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The Impact of Crisis Communication Sentiment on COVID-19 Social and Economic Outcomes

A Textual Analysis of US-state Governor Press Releases

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Master Thesis in Business Analytics

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

The global spread of COVID-19 has caused unprecedented social and economic disruption the world over, forcing political leaders to act quickly and enact public policy that mitigated the impact of the virus. Despite early intervention, the United States quickly became an epicenter of the COVID-19 pandemic. Due to Federalism in the United States public health system, the implementation and public communication of COVID-19 policy became the responsibility of state Governors. Since March of 2020, state Governors have communicated heterogeneously through press briefings that addressed the risks of the COVID-19 virus and their reactive public policy. However, with no centralized federal response, the severity of restrictions, enforcement, and language used to combat COVID-19 has differed substantially between states and with a wide degree of variation in crisis communication effectiveness. By examining Governor press briefings from March 2020 to December 2020, this research seeks to isolate the impact of Governor speech sentiment in COVID-19 press briefings on their respective state social and economic outcomes during the pandemic. In line with this initial inquiry, we investigate the role of Governor party affiliation in altering the sentiment of Governor communication. Our analysis aims to provide insight into the effect of language and party affiliation in crisis communication from political leaders. In doing so, we seek to enable the fine-tuning of future mitigation policies and crisis communications to reduce future crises' human and economic costs. Specifically, we find: (1) there is no statistically significant relationship between an increase in negative language sentiment and an increase in positive state social outcomes during the periods observed; (2) there is no statistically significant relationship between an increase in negative language sentiment and a rise in negative state economic outcomes during the periods observed; (3) there is no statistically significant relationship between the political affiliation of Governors and the degree of positive or negative sentiment used in COVID-19 press briefings during the periods observed. We conclude with a discussion of research limitations and directions for future research.

Preface

This master's thesis was completed as part of the 2022 Business Analytics (BAN) double degree master's program at the Norwegian School of Economics and the Ivey Business School.

This paper uses textual data and statistical analysis to examine the impact of United States Governor communication sentiment in COVID-19 press briefings on their respective states' social and economic outcomes between March 2020 to December 2020. We additionally investigate the moderating role of party affiliation in altering the sentiment of Governer speech. We conducted this research to provide insight into the effect of language in public policy communication to enable the fine-tuning of mitigation policies to reduce future crises' human and economic costs.

We chose this topic based on a mutual interest in textual analytics, econometrics, and government policy. Working with textual data and developing a web scraper was incredibly rewarding but, at times, extremely tedious and prone to error. COVID-19 has affected the academic life of students and faculty immensely. Having the opportunity to study COVID-19 as part of completing our education provided a fantastic way to end our master's and demonstrate the skills we have gained.

We graciously acknowledge our thesis advisor, Dr. Christian Langerfeld, for his feedback, assistance, and consultation while completing this thesis.

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1. Introduction

COVID-19 is a global public health crisis that has caused unprecedented social and economic disruption the world over, altering the normality of daily life and capturing the attention of political leaders, public health organizations, and citizens alike. The World Health Organization first recognized the spread of COVID-19 as an international public health emergency in January 2020, with the director-general, Tedros Ghebreyesus, declaring it a pandemic in March of 2020 (WHO, 2020). In response to the COVID-19 crisis, political leaders enacted new public policies, introducing both pharmaceutical intervention (PI) and non-pharmaceutical intervention (NPI) strategies aimed at mitigating the harm caused by the virus (Chen et al., 2020; Baldwin and Weder, 2020; Gopinath, 2020). Despite federal travel restrictions and early intervention measures, the United States quickly became an epicenter of the COVID-19 pandemic. By the end of 2020, COVID-19 had infected more than 20,000,000 Americans, killing an estimated 340,000 of those infected (AJMC, 2021).

Although there remains debate upon when COVID-19 first entered the United States, the first publicly disclosed case of COVID-19 was reported in Seattle, Washington, in mid-January 2020 (Holshue et al., 2020). Due to the separation of power caused by Federalism in the United States public health system, the federal government had limited ability to dictate a centralized response, making the implementation and public communication of COVID-19 policy the responsibility of state Governors and local officials (Mariner, 2003; Gordon, Huberfeld, and Jones, 2020). Washington was the first to declare a state of emergency, and other Governors followed soon after. By mid-March 2020, nearly all 50 state Governors had announced states of emergency, and the formulation of COVID-19 public policy commenced.

With no large-scale federal response to COVID-19, state Governors, fettered by minimal regulation or intervention by local powers, have had the autonomy to enact and communicate public policies in a heterogeneous manner to a vulnerable and frightened public (Boin, 2009; Rose, 2021). This decentralization of public policy and COVID-19 related rhetoric has caused substantial differences in the severity of restrictions, enforcement, and language used by differing state Governors to combat COVID-19 and mitigate the harm caused by the virus (Curley and Federman, 2020; Curley, Harrison, and Federman, 2021). In addition, the politicization of the pandemic has caused many to question the objectivity of Governor communication and the role that party affiliation played in shaping the response and rhetoric of Governors (Solano et al., 2020). The decentralization of the COVID-19 response within the United States has provided the opportunity for further analysis of its effects. By examining the COVID-19 rhetoric of state Governors, we seek to understand the differential impact of language on the state-level social and economic outcomes during the COVID-19 pandemic.

Since March of 2020, Governors have communicated evolving public policy to their constituents through continual press briefings addressing the risks posed by the COVID-19 pandemic and their actions taken in response to the virus (Taylor and Binford, 2021). Thus, state Governor press briefings can be seen as snapshots in time, documenting the response of state Governors while providing insight into the objectivity and efficacy of Governor communication to the public. While research exists on the effectiveness of COVID-19 public policy (Chen et al., 2020), the economic and social impact of the virus (Kaye et al., 2021), and the divergent characteristics of state public policies (Curley and Federman, 2020; Curley, Harrison, and Federman, 2021), the effect of Governor rhetoric on the social and economic outcomes of the pandemic remains unknown. To address this gap in the literature, an essential line of research on the impact of COVID-19 in the United States is the exploration of the language and rhetoric strategies used by state Governors to communicate COVID-19 information and public policy.

By examining relevant research on public policy, crisis communication, and language sentiment, we implement statistical models that seek to isolate the impact of language used by state Governors on their respective state economic and social outcomes. The assumed mechanism of this interaction is that the sentiment of language used by state Governors influences the public perception of the virus's risk to society, thus altering the behavior of individuals, leading to identifiable differences at the aggregate level. By observing the language used in state Governor press briefings, in conjunction with the differing economic and social outcomes of each respective state, we attempt to understand the scale of this impact and isolate the effect of language in mitigating the impact of the virus. In line with this research, we investigate the role Governor party affiliation had in altering the tonality and objectivity of Governor communication. In doing so, this paper seeks to offer insight into the effect of language and party affiliation in public policy communication to enable the fine-tuning of mitigation policies and reduce the human and economic costs of future crises.

2. Literature Review

2.1 United States Public Policy Response to COVID-19

The global spread of COVID-19 has altered the normality of life at nearly all levels, causing unprecedented social and economic disruption while forcing political leaders to act quickly and mitigate the virus's impact on society (Baldwin and Weder, 2020; Gopinath, 2020). Many countries, including the United States, have rapidly introduced public policies addressing the COVID-19 crisis, adopting both pharmaceutical intervention (PI) and non-pharmaceutical intervention (NPI) strategies to reduce the spread and harm caused by COVID-19 (Chen et al., 2020).

The United States is a federal constitutional republic, which means that the power to govern, enact policy, and respond to a crisis is separated between the federal government and the elected Governors of the collective 50 states. Federalism of the US public health authorities means that the federal government, led by the United States President, has limited power in dictating the actions taken by state Governors during times of crisis (Mariner, 2003; Gordon, Huberfeld, and Jones, 2020). As a result, the United States' response to COVID-19 has been predominantly led by state governments and elected Governors (Curley, Harrison, and Federman, 2021). Consequently, state Governors are responsible for formulating COVID-19 public policy and communicating it to their constituents. This separation of power makes Governor communication vital as it informs both the general understanding of mitigation efforts and the public perception of COVID-19.

Within the United States, this public policy, formulated at the state level, has played a dominant role in addressing the COVID-19 crisis (Curley and Federman, 2020). PI strategies within the United States have focused predominately on citizen vaccination, intending to achieve herd immunity through rapid proliferation and adoption of the COVID-19 vaccine (Ryan and Van Kerkhove, 2020). However, as the COVID-19 vaccine was not available in the initial stages of the pandemic, early public policy instead focused on NPI strategies intended to mitigate the overall harm and spread of the COVID-19 virus. In the United States, NPI strategies have enforced new restrictions and suspensions, such as shelter-in-place orders, school/business closures, and travel restrictions. NPI strategies have also supplied economic stimuli such as donations, loans, and debt forgiveness programs (Chen et al., 2020; Curley, Harrison, and Federman, 2021; Ali et al., 2021).

The efficacy of this rapidly evolving public policy depends heavily on the effectiveness of the Governor's communication to the public and the willingness of citizens to comply (Taylor and Binford, 2021). Furthermore, the impact caused by COVID-19 and the resulting policy restrictions were heterogeneous in its effect across the United States, with limitations, suspensions, and enforcement efforts varying widely in severity between states (Curley and Federman, 2020). Moreover, states with a larger share of marginalized demographic communities, lower GDP, and a lower share of workers capable of working from home were more vulnerable to alterations caused by the enforcement of mandatory mitigation efforts (Chen et al., 2020; Riley et al., 2021; Kaye et al., 2021). Worsening this divide, differences within state institutions, economic characteristics, and laws for paid sick leave significantly impacted the economic and social harm faced by citizens of a given state (Dingel and Neiman, 2020).

In the short run, mandatory mitigation efforts enforced by government policy have the effect of exacerbating the economic and social impact of the COVID-19 pandemic by halting activities, particularly those requiring in-person interaction, and altering the normality of daily life (Chen et al., 2020; Kaye et al., 2021). However, disruption of these activities may occur, regardless of coercive policy, as fear, perceived risk of contagion, and the public perception of the virus have been shown to cause voluntary alteration in the behavior of workers, consumers, and business leaders alike (Eichenbaum, Rebelo, and Trabandt, 2020). This voluntary alteration of behavior is supported by a decline in economic activity preceding, not following, the enforcement of mandatory mitigation policies within the different states observed, calling into question the effect that Governor policy communication had on both citizens' behavior and perception of the virus (Chen et al., 2020).

Considering the substantial differences in the impact and efficacy of state COVID-19 public policy implementation, communication, and severity, an investigation of the role that Governor crisis communication had in shaping citizens' understanding of mitigation efforts and their perception of COVID-19 is of great importance.

2.2 Crisis Communication

Crisis communication is a broad field of study that includes collecting, interpreting, and disseminating sensitive information required to address a given crisis. Crisis communication intersects with various research fields, such as public relations, risk management, and in the context of COVID-19, public policy communication from political leaders (Coombs and Holladay, 2010; Watkins and Clevenger, 2021). This paper defines a crisis as the breakdown of the pre-existing socio-political and economic framework supporting the state's health, safety, and public order (Boin, 2009; Boin et al., 2010). During times of crisis, political leaders are responsible for protecting their constituents from unnecessary economic and social harm through the proper formulation and communication of public policy intended to mitigate the economic and social detriment of a crisis (Kearns et al., 2019; Comfort et al., 2020). To effectively reduce this harm, political leaders must identify emerging threats, anticipate their consequences, and communicate policy decisions clearly and objectively to a vulnerable and frightened public (Boin, 2009; Boin et al., 2010).

With new evidence, misinformation, and evolving public policy, the communication of state Governors became a key factor of importance as it shaped both the general understanding of mitigation efforts and citizens' perception of COVID-19. Differing state Governors have been shown to respond in a heterogeneous manner during times of crisis (i.e., natural disasters, terrorist attacks, recessions). Still, these previous threats and their impact on citizens were far more centralized than the COVID-19 pandemic, which has impacted the United States in its entirety and disrupted the normality of daily life (Rose, 2021). Apart from this, the politicization of the pandemic, referred to as pandemic politics, has called into question the objectivity of Governor communication and the role that party affiliation has in shaping the public policy and language used by Governors (Solano et al., 2020). This politicization becomes evident upon the investigation of enforcement severity, media misinformation, and the delaying of restrictions such as school/business closures, stay-at-home orders, and mask mandates, with Democratic Governors often responding more quickly and including more severe enforcement language than their

Republican counterparts (Halpern, 2020; Fowler et al., 2020; Bursztyn et al., 2020; Curley, Harrison, and Federman, 2021).

With no large-scale federal response, the severity of restrictions, enforcement, and language used to combat COVID-19 differed substantially between states and with a wide degree of variation in communication effectiveness. Since March of 2020, Governors have communicated evolving public policy to their constituents through press briefings addressing the COVID-19 pandemic and their actions taken in response to the virus (Taylor and Binford, 2021). As such, state Governor press briefings can be seen as snapshots in time, documenting the response of state Governors while providing insight into the objectivity and efficacy of Governor communication to the public. Effective communication during a public health crisis is essential. Citizens rely on objective and credible information to understand the risks posed to them and the alterations in behavior needed for proper compliance (Austin, Liu, and Jin, 2012). With such high degrees of variation in state government public policy and crisis communication efficacy, an essential line of research on the state-level impact of COVID-19 is the exploration of the language and rhetoric strategies used by state Governors to communicate COVID-19 public policy.

By investigating the sentiment of Governor COVID-19 press briefings, in conjunction with the corresponding social and economic indicators of their respective states, we seek to gain insight into the effect of language sentiment on the social and economic impact caused by the COVID-19 pandemic and the resulting effectiveness of state public policy communication.

2.3 Sentiment in Communication

Sentiment analysis, also referred to as opinion mining, analyzes written text to extract people's attitudes, opinions, and emotions through techniques, methods, and tools that classify the subjectivity of language used in communication (Bing, 2012; Feldman, 2013). Attitudes, opinions, and emotions are central drivers of human activity. Positive and negative communication sentiment influences beliefs and motivates behavior by altering the evaluations, perceptions, and selective attention of the communication receiver, shifting what information they deem most relevant (Tyng et al., 2017). This impact on behavior has made sentiment analysis one of the most actively researched areas in natural language processing (Mäntylä, Graziotinb, and Kuutila, 2018).

Attitudes, opinions, and emotions are subjective and fall into polarities such as good/bad, positive/negative, and pro/con, with neutrality at the center of the spectrum (D'Andrea et al., 2015). Sentiment analysis enables this subjective information to be efficiently processed and classified from substantial volumes of aggregated textual information that would otherwise be infeasible to read and code manually. Thus, sentiment analysis extracts subjectivity and polarity from the language used in communication and identifies the semantic orientation of words, sentences, or documents targeted toward entities such as organizations, events, policies, products, and attributes (Taboada et al., 2011; Feldman, 2013; D'Andrea et al., 2015; Liu and Lei, 2018).

Valuable information is gained by understanding the attitudes and opinions expressed within the communication of individuals at an aggregate level. For this reason, sentiment analysis is commonly used in the domain of customer reviews for products, services, or brands. By automating the classification of customer reviews provided on company websites or social media platforms, such as Twitter or Facebook, companies gain insight into the evaluations of their customers quickly. This form of sentiment analysis is also applied to political candidates during election campaigns. Companies and campaign organizers alike can identify negative trends in communication regarding the candidate or firm's offerings through sentiment analysis and respond justly. During the COVID-19 pandemic, this same form of social media sentiment analysis has been used extensively to analyze the public reaction to new restrictions, lockdown measures, and policy changes (Barkur, Vibha, and Kamath, 2020; de Las Heras-Pedrosa, Sánchez-Núñez, and Peláez, 2020). Apart from this, sentiment analysis is often used to study financial markets. Numerous articles, blogs, and news organizations provide opinion pieces and evaluations that impact investor confidence in publicly traded companies. Sentiment analysis provides insight into the effect of this communication by relating observed changes in public sentiment to fluctuations in the company's stock valuation or additional metrics of relevance (Li et al., 2014; Hamraoui and Boubaker, 2022).

Sentiment analysis is not only used to evaluate and classify the attitudes and opinions of individuals at an aggregate level; it also provides insight into the subjective information contained within the communication of authoritative figures and organizations. In the context of government and public policy, sentiment analysis is used to detect polarity in political views, classify support or opposition to new legislation, detect (in)consistency between the statements and actions of political leaders, and study the effects of positive and negative campaigning on election results (Lau, Pomper, and Graber, 2006; Thomas et al., 2006; Balahur et al., 2009; D'Andrea et al., 2015; Liu and Lei, 2018). Within media communication, sentiment analysis is used to examine the polarity, tonality, and degree of conflict or misinformation contained in deferring media stories, studying its effect on the behavior of the media consumer (Esser and Stromback, 2012; Bursztyn et al., 2020). During the COVID-19 pandemic, this form of sentiment analysis on communication from authoritative figures and organizations have been used to evaluate the credibility and consistency of public health messaging to identify its impact on communication effectiveness and improve the efficacy of future crisis communication (Poth et al., 2021; Bulut and Poth, 2022)

COVID-19 press briefings from state Governors serve as a mechanism to communicate public policy and inform citizens of the risks posed to them by the virus. Media campaigns for public health purposes commonly use varying degrees of negative sentiment in communication to motivate changes in behavior by increasing the receivers' level of perceived risk while focusing their attention on the negative consequences of failing to comply (Dunlop, Wakefield, and Kashima, 2008). But with the language used by Governors to communicate with citizens and disseminate COVID-19 public policy differing substantially between states in its degree of severity and objectivity, an essential line of research on the impact of COVID-19 in the United States is the exploration of the language and rhetoric strategies used by Governors during COVID-19 press briefings (Mäntylä, Graziotinb, and Kuutila, 2018; Curley and Federman, 2020; Curley, Harrison, and Federman, 2021).

More specifically, by observing the language used in state Governor press briefings, in conjunction with the differing economic and social outcomes of each respective state, we attempt to understand the scale of this impact and isolate the effect of language sentiment in public policy communication and the mitigation of harm caused by the COVID-19 crisis. Based on the consideration of differences within Governor public policy, crisis communication efficacy, political affiliation, and the effect of sentiment on opinion formation, we expect that the sentiment of Governor press briefings will affect the social and economic impact caused by the COVID-19 pandemic such that:

H1: Higher levels of negative sentiment in Governor communication will positively impact state social outcomes, measured in monthly COVID-19 cases and monthly COVID-19 related deaths.

H2: Higher levels of negative sentiment in Governor communication will negatively impact state economic outcomes, measured in state unemployment rate and average weekly earnings.

H3: Political alignment of state Governors will moderate press release sentiment such that Governors deemed Democrat will engage in higher levels of negative sentiment than their Republican counterparts.

3. Data

3.1 Data Collection

The data used in our analysis fall into six categories: demographic data used as control variables; restriction indexes used as control variables; Governor party affiliation used as a control variable; economic indicators used as dependent variables; social indicators used as dependent variables and Governor COVID-19 press briefing data used as the basis for all independent variables of interest.

3.1.1 Demographic Data

State-level demographic data was collected from the United States Bureau of Labour Statistics and includes yearly population totals of demographic groups reported as annual average employment statistics (U.S. Bureau of Labor Statistics, 2022). This data served to establish the demographic composition of each state rather than as an understanding of employment level, as more detailed monthly employment data was used as a dependent variable in the analysis.

3.1.2 Restriction Indexes

State-level restriction indexes were collected from the COVID-19 Government Response Tracker developed by the Blavatnik School of Government at the University of Oxford (Hale et al., 2021). The data includes 23 restriction indicators measured daily. The indicators track school closures, travel restrictions, vaccination policies and many other NPIs. The creators of this data set combined these different indicators to create four indexes representing numerous components of government response: Stringency, Government Response, Containment, and Economic Support. This paper utilizes these indexes to control for government action in the analysis. The importance of these variables is discussed further in the Methodology section.

3.1.3 Party Affiliation

Data on Governor party affiliation was collected from National Governors Association (NGA, 2022), a bipartisan organization that provides information, key updates, and news about United State Governors. The data is restructured as a binary variable equal to 1 if the state Governor is Republican and 0 if they are a Democrat. While a state Governor can be an independent in the United States political system, this party affiliation has no occurrences in any period observed. The binary party affiliation variable is used as a control variable in this analysis and a primary independent variable in the testing of H3.

3.1.4 Economic Indicators

The data used to construct the state-level economic indicators used in our analysis came from The Urban Institute's State Economic Monitor, an online resource that tracks economic and fiscal trends across all 50 states (Peiffer et al., 2022). Additionally, consolidated state Economic Monitor data was collected from the United States Bureau of Labour Statistics (U.S. Bureau of Labor Statistics, 2022). The data collected from these sources include state GDP values, employment statistics, individual earnings, and monthly housing prices.

3.1.5 Social Indicators

In this paper, social indicators refer to the impacts of the COVID-19 pandemic that span beyond the economy. Data on differing social indicators were collected from the Centre for Disease Control and Prevention, the national public health agency in the United States (CDC, 2022). This data included COVID-19 cases and deaths from the pandemic, consolidated at the monthly level to ensure compatibility with other sources. However, due to the time frame of this study, further discussed below, other social indicators, such as vaccination rates, were not used in our analysis.

3.1.6 Governor Press Briefing Data

Governor press briefing transcripts were collected from Rev.com, a speech-to-text transcription company that consolidates many forms of speech data as textual sources (Rev, 2021). This resource consists of 895 web pages of transcribed state Governor press briefings. Speaker-level data was collected by scraping transcripts from 854 of these COVID-19 focussed press briefings hosted by state Governors that included enough information for analysis. To collect this data, we constructed a web scraper in R that pulls speaker names, complete transcript text, and other important contextual information such as the state name and date of the press briefing, formatting it to allow further sorting and cleaning. The result was 11,880 speaker-transcript observations encompassing Governors, press members, and health experts. Transcript speakers were then filtered by comparing the last name and state of Governors to a master list to exclude non-Governor speech. The final consolidated textual data included 854 text blocks of Governor press briefing transcripts. The inclusion of additional press briefing speakers, such as press members and health experts, was considered, but as not all state press briefings had these other speakers, filtering the transcripts to only include the speech of Governors was deemed most appropriate.

3.2 Data Preparation and Sample Selection

3.2.1 Data Preparation

The data used in this paper takes the form of an unbalanced panel data set, consisting of incomplete observations across all US states. This inconsistency in data is due to the sporadic nature of

Governor press briefings, resulting in an inability to have an observed press briefing in every period of data for every state. However, the data on demographic characteristics, restriction indexes, party affiliation, economic indicators, and social indicators are available across all periods.

The data gathered also varies in frequency. State social indicators and restriction indexes were compiled daily, while state economic and demographic data were collected monthly and yearly. This frequency disparity requires data consolidation at the monthly level to make the data complete while allowing for different modelling approaches. The following transformations were performed on the different data sets to allow for compatibility:

1. Daily social indicators were summed, resulting in monthly totals of the case and death data.
2. Daily restriction indexes were averaged to arrive at a monthly mean index value for stringency, government response, containment, and economic support.
3. Demographic population totals were spread evenly across the months in the year in which they were recorded due to the relative stability of these values.
4. Governor party affiliation was spread evenly across the period in which the Governor was in office.
5. Governor press briefings that occurred in the same month were combined to create one block of text for each Governor in each month where one or more press briefings occurred.

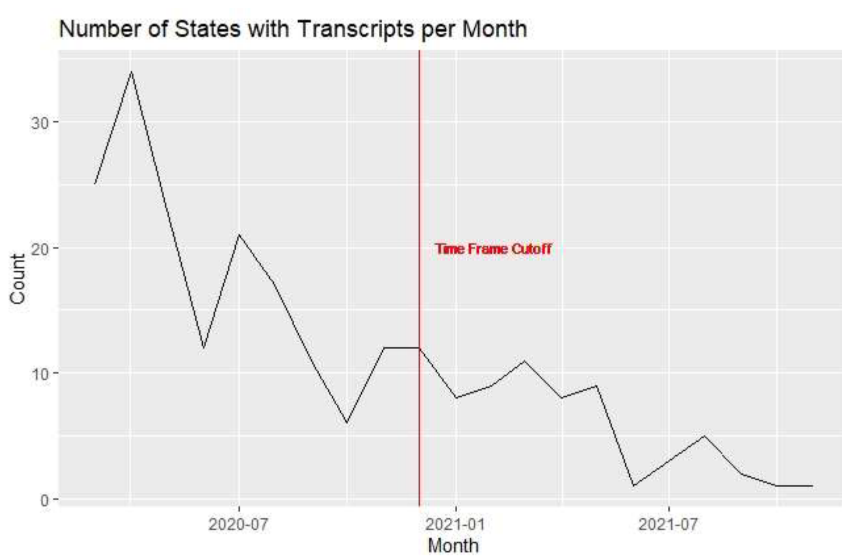
The consolidation of Governor press briefings significantly reduced total observations from the original 854 speech occurrences to 228 monthly observations of Governor transcripts across all states. Further details on the way Governor press briefing data were dealt with is discussed further in the Methodology section of this paper.

While most textual analytics methods require the cleaning and restructuring of the textual data for use in the development of differing measures, the use case for the data acquired in this paper does not meet many of the typical requirements. Techniques such as creating a document term matrix, removing stop words, removing punctuation, and observing n-grams do not fit the criteria of this analysis. Cleaning and restructuring techniques are unnecessary as the SetimentR package, discussed later, requires text in sentence structure and the possibility for common stop words to be used as valence shifters in specific scenarios (Li, 2022).

3.2.2 Sample Selection

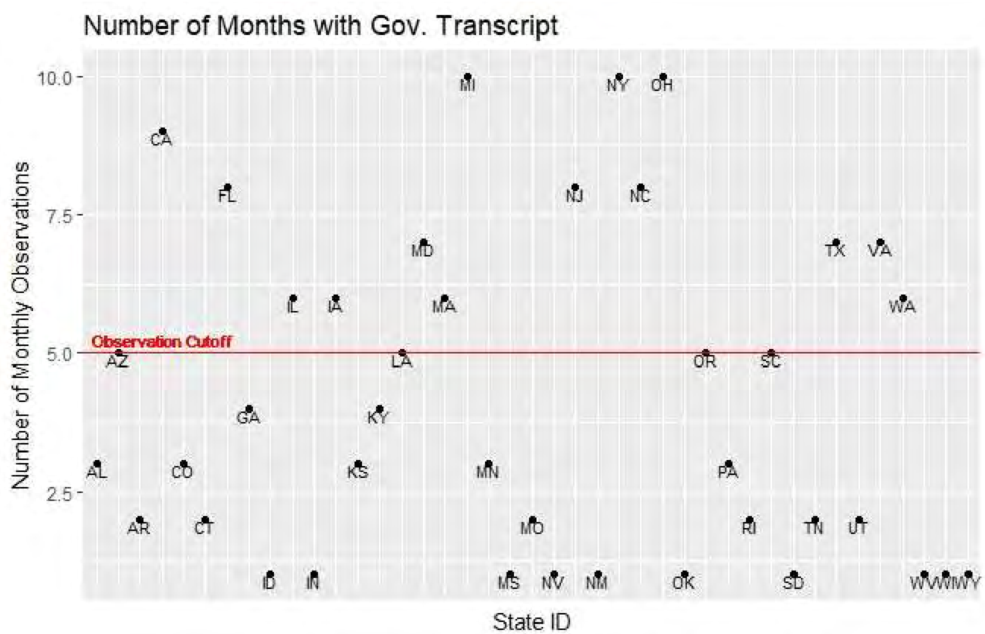
An issue that arose upon the investigation of all Governor press briefing transcripts came in the form of a significant drop-off in observations as time went on. The drop-in Governor press briefings can broadly be understood when thinking about the information communicated in Governor press briefings. As the pandemic ages and the population becomes more aware of the risk, the need for ongoing crisis communication of the threat posed to citizens and changes to public policy decreases. To properly account for the decline in the frequency of Governor press briefings and enable accurate comparisons between states, this analysis focuses on a time frame in which at least ten or more states held monthly press briefings. After observing the data, the time frame that appeared to best fit this criterion was the first ten months of Governor press briefings from March 2020 to December 2020. This shift in time frame preserves the integrity of the analysis by minimizing the number of missing Governor press briefing observations while maximizing the number of states compared in our research. The number of states with at least one transcript in each month of data gathered is displayed in Figure 1 with a vertical line representing the time frame cut-off used.

Figure 1: Drop-off in Transcript Frequency



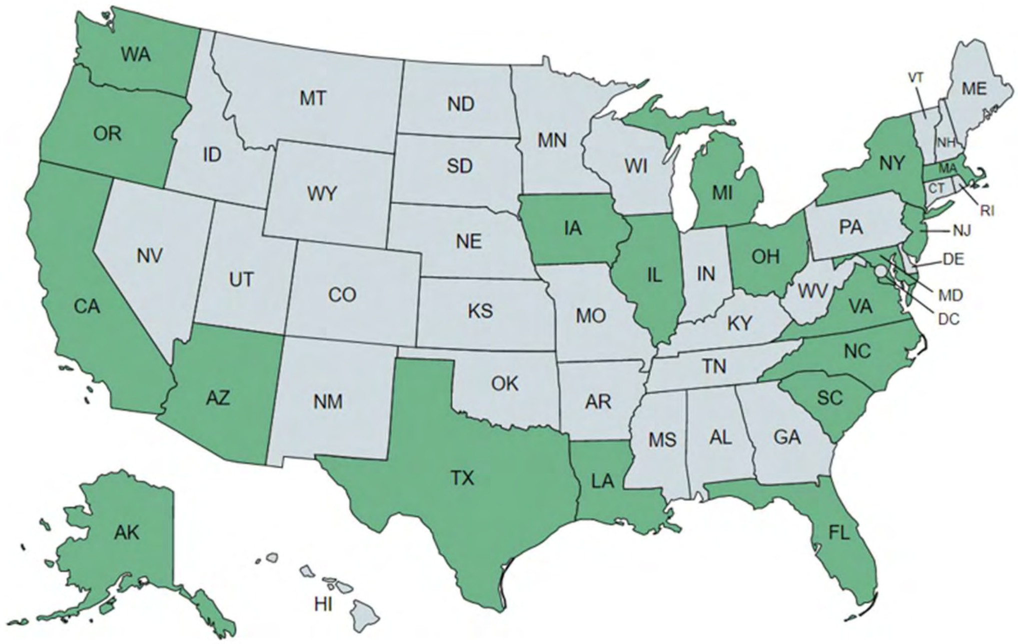
Following the reduction in the time frame of Governor press briefings, the number of monthly occurrences of Governor press briefings fell from 228 to 173. However, the distribution of differing state press briefings remained unbalanced, with some states only hosting one press briefing at the tail end of the spectrum. To account for differences in distribution, a sample of states that met a threshold of five months of speech data in this period was selected. This sample selection was conducted to reduce gaps in the data and increase the accuracy of comparison between states. The number of months where a least one Governor press briefing occurred in each state during the sample period can be observed in Figure 2.

Figure 2: Transcript Count



A list of the states with more than five monthly occurrences of Governor press briefings from March 2020 to December 2020 was created and used to filter all other data sets to only include those in the sample set. Different samples were constructed with different cut-off values. Yet, five observations provided the best trade-off of sample size and ability to observe textual data in as many analysis periods as possible. The result is a sample of 18 states with five or more observations in this time frame totalling 128 observations. While this sample does not involve randomization, observing variable variation paired with a qualitative understanding of state characteristics implies enough variation between the sampled states to draw conclusions for the greater population. A map of the 18 states included in the sample can be found in Figure 3.

Figure 3: Sample States



3.3 Summary Statistics

Table 1 displays summary statistics for the variables used in this analysis observed over the ten months from March 2020 to December 2020. These variables are broken down into independent, dependent, and control variables. Independent variables include the sentiment measures used. Dependent variables include the social and economic indicators used to understand the impact of the virus on society. Finally, control variables encompass data used to ensure that the estimated effect of the independent variables reflects only the effect of communication rather than including the effect of other observable influences.

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Independent Variables					
Average Sentence Sentiment SW	128	0.06	0.02	0.01	0.11
Average Sentence Sentiment JR	128	0.15	0.04	0.04	0.25

Dependent Variables					
Monthly Cases	180	66,163.92	105,596.20	497	1,018,584
Monthly Deaths	180	1,182.33	1,438.96	7	7,027
Unemployment Rate	180	9.03	3.62	2.60	22.70
Avg Weekly Earnings	180	1,119.16	126.38	942.52	1,384.07
Control Variables					
Population	180	9,554.83	7,330.97	2,479	31,084
Minority Population Percentage	180	0.24	0.08	0.09	0.41
Percent Republican	180	0.44	0.50	0	1
Stringency Index	180	52.31	13.80	17.39	87.03
Economic Support Index	180	47.72	21.96	0.00	100.00

The first notable value in Table 1 is the difference between the N value of the independent variables and the others. The gap of 52 observations of sentiment in the data compared to the other variables arises from the sporadic distribution of Governor press briefings mentioned above.

The independent variables include both sentiment scores, whose calculation is discussed later in the paper. Notably, the sentiment score using the Sentiword lexicon appears to have a much smaller scale yet a larger scaled standard deviation than the sentiment score using the Jockers-Rinker lexicon. This difference is significant when looking at the results and understanding the economic impact of changes in the dependent variables.

The dependent variables span health and economic measures. The standard deviation of the monthly cases stands out as it is very high compared to other variables. This significant standard deviation is understandable given common knowledge of how the pandemic behaved during the period of this study. Additionally, the other measures see substantial distances from the mean value to the max and min, suggesting significant levels of variation in the data that may impact the results given the sample size. Finally, the scale of cases and deaths at both the mean and the max values in the sample suggests that using some form of transformation might help gain a more meaningful understanding of the resulting coefficients.

The control variables included in this analysis attempt to encompass state or time characteristics that are expected to impact the dependent variables significantly. Control variables were selected based on previous research investigating the impact of COVID-19 on different countries and states

(Chen et al., 2020; Riley et al., 2021; Kaye et al., 2021). By controlling for these variables, the goal is to extract the actual effect of sentiment on economic and social indicators. The most interesting insight from these variables is the widespread distribution of values across sample states. With state populations ranging from roughly 2.5 million to 31 million, states containing significant variation in population size are shown to be included in the sample. The same can be said for the minority population percentage, state pandemic stringency, and economic support. Finally, the most important value comes from the distribution of states that are Republican versus Democrat. With a mean value of the binary variable of 44%, the sample has a relatively even distribution of Governors with both Republican and Democrat party affiliations.

4. Methodology

Sentiment analysis methodology follows three main approaches, machine-learning, lexicon-based, and hybrid models (D'Andrea et al., 2015). The machine-learning approach utilizes a multitude of classification-based methods, such as Recurrent Neural Network (RNN) and Support Vector Machine (SVM), to determine the semantic orientation of text and phrases through training and validation upon a split dataset (Kaur et al., 2021). In contrast, the lexicon-based approach utilizes a sentiment lexicon, a dictionary of words associated with a semantic orientation (I.e., positive/negative). It determines the sentiment of a target text based on the use of specific phrases or words that relate to a given sentiment value contained in the lexicon dictionary. Different lexicons assess the semantic orientation of words and phrases uniquely, as language and terminology carry different semantic orientations depending on the domain and setting. For example, when used in a financial or accounting environment, the term liability does not have the same semantic meaning as when used in general conversation (Loughran and McDonald, 2016). For this reason, it is essential to properly select the lexicon used for analysis when using a lexicon-based approach to sentiment analysis (Feldman, 2013; Asghar et al., 2017).

Sentiment analysis can be applied at three different levels of text: aspect-level, sentence-level, and document-level (Bing, 2012; Feldman, 2013; D'Andrea et al., 2015). Aspect-level sentiment analysis provides a granular sentiment assessment by attributing a polarity score to each aspect word of a sentence about an opinion target, such as a company service review. Aspect-level sentiment analysis seeks to determine the opinion expressed towards the target entity instead of looking at the language used (Schouten and Frasincar, 2016). In contrast, sentence-level sentiment analysis assesses the subjectivity of a sentence by determining if it expressed a positive, negative, or neutral opinion (Wiebe and Riloff, 2005; Khan, Baharudin, and Khan, 2011). Document-level sentiment analysis estimates the overall sentiment of a given document, assuming each document expresses an opinion towards an entity. However, a document-level analysis may become complicated if differing views about the entity appear within the same document (Bing, 2012).

4.1 Sentiment Measure Development

The approach to developing an accurate sentiment score for Governor speech is essential to ensure that the effects measured truly reflect the impact that language has on the economic and social outcomes of the pandemic. After investigating the Governor's press briefing data in the sample selected, the lexicon-based approach to sentiment analysis was most appropriate for our subsequent analysis for the following reasons. The sample data covers multiple state Governor press briefings from March 2020 to December 2020, with an unbalanced number of transcripts for each Governor, due to varying frequency at which differing state Governors conducted press briefings. This imbalance makes splitting data into training and test sets for machine learning more difficult. Moreover, splitting transcript data into a training and test set would significantly reduce the already limited number of transcripts available. This limitation in the number of transcripts comes from the time frame of Governor press briefings being reduced to preserve the integrity and comparability of differing state Governor press briefings.

When considering the structure and purpose of our subsequent study, the selection of sentence-level sentiment analysis was most appropriate for the following reasons. The sentence-level analysis enabled each sentence delivered by a Governor during a press briefing to be analyzed and averaged to assign an accurate sentiment score for each unique occurrence of a press briefing. This approach provides an excellent middle ground between aspect and document-level analysis while assessing the objectivity of the Governor's speech during a press briefing.

After selecting sentence-level lexicon-based sentiment analysis, different sentiment lexicons were evaluated to look for trends in results and determine an appropriate lexicon. Given the nature of the Governor's communication to the public and the non-domain specific terminology being used, the performance of the Jockers-Rinker (Hu and Liu, 2004; Jockers, 2017) and Sentiword (Baccianella et al., 2017) lexicons were compared for increased reliability. We chose these two lexicons as they are commonly used in opinion mining and comprehensive in dictionary size. The Jockers-Rinker lexicon contains 11,710 words, and the Sentiword lexicon includes 20,093 words. In addition, both lexicons are designed for general-purpose sentiment analysis, meaning the classification of sentence sentiment is unrelated to a specific field or domain, better serving the purpose and context of our analysis.

4.1.1 SentimentR Package

The sentiment scores of Governor press briefing transcripts were created using the SentimentR library in R (Rinker, 2021). The SentimentR library has a variety of functions and lexicons that can be used to develop sentiment scores for blocks of text of varying complexity and consolidation. For each Governor, press briefing transcripts were consolidated monthly for every state where one or more transcripts occurred. The consolidated transcripts were then assigned a unique identifier corresponding to the Governor conducting the press briefing in that month. Sentences were extracted from the consolidated transcript file using the get_sentences function. The get_sentences function returns a list of sentences stored as vectors that can be assigned a sentence-level sentiment score.

Following the identification and structuring of sentences, the sentiment_by() function was then used to assess the polarity of each sentence, using both the Jockers-Rinker and Sentiword lexicons, assigning each sentence a polarity score. For each period's consolidated Governor transcript, the sentiment_by() function assigned a polarity score for each sentence based on the lexicon used. The sentiment_by() function then calculates an overall press briefing sentiment score for every Governor in each month by downweighting the importance of sentences assigned a neutral polarity score and averaging the sentence level polarity contained in each consolidated Governor transcript. The overall sentiment score for every Governor in each month was then joined with the monthly social and economic data it corresponded to, allowing for further analysis of the impact of Governor press briefing sentiment on state economic and social performance during the COVID-19 pandemic.

4.2 Economic Models

Economic models of increasing complexity were developed to measure the effect of sentiment on the dependent variables of interest and the impact of partisanship on Governor speech sentiment. The tested economic models were constructed using various combinations of control variables and regression models. When constructing the different economic models, the goal was to arrive at results that estimated causality rather than correlation to allow for the confirmation or rejection of the hypotheses outlined above. The limitations of each model and the results that can be drawn are discussed in the Results section of this paper.

4.2.1 Linear Regression Models

As a starting point for the analysis, a simple linear regression was completed with economic and social indicators as a function of average sentiment in each state across all periods.

(1) Simple Linear Regression

$$indicator = \beta_0 + \beta_1\, sentiment + \mu$$

(2) Linear Regression with Controls

$$\begin{aligned} indicator = \beta_0 + \beta_1\, sentiment + \beta_2\, pop + \beta_3\, demog + \beta_4\, republican \\ + \beta_5\, stringency + \beta_6\, EconSupport \end{aligned}$$

These two models represent a starting point by looking at the data at an aggregate level. Multiple different economic and social indicators are used in each instance as the dependent variables. Additionally, the two sentiment scores outlined above are used as the primary independent variable of focus. In model (2), control variables are added to isolate the impact of sentiment on the indicators by accounting for the variation in the dependent variable caused by population values (pop), minority population percentage (demography), binary party value (republican), government restrictions (stringency) and government economic support (EconSupport).

4.2.2 Time Series Models

Given the nature of the data and the importance of understanding how the dependent and independent variables change over time, several time-series regressions were employed to draw out causality in the data. For these models, a pooled OLS approach was used to try and gain insight into the true impact of the Governor's speech on the social and economic indicators gathered. In an attempt to isolate causality and to allow for a delay in the impact of sentiment on the indicators, lagged values of sentiment were used in these regressions. It is important to note that for these models, January 2021 demographic data, restriction indexes, economic indicators, and social indicators are added to allow for analysis of the effect that Governor speech sentiment had across all 128 observed instances in the March to December period.

The following economic models represent a high-level overview of the analysis completed at differing levels of complexity:

(3) Time Series Regression

$$indicator_{it} = \beta_0 + \beta_1\, sentiment_{it-1} + \mu_{it}$$

(4) Time Series Regression with Controls

$$\begin{aligned} indicator_{it} &= \beta_0 + \beta_1\, sentiment_{it-1} + \beta_2\, pop_i + \beta_3\, demog_i + \beta_4\, republican_i \\ &\quad + \beta_5\, stringency_{it} + \beta_6\, EconSupport_{it} + \mu_{it} \end{aligned}$$

(5) Time Series Regression with Two-Way fixed Effects

$$\begin{aligned} indicator_{it} &= \alpha_i + \lambda_t + \beta_1\, sentiment_{it-1} + \beta_2\, stringency_{it} \\ &\quad + \beta_3\, EconSupport_{it} + \mu_{it} \end{aligned}$$

Model (3) takes a fundamental approach to modelling the relationship by running a pooled OLS regression with economic and social indicators as the dependent variables and the sentiment measures as the independent variables. Governor sentiment measures were lagged for one month to account for the issue of Governor press briefing frequency and the assumption that economic and social indicators would take time to react to public policy interventions and Governor communication. In Model (4), additional control variables are added, similar to the Model (2) approach. The goal is to isolate the impact of sentiment by controlling for characteristics that change across states and time. Finally, in Model (5), both time and entity fixed effects are added to the model. In the context of COVID-19, Time-fixed effects are significant due to the considerable variation in the virus's behaviour over time. This variation is largely universal across locations and thus can be included as a time-fixed effect. Entity fixed effects are also crucial in this context as there are many characteristics specific to states that are not captured in the control variables in Model (4). Since entity fixed effects are included in this model, control variables that do not vary over time are removed from the model leaving only "stringency" and "EconSupport". By giving each state an intercept in the regression, these state-specific control variables and other unobservable differences are captured in the model, further isolating the impact of Governor speech sentiment on the indicators observed.

4.2.3 Party Affilation Linear Regression Models

While the primary focus of our analysis is to understand the impact of Governor sentiment in COVID-19 press briefings on the social and economic outcomes of each respective state, an additional area of interest is the relationship between the sentiment measures and party affiliation. Models (2) and (4) above include a binary party control variable to account for the potential relationship occurring in the data. However, to further inspect this relationship, the following economic models were applied to the data to understand if sentiment is a function of partisanship and other control variables. Since the partisanship of state Governors does not change across the period observed, a linear regression approach was implemented using consolidated totals and averages of the other variables.

(6) Simple Partisan Linear Regression

$$sentiment = \beta_0 + \beta_1\, republican + \mu$$

(7) Partisan Linear Regression with Controls

$$sentiment = \beta_0 + \beta_1\, republican + \beta_2\, TotalCases + \beta_3\, TotalDeaths + \beta_4\, unemployment \\ + \beta_5\, AvgWeeklyEarnings + \mu$$

Model (6) closely mimics Model (1), with the observed change occurring in the dependent and independent variables. This new model uses the sentiment scores previously discussed as dependent variables, with the independent variable of interest now being the party affiliation of the Governors in each state. Model (7) then adds additional control variables to the basic model to further isolate the impact of party affiliation on Governor communication sentiment. The control variables for this model differ from those included in previous economic models. Since there is no presumed relationship between sentiment and control variables such as population, demography, stringency, and economic support, these variables were not included. Instead, the variables that are assumed to be correlated with sentiment, such as the economic and social indicators previously used as dependent variables, have been included to isolate the role of party affiliation in average Governor speech sentiment.

4.3 Implementation

After establishing the high-level economic interactions believed to model the real-life impact of the Governor's speech sentiment on the social and economic outcomes of COVID-19 and the role that party affiliation plays in moderating sentiment, the next step was to implement these models on the data available. The testing of different economic and social indicators allowed for a full range of analytical models to be developed. These models focus on a separate indicator to discover the scale and breadth of Governor communication sentiment's impact on the indicators observed.

4.3.1 Linear Regression Approach

To evaluate the impact of communication using simple linear regression, the data, previously consolidated monthly, needed to be transformed to reflect one data point for each state in the sample. The following operations were completed to achieve the required transformation of the data:

1. Social indicators were summed, providing totals of the COVID-19 cases and deaths incurred by each state.
2. Economic indicators were averaged to arrive at average unemployment and weekly earnings values for each state.

3. Restriction indexes were averaged to achieve mean index values for stringency and economic support.
4. Demographic population totals were averaged to represent demographic composition across all periods accurately.
5. Party affiliation was averaged, resulting in the binary value for a given state in the period being equal to either 1 if the Governor is Republican or 0 if Democrat.
6. Sentiment scores were averaged to achieve a mean speaker sentiment score over all periods.

With these values consolidated at the state level, 16 regressions were completed with different economic and social indicators as dependent variables. These regressions were conducted using the base R lm function to implement the 8 linear economic models using the two sentiment measures being evaluated. The results of the eight linear models using control variables are discussed below to provide the most insight into the interactions discovered.

4.3.2 Time Series Regression Approach

Time series regression requires data formatted as a panel set using both time and entity indexes for tracking the variables over time. The data outlined in the Data Preparation and Sample Selection section was restructured from a data frame to a panel dataset using the state id and the first day of the month as the indexes. This data restructuring allowed the pooled linear regression models outlined above to be used.

The plm function from the "plm" package in R Studio was utilized to implement the pooled linear regressions using different dependent variables and sentiment measures (Croissant and Millo, 2008). The plm function allows for the inclusion of control variables and both time and entity fixed effects when running a time series pooled OLS regression. By setting the model value to either "within" or "pooling", the model can be used to apply fixed effects or a traditional pooling method. By adding the effect value of "twoway", time and entity fixed effects can be added to the model. This package allowed the flexibility to test 24 models with differing variables, control levels, and fixed effects. For simplicity, only the results for the models, including control variables and fixed effects, are discussed.

4.3.3 Party Affilation Linear Regression Approach

Given that Governor party affiliation does not change over the period observed, Models (6) and (7) utilize a similar linear model as in the linear regression approach to understanding the effect of sentiment on social and economic outcomes. Thus, the same transformations were applied to the variables used in this model. Again, the base R lm function was used to implement these 4 models using the two different sentiment measures. The linear regression results, including controls, are discussed to provide the most insight into the relationship between party affiliation and Governor speech sentiment.

5. Results and Discussion

The results outlined below demonstrate that increasing the level of complexity used in modelling the relationship between Governor speech sentiment can cause differing conclusions in the direction and statistical significance of the causal relationship. Understanding these differences is essential to draw conclusions and insights into the statistical relationships present and the potential causes of the effects detected. A simple linear regression model was first used to gain a high-level understanding of the data by examining the data at an aggregate level. We then added control variables to isolate further the impact of sentiment on the social and economic outcomes observed and identify underlying relationships of interest. We then progressed to time-series regression models of increasing complexity to understand further how the dependent and independent variables changed over time and draw out the presence of causality rather than correlation. To further evaluate the validity and statistical significance of our results, we utilized a Cross Lagged Fixed Effect Regression approach to investigate the presence of reverse causality and further investigate the results of our analysis. We then adapted the linear regression with controls to identify the effect of party affiliation in moderating the sentiment used by Governors. A list of all models tested for this thesis can be found in Appendix A. A discussion of each model's results, interpretation, and limitations follows its implementation, and we conclude our discussion with an analysis of the hypotheses tested.

5.1 Linear Regression

The linear regression approach to testing the hypotheses of this paper attempts to gain a base-level understanding of how each of the four dependent variables interact with the dependent and control variables. Using the linear regression as a starting point, we aim to see which high-level effects should be inspected further.

Table 2: Linear Regressions with Controls

	Dependent variable:							
	Log Total Cases		Log Total Deaths		Average Unemployment Rate		Average Weekly Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Sentiword Sentiment	-10.71		-8.21		0.46		5,136.54*	
Average Jockers Rinker Sentiment		-0.22		-1.53		-1.35		2,050.81
Population	0.0001***	0.0001***	0.0001***	0.0001***	0.0001	0.0001	-0.002	-0.002
Minority Population	0.15	0.15	1.07	1.06	-6.15	-6.16	34.58	53.92
Republican	0.05	0.04	0.13	0.09	-1.18	-1.22	1.28	58.57
Average Stringency Index	-0.02	-0.01	-0.003	-0.001	0.13**	0.12*	12.20**	14.25**
Average Economic Support Index	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	2.43	2.09
Constant	14.18***	13.13***	9.26***	8.91**	4.71	5.21	83.29	-65.60
Observations	18	18	18	18	18	18	18	18
R^2	0.82	0.80	0.61	0.60	0.66	0.66	0.52	0.46
Adjusted R^2	0.72	0.69	0.40	0.38	0.47	0.47	0.27	0.16
F Statistic (df = 6; 11)	8.29***	7.33***	2.88*	2.77*	3.54**	3.54**	2.02	1.56
Note:						*p<0.1; **p<0.05; ***p<0.01		

Table 2 displays the coefficients and test statistics for the 8 linear regression models with control variables included. The results of the simple linear regression without controls outlined in Model

(1) can be found in Appendix B. In understanding the results from the linear models with controls, the focus should be on coefficients showing statistical significance. While it is difficult for any econometric model to find statistical significance in regressions with a small sample size, it is still interesting to see the sign of the coefficients to draw correlations as a start. Except for model 7 and 8, all models have F statistics that are statistically significant at the 10% level at least. These significant values suggest that models 1 through 6 outperform the mean and thus include relationships that can be extracted and interpreted according to their statistical significance.

Both sentiment measures appear to negatively correlate with total cases and total deaths across the time frame of this sample. While the coefficients across all models are not statistically significant, this observed interaction suggests the following. States with a higher average polarity score, reflecting more positive language being used across all press briefings, are associated with more positive social outcomes from the virus. This finding contrasts with H1, hypothesizing that Governors who spoke more positively about the virus would experience worse social outcomes in their states. However, the findings of this analysis are mitigated by the lack of statistical significance in the results. When looking at the economic indicators, interesting results can be found in the seemingly contradictory coefficients for the Sentiword measure between the average unemployment rate and average weekly earnings. While one would expect the unemployment rate to fall when average weekly earnings rise, the results of this analysis support an opposite conclusion. States with more positive Governor press briefing sentiment are associated with higher average unemployment levels and average weekly earnings, offering only partial support to the effects hypothesized in H2. Conversely, the Jockers-Rinker sentiment measure suggests a negative relationship with unemployment. These interesting results should continue to be observed as the level of analysis deepens. The only regression that resulted in statistical significance for either of the sentiment measures is Model (7), regressing the average Sentiword sentiment score against average weekly earnings. The coefficient of 5,136.54 is significant at the 10% level, suggesting an increase in sentiment by one standard deviation would result in a $102.7 increase in average weekly earnings. However, the F statistic for this model is not significant, limiting the implications drawn from this coefficient. While statistical significance is not reached across all regressions, except for average weekly earnings for the Sentiword measure, the inference surrounding the sign of the coefficients is still interesting and should be inspected further.

Beyond the primary dependent variables, statistical significance is achieved by the population control variable for both social indicators in models 1 through 4, with a coefficient value of 0.0001 that is significant at the 1% level across all four models. This coefficient suggests for each 1000 person increase in state population, the total cases in that state will increase by 0.0001%. While this is seemingly a small impact, the differences in state population size are multiples larger than 1000, and thus the case count increases significantly in larger states. The Stringency Index shows statistical significance for the economic indicators across models 5, 6, 7, and 8. The coefficients for the models regressed on the unemployment rate of 0.13 and 0.12 are significant at the 5% and 10% levels, respectively. These coefficients represent a 1.8 and 1.7 percentage increase in unemployment with an increase in stringency of one standard deviation. The coefficients for models regressed on average weekly earnings of 12.20 and 14.25 are significant at the 5% level and represent an increase in average weekly earnings of $168.4 and $196.7 with an increase in the Stringency Index of one standard deviation. This finding suggests that the differing level of stringency in a state have a statistically and economically significant impact on economic outcomes. While other control variables do not show significance in these models, they should be observed going forward to see whether new models suggest different results.

5.1.1 Limitations

The first major limitation of the linear approach outlined in Table 2 is the sample size. With the values of the variables summed or averaged to encompass a representative value for the entire sample period, the sample size falls to 18. This small sample size means that drawing conclusions from the data is complex and interpreting the results as representative of the entire population should be done with caution. Additionally, this model does not effectively draw out causality. Given the reactive nature of Governor press briefings, it is possible that the average sentiment measure is being influenced by the social and economic indicators rather than the other way around. This limitation is one potential reason why states with more positive average sentiment appear to have fewer cases, contrasting the expectations of H1.

Moreover, the sentiment measures and control variables averaged to arrive at the sample period level values, may be either flawed or lack important variation. The sentiment of Governor press briefings and the stringency and economic support indexes change drastically within states over time. Thus, simply taking the average can result in an unrepresentative indication of how the values will change as the pandemic fluctuates over time. These limitations lead to the next model evaluated in this paper. The linear regression model is expanded to a time series regression to account for the changes in these and other variables over time, with the goal of observing the impact of changes in sentiment across the states observed.

5.2 Time Series Regression

The first time-series regression observed uses a pooled OLS regression to analyze the interaction between the Sentiword and Jockers-Rinker sentiment measures and the economic and social indicators. As previously discussed, the lagged value of these measures was used to account for the expected time delay in the impact of the Governor's speech sentiment.

Table 3: Lagged TS Regressions with Controls

	Dependent variable:							
	Log New Cases		Log New Deaths		Unemployment Rate		Average Weekly Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Sentiword Sentiment	-11.17^{**}		-4.98		32.73^{***}		604.34	
Lagged Jockers Rinker Sentiment		-4.85^{**}		-1.10		17.19^{***}		26.97
Population	0.0001^{***}	0.0001^{***}	0.0001^{***}	0.0001^{***}	0.0000	0.0000	0.003^{**}	0.004^{***}
Minority Population	0.39	0.20	-0.09	-0.12	-8.88^{***}	-8.16^{***}	304.98^{**}	303.00^{**}
Republican	-0.04	-0.20	0.13	0.08	-1.19^{**}	-0.68	-34.88	-31.59
Stringency Index	-0.03^{***}	-0.03^{***}	0.01	0.01	0.22^{***}	0.22^{***}	2.15^{**}	2.00^{**}
Economic Support Index	-0.01^{*}	-0.01^{*}	-0.01^{**}	-0.01^{**}	-0.02	-0.01	1.31^{**}	1.22^{**}
Constant	12.32^{***}	12.71^{***}	6.49^{***}	6.38^{***}	-0.98	-2.89	807.74^{***}	847.89^{***}
Observations	128	128	128	128	128	128	128	128
R^2	0.40	0.40	0.28	0.28	0.53	0.54	0.30	0.30
Adjusted R^2	0.37	0.37	0.25	0.24	0.51	0.52	0.27	0.26

F Statistic (df = 6; 121)	13.64***	13.33***	7.89***	7.68***	23.17***	23.73***	8.83***	8.53***
Note:						*p<0.1; **p<0.05; ***p<0.01		

Table 3 displays the coefficients and test statistics for the 8 pooled OLS regression models run using control variables. The results of the 8 pooled OLS regression models without controls can be found in the Appendix C. The expansion of the previous linear model to this pooled approach attempts to draw further causality and statistical significance by both increasing the sample size and gaining the ability to measure changes in the dependent, independent, and control variables over time. All above models have an F statistic value that is significant at the 1% level. These values suggest that the models outperform the mean and thus include relationships that can be extracted and interpreted according to their individual statistical significance.

A noticeable trend arises in the results of these regressions when looking at models 1, 2, 5, and 6. The Sentiword and Jockers-Rinker sentiment measures arrive at statistically significant coefficients in each of these models. Looking first at models 1 and 2, using the log of monthly cases as the dependent variable, the Sentiword sentiment measure has a coefficient of -11.17, with the coefficient for the Jockers-Rinker sentiment measure being -4.85. Both coefficients are significant at the 5% level. The differing objective size of these coefficients is understood to be caused by the scale of these sentiment measures; illustrated by the summary statistics in Table 1. These coefficients suggest that an increase of one standard deviation in the Sentiword and Jockers-Rinker sentiment measures would result in a 0.22% and 0.19% decrease in monthly cases respectively. Models 5 and 6, which use the unemployment rate as the dependent variable, show coefficients of 32.73 and 17.19, significant at the 1% level. These coefficients suggest that an increase in the Sentiword and Jockers-Rinker sentiment measures by one standard deviation would increase the unemployment rate by 0.65 and 0.69 percentage points respectively.

The results of these two economic models using the two different sentiment measures are in direct contrast with H1 and H2. It was expected that increasing levels of negative sentiment would lead to better social outcomes and worse economic outcomes by altering citizens' level of fear and perception of the risk posed by COVID-19. However, these results suggest that increasing levels of negative sentiment would instead lead to worse social outcomes (higher monthly cases) and better economic outcomes (lower unemployment rate). While the coefficients for the other social and economic indicators in models 3, 4, 7, and 8 are not statistically significant, they have a similar correlation direction as in the previous linear model.

When expanding the economic model from the linear regression to this time series model, many more control variables achieve statistical significance. Firstly, the statistically significant coefficients observed for population in the linear model expand to include models 7 and 8, with coefficients remaining at 0.0001 for models 1 through 4 and coefficients of 0.003 and 0.004 for models 7 and 8, respectively. These coefficients are significant at the 1% level, except for Model 7, at the 5% level. Secondly, the coefficients for the minority population percentage variable become significant at the 5% level for models 5 through 8. These coefficients of -8.88, -8.16, 304.98, and 303.00 represent a high-level increase in unemployment and increased average weekly earnings as the minority population percentage increases. The coefficients for the Stringency Index are statistically significant at the 1% level for models 1, 2, 5, and 6 and the 5% level for models 7 and 8. These results suggest that increasing the pandemic stringency would decrease monthly COVID-19 cases, increase the unemployment rate, and increase average weekly earnings.

The economic support index has coefficients significant at the 10% level for models 1 and 2 and the 5% level for models 3, 4, 7, and 8. These coefficients imply that increasing economic support would lead to decreased monthly COVID-19 cases, decreased deaths associated with the pandemic, and an increase in average weekly earnings. The final control variable that achieves statistical significance is the Republican variable, a binary variable equal to 1 if the Governor of that state is Republican and 0 if they are a Democrat. This variable has a statistically significant coefficient at the 5% level in Model (5), which suggests that states with a Republican Governor experienced a lower unemployment rate during the period of this study. Interestingly, the same effect is not found in the same model using the Jockers-Rinker sentiment score, which may be due to the relative limited size of the Jockers-Rinker lexicon (11,710 words) compared to the Sentiword lexicon (20,093 words).

Table 4: Lagged TS Regressions with Fixed Effects

	Dependent variable:							
	Log New Cases		Log New Deaths		Unemployment Rate		Average Weekly Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Sentiword Sentiment	-1.81		-8.69*		-4.74		-103.25	
Lagged Jockers Rinker Sentiment		0.56		-2.05		-0.35		30.54
Stringency Index	-0.01	-0.004	-0.01	-0.002	-0.0001	0.003	-0.13	-0.02
Economic Support Index	0.003	0.003	0.01	0.01	0.003	0.002	0.07	0.07
Observations	128	128	128	128	128	128	128	128
R^2	0.01	0.004	0.04	0.02	0.004	0.001	0.02	0.01
Adjusted R^2	-0.29	-0.29	-0.24	-0.27	-0.29	-0.29	-0.27	-0.28
F Statistic (df = 3; 98)	0.17	0.13	1.48	0.66	0.14	0.03	0.68	0.29
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 4 displays a different approach to the previous time series regression discussed above. This approach introduces the advent of time and entity fixed effects. While the previous model attempted to control for all observable variables, it is possible to imagine that many unobservable factors impact the economic and social indicators used in the regression. Thus, by including entity fixed effects, these unobserved variables are controlled by giving each state a separate alpha or intercept value. Additionally, by having a time-fixed effect, the cyclicality of the pandemic observed since early 2020 is accounted for by giving each period a separate lambda value representing the time trend. The inclusion of entity fixed effects removes the need to include time fixed control variables throughout the study, including population size, minority population percent, and Governor party affiliation. All 8 of the models in Table 4 have F statistics insignificant at even the 10% level. This statistical insignificance suggests that these models do not perform better than a model with no independent variables, and thus conclusions drawn from the results should be taken with caution.

After including both time and entity fixed effects, the regression results present a very different picture of the impact of Governor speech sentiment on nearly all social and economic indicators. While all models except for model 3 display coefficients without statistical significance for their respective sentiment measures, it is still interesting to observe how the sign in front of these coefficients behaves. As in previous models, the relationship between sentiment and monthly cases remains negative. However, in models 5, 6, and 7, the sign has flipped from previous approaches. These new coefficients now suggest that an increase in sentiment is correlated with a decreased unemployment rate and average weekly earnings, except for model 8. The only model which results in a statistically significant coefficient for one of the sentiment measures is model 3. The coefficient of -8.69, which is significant at only the 10% level, suggests that an increase in sentiment leads to a decrease in deaths associated with the pandemic. The scale of this coefficient can be understood as a 0.17% decrease in monthly deaths for a one standard deviation increase in the Sentiword sentiment measure. As in the previous approach, this result contrasts with H1 as it suggests that increasing levels of negative sentiment led to positive social outcomes (decreased monthly deaths). However, this inverse relationship can not be concluded with certainty as the F statistic for this model is not significant, still leading to the rejection of H1.

The only two remaining control variables, Stringency Index and Economic Support Index, no longer have statistically significant coefficients in any new models. This finding suggests that although these variables change across states and time, other unobserved entity and time effects may correlate with state stringency and economic support responses, leading to multicollinearity with the two fixed effects.

5.2.1 Limitations

By expanding the economic model to account for changes in independent variables over time, the time-series regression models can more accurately estimate the impact of small changes in sentiment. However, while the coefficients outlined above can be seen to be statistically and economically significant for some models, some essential potential issues could be causing the estimated effects beyond what is assumed in the economic model. The time series models mitigate somewhat the sample size and measurement issues present in the linear regression, but the problem of causality still exists, given the nature of the data. The speech of Governors surrounding the COVID-19 pandemic has the potential for correlation with the impact that the pandemic is having both worldwide and locally. Thus, there is a high potential for simultaneous or reverse causality to be present. The sentiment of the Governor's speech on the pandemic could be caused by the economic and social indicators, not the other way around. If this is the case, then it can be concluded that the results above are flawed.

5.3 Cross Lagged Fixed Effects Regression

New economic models were developed to account for the limitations of the time series regression. These models aim to isolate the causal impact of Governor speech sentiment on economic and social indicators by testing for reverse causality.

(8) Cross Lagged Fixed Effects Regression Dependent

$$indicator_{it} = \alpha_i + \lambda_t + \beta_1\, sentiment_{it-1} + \beta_2\, indicator_{it-1} + \beta_3\, stringency_{it} + \beta_4\, EconSupport_{it} + \mu_{it}$$

(9) Cross Lagged Fixed Effects Regression Independent

$$sentiment_{it} = \alpha_i + \lambda_t + \beta_1\, indicator_{it-1} + \beta_2\, sentiment_{it-1} + \beta_3\, stringency_{it} + \beta_4\, EconSupport_{it} + \mu_{it}$$

The above economic models display a Cross Lagged Fixed Effect approach. Model (6) is derived from the previous time series Model (5). The major change in this model is that the lagged value of the dependent variable is introduced to determine whether the value of y is being impacted by past values of x rather than past values of y. Model (7) is then used to try and see if there is reverse causality present. This is done by switching the dependent variables with the primary independent variables of focus (sentiment scores) to see if there is an effect on sentiment caused by previous values of economic and social indicators when controlling for the past sentiment.

These models are applied only using the Sentiword sentiment measure as this measure displayed the largest number of statistically significant coefficients across all previous models. Additionally, these models were only tested on monthly cases, monthly deaths, and the unemployment rate, as these dependent variables displayed statistically significant effects in the more robust time series regressions. The results of these regressions can be found in Tables 5 to 7.

Table 5: Cross Lagged Model with Fixed Effects – New Cases

	Dependent variable:	
	Log New Cases	Sentiword Sentiment
	(1)	(2)
Lagged Sentiword Sentiment	1.29	-0.30**
Lagged Log New Cases	0.56***	0.002
Stringency Index	0.004	-0.001*
Economic Support Index	-0.002	-0.0001
Observations	128	86
R^2	0.45	0.15
Adjusted R^2	0.28	-0.28
F Statistic	20.12*** (df = 4; 97)	2.55** (df = 4; 56)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 5 displays the results of the cross-lagged model with fixed effects and relevant control variables. Both models 1 and 2 have resulting F statistics that are significant at the 1% and 5% levels, respectively. These values suggest that the models outperform the mean and thus include relationships that can be extracted and interpreted according to their individual statistical significance.

In these two models, lagged log new cases have a statistically significant impact at the 1% level on log new cases. The coefficient of 0.56 displays that an increase in cases of 1% causes a .56% increase in cases in the following month. A similar effect can be seen by observing model 2, where the previous month's Governor speech sentiment has a statistically significant impact on current sentiment at the 5% level. The coefficient of -0.30 suggests that an increase in the previous month's Governor speech sentiment by one standard deviation decreases the current sentiment by 0.006. While this result is statistically significant, the impact of this effect is relatively small given the distribution of the sentiment scores in the sample.

Most notably, there appears to be no causality inferred in the results above. This effect is shown by the fact that in model 1, the coefficient for lagged sentiment is not statistically significant after controlling for lagged new cases. Conversely, no reverse causality is found, as the coefficient for lagged log new cases in model 2 is not statistically significant. Thus, while previous models seemed to imply causality, the lagged sentiment value was purely capturing the lagged value of log new cases, thus overrepresenting the statistical significance of the coefficient. The results of this model lead to the rejection of H1 due to a lack of a statistically significant impact of sentiment on new cases.

While in previous models, both the Stringency Index and Economic Support Index appeared to play no statistical role in the results, model 2 suggests otherwise. The statistically significant coefficient for the Stringency Index at the 10% level indicates that after controlling for past sentiment and past cases, an increase in stringency appears to have a negative effect on Governor speech sentiment.

Table 6: Cross Lagged Model with Fixed Effects – New Deaths

	Dependent variable:	
	Log New Deaths	Sentiword Sentiment
	(1)	(2)
Lagged Sentiword Sentiment	-3.76	-0.31^{**}
Lagged Log New Deaths	0.67^{***}	0.001
Stringency Index	0.004	-0.001^{*}
Economic Support Index	0.0004	-0.0001
Observations	128	86
R^2	0.57	0.15
Adjusted R^2	0.44	-0.29
F Statistic	32.48^{***} (df = 4; 97)	2.48^{*} (df = 4; 56)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6 displays the same two models as in Table 5, with the main difference being the change in the dependent variable to log new deaths. Both models 1 and 2 have resulting F statistics that are significant at the 1% and 5% levels, respectively. These values suggest that the models outperform the mean and thus include relationships that can be extracted and interpreted according to their individual statistical significance.

Statistically significant coefficients for lagged log new deaths in model 1 and lagged Sentiword sentiment arise at the 1% and 10% levels, respectively. The lagged new deaths coefficient of 0.67 implies that an increase in deaths by 1% will lead to a resulting increase of .67% in the following month. In model 2, the coefficient for the lagged sentiment of -0.31 suggests that an increase in sentiment by one standard deviation will increase sentiment in the following period by 0.006. Similar to the new case model, this effect is not significant enough to draw critical insights. There appears to be no causality or reverse causality, as shown by the lack of statistical significance for the lagged sentiment coefficient in model 1 and the lagged log new deaths coefficient in model 2. The results of this model lead to the rejection of H1 due to the lack of a statistically significant effect of sentiment on new deaths.

The Stringency Index variable is the only control that achieves statistical significance. In model 2, the coefficient of -0.001 is significant at the 10% level and suggests that an increase in stringency results in decreased Governor speech sentiment.

Table 7: Cross Lagged Model with Fixed Effects – Unemployment Rate

	Dependent variable:	
	Unemployment Rate (1)	Sentiword Sentiment (2)
Lagged Sentiword Sentiment	-6.55	-0.32^{**}
Lagged Unemployment Rate	0.28^{***}	0.001
Stringency Index	-0.01	-0.001^{**}
Economic Support Index	0.01	-0.0000
Observations	128	86
R^2	0.11	0.15
Adjusted R^2	-0.17	-0.29
F Statistic	2.85^{**} (df = 4; 97)	2.47^{*} (df = 4; 56)
Note:		*p<0.1; **p<0.05; ***p<0.01

The models displayed in Table 7 reflect the same economic models as the previous cross-lagged approaches using the unemployment rate as the dependent variable of interest. Models 1 and 2 have resulting F statistics that are significant at the 5% and 10% levels, respectively. These values suggest that the models outperform the mean and thus include relationships that can be extracted and interpreted according to their individual statistical significance.

Statistically significant coefficients arise for the lagged unemployment rate in model 1 and lagged Sentiword sentiment in model 2. The coefficient of 0.28 for the lagged unemployment rate in model 1 is statistically significant at the 1% level. It implies that an increase in the unemployment rate by 1% leads to a further rise in the unemployment rate in the following period of 0.28%. The coefficient of -0.32 for lagged sentiment is statistically significant at the 5% level. It implies that an increase in sentiment by one standard deviation will increase the Governor's speech sentiment in the following period by 0.006. This increase, although statistically significant, is not large enough to draw insights from. These models show no statistically significant causality or reverse causality, as demonstrated by the lack of statistical significance for the lagged sentiment coefficient in model 1 and the lagged unemployment rate coefficient in model 2. The results of this model lead to the rejection of H2 due to a lack of a statistically significant effect of Governor speech sentiment on the unemployment rate.

The Stringency Index variable is the only control variable that achieves statistical significance. In model 2, the coefficient of -0.001 is significant at the 5% level and suggests that an increase in stringency results in decreased Governor speech sentiment.

5.3.1 Limitations

The limitations of the cross-lagged fixed effects regression fall solely in the inputs available for this analysis. The cross-lagged fixed-effect model has been shown to isolate causality by combining all relevant controls, both observable and unobservable, with the additional control for lagged observations of the dependent variable (Leszczensky and Wolbring, 2019). This model's limitations capture the limitations of the overall analysis and will be discussed thoroughly in the Limitations section of this paper.

5.4 Party Affilation Linear Regression

The final model implemented aims to understand the relationship between Governor party affiliation and the sentiment in their speech in COVID-19 press briefings. The model uses a linear regression with the two different sentiment measures as the dependent variables and the binary Republican variable as the independent variable of interest. Additionally, the economic and social indicators are used as control variables.

Table 8: Party Linear Model with Controls

	Dependent variable:	
	Average Sentiword Sentiment	Average Jockers Rinker Sentiment
	(1)	(2)
Republican (bin)	0.01	-0.02
Log Total Cases	0.004	0.02
Log Total Deaths	0.001	-0.002
Unemployment Rate	-0.003	-0.01
Average Weekly Earnings	0.0000	-0.0000
Constant	-0.01	0.05
Observations	18	18
R^2	0.19	0.18
Adjusted R^2	-0.15	-0.16
F Statistic (df = 5; 12)	0.55	0.53
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8 displays the coefficients and test statistics for the 2 Governor party affiliation linear regression models with controls. The simple linear regression model results without controls can be found in Appendix D. The first insight from Table 8 is that no variables achieve statistical significance, including the constant and F statistic, suggesting no statistically significant relationship in either model tested. These findings lead to the rejection of H3. The assumed interaction of H3 was that the political alignment of Governors would impact the speech sentiment used in COVID-19 press briefings, such that Democratic Governors would be more likely to engage in negative speech sentiment than their Republican counterparts. If true, the coefficient for the Republican binary variable would have been positive and statistically significant. However, the lack of statistical significance suggests no relationship between political alignment and speech sentiment in either direction in the models evaluated.

Additionally, there are differing non-significant relationships between the two different sentiment measures, with the Sentiword measure having a positive coefficient and the Jockers-Rinker measure having a negative coefficient. This observed difference in sentiment measures further supports the claim that political alignment and sentiment correlations are likely random. Moreover, all control variables included in this model do not achieve statistical significance, suggesting no causal relationship between the period totals and averages of Governor speech sentiment and state COVID-19 indicators examined.

5.4.1 Limitations

The limitations of the Governor party affiliation linear regression models mirror those of the previous linear models tested. Firstly, the sample size of this data limits the possibility for the model to achieve statistically significant results. Even with a relatively even distribution between Republican and Democratic Governors, the sample size of 18 is not large enough to draw out statistically significant coefficients for any of the independent variables. While the possibility for reverse causality is not relevant in this case, there is still an argument for the direction of the relationships between the dependent variables and the social and economic indicator control variables. Finally, as in the previous linear model, the way in which the variables needed to be consolidated to represent a single observation for each state does not necessarily encompass the way the variables change over time and thus limits the applicability of the model and the implications that can be drawn.

5.5 Hypothesis 1

In the evaluation of H1, we conclude that there is no statistically significant relationship between an increase in negative language sentiment and an increase in positive social outcomes during the periods observed. This conclusion evolved as the analysis was deepened to control for observed and unobserved variables expected to impact the results of this investigation. In the preliminary linear regression with control variables, the F statistic for the four models using social indicators as the dependent variables was statistically significant. However, no significant coefficients appeared for the evaluated Sentiword or Jockers-Rinker sentiment measures. Moreover, the direction of the relationship suggested that there could be an inverse relationship present, contrasting the expectations of H1.

Expanding this linear model into a lagged time-series regression with controls, the conclusion surrounding this inverse relationship was supported by a statistically significant relationship between the Sentiword and Jockers-Rinker sentiment measures for new COVID-19 cases only. This relationship appeared in the opposite direction presented in H1 and was the first sign that reverse causality may be occurring. Further investigation of this effect using a time-series regression with fixed effects provided a statistically significant coefficient for new deaths only when using the Sentiword sentiment measure. But the implications drawn from this coefficient are limited by a lack of F statistic significance. The cross-lagged model with fixed effects disproved with certainty the assumptions made under H1 by displaying no statistically significant relationship between the sentiment measure and the two social indicators, as shown by the lack of a significant coefficient in this model. These findings across all levels of the analysis show no causal relation between the sentiment of the Governor's speech and the social outcomes of the pandemic during the periods observed.

5.6 Hypothesis 2

In opposition to the assumptions made under H2, we conclude that there is no statistically significant relationship between an increase in negative language sentiment and a rise in negative state economic outcomes during the periods observed. Similar to the evaluation of H1, the conclusions made evolved as the analysis expanded. The preliminary linear regression with controls had statistically significant F statistics for unemployment but not average weekly earnings. Moreover, only a significant coefficient for average weekly earnings is found using the Sentiword measure. Although this finding offers partial support to H2, the lack of F statistic significance greatly limits the implications that can be drawn from this coefficient.

When expanding the economic model to a time-series regression with controls, the F statistics achieve significance with a statistically significant coefficient for unemployment using both the Sentiword and Jocker-Rinkers measures. However, the direction of these coefficients contrasts the expectations of H2, suggesting that an increase in positive sentiment would lead to a rise in unemployment. Further investigation of this finding using a time series regression with fixed effects presented non-statistically significant F statistics and no significant coefficients using either sentiment measure. The cross-lagged model with fixed effects further disproved the assumptions made under H2 by displaying no statistically significant relationship between the Sentiword sentiment measure and the previously significant coefficient for the unemployment rate, as shown by the lack of significance in this model. These findings across all levels of the analysis show no causal relation between the sentiment of the Governor's speech and the economic outcomes of the pandemic during the periods observed.

5.7 Hypothesis 3

In the evaluation of H3, we conclude that there is no statistically significant relationship between the political affiliation of Governors and the degree of positive or negative sentiment used in COVID-19 press briefings during the periods observed. No variables, including the F statistic, achieved statistical significance in either the linear regression with or without controls. Moreover, as all control variables included failed to achieve statistical significance, no causal relationship between Governor speech sentiment, party affiliation, or the observed state COVID-19 indicators can be attributed. Apart from this, differing non-significant relationships were found between the Sentiword and Jockers-Rinker sentiment measures tested, offering further evidence that the correlation between sentiment and party affiliation was random in occurrence and can not be used to attribute causality.

6. Conclusion

This research sought to understand the impact of US Governor speech sentiment in COVID-19 press briefings on their respective states' social and economic outcomes from March 2020 to December 2020. In line with this initial inquiry, we investigated the degree to which Governor party affiliation altered the tonality and objectivity of Governor communication to explain further the causes behind the sentiment observed. These initial research questions were then deconstructed into three falsifiable hypotheses and tested across 50 models of increasing complexity. The first hypothesis (H1) assumed that an increase in the level of negative sentiment used by Governors in press briefings would improve positive state social outcomes, measured in monthly COVID-19 cases and monthly COVID-19 related deaths. The second hypothesis (H2) assumed that an increase in the level of negative sentiment used by Governors in press briefings would lead to a rise in adverse state economic outcomes, measured in the state unemployment rate and average weekly earnings during the periods observed. The final hypothesis (H3) assumed that Governor party affiliation would moderate press release sentiment such that Governors deemed Democrat will engage in higher levels of negative sentiment than their Republican counterparts. By testing these hypotheses, our analysis aimed to provide insight into the effect of language and party affiliation in crisis communication from political leaders. In doing so, we sought to enable the fine-tuning of future mitigation policies and crisis communications to reduce future crises' human and economic costs.

From the results of our analysis, we conclude there is no causal relationship between the speech sentiment of Governors in COVID-19 press briefings and the observed social and economic outcomes of their respective states between March 2020 to December 2020. Moreover, we find no statistically significant relationship between Governor party affiliation and COVID-19 press briefing sentiment during the periods observed. Under simple statistical investigation, it may appear that the sentiment of Governor communication impacted the social and economic outcomes of their respective states. However, more rigorous statistical inspection using a Cross Lagged Regression approach demonstrated that the previously observed impacts of sentiment were caused by values of the social and economic indicators in previous periods rather than the sentiment of Governor COVID-19 press briefings.

Through this research, we contribute to the growing field of literature on textual analytics and sentiment analysis by demonstrating its applications in analysing the impact of the language used by political leaders and authoritative organizations (Liu and Lei, 2018; Poth et al., 2021; Bulut and Poth, 2022). We also document the importance of lexicon selection and rigorous statistical evaluation in interpreting the effects of sentiment in economic models. The efficacy of our research faced several limitations providing the opportunity for future research.

7. Limitations and Future Research

The findings of this paper provide insights into the effect of state Governor COVID-19 press briefing sentiment on the social and economic outcomes of their respective states. In addition, we investigate the impact that party alignment has on Governor speech sentiment. However, there are limitations to our analysis stemming from the time period and sample observed, the scarcity of Governor press briefing data, and the variety of media sources consumed by citizens in a natural setting.

7.1 Time Period and Sample Selection

The first limitation to this analysis was the reduction of the time horizon observed, ranging from March 2020 to December 2020, and the need to select a sample of Governor COVID-19 press briefings from this already reduced time horizon. Our initial intention was to analyze Governor COVID-19 specific press briefings from March 2020 till their end in November 2021. However, there was a significant drop-off in press briefing observations as the pandemic aged. This steep drop-off in press briefings required narrowing our analysis to March 2020 through December 2020 due to the increased frequency of press briefings during this time frame. This reduction in time frame preserved the integrity of the analysis by minimizing the number of missing Governor COVID-19 press briefing observations while maximizing the number of states compared. However, this reduction caused a significant loss in total state-level data observed and reduced the number of monthly aggregated Governor press briefing observations from 228 to 173.

Furthermore, despite this reduction in the time frame, the distribution of Governor COVID-19 press briefings remained unbalanced between differing states. Some of the 50 states only provided a single press briefing during the reduced time frame, creating the need for a sample of states with at least 5 COVID-19 press briefings from March 2020 to December 2020. By restricting our analysis to only those states that met the sample selection criteria, our research was reduced to 18 states only. In addition, the number of monthly aggregated Governor press briefing observations fell from 173 to 128 following sample selection. This relatively small sample made it challenging to conclude causal relationships at any statistically significant level, limiting the efficacy of our analysis and the conclusions we could draw. Fortunately, the sample of states selected was split relatively evenly between Democrat and Republican states, allowing for further investigation of party affiliation's effect on Governor communication sentiment.

Apart from these structural limitations, there may be characteristics within the observed time horizon and sample that do not indicate regular economic activity or social outcomes. Moreover, these irregular characteristics may have only become evident as the pandemic progressed and the impact of COVID-19 became more pronounced. Although these time-specific characteristics are factored into the more complex economic models, there is potential that the behavior of the variables observed in this more limited time frame follows a path that would not allow for statistical relationships to present themselves. Thus, future research arises in assessing the impact of Governor speech sentiment over a more significant time horizon. Expanding the number of months observed or examining weekly or daily data points may allow further insights into the relationships between the variables inspected in this analysis. However, this expansion is complicated by the infrequency and scarcity of Governor COVID-19 press briefings; a limitation addressed in subsequent sections. An increase in the time horizon may require additional communication data, such as state executive orders, media coverage, Governor social media posts, or other public communications from state officials to be analysed.

7.2 Press Breifing Frequency

The Governor COVID-19 press briefings observed act as snapshots in time and provide textual data that illuminates how differing Governors spoke about public policy and the risks posed to citizens at specific points throughout the COVID-19 pandemic. This glimpse into the rhetoric of Governors provides an interesting and relatively uniform understanding of how different Governors perceived the threat of the COVID-19 pandemic and illustrates the actions they took in response. However, our comparative analysis of state social and economic outcomes is limited by the frequency and number of press briefings hosted by differing state Governors. As the pandemic aged and the population became more aware of what risks COVID-19 posed, the need for ongoing crisis communication from Governors and changes to public policy decreased, resulting in less frequent Governor press briefings over time. Moreover, differing Governors hosted far more or far fewer press briefings than others, making a comparative analysis of their impact on the economic and social outcomes of the pandemic far more complex. Thus, our analysis of Governor speech sentiment is limited in the number of available observations, resulting in a limited sample size when states are filtered for the total number of observations of Governor speech.

This limitation leads to potential future research in understanding the speech sentiment of public figures on economic and social outcomes, even beyond the time related to the pandemic. The first expansion is to observe how Governors speak about the pandemic in press briefings that are not explicitly about COVID-19. While the pandemic-specific press briefings used in this analysis are varied, other Governor press briefings occur regularly. These press briefings undoubtedly include pandemic-related speech, even if it is not the main focus. Therefore, these more general speech observations could be analysed using a topic model to extract speech specific to the pandemic and provide a complete picture of the Governor's sentiment toward COVID-19. Apart from this, sentiment analysis could be expanded to other textual data sources to better understand the relationships present between the communication of the Governor or other public figures and the economic or social outcomes of the pandemic, regulation, or future crises. Other textual sources of interest could be state executive orders, local state media coverage, Governor social media posts, or other public communications from state officials. These resources also have limitations, namely in the language used and the variety of speakers participating in communication with the public. However, some form of consolidation or meta-analysis could provide insights into how these different platforms of sentiment expression interact and the greater social and economic impact they have on society.

7.3 Media Sources

An overarching limitation to our analysis is the variety of news sources consumed by citizens and the ongoing battle against misinformation within the United States (Halpern, 2020; Fowler et al., 2020; Solano et al., 2020). Identifying the causal effect of Governor sentiment in COVID-19 press briefings on the behaviour of citizens in a natural setting contains many challenges. In an ideal world, Governors directions, public policy orders, and pandemic-related communications would be seen by citizens as reliable and acted upon accordingly. However, citizens of a given state have ideological differences, firmly held prior beliefs, and consume a variety of media sources that cover COVID-19 in substantially different ways (Bursztyn et al., 2020). In addition to others, these confounding factors make it extremely difficult to rule out alternate explanations for changes to a given states economic and social health or isolate the causal effect of Governor communication sentiment on such measures. Future research on this topic may benefit from focusing on a more limited selection of states and evaluating the impact of communication sentiment from multiple authoritative communication channels within those states. By assessing the communication of Governors, local newspapers, and state media figures, a more comprehensive understanding of the effect of communication sentiment on the state's social and economic outcomes during the pandemic may be gained. This alternative approach to analysis would still face limitations from the plethora of non-traditional media sources and social media influencers that impact the public understanding and beliefs about the virus. Nevertheless, by increasing the variety of authoritative communication channels analysed, a more comprehensive understanding of the effect of communication sentiment on the social and economic outcomes of the COVID-19 pandemic may still be gained.

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9. Appendix

Appendix A: Table of All Models

Economic Model	*Model Name*	*Dependent Variables*	*Main Independent Variables*	*Total Models*
(1)	Linear Regression	Total Cases, Total Deaths, Average Unemployment Rate, Average Weekly Earnings	Sentiword Sentiment Measure, Jockers Rinker Sentiment Measure	8
(2)	Linear Regression w Controls	Total Cases, Total Deaths, Average Unemployment Rate, Average Weekly Earnings	Sentiword Sentiment Measure, Jockers Rinker Sentiment Measure	8
(3)	Lagged Time Series Regression	New Cases, New Deaths, Unemployment Rate, Average Weekly Earnings	Sentiword Sentiment Measure, Jockers Rinker Sentiment Measure	8
(4)	Lagged Time Series Regression w Controls	New Cases, New Deaths, Unemployment Rate, Average Weekly Earnings	Sentiword Sentiment Measure, Jockers Rinker Sentiment Measure	8
(5)	Lagged Time Series Regression w Fixed Effects	New Cases, New Deaths, Unemployment Rate, Average Weekly Earnings	Sentiword Sentiment Measure, Jockers Rinker Sentiment Measure	8
(6)	Party Linear Regression	Sentiword Sentiment Measure, Jockers Rinker Sentiment Measure	Binary Republican Variable	2
(7)	Party Linear Regression w Controls	Sentiword Sentiment Measure, Jockers Rinker Sentiment Measure	Binary Republican Variable	2
(8)	Cross Lagged Fixed Effects Regression 1	New Cases, New Deaths, Unemployment Rate	Sentiword Sentiment Measure	3
(9)	Cross Lagged Fixed Effects Regression 2	Sentiword Sentiment Measure	New Cases, New Deaths, Unemployment Rate	3
				50

Appendix B: Linear Regression without Controls

Linear Regressions

	Dependent variable:							
	Log Total Cases		Log Total Deaths		Unemployment Rate		Average Weekly Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Sentiword Sentiment	9.77		8.19		-26.45		-85.26	
Average Jockers Rinker Sentiment		2.75		-0.14		-14.21		-832.31
Constant	12.57^{***}	12.71^{***}	8.65^{***}	9.14^{***}	10.56^{***}	11.24^{***}	$1{,}124.09^{***}$	$1{,}248.26^{***}$
Observations	18	18	18	18	18	18	18	18
R^2	0.03	0.01	0.02	0.0000	0.04	0.06	0.0001	0.03
Adjusted R^2	-0.03	-0.05	-0.04	-0.06	-0.02	-0.004	-0.06	-0.03
F Statistic (df = 1; 16)	0.47	0.18	0.29	0.0004	0.63	0.94	0.001	0.57
Note:								*p<0.1; **p<0.05; ***p<0.01

Appendix C: Time Series Regression without Controls

Lagged TS Regressions

	Dependent variable:							
	Log Total Cases		Log Total Deaths		Unemployment Rate		Average Weekly Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Sentiword Sentiment	9.77		8.19		-26.45		-85.26	
Average Jockers Rinker Sentiment		2.75		-0.14		-14.21		-832.31
Constant	12.57^{***}	12.71^{***}	8.65^{***}	9.14^{***}	10.56^{***}	11.24^{***}	$1{,}124.09^{***}$	$1{,}248.26^{***}$
Observations	18	18	18	18	18	18	18	18
R^2	0.03	0.01	0.02	0.0000	0.04	0.06	0.0001	0.03

Adjusted R^2	-0.03	-0.05	-0.04	-0.06	-0.02	-0.004	-0.06	-0.03
F Statistic (df = 1; 16)	0.47	0.18	0.29	0.0004	0.63	0.94	0.001	0.57
Note:								*p<0.1; **p<0.05; ***p<0.01

Appendix D: Party Linear Regression without Controls

Party Linear Regression

	Dependent variable:	
	Average Sentiword Sentiment	Average Jockers Rinker Sentiment
	(1)	(2)
Republican (bin)	0.01	-0.002
Constant	0.05^{***}	0.16^{***}
Observations	18	18
R^2	0.11	0.002
Adjusted R^2	0.06	-0.06
F Statistic (df = 1; 16)	2.00	0.03
Note:		*p<0.1; **p<0.05; ***p<0.01