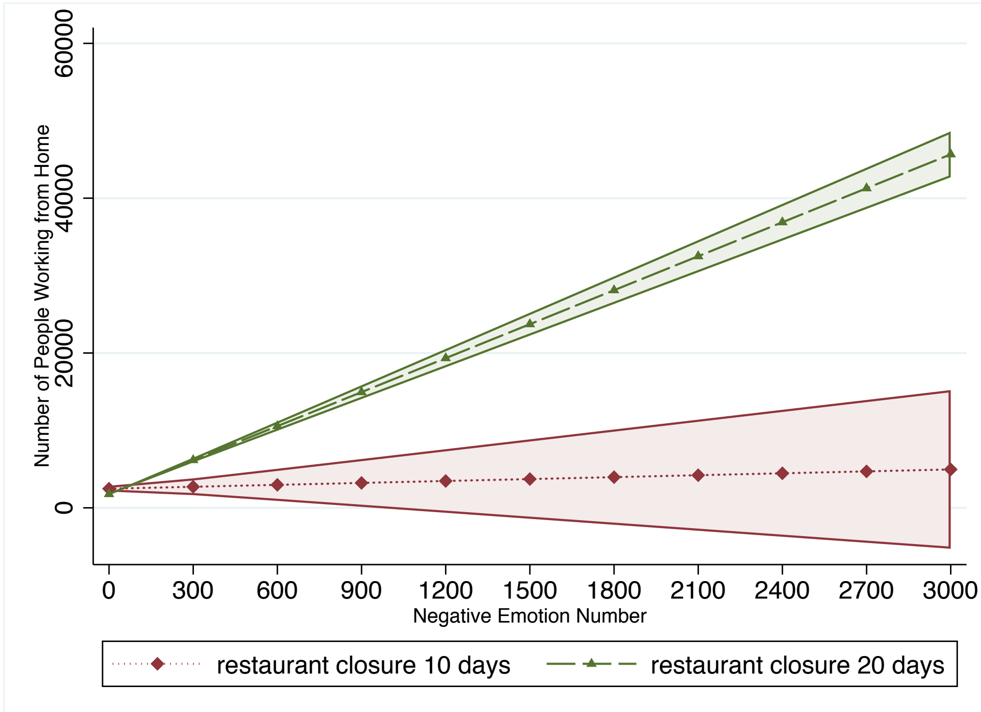


Figure 3e. Interaction effect between restaurant closure policy and public emotion on public mobility

Figure 3f shows the interaction effect between public emotions and entertainment facility and gym closure order on the public's behavior of staying at home based on model 4 in table 2. The interaction effect indicates that entertainment facilities and gym closure orders mitigate the relationship between public emotions and staying at home. As the public's negative emotions increased from 0 to 3,000: for counties with entertainment facilities and gym closure orders for ten days, the predicted number of people staying at home increased from 2,000 per county to 19,000 per county; however, for counties with the order for 20 days, the predicted number of people staying at the home increase from 2,000 per county to 50,000 per county.

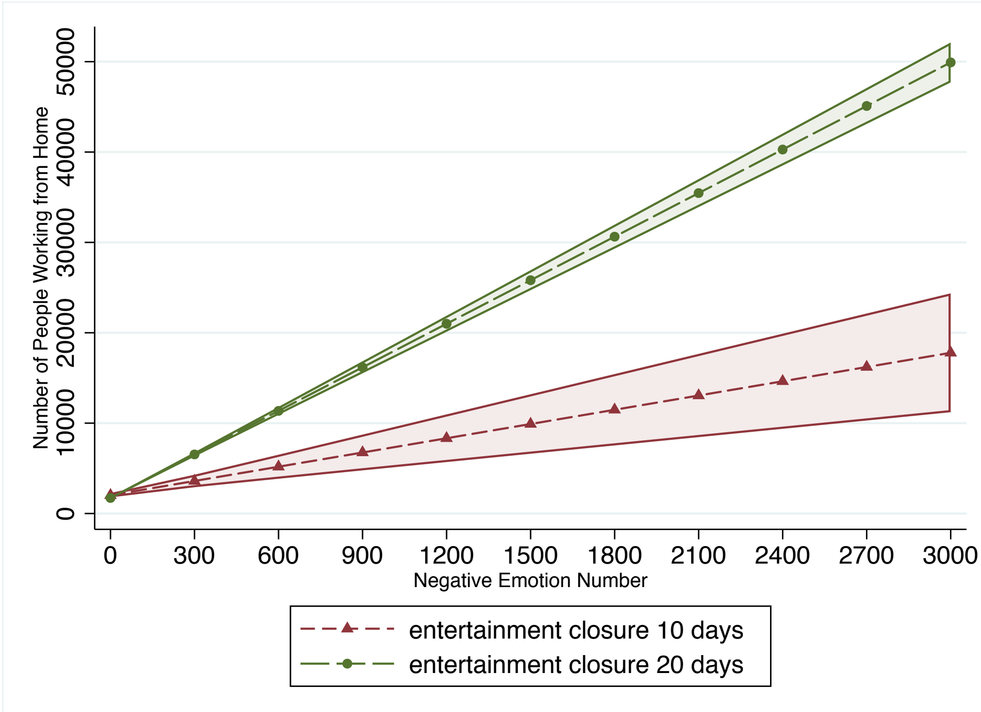


Figure 3f. Interaction effect between entertainment facility and gym closure policy and public emotion on public mobility

Table 3 shows the interactions between governors' political ideology, negative public emotion, and stay-at-home policy on public mobility. Figure 4a shows the interaction effect between the governor's political ideology and public emotion on public mobility based on model 1 in table 3. As the total number of negative emotions a county had experienced increased, the predicted number of people staying at home increased; however, the counties with Democratic governors had experienced a statistically significantly higher number of people staying at home than others. Furthermore, figure 4b visually shows the result from model 2 in table 3. At the initial stage of the stay-at-home policy, counties with republican governors have more people staying at home. However, as the days of the stay-at-home policy increased, especially after 15 days, Democratic lead counties tend to have more people staying at home than counties under Republican governors. Figure 4c geographically shows the interaction effect between the governor's political ideology and health policy on public behavior of staying at home. Most counties that had a lower rate of staying at home are in states that did not issue the stay-at-home policy. However, most of the states that did not issue stay-at-home policies are under the lead of Replicant governors except Kentucky and Connecticut.

Table 3. Interaction Effects between Public Emotion and Governor Political Ideology

Variables	(1) governor*emotion	(2) governor*home
Negative emotions	20.67***	18.82***
	(0.368)	(0.307)
Infected	1.875***	1.887***
	(0.0277)	(0.0277)
Trump 2016 rate	-172.0	-67.02
	(589.2)	(593.9)
Per capita income	0.104***	0.0995***
	(0.0161)	(0.0163)
65 years old rate	-2,423	-2,100
	(1,405)	(1,415)
College degree rate	-13.33	-10.94
	(11.59)	(11.72)
People of color rate	2,602***	2,534***
	(503.1)	(506.4)
Log population	1,818***	1,817***
	(50.21)	(50.48)
Stay at home	70.90***	136.6***
	(14.60)	(25.93)
50 gathering ban	-13.45	-15.95
	(11.97)	(12.05)
Public schools	-66.57***	-57.55**
	(19.19)	(19.57)
Restaurants dine in	-72.42***	-76.10***
	(18.32)	(18.46)
Entertainment gym	-15.84	-11.35
	(13.44)	(13.62)
Republican Governor	527.4***	1,577***
	(156.2)	(387.8)
Republican Governor*Negative emotions	-5.879***	
	(0.659)	
Republican Governor*Stay at home		-86.52**
		(27.94)
Constant	-16,693***	-17,829***
	(955.4)	(1,041)
Observations	27,989	27,989
Number of Counties	3,110	3,110

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

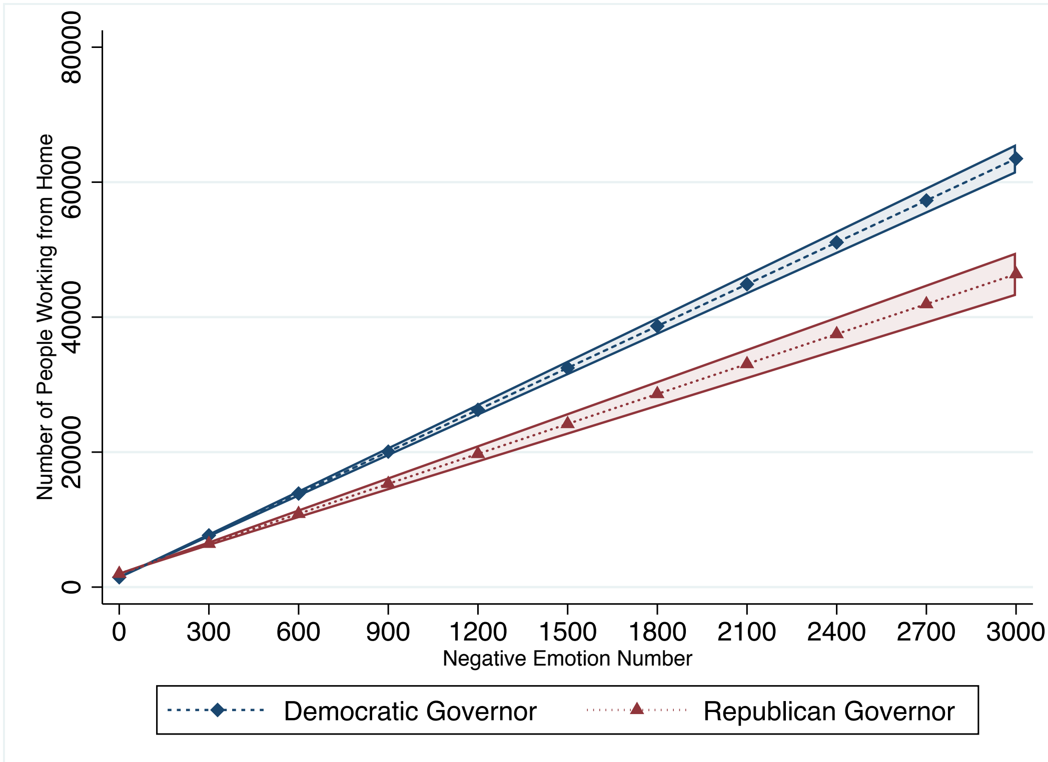


Figure 4a. Interaction effect between governor political ideology and public emotion on public mobility

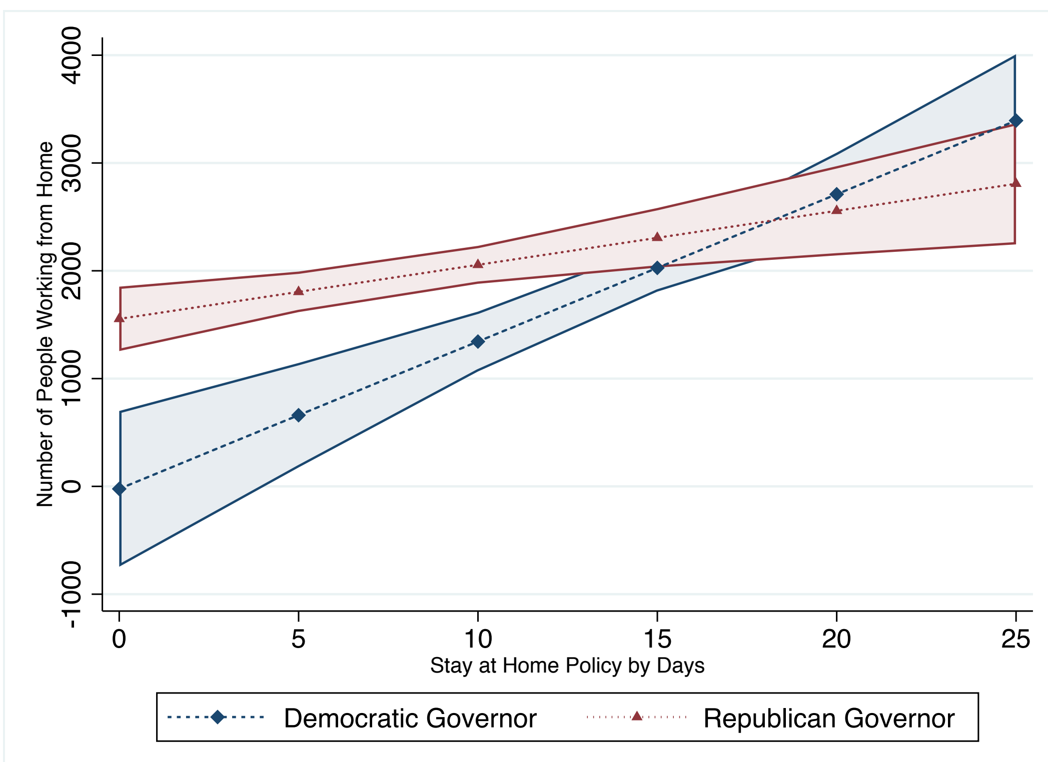


Figure 4b. Interaction effect between governor political ideology and stay at home policy duration

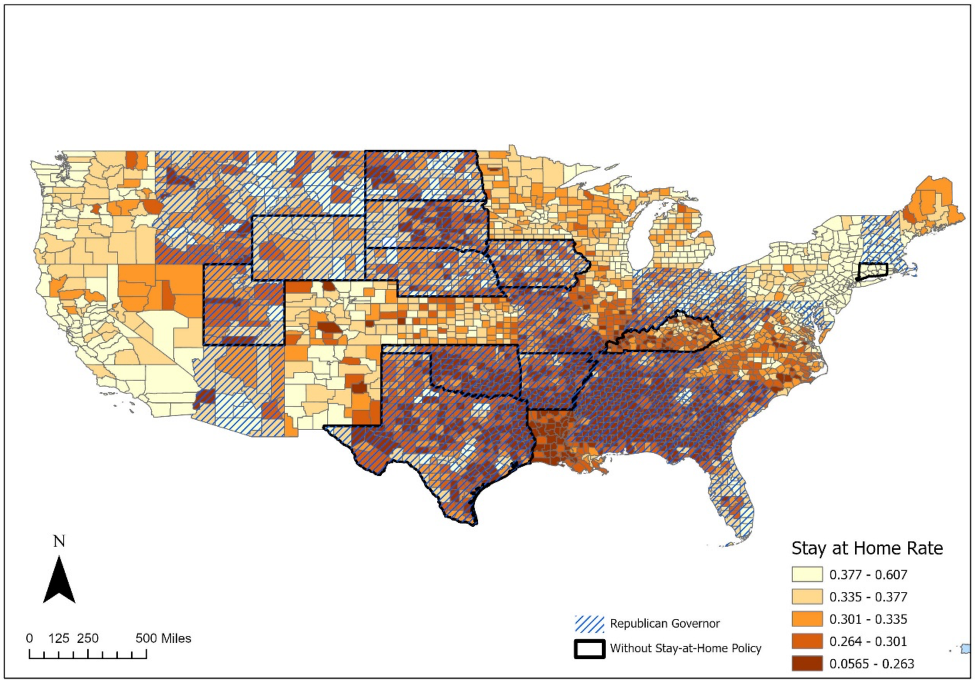


Figure 4c. Negative Emotion Rate and Stay at Home Rate

Note: The cut points of stay at the home rate on April 9th across the 48 states of the U.S. are based on the Quantile method.

Discussion and Conclusion

This study found public negative emotion in a community (county) is positively associated with the number of people staying at home and negatively associated with the number of people working part-time or having delivery behaviors. It confirms the earlier studies that public emotions are critical indicators of public behaviors (Cullen et al., 2020; Della Porta & Giugni, 2013; Sjöberg, 2007). These results suggest that public emotion reactions toward COVID-19 could reflect public's risk avoiding behavior. Communities (counties) with more negative emotions related to COVID-19 are more likely to have risk avoiding behaviors by changing their working modes such as decrease the chance of working full-time or part-time at working place and increase the chance of working from home. This indicates that public emotional reactions towards health crisis are significantly associated with their risk-avoiding behaviors.

More importantly, this study found that policy interventions play significant roles in the relationship between public emotions and public movement. With health policies' intervention, the association between public emotions and public movement is stronger. As the number of negative emotions increase, counties under policies (including social distance policy, public school closure, small business closure especially restaurants, entertainment facilities and gym closure) longer are associated with stronger risk-avoiding behavior – working from home. However, for counties that were not affected by these policies, as the total number of negative emotions increase per county, the risk-avoiding behavior - working from home only increased slightly.

Additionally, this study found that governors' political ideology significantly interacts with public emotions on risk-avoiding behavior - working from home. As the total number of public's negative emotions increase, public's risk-avoiding behavior - working from home increase more significantly for counties under Democratic governor than counties under Republican governors. Governors' role confirms that political division could decrease the policies' effectiveness (de Bruin et al., 2020; Dixit & Weibull, 2007; Fiorina & Abrams, 2008; Gao & Radford, 2021; Makridis & Rothwell, 2020; Weber et al., 2021; West et al., 2021). This also confirms my argument that Governors' political ideology plays a significant role in the relationship between public emotion and public health behavior.

Furthermore, this also shows that the big data like emotions mined through social media are indicators for public behaviors captured by big data companies like SafeGraphy. This is valuable information as more and more scholars begin to use social networks data and other big data produced by technologies companies like SafeGraphy. This is study is the first time to combine big data mined from social networks and big data produced by technologies like SafeGraphy in evaluating public policies' impact. Future studies regarding using big data produced by modern technologies to resolve social problems should be encouraged as these data are increasingly available to scholars, especially after the COVID-19 pandemic.

However, this study has several drawbacks. First, this study can’t confirm the casual relationships between public emotions and public movement. The results can only confirm the association relationships between emotions and public behaviors but can’t be explained as public emotions such as fear causes people to stay at home or work from home since there is a possible opposite way to describe the relationship, such as staying at home cause people to have negative emotions. Additionally, the time range for this study is from February 11 to April 9, which is not long enough to consider some factors’ changes, such as some policies like stay-at-home changed multiple times during the pandemic. This study can only explain the first three months of the pandemic in the U.S., and more data is desired for my future study.

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Overall Conclusion

The first article found that online health information can function as complementary resources for individuals with certain conditions like depression while not for individuals with heart diseases or high blood pressure. Further research about the importance of online health information for different diseases is necessary since online health information's complementary value is only valid for specific conditions such as mental health. Interestingly, online health information is essential for individuals with employer-based insurance, which suggests that individuals who pay more out of pocket are more likely to use online health information. Additionally, online health information is important for vulnerable individuals who have more barriers to health information resources, such as dissatisfaction in communication with doctors. The interaction effects between income and various factors, including depression and barriers to health resources, reinforce complementary and alternative values, especially among low-income communities. As the diseases are discussed separately in this study, more research is needed to examine how people with multiple health conditions use online health information. Additionally, new research with updated data is necessary as the health policies have changed a lot over the past several years. The research presented in this paper does not confirm a correlation between having health insurance and online health information searching behaviors. Furthermore, this study suggests that 1) online health information have two important economic values – complementary and alternative for the public, and 2) barriers to accessing online health information should be removed so that the people who need access to this information the most can obtain it to maximin the economic value bring by the Interest.

Chapter 2 shows that the negative emotions of the public on social media do not have a trend of social clustering (or spillover effects) at the beginning stage. However, these emotions began to show social dependence or spillover effects by the end of February, confirming that Tobler's first law applies the public's emotion on social media. The spillover effect of public emotions towards COVID-19 means that public emotions are affected by their close neighbors. Furthermore, the change of spillover effects also confirms a study by Dredze, Osborne, and Kambadur (2016) that timing matters in analyzing Twitter data with geolocation. Additionally, counties with more infected cases of COVID-19 have significantly higher negative emotions, which indicates that the public emotions detected from the social network could reflect the public's emotional footprint as the public's health situation was being threatened by a new health crisis (Arora et al., 2020; Dyer & Kolic, 2020). Health policies such as the stay-at-home policy affect the number of negative emotions in a county. As the days counties under stay-at-home policy get longer, the public's negative emotions increase. This result indicates that future studies regarding using social network data for emotion studies should consider the policy interventions' impacts. Furthermore, political ideology affects county-level emotional reactions. Counties with low support rate for Trump have stronger negative emotions towards COVID-19. This confirms that conflict extension or political polarization impacts public's emotion reaction towards a health crisis. Regarding the impacts of counties' socioeconomic characteristics on the public' emotions, this study also found that counties with a higher percentage of people of color population with a college degree or counties with higher per capita income have a higher rate of negative emotions towards COVID-19.

Chapter 3 found public negative emotion in a community (county) is positively associated with the number of people staying at home and negatively associated with the number of people working part-time or having delivery behaviors. It confirms the earlier studies that public emotions are critical indicators of public behaviors (Cullen et al., 2020; Della Porta & Giugni, 2013; Sjöberg, 2007). These results suggest that public emotion reactions toward COVID-19 could reflect public's risk avoiding behavior. Communities (counties) with more negative emotions related to COVID-19 are more likely to have risk avoiding behaviors by changing their working modes such as decrease the chance of working full-time or part-time at working place and increase the chance of working from home. This indicates that public emotional reactions towards health crisis are significantly associated with their risk-avoiding behaviors. More importantly, this study found that policy interventions play significant roles in the relationship between public emotions and public movement. With health policies' intervention, the association between public emotions and public movement is stronger. As the number of negative emotions increase, counties under policies (including social distance policy, public school closure, small business closure especially restaurants, entertainment facilities and gym closure) longer are associated with stronger risk-avoiding behavior – working from home. However, for counties that were not affected by these policies, as the total number of negative emotions increase per county, the risk-avoiding behavior - working from home only increased slightly.

Additionally, this study found that governors' political ideology significantly interacts with public emotions on risk-avoiding behavior - working from home. As the total number of public's negative emotions increase, public's risk-avoiding behavior - working from home increase more significantly for counties under Democratic governor than counties under Republican governors. Governors' role confirms that political division could decrease the policies' effectiveness (de Bruin et al., 2020; Dixit & Weibull, 2007; Fiorina & Abrams, 2008; Gao & Radford, 2021; Makridis & Rothwell, 2020; Weber et al., 2021; West et al., 2021). This also confirms my argument that Governors' political ideology plays a significant role in the relationship between public emotion and public health behavior.

Furthermore, this also shows that the big data like emotions mined through social media are indicators for public behaviors captured by big data companies like SafeGraphy. This is valuable information as more and more scholars begin to use social networks data and other big data produced by technologies companies like SafeGraphy. This is study is the first time to combine big data mined from social networks and big data produced by technologies like SafeGraphy in evaluating public policies' impact. Future studies regarding using big data produced by modern technologies to resolve social problems should be encouraged as these data are increasingly available to scholars, especially after the COVID-19 pandemic.

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