COVID-19 Tweets of Governors and Healthcare Professionals: Deaths, Masks, and the Economy

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Abstract

As COVID-19 spread throughout the United States, governors and healthcare professionals (HPs) received a surge in following on Twitter. This paper seeks to investigate how HPs, Democratic governors, and Republican governors discuss COVID-19 on Twitter. Tweets dating from January 1st, 2020 to October 18th, 2020 from official accounts of all fifty governors and 46 prominent U.S.-based HPs were scraped using Twint (N = 192,875) and analyzed using a custom-built wordcount program. We did not find existing literature directly related to this subject, which is understandable given the novel nature of COVID-19.

The most significant finding is that Democratic governors mentioned death 4.3 times the rate of Republican governors in their COVID-19 tweets. In 2019, Democratic governors still mentioned death at 2.09 the rate of Republicans. We believe we have substantial evidence that Republican governors are less comfortable talking about death than their Democratic counterparts.

We also found that Democratic governors tweet about masks and solutions more often than Republicans. However, there isn't a large difference between the proportion of COVID-19 tweets, tweets about the economy, tweets about stay-at-home measures, tweets about vaccines, and tweets containing "science-like" words between governors of the two parties.

HPs tweeted about death and vaccines more than the governors. They also tweeted about solutions and testing at a similar rate compared to governors and mentioned lockdowns, the economy, and masks less frequently. We ran linear regressions and did not find conclusive evidence that state-level COVID-19 situations impacted how governors tweet about the pandemic on Twitter.

Introduction and Literature Review

The coronavirus pandemic has hijacked our lives and became the defining event of 2020. In the United States, state governments became central to the pandemic effort as governors found themselves in the spotlight. Google Trends data reveals that web and news searches for Governor Jay Inslee of Washington, Governor Andrew Cuomo of New York, and Governor Gavin Newsom of California—three states that witnessed early coronavirus outbreaks—surged significantly since early March (Google Trends, n.d.). This popularity spike is also reflected in the number of followers these governors gained on Twitter. For example, Gov. Inslee of Washington added 663 followers in February and 82,594 in March, Gov. Newsom added 2,137 followers in February and 101,401 in March, and Gov. Cuomo added 1,472 followers in February and 633,652 in March (Social Blade, n.d.).

A parallel development on Twitter is the rise in popularity of healthcare professionals (HPs). For example, prominent doctors such as Robert Redfield, Scott Gottlieb, and Eric Feigl-Ding all saw their Twitter accounts surge in popularity as the pandemic broke out (Social Blade, n.d.). This trend has not eluded the media (Wells, 2020). In fact, there exist multiple online guides recommending readers whom to follow on Twitter to learn more about the coronavirus pandemic (e.g., Brown, 2020; Elemental Editors, 2020). The rising popularity of governors and doctors on Twitter warrants a closer look, especially given that Twitter has seen a record-breaking increase of users between April and June (Wise, 2020). The dissemination of COVID-19 related information is essential to an effective pandemic response. This paper seeks to investigate how HPs, Democratic governors, and Republican governors address COVID-19 on Twitter.

Large differences in state-level COVID-19 policies exist and are mostly due to politics (Adolph et al., 2020). Thus, we begin our analysis with the Twitter accounts of governors. We found two existing studies looking at governors' COVID-19 messaging. Grossman et al. specifically examined the effects of stay at home orders and messaging and found that they resulted in significant mobility reductions, with larger reductions from Democratic states and counties (2020). Sha et al. used dynamic topic modeling to examine the topics mentioned in the tweets of U.S. governors and cabinet officials (2020). Studies on COVID-19 tweets by HPs are rare. The only one that we were able to identify is from Boğan et al., who examined 251 Twitter accounts by emergency medicine physicians and residents in Turkey and classified their tweets into categories such as comments and suggestions (42.4%) and institutional announcements (18.6%) (2020). Other than the three aforementioned studies, we couldn't find anything else on the topic at the time of writing. This is understandable given the novelty of the subject, and we hope to add to the existing literature.

Outside of COVID-19, research on Twitter as a healthcare communications venue for HPs is also not plentiful. A couple of studies focus on tweeting during professional conferences (Salzmann-Erikson, 2017; Lemay et al., 2019; Ziemba et al., 2020), and one study that examined the #TipsForNewDocs hashtag (Rashid et al., 2018). However, there is a large body of literature that examines the differences between the language used by conservatives and liberals. Neiman et al. analyzed the language used by U.S. federal-level politicians in speeches, press appearances, and presidential debates (2015). They found that political elites do not systematically differ when it comes to value-related language. There also exist several studies on how partisans use Twitter. A comprehensive study on tweets can be found at Sterling et al., who tested 27 hypotheses on how the "linguistic styles" of liberals and conservatives differ. They used tweets from 25,000 users and found a significant difference in 23 cases. They also found that political extremists use language differently compared to moderates in 17 different dimensions (2020). Another example is Sylwester & Purver, who found seven differences between Twitter users who exclusively follow @GOP and those who exclusively follow @TheDemocrats, the two parties' official Twitter accounts. They found that Democrats are more likely to use swear words, feeling-related words, positive sentiment, and first-person singular pronouns, whereas Republicans are more likely to use religion-related words and first-person plural pronouns (2015).

Due to the novel nature of COVID-19, there are large gaps in our knowledge. Thus, the current literature offers little guidance on where research is most needed. This paper is intended to provide a starting point for future research on health and political communication during the COVID-19 pandemic and answer a few basic questions.

We start by first looking at how often the groups and individual users mention the pandemic, which we believe to be a good indicator of the importance one puts on the issue and how comfortable a person is with the subject. We grouped the governors based on party not only because of convention but also due to how politics is driving the COVID-19 response, even at the local level (Hartney & Finger, 2020). Next, we examine how these users talk about the pandemic's consequences and solutions, what we believe to be the two central themes surrounding coronavirus messaging. For consequences, we focused on the differences between words relating to the economy and words relating to deaths since there is an ongoing debate on COVID-19 restrictions and its effects on the economy (Samuels & Klar, 2020; Holland & Hunnicutt, 2020). For solutions, we looked at the prevalence rate of a range of words relating to different solutions (masks, testing, vaccine, etc.) in the tweets of governors and HPs and the rate at which these groups mention any solutions in their tweets.

We also wanted to examine the degree to which governors mimicked the language of HPs. We believe that this can be seen as a measure of how much a governor wishes to be associated with the scientific community, given that a subset of conservatives have little trust in science and thus have lower social distancing intentions (Koetke et al., 2020). We attempt to measure this by looking at the prevalence of technical language (e.g., "R0," "asymptomatic," "aerosol") in tweets.

To summarize, we seek to answer the following questions:

RQ1: Do Democratic governors and Republican governors differ in how often they tweet about COVID-19?

RQ2: Do Democratic governors, Republican governors, and HPs (henceforth referred together as DRHs) differ when talking about the consequences of the pandemic?

RQ3: Do DRHs differ when talking about solutions to the pandemic?

RQ4: Do DRHs differ in the prevalence of technical language in their COVID-19 related tweets?

Methodology

Selecting Twitter Accounts

We first obtained the official accounts of governors. Official accounts are accounts clearly labeled for the governor's office (e.g., @LouisianaGov, @GovJanetMills), as opposed to personal or campaign accounts (e.g., @JohnBelEdwards, @JanetMillsforME).

We decided to have a broader definition of HPs to include epidemiologists, virologists, and biologists. This is because we believe that there is no fundamental difference between doctors, virologists, and epidemiologists to the average Twitter user. They are all professionals who are viewed as experts on the coronavirus and related issues. In this paper, HPs will refer to individuals who hold any of the following qualifications: MD, MPH (Master of Public Health), Ph.D., or professorship in epidemiology, biology, or virology.

We obtained a list of HPs tweeting about COVID-19 by first starting with eight arbitrarily chosen HPs (see "Initial HPs" list in appendix 2) who are publicly known to tweet about COVID-19 and have over a hundred thousand followers. We then looked at everyone followed by these eight users and filtered for those who had specific keywords in their username, Twitter handle, or bio (see appendix 2). We only include users with at least 20,000 followers. This first round resulted in 341 users. We then downloaded all tweets sent by these users between April 1st and April 30th. We first excluded all accounts (n=126) without at least 30 COVID-19 related tweets (defined as having a word from the COVID-19 keywords dictionary in appendix 1). We then excluded users who do not tweet about COVID-19 in at least 33% of their tweets (n= 105). We believe that a user who does not tweet about COVID-19 often and in at least 33% of their tweets are not followed for their expertise on COVID-19 and are therefore not subjects of this study. Interestingly, this excluded Dr. Bergstrom (an "Initial HP"), who only tweeted about COVID-19 in 29.3% of his tweets. Of the remaining 110, we manually went through to exclude organizations and check that all individuals are based in the US and hold the qualifications listed above. This resulted in a final list of 46 healthcare professionals, which can be found in appendix 2.

Obtaining Tweets

We then downloaded all tweets by these accounts from January 1st, 2020 to October 18th, 2020, using the Twint Python API (Twintproject, 2020). We totaled 56,552 tweets from Governors and 136,293 tweets from HPs.

We conducted content analysis using a wordcount program written in python. The program reads a dictionary and checks if a word from that dictionary is present in a tweet. It makes no distinction between tweets that mention a word once or multiple times. We then looked at the number of tweets that contained words from a specific dictionary. We opted for this binary method instead of a percentage score for each tweet—which would be similar to the LIWC algorithm by Pennebaker et al.—due to how short tweets are (2015). This binary count is also used in other tweet-oriented text analysis papers such as Sterling et al. (2020).

We used custom dictionaries in appendix 1 in conjunction with our wordcount program to answer our research questions. For RQ1, we looked at the ratio between tweets that contain words from the "COVID-19 Keywords" dictionary and the total number of tweets. We then deleted all non-COVID-19 related tweets when examining RQ2-4. For RQ2, we looked at the ratio of tweets that contained words relating to the economy and the total number of COVID-19 tweets as well as the ratio between tweets containing words relating to deaths and the total number of COVID-19 tweets using the "Consequences Keywords" dictionary. This ratio was calculated for each individual governor, the two parties, and HPs. For RQ3, we measured the ratio between tweets that contained words from the "Solutions" dictionary (a subset of "COVID-19 Keywords") and total COVID-19 words for each individual governor, the two parties, and HPs. We also measured the ratio of tweets containing individual solutions (e.g. "mask," "vaccine") and total solutions tweets for each individual governor, the two parties, and HPs. For RQ4, we measured the ratio between tweets that contained words from the "Technical Language" dictionary (a subset of "COVID-19 Keywords") and total COVID-19 words for each individual governor, the two parties, and HPs.

After comparing and examining the differences, we then compared the ratios and the raw counts of tweets that contained words from a particular dictionary for each governor to the cases, tests, and deaths per capita of their state. We obtained the data for total cases and deaths from the CDC and used the U.S. Census Bureau's 2019 population estimate for each state (2020; 2019). We used state level testing data from the COVID-19 tracking project (2020). Case, death, and testing numbers are from Oct 18th, 2020.

Results

Table one and figure one display the total number of tweets containing words from each dictionary. Note that non-COVID-19 related tweets are removed from analysis after RQ1. Thus, if a tweet read "Justice Ginsburg died," it would not be counted as a COVID tweet and thus will not be counted in the "Total Death Tweets" column.

It is also important to keep in mind that a tweet like “Masks stop aerosols” will be counted in the technical language section, the solutions section, and the masks section.

Figure 1. Prevalence rate of different types of tweets.

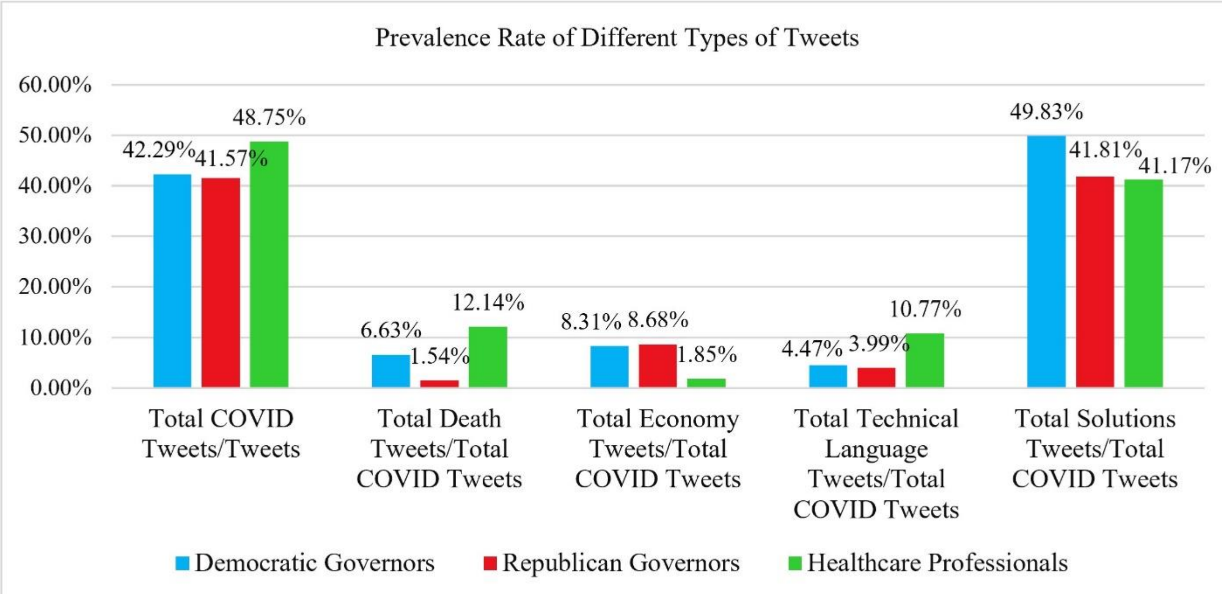


Table 1. Number of tweets in each category.

	Total Tweets	Total COVID Tweets	Total COVID Tweets/Total Tweets	Total Death Tweets	Total Death Tweets/Total COVID Tweets
Democratic Governors	29,297	12,389	42.29%	821	6.63%
Republican Governors	27,255	11,331	41.57%	174	1.54%
Healthcare Professionals	136,293	66,449	48.75%[1]	8,066	12.14%
	Total Economy Tweets	Total Economy Tweets/Total COVID Tweets	Total Technical Language Tweets	Total Technical Language Tweets/Total COVID Tweets	
Democratic Governors	1,029	8.31%	554	4.47%	
Republican Governors	983	8.68%	452	3.99%	
Healthcare Professionals	1,231	1.85%	7,159	10.77%	
	Total Solutions Tweets	Total Solutions Tweets/Total COVID Tweets			
Democratic Governors	6,174	49.83%			

[1] Since we limited our investigation of HPs to those who tweet about COVID-19 at least 33% of the time, we do not attach any significance to this proportion.

Republican Governors	4,737	41.81%			
Healthcare Professionals	27,358	41.17%			

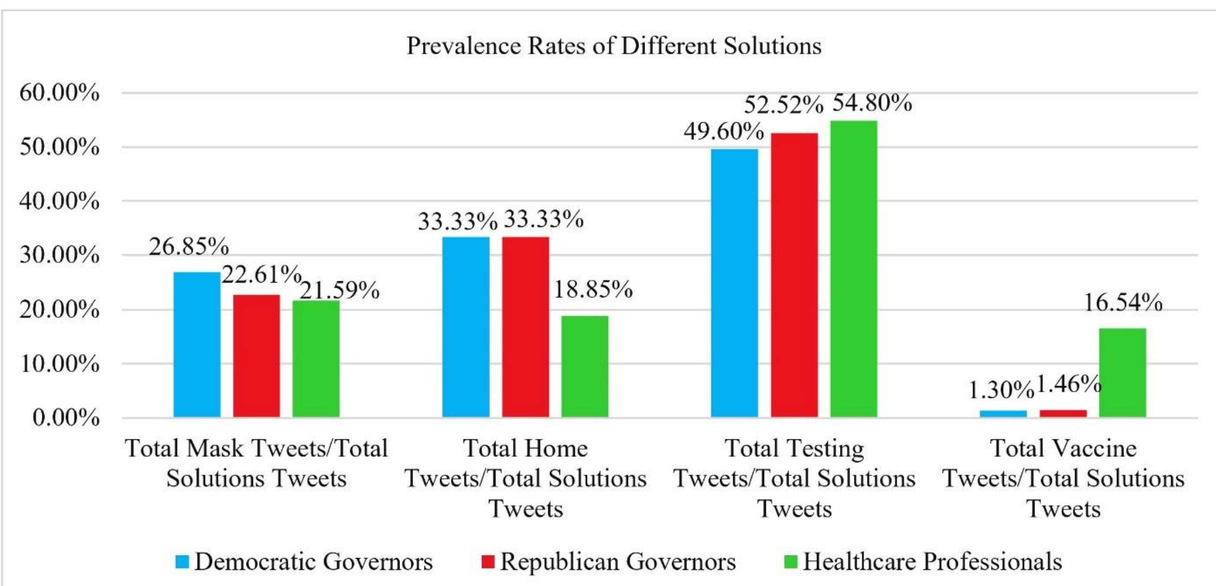
Since we scrapped and examined every single tweet by governors from January 1st to October 18th, this is effectively a census. We also treat tweets from HPs as a census since we did not have a "sample size" in mind and tried to get as many HPs that met our criteria as possible. We also believe that we were able to obtain most HPs who have over 20,000 followers and tweet about COVID-19 at least 33% of the time. Unless otherwise stated, the following analysis will be focused on ratios or prevalence rates.

Figure 1 and Table 1 answer most of our research questions. For example, we can see that Democratic governors tweet marginally more in absolute numbers and percentage points than Republican governors about COVID-19. We also see that Republican governors talk about the economy marginally more than Democrats and around 4.7 times the rate HPs. Conversely, Democratic governors mention death in their tweets at more than four times the rate of Republican governors, and HPs mention death at almost eight times the rate of Republican governors.

Unsurprisingly, HPs have the highest proportion of technical language in their tweets. This is by design since technical language keywords are meant to be a proxy of how "scientific" a user sounds in their tweets. It appears that Democratic governors use technical language marginally more (12.1% more, to be exact) than Republican governors.

We then examined tweets about solutions to the pandemic. Democratic governors talk about solutions 19% more often than Republicans, who talk about them at a similar rate as HPs. We decided to investigate a few subsets of the solutions dictionary: words relating to testing[2], words relating to staying at home[3], "mask," and "vaccine." The results of this analysis can be found in table 2 and figure 2. Note that the percentages are derived by dividing the total tweets of that category by the total number of solution tweets as opposed to the total number of COVID-19 tweets.

Figure 2. Prevalence rates of different solutions



[2] "test" "trace" "tracing"

[3] "stay at home order, "stay-at-home order" "stay home" "stayhome" "quarantine" "lockdown" "distanc"

Table 2. Prevalence rate of difference solutions.

	Total Mask Tweets	Total Mask Tweets/Total Solutions Tweets	Total Home Tweets	Total Home Tweets/Total Solutions Tweets
Democratic Governors	1,658	26.85%	2,058	33.33%
Republican Governors	1,071	22.61%	1,579	33.33%
Healthcare Professionals	5,906	21.59%	5,156	18.85%
	Total Testing Tweets	Total Testing Tweets/Total Solutions Tweets	Total Vaccine Tweets	Total Vaccine Tweets/Total Solutions Tweets
Democratic Governors	3,062	49.60%	80	1.30%
Republican Governors	2,488	52.52%	69	1.46%
Healthcare Professionals	14,993	54.80%	4,526	16.54%

As we can see, there are some subtle differences between each group. Democratic governors talk about masks in their tweets more frequently than Republicans. This gap becomes even larger if we consider the ratio between total mask tweets and total tweets, where Democratic governors (5.66%) mention “mask” in of their tweets 44% more than Republican governors (3.93%). Republican governors mention testing more in their solutions tweets than Democrats, though this difference goes away as well if we considered Total Testing Tweets/ Total Tweets, where Democrats (10.45%) have a slightly higher proportion than Republicans (9.13%). HPs mention masks and stay at home measures less frequently than governors, but they mention vaccines at a significantly higher rate.

The obvious question now is: are the differences between Democratic and Republican governors due to the party affiliation of the governor, or due to differences in COVID-19 situations within each state? For example, do Democratic governors talk about deaths more in their tweets because there are more deaths in their states?

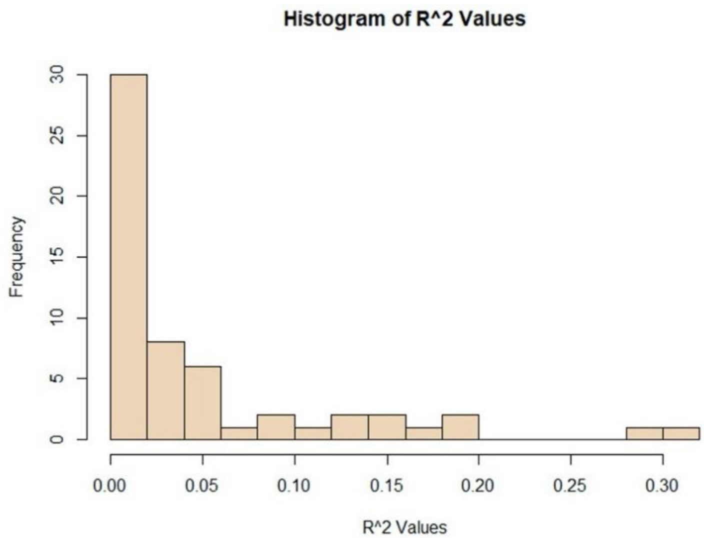
To answer this question, we calculated the coefficient of determination (R^2) between state-level COVID-19 data and the tweets from that state’s governor. We choose three key state-level COVID-19 datapoints: deaths per capita, cases per capita, and tests per capita. We obtained the coefficient of determination between these variables and the total counts of every dictionary, as well the ratio between Total COVID-19 Tweets and Total Tweets and the ratios between tweets belonging to a dictionary and total COVID-19 tweets. All R^2 values are shown in Table 3.

Table 3. The R^2 value between state-level COVID-19 data and governor tweets. Dark blue cells have higher values.

	Total	Total COVID-19 Tweets	Total COVID-19 Tweets /Total	Total Death Tweets	Total Death Tweets/ Total COVID-19 Tweets	Total Economy Tweets	Total Economy Tweets/ Total COVID-19 Tweets
Cases Per 100k	0.00072	0.00550	0.04856	0.01845	0.04662	0.00878	0.01931
Death Per 100k	0.18584	0.17575	0.00500	0.14783	0.01492	0.00783	0.12907
Tests Per Capita	0.00022	0.00232	0.04668	0.02179	0.02431	0.02140	0.03581
	Total Technical Language Tweets	Total Technical Language Tweets/ Total COVID-19 Tweets	Total Solutions Tweets	Total Solutions Tweets/ Total COVID-19 Tweets	Total Masks Tweets	Total Masks Tweets/ Total COVID-19 Tweets	
Cases Per 100k	0.00087	0.00062	0.00779	0.00939	0.00789	0.00180	
Death Per 100k	0.28612	0.12331	0.19960	0.05749	0.07834	0.00170	
Tests Per Capita	0.04629	0.09690	0.00795	0.03048	0.00000	0.01530	
	Total Home Tweets	Total Home Tweets/ Total COVID-19 Tweets	Total Test Tweets	Total Test Tweets/ Total COVID-19 Tweets	Total Vaccine Tweets	Total Vaccine Tweets/ Total COVID-19 Tweets	
Cases Per 100k	0.01637	0.03134	0.00176	0.00139	0.01376	0.02233	
Death Per 100k	0.05893	0.00597	0.31142	0.14354	0.08790	0.00063	
Tests Per Capita	0.00028	0.00595	0.02708	0.10845	0.00120	0.00251	

The highest R^2 value in the chart can be found when we correlate deaths per 100,000 residents in a state and the total number of tweets relating to testing by their governor. We also see relatively high correlation between deaths per 100k and total tweets, total COVID-19 tweets, total technical language tweets, and total solution tweets. However, most variables have very low coefficient of determination, as seen in the histogram in Figure 3.

Figure 3. Histogram of R^2 values



We believe that there isn't sufficient evidence to claim that state-level COVID-19 data is the main driver of the differences regarding how governors tweet about COVID-19. Although there are some higher R^2 values, we believe that this could be due to random chance, given that we looked at 57 coefficients of determination. Furthermore, tweets that deals with death, solutions, and masks—subjects that Democratic and Republican governors mentioned at significantly different rates—all have very low R^2 values. Nevertheless, we plotted scatterplots for all cells that had a R^2 value larger than .15 in figures 4 and 5 to give the reader more information on the issue. We used the ggplot2 package in R. The dark grey area represents the standard error.

Figure 4. Total Testing Tweets & Deaths Per Capita

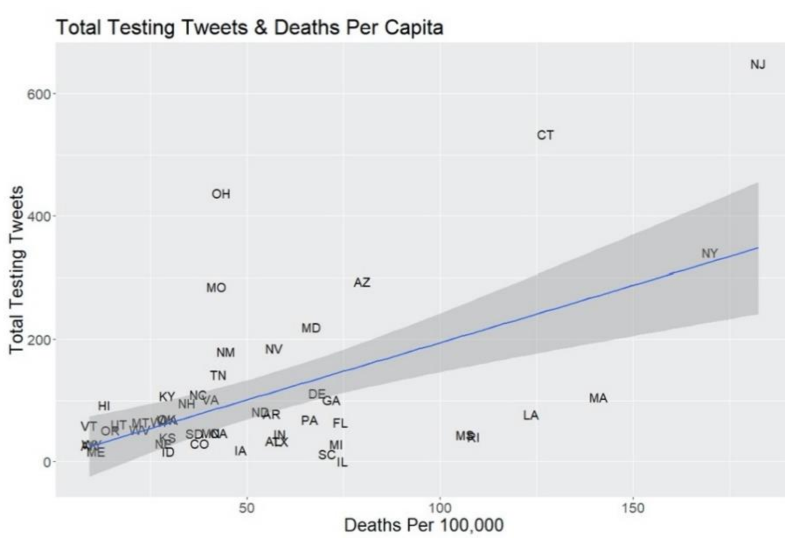
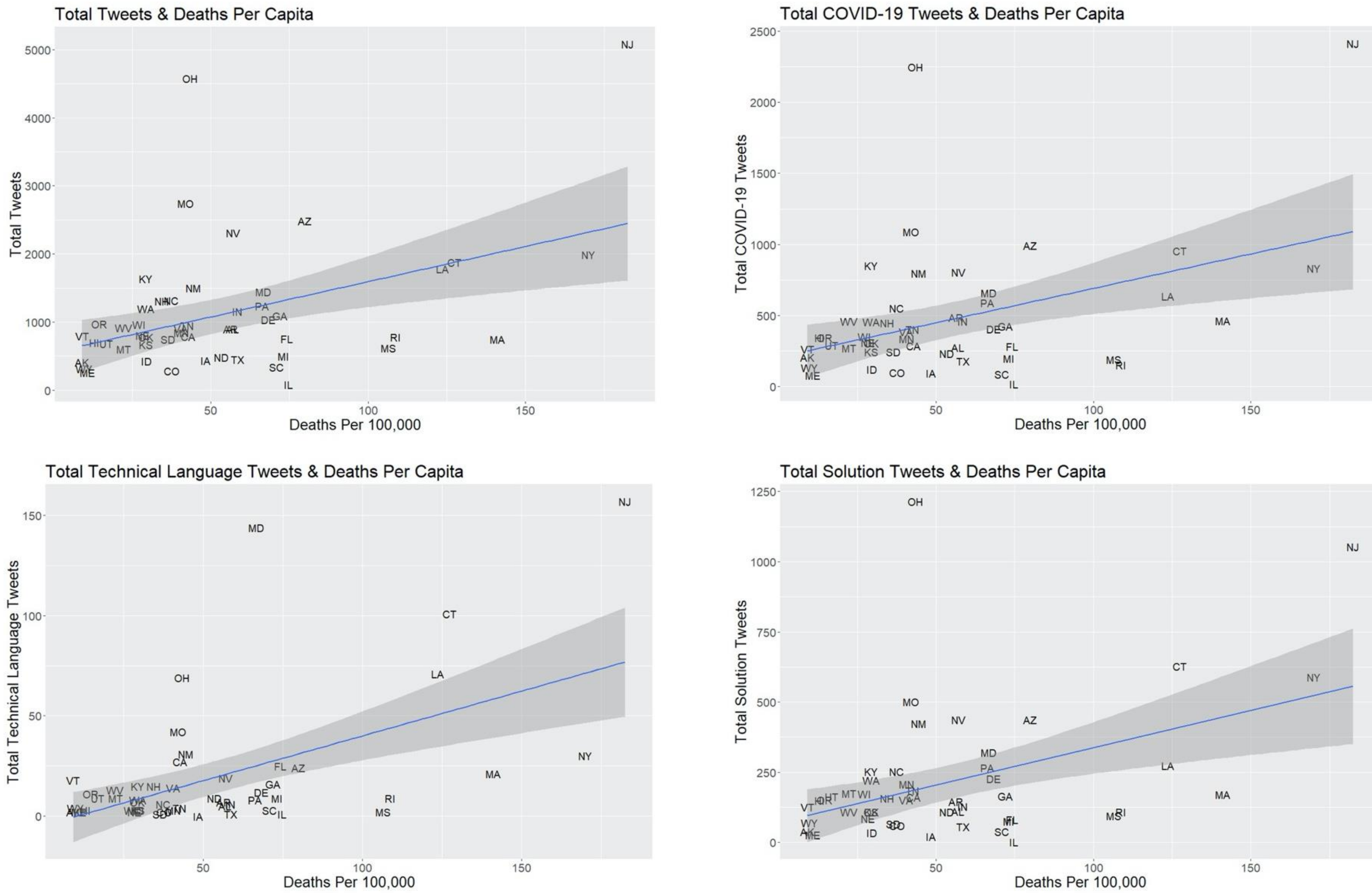


Figure 3. Four more scatterplots for variables with $R^2 > .15$



Further Analysis on Consequences Keywords

The most significant difference between Democratic Governors and Republican Governors is how often they mention death in their COVID-19 tweets. This gives rise to a related research questions: Do Democratic governors talk more about death only in the context of COVID-19, or are Democratic governors more comfortable with deaths in general than Republican governors?

Additionally, do Democratic governors talk about the economy almost as much as Republicans as a response to Republican's emphasis on the economy (e.g., Samuels & Klar, 2020), or do the two groups talk about the economy equally as often on Twitter before COVID-19? This question is inspired by the fact that death and the economy are discussed pre-pandemic by governors as well as during the pandemic, whereas masks and quarantine are pandemic-specific topics. Thus, looking at how governors use language pre-pandemic on these two topics will give us more context regarding what they are tweeting during the pandemic.

We obtained tweets from governors' official accounts from January 15th, 2019, to October 18th, 2019 (N=32053). We started on January 15th because many governors were inaugurated on January 14th. We also had to use different governor Twitter accounts for Kentucky (Republican) and Mississippi (Republican) since a different politician was in office in 2019. Another note is that Governor Bill Lee (Republican) of Tennessee was inaugurated on January 19th, 2019 even though we scrapped his tweets starting from January 15th. We once again used the death and economy words from the consequences dictionary in conjunction with our wordcount program. The results are displayed in table 4.

Table 4. Governors' tweets in 2019

	Total Tweets	Total Death Tweets	Total Death Tweets/ Total Tweets	Total Economy Tweets	Total Economy Tweets/ Total Tweets
Democratic Governors	17,019	310	1.82%	1,455	8.49%
Republican Governors	15,034	131	0.87%	1,586	10.55%

Democratic Governors mentioned death 2.09 times the rate of Republicans, which is less than the difference between the two groups when it came to Total Death Tweets/ Total COVID-19 Tweets in 2020, where Democratic governors mentioned death at 4.32 the rate of Republican governors. For economy related tweets, Republicans talk about the economy 24.3% more than Democrats in 2019. In 2019 COVID-19 tweets, Republican governors talk about the economy 4.4% more than Democrats. It may appear that both Democratic and Republican governors talked about the economy at a higher percentage in 2019 than in 2020. However, this is because we removed non-COVID-19 related tweets before analyzing for mentions of economy and death in the 2020 dataset. When we reran the program on the entire 2020 tweet dataset for governors (N = 56,552) without first limiting our analysis to COVID-19 tweets, we get the results in table 5.

Table 5. Consequences Keywords for all tweets in 2020

	Total Tweets	Total Death Tweets	Total Death Tweets/ Total Tweets	Total Economy Tweet	Total Economy Tweets/ Total Tweets
Democratic Governors	29,297	1,294	4.42%	2,612	8.92%
Republican Governors	27,255	419	1.54%	2,815	10.33%

Comparing table 4 and table 5, we can see that the total number of tweets increased significantly between 2019 and 2020 for both parties (72% for Democrats and 81% for Republicans). However, the proportion of tweets that are about the economy barely changed. The proportion of death related tweets increased 77% for Republican governors an 143% for Democratic governors. However, note that the prevalence rate of death in 2020 for Republican governors is still lower than the prevalence rate of death for Democratic governors in 2019, before the pandemic.

The full dataset, including state-level COVID-19 data, data on tweets for individual governors, and all tweets scrapped with Twint, can be found at github.com/zzhang-18/Tweet-Analysis.

Discussion

This study provides a broad overview of how healthcare professionals (HPs), Democratic governors, and Republican governors tweet about COVID-19.

Starting with governors, we found that Democratic and Republican governors do not differ substantially in the rate at which they mention COVID-19 in their tweets, the rate at which they mention technical language in their COVID-19 tweets, and the rate at which they mention testing, vaccines, and stay-at-home measures in their tweets about solutions to the pandemic. We also found that how a governor tweets is not strongly correlated with the COVID-19 data in a state. We believe that the technical language dictionary is a good proxy of how “science-like” a group sounds since HPs use them at a much higher rate. Thus, we claim that Republican governors and Democratic governors are about the same in terms of how science-like they speak given their similar technical language usage rates.

We find substantial differences between the governors regarding the rate at which they mention masks and solutions to COVID-19 in their tweets. Democratic governors talk about these two subjects more than Republican governors. This supports media reports of the politicization of mask-wearing in the United States (Aratani, 2020). Our interpretation regarding the differences in solution tweets is that Republican governors might be more inclined to think that state governments could not do anything more against COVID-19, thus there is less need to talk about solutions to COVID-19 (Falconer, 2020; Marley, 2020). The weakness of this interpretation is that it would also imply that Republican governors will tweet about COVID-19 less frequently than Democrats. Where in reality, Democratic governors only mention COVID-19 in their tweets 1.7% more than Republicans.

Finally, we investigated how the groups talk about consequences of the pandemic. When examining COVID-19 tweets, Republican governors mention the economy 4.4% more than Democratic governors, who in turn mention death 331.5% more than Republican governors—the most substantial difference in the entire study. We wanted to know if this is a universal tendency between Democrats and Republicans, and investigated data from a similar period in 2019, where Republican governors tweeted about the economy 24.3% more than Democratic governors, who tweeted about death 109.2% more than Republican governors.

Our data on COVID-19 tweets support the assertion that Republican governors tend to be more focused on the economic impact of COVID-19 (e.g. Nagourney & Peters, 2020) and downplay the human impact of the pandemic (e.g., Sullivan, 2020; Gittleson, 2020) when compared to Democratic governors. With the data from 2019, however, we claim that this difference could be reflective of deeper disparities between Democratic and Republican politicians. Our interpretation is that Democratic governors have always been more comfortable talking about death than Republican governors, who in turn like to focus on the economy. As a result of the Republican rhetoric surrounding COVID-19 and the economy, Democratic governors responded by mentioning the economy more in their COVID-19 tweets to match the rhetoric of Republican governors. However, although Republican governors talked about death at a higher rate than they did in 2019, their rate of Total Death Tweets (in all their tweets, not just the COVID-19 tweets) to Total Tweets ratio in 2020 is still lower than the Total Death Tweets to Total Tweets ratio of Democratic governors in 2019, before the pandemic. We believe that we have substantial evidence that Republican governors are unwilling to talk about death in general, a trend that extends to COVID-19. One possible explanation for this unwillingness is the moral foundation theory (Graham et al., 2013), which claims that liberals tend to focus on the moral foundations of Harm/Care and Fairness/Cheating more than conservatives.

We included HPs for three reasons: to provide a comparison group to the governors, to see if governors are trying to mimic the language of HPs, and to investigate them as a group in their own right.

Although we expected that the HPs would mention deaths and technical language more than the governors and less about the economy, other findings are unexpected. HPs mentioned solutions to the pandemic less frequently than governors. They also mentioned masks and stay at home measures less, while tweeting about vaccines at over ten times the rate of governors when we consider vaccine tweets/ total COVID-19 tweets. A possible explanation is that HPs mention masks and stay-at-home measures less since these are considered “obvious” solutions to the pandemic, and where they believe their expertise is needed is with regards to more complicated subjects such as vaccines. HPs also do not need to say the same things repeatedly to reinforce their message to constituents, which politicians need to do. HPs could also talk about vaccines more because they consider that to be a more medical solution as opposed to policy solutions such as stay-at-home measures. Finally, HPs could be following the politicians’ rhetoric and selectively tweeting about subjects that they believe are not sufficiently covered by politicians. Nevertheless, our results provide basic information on how HPs tweet about COVID-19 on Twitter compared to Governors.

We believe that the most significant finding of this study is that Republican governors have consistently talked about death significantly less than Democratic governors, both in 2019 and in 2020. We believe that this death aversion from Republican governors could have implications beyond COVID-19 in policymaking and other arenas.

Limitations and Future Directions

We urge future researchers to investigate if the difference in death mentions is a phenomenon that extends to conservative and liberal politicians or media outlets in general and if any verifiable consequences result from this behavior. Another interesting question is whether or not death mentions is a proxy for death anxiety and mortality salience between conservatives and liberals in general, and if that a driver behind the different degrees of social distancing behaviors. Another way to investigate death anxiety is to conduct cross cultural analysis. For example, do Swedes, who are known for their lenient COVID-19 rules, have less death anxiety compared to their Norwegian counterparts, who have much stricter COVID-19 measures (Helsingen et al., 2020). Finally, researchers could examine if there is a way to manipulate death anxiety to increase compliance with social distancing measures.

A central limitation of the study is the word count methodology that we elected to use. Although analysis with wordcount programs is common and reveal useful information, there are limitations in the type of data they provide. For example, while Democratic governors and Republican governors mentioned stay at home measures at similar rates, we do not know the tweets' context. “Lockdowns need to stop” and “we need harsher lockdown measures” are identical to our analysis program. Furthermore, there are more sophisticated text analysis methods and programs such as Wordstat and machine learning algorithms. We elected to use a word count program for its simplicity and speed, since we believe that it is important to examine COVID-19 communications and report on it while the pandemic is still ongoing to inform policymaking and future research. However, future researchers should take advantage of the wide variety of methodologies available to examine these texts. For example, to measure the linguistic similarity between governors and HPs, we used the technical language dictionary in appendix 1, which we arbitrarily wrote. However, there are machine learning algorithms, such as topic modeling, that allow researchers to examine linguistic similarity in a more systematic fashion.

Another limitation is that we focus our analysis on tweet texts, whereas many governors (such as Governor Eric Holcomb of Indiana) post videos briefings on Twitter. Future research could also examine the content of these videos and other healthcare communication venues used by politicians and HPs. Our analysis of tweet texts is also limited by the tweet scraping package—Twint— used in this study. We chose Twint in response to Twitter recently changing their backend API, which made many existing tweet scrapers obsolete, with one user calming that they “can not complete [their] master thesis” as a result (Cairns & Shetty, 2020; herdemo, 2020). Most tweet scrapers, such as Rtweet, could only scrape the most recent 3,200 tweets from a given user. Moreover, Twitter charges a premium for those who wish to have access to the full archive (Twitter Developer, n.d.), which is why we chose to use Twint—a free API. Twint provides us with the text of each tweet for regular tweets. For replies and retweets, it provides us with only the reply text. It does not show us the text of the tweet which was replied to or retweeted. For example, if someone tweeted “Masks stop aerosols,” and a governor retweeted their tweet saying, “That’s right,” Twint would show the tweet as “That’s right” by the governor, and not the original “Masks stop aerosols” tweet. However, if the governor retweeted the original tweet without adding a comment, then the tweet will not be captured by Twint. Twint will also give a URL for any image or video content. Thus, photos or videos in a tweet will display as a URL at the end (i.e. “Look at this photo https://t.co/vMwfgtvFQj”) in our dataset.

This paper did not examine any potential correlation between governors’ tweets and the policies they implemented. Thus, questions such as “Do states with mask mandates have governors that talk about masks more often in their tweets?” are left for future researchers to answer.

Finally, our analysis looks at the period from January to October as a homogeneous block, even as cases and deaths varied wildly throughout. Future researchers could seek to conduct a time-sensitive analysis and see how the tweets by different users varied over time and if they are dependent on the location and time specific COVID-19 situation. We also treated HPs as a homogeneous block, even though there are disagreements between HPs (e.g. For information on criticism of Eric Feigl-Ding by Marc Lipsitch, see Bartlett (2020)).

Despite these limitations, we believe that our study adds valuable information to the literature and provides a foundation for future studies. Future researchers should seek to investigate the death aversion of Republican governors. They could also use more advanced tweet scraping methods and text analysis software to learn more about how political elites, influential healthcare professionals, and other opinion leaders talk about COVID-19 on Twitter and beyond.

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[4] Google trends data can be accessed using the compare tool. This study uses search topics as opposed to search terms.

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[5] Similar to google trends, data of individual users could be accessed by typing in their Twitter username (e.g. @GovInslee)

Appendix 1: Custom Dictionaries.

None of the keywords are case sensitive and stemming is used for all keywords in appendix one and two. That is, “biolog” means that both “biology” and “Biologist” will be captured.

COVID-19 Keywords:

Virus names: coronavirus, 2019ncov, 2019-ncov, hcov-19, hcov 19, covid, sarscov2, sars-cov
General: epidemi, pandemic, disease, outbreak, infection, flatten the curve, ventilator
Solutions: stay at home order, stay-at-home order, stay home, stayhome, quarantine, lockdown, distanc, 6 feet apart, six feet apart, mask, vaccine, test, trace, tracing, hand washing, wash hand
Technical Language: positivity, aerosol, rate of positive, positive rate, % positive, percent positive, asymptomatic, R0, reproduction number, sarscov2, sars-cov, N95, respirator
Famous figures and organizations: Fauci, Birx, CDC,
Note: the virus names, general, solutions, technical language, and famous figures keywords are subsets of the COVID-19 keywords dictionary.

Consequences Keywords:

Death related: “ die”, dead, death, dying, coffin
Economy related: employment, economy, jobs, business, stock market
Note: the whitespace in front of the word “ die” is used to filter out other words such as “studied”

Appendix 2: List of Influential Healthcare Professionals

Table 6. Initial HPs

UserID	Twitter Handle	Username	Criteria for inclusion	Followers (On Oct.30, 2020)
40156330	ScottGottliebMD	Scott Gottlieb, MD	MD	430,088
86626845	EricTopol	Eric Topol	MD	338,084
18831926	DrEricDing	Eric Feigl-Ding	Professor of epidemiology	316,215
224896427	trvrb	Trevor Bedford	Professor of epidemiology	268,998
75937326	mlipsitch	Marc Lipsitch	Professor of epidemiology	215,013
426909329	CDCDirector	Robert R. Redfield	MD	218,098
389313566	FaheemYounus	Faheem Younus, MD	MD	173,294
3238448948	CT_Bergstrom	Carl T. Bergstrom	Ph.D. in biology	127,119

When searching through the followers of initial HPs, we consider the following criteria. If any of them are met, then the user is included in our list.
User’s Twitter handle contains: Dr, MD, Doctor, MPH
User’s username contains: Dr, Doctor, MD, M.D., MPH
User’s bio contains: biolog, “ dr ”, dr., doctor, epidemiolog, “ MD ”, M.D., virolog, “ MPH “, public health
The space around “ dr “, “ MPH “ and “ MD ” are included to filter out words like “Andrew.”

Table 7. List of all healthcare professionals included in the study

User ID	Username	Qualification
426909329	CDCDirector	MD
232193350	rajshah	MD
2904169317	SteveFDA	MD
389313566	FaheemYounus	MD
18831926	DrEricDing	Doctorate in Epidemiology
605153786	DrLeanaWen	MD
40156330	ScottGottliebMD	MD
11274452	kevinmd	MD
1651522832	DrDenaGrayson	MD
86970530	tmprowell	MD
950783972	RepBera	MD
38531995	DrOz	MD
227429355	AmeshAA	MD
348075929	VirusWhisperer	MD
230769694	syramadad	MD
508591081	AbraarKaran	MD
29328876	sandrogalea	MD
18170896	drsanjaygupta	MD
17297668	larrybrilliant	MD
1094762324097822720	michaelmina_lab	MD
17240190	daniel_kraft	MD
35815074	JenniferNuzzo	DrPH in epidemiology
239210681	Bob_Wachter	MD
831279407088148480	Craig_A_Spencer	MD
817869452473548800	DrAlGrossAK	MD
151965668	AliRaja_MD	MD
86626845	EricTopol	MD
28023025	chngin_the_wrld	Ph.D. in Epidemiology

284093185	Farzad_MD	MD
58006725	celinegounder	MD
487673211	cmyeaton	MPH
887363635692969984	hiral4congress	MD
953924228306305024	Cleavon_MD	MD
317593544	priteshgandhimd	MPH
75937326	mlipsitch	Ph.D. in Epidemiology
1089859058	RepRaulRuizMD	MD
564099543	drjudymelinek	MD
846801440706351104	DrRobDavidson	MPH
593289567	PeterHotez	MD
65497475	eugenegu	MD
139173680	drjohnm	MD
745824471689244672	dremilyportermd	MD
394087611	angie_rasmussen	Ph.D. in Microbiology
170877963	DrSidMukherjee	MD
2710796718	BhadeliaMD	MD
30844417	gregggonsalves	MPH