Journal of Quantitative Description: Digital Media 2(2022), 1–72 10.51685/jqd.2021.011

If a Tree Falls in the Forest: Presidential Press Conferences and Early Media Narratives about the COVID-19 Crisis

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Throughout the COVID-19 crisis, as Americans confronted questions about social distancing, masking wearing, and vaccines, public safety experts warned that the consequences of a misinformed population would be particularly dire due to the serious nature of the threat and necessity of severe collective action to keep the population safe. Thus, the media and the political elites (e.g., President of the United States) who possess the power to set the information agenda around COVID-19 bear a huge responsibility for the general welfare. Through automated text analysis of complete transcripts of national cable, network, and local news, we explore their narratives surrounding the COVID-19 pandemic and we characterize the differences in which topics were covered and how they

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Date submitted: 2021-09-23

were covered by various media sources. Our analysis reveals polarized narratives around blame, racial and economic disparities, and scientific conclusions about COVID-19. Among the various agenda-setting mechanisms available to the president is daily press conferences, which provide a unique opportunity to leverage public exposure, accelerated by the state of crisis. We found both resonance and contrast between the narratives of media and President press conferences. However, as online search data revealed, public information-seeking behavior resemble media coverage more than the President's messages.

Keywords: COVID-19, Agenda Setting, Media Effects

The COVID-19 crisis dominated the mainstream media in the spring of 2020. In this paper, we examine two closely related questions. First, what were the common narratives within the news media during the early phase of the COVID-19 pandemic in the United States? Second, how were these narratives reflected by the public and what was their relationship with public information-seeking behavior?

Understanding the media landscape of the early COVID-19 crisis period is important for three reasons. First, while there is a substantial amount of media scholarship about the COVID-19 crisis, it tends to focus on geographic differences in COVID-19 media (Kim et al., 2020; Dambanemuya et al., 2021), patterns of media consumption (Reisdorf et al., 2021) and social media usage (Lu et al., 2021) or on misinformation (Morrow and Compagni, 2020; Bode and Vraga, 2021; Motta et al., 2020; Roozenbeek et al., 2020). There is very limited work on mapping out variation within the broader media narratives provided via TV news, the most commonly consumed form of news within the US (Allcott et al., 2020). Furthermore, understanding the kind of content offered by TV news at this juncture allows better insight into the public narratives and mechanisms behind behavior outcomes. We seek to remedy this gap in the literature by utilizing automated text analysis techniques that allow us to measure content polarization within the TV news landscape.

Second, tracing the progress of these narratives and their interplay with presidential press conferences allows us to study presidential agenda setting in a public health crisis. While a sizable literature looks at presidential (Peake, 2001; Canes-Wrone, 2001; Wanta and Foote, 1994) and media agenda setting (Scheufele, 1999; Chong and Druckman, 2007; King et al., 2017), the COVID-19 pandemic is a unique setting for several reasons. For the first few months of the crisis, the Coronavirus Task Force held daily televised briefings which featured President Trump. For presidential communications, these briefings were unusually well-viewed by the public. On March 29, 2020 the President issued this statement on Twitter, "President Trump is a ratings hit. Since reviving the daily White House briefing Mr. Trump and his coronavirus updates have attracted an average audience of 8.5 million on cable news, roughly the viewership of the season finale of 'The Bachelor.'"[1] This represents an extreme opportunity for the president to exercise the bully pulpit, speaking directly to Americans rather than mediated by the media.

Finally, studying the dynamics of media and public opinion during the early phases of a crisis is especially important. Our study focuses on the period between Jan 1 and April 30, 2020. This time period is critical as this is when both partisan and non-partisan actors solidified their positions on the crisis and decided on the messages they wanted to send in the months to come. Similarly, dynamics of partisan opinion during this time period were unusually malleable, as evidenced by the wavering positions of Republican voters on the seriousness of the crisis in late March (Badger and Quealy, 2020). After this early period, partisan and non-partisan cues ossified into a clear set of messages, but the early period of the crisis was still highly fluid in terms of public opinion.

In this paper, we comprehensively analyze the television news coverage of COVID-19 during the first 100 days of the crisis. Our analysis encompassed all local, network, and cable news aired over approximately 800 television stations across all 210 Designated Market Areas in the United States from 01/01/2020 to 04/30/2020. In addition, it incorporated the exact content of the 39 Presidential daily press conferences, television viewership data, and detailed internet search data during this time period as signals of presidential agenda, public exposure to information, and public response.

We found a diverse range of narratives in televised coverage of COVID-19, including

[1] https://twitter.com/realDonaldTrump/status/1244320570315018240

topics that cover: the economy, safety measures, specific outbreaks, equipment, treatment, food chains, and blame. To understand how coverage choices reflect ideological agendas, we compared COVID-19 coverage of liberal and conservative leaning national televised news sources (MSNBC and FOX News). We measured two aspects of coverage polarization across MSNBC and FOX: topic polarization, which captures imbalance between coverage of a topic across these channels; and term polarization, which captures the extent to which these channels discuss the same topic differently. The most polarized topics reveal extraordinarily different agendas. For example, MSNBC focused heavily on *Racial Disparities* surrounding the impact of the COVID-19 pandemic, which received almost no mention on FOX. FOX focused on *China Blame*, while MSNBC focused blame on the Trump Administration through *PPE Shortage*, *Lack of Testing* and *Contact Tracing.* MSNBC's coverage highlighted faith in *Facts and Science* to a much greater extent than FOX. Together MSNBC and Fox painted a very different pictures of the pandemic, which may have contributed to early behavioral differences observed among partisans (Gollwitzer et al., 2020).

We also traced the dissemination of these narratives, from the president's press conferences and TV newscasts to public information-seeking behavior. Our analysis reveals that, in many cases, the television media provided live coverage of the president's daily press conferences, directly amplifying his message. The time period immediately after the press conferences featured increased levels of polarization of COVID-19 related content across the national networks. Further, we found increased similarity between the press conferences and subsequent coverage for all cable news channels, even those that are not typically ideologically aligned with him. However, despite unprecedented access to the public's attention, we show in this paper that public attention was more congruent with the media messages than the president's. Web search behavior around COVID-19 reflected the media's coverage choices to a far greater extent than the content of the president's briefings.

The rest of the paper is organized as follows. In the next section, we further describe the theoretical perspectives that drive this paper. The third section describes both the within-topic and between-topic polarization of media narratives about COVID-19. The fourth section focuses on the resonance and contrast between presidential press conferences and media narratives about COVID-19. The fifth section focuses on the dynamics of public attention through search, and their relationship to both media and press conference narratives. The final section discusses the implications of our findings.

Media and Presidential Narratives in a Time of Crisis

While COVID-19 is a unique public health crisis, this paper speaks to prior literature on the content and effects of media and government messaging about natural disasters. Disaster response can have very serious consequences for presidential administrations. Theories of retrospective voting in political science argue that voters punish politicians for poor performance in office (Fiorina, 1981; Healy and Malhotra, 2013). As a result, a poor government response to natural disasters can negatively influence the incumbent's voteshare when they run for re-election. Most research in this context examines the effects of fiscal expenditures on disaster relief (Healy and Malhotra, 2009; Gasper and Reeves, 2011; Bechtel and Hainmueller, 2011).

However, spending is not the only form of disaster response that matters. Government messaging about natural disasters is a crucial source of information for citizens trying to stay safe. In many cases, government messaging prioritizes dissemination of useful information over strategies of blame mitigation (Liu et al., 2018). Liu et al. (2020) finds that leaders focus on conveying "crisis perceptiveness, humility, flexibility, presence, and cooperation" during their crisis communications to the public. The case of Donald Trump's COVID-19 press conferences is therefore an unusual one, given their free-wheeling nature and focus on a wide variety of topics beyond the mere dissemination of disaster-related information. Studying the the interplay between government and media narratives in a situation where government narratives deviate so strongly from the norm deepens our understanding of government crisis communication.

The COVID-19 crisis was also an unusual disaster reporting situation for the media. In most cases, mass media coverage of a disaster tends to be short-lived and have a narrow geographic focus (Houston et al., 2012). Scholars have found that media coverage of disasters can have substantial psychological effects on viewers (Houston et al., 2018), as well as shaping their political attitudes and voting behavior(Rubin, 2020; Chon and Fondren, 2019). The unusual duration and geographic scope of the COVID-19 pandemic relative to other natural disasters is uncharted territory for the media when it comes to disaster reporting.

Understanding media choices in this context sheds light on how disaster reporting processes function in a long-term, geographically-dispersed situation.

In this paper, we describe media narratives of the early COVID-19 crisis and situate these narratives in the context of both presidential messaging and the dynamics of public attention. Most Americans do not follow the news particularly closely (Allen et al., 2020). They may catch the evening news on television, or see headlines on their desktop landing page or favorite news app, but only a small fraction of the US watches live news coverage during the day or checks their Twitter account for the latest news. We focus on the dominant form of news in the US: television. Between desktop, mobile, and television, television captures 85% of news consumption by minutes (Allen et al., 2020). We examine the differences in content on cable, national network, and local news.

We expect these three categories of TV news to have substantially different COVID-19 content, reflecting the variation in their audiences and constraints. First and foremost, the news cannot reflect a "mirror image" of the day's events simply because way more thing happen that could be news than the 24 hours of coverage any station has each day. By definition, news outlets are forced to make choices about which stories are considered newsworthy and which are not. Further, even after deciding on a particular story, they must make choices about the specific topics and framing of that story. For example, while COVID-19 was a major story on TV news in March and April 2020, outlets could focus on topics as diverse as social distancing, potential Chinese origins, and economic fallout, and for each of these topics, multiple frames were available. Is social distancing a necessary sacrifice to prevent the spread of the disease, or an example of liberal overreach? Should China be blamed for the spread of the pandemic, or not? Is the Trump Administration adequately dealing with the unemployment crisis caused by the virus? These differences in topic selection and framing can be further exacerbated by the differences between cable and local news, as they not only cater to different audiences with different demands, but are subject to different constraints.

We go beyond outlining media narratives by focusing on their relationship to both the presidential COVID-19 press conferences and to the dynamics of public attention. Media narratives are not generated in a vacuum - the president has substantial agenda setting power, which is highly likely to influence media narratives on a given day, especially in context of the COVID-19 crisis. Furthermore, we are interested in the degree to which specific media narratives resonate through the public's collective attention, represented by web search behavior.

The project of tracing COVID-19 narratives through the media ecosystem is one that benefits from a descriptive focus. A number of threats to causality making inferring the causal relationships between the difference elements difficult. The relationship between presidents and media is a topic of study in and of itself. Presidencies differ dramatically in their media-relations styles, and the Trump White House was unusually prone to media leaks. A compelling case can be made for any set of causal relationships between presidential COVID-19 press conference and press coverage of similar themes. For example, the media may straightforwardly comment on the events of the day's press conference. Alternatively, given Trump's media sensitivity and impromptu speaking style, his press conference presentations may reflect the major talking on Fox News of the previous half-hour. Finally, some third event, such as the release of a new scientific study, may drive both media coverage and press conferences. Elucidating the relationship between public attention and elite communications is similarly difficult.

Despite these difficulties, it is critical to accurately describe media narratives, their congruence with governmental narratives, and their relationship to public attention. If media is meant to be a watchdog that critically evaluates government narratives and provides a diversity of perspectives, overt congruence with government narratives represents an abdication of the media's duty to the public. From a more practical perspective, government communications are limited in length and are meant to serve a very specific role. If the media merely repeats things that the president said in the previous half hour, without adding new narratives or new pieces of information, it is inefficiently using the time that could be best used to inform the public. As Trump noted, the presidential COVID-19 press conferences had unusually high viewership - if citizens wanted exposure to these ideas, they could simply watch the recorded press conference. Finally, repetition of press conference topics in order to evaluate them through a partisan or horserace lens should be limited, as they give little information about the pandemic itself.

We use web search data in order to understand the dynamics of collective attention during the pandemic. Web search data has several attributes that make it a particularly compelling data source in this context. First, scholars have found that many web searchers engage with search in order to find answers to specific questions, rather than engaging in casual browsing (Howard and Massanari, 2007). As a result, web search data is a measure of revealed preferences - the questions that people are interested in asking, but may not feel comfortable expressing on a survey or on social media. This is important in the context of the COVID-19 pandemic, as opinion about the pandemic and about appropriate mitigating measures soon became polarized by party. Given the well-known existence of partisan cheerleading effects (Schaffner and Luks, 2018), it is possible that partisans' survey responses about hydroxychloroquine or masks might represent a desire to "cheer" for the COVID policies advanced by their preferred party. However, if we were to find limited search interest in hydroxychloroquine despite the substantial media coverage, this might suggest that Republican survey enthusiasm for the drug is merely expressive. Second, web search data is highly temporally granular - we can measure public attention at a much more fine-grained level than most surveys. As such, search data allows us to more accurately map the connections between media coverage and public collective attention than survey data.

Of course, like any data source, web search data does not exist in a vacuum. Previous scholarship has touched on the way in which web searching behavior can amplify information gleaned from interpersonal or other offline sources (Kayahara and Wellman, 2007). This further underscores the power of search to aggregate and describe patterns of collective attention that may originate from multiple sources.

Methods and Results

Here, we provide a very brief overview of our data and methods. The majority of our methodological details are situated in the appendix.

A substantial portion of the academic work around behavioral responses to COVID-19 focuses on movement data across various populations (Allcott et al., 2020; Gao et al., 2020; Gollwitzer et al., 2020; Wellenius et al., 2020). This paper takes a different approach. We focus on the extraordinary variation in elite cues and guidance to the public, the ways in which these messages were disseminated through TV news, and presidential press conferences, and their relationship to the public's information-seeking behavior.

We leverage data from multiple sources including: television news transcripts, presidential press conference transcripts, Nielsen television viewership, and Bing search data to explore narratives and agenda-setting around COVID-19 media coverage.[2] We use automated text analysis of complete transcripts of national cable news, network news and local news from around 800 local TV channels across all 210 Designated Media Areas to determine what the mainstream media is saying. We use an expansive COVID-related keywords search to pull out any content that could be about COVID-19. We supplemented this with automated text analysis of presidential press conferences transcripts to determine how the press conferences was covered by mainstream television media. We also use television viewership data, specifically focusing on just total numbers of viewers per half hour, to understand both the magnitude and relative public exposure to viewing of cable news overall and during presidential press conferences. Finally, we use Bing search data to understand the general public's information-seeking behavior regarding different narratives and topics.

Early Media Narratives about COVID-19 are Highly Polarized

We start by investigating the top most polarized phrases, using their log-odds ratios (Demszky et al., 2019) between Fox News (or FOX) and MSNBC. Figure 1 shows the top 25 polarized n-grams (with two or more words) between the two networks. Note the top terms on MSNBC focus on the Trump Administration and marginalized communities, while the top terms on FOX focus on blaming China and other news organizations. This figure, while interesting, mixes between selection of topic choices, and framing coming from within topic terms.

In Table 1 we pull for a slightly longer list of terms to show a few themes. First we manually cluster some of the "general" terms to highlight how FOX blamed China and the mainstream media, while MSNBC focused on those most affected directly by the pandemic: workers at processing plants and minority populations. Further, countering FOX's main

[2]The Microsoft's Institutional Review Board (ID: 659) approved the use of search data for this research.

narrative, MSNBC focused on blame towards President Trump. Table 1 also shows the different words associated with a few interesting keywords, to better illustrate framing. When discussing hydroxycholoroquine ("chloroq"), FOX focused on the success and promise of this potential treatment, while MSNBC focused on skepticism (misinformation) and related mentions of ill-advised remedies (such as injecting disinfectants or ingesting bleach). Both networks talked about "reopening economy", but FOX focused on the benefits, while MSNBC focused on the risks. Not surprisingly for "testing" FOX focused on the plans, some of which failed to materialize, while MSNBC focuses on the problems.

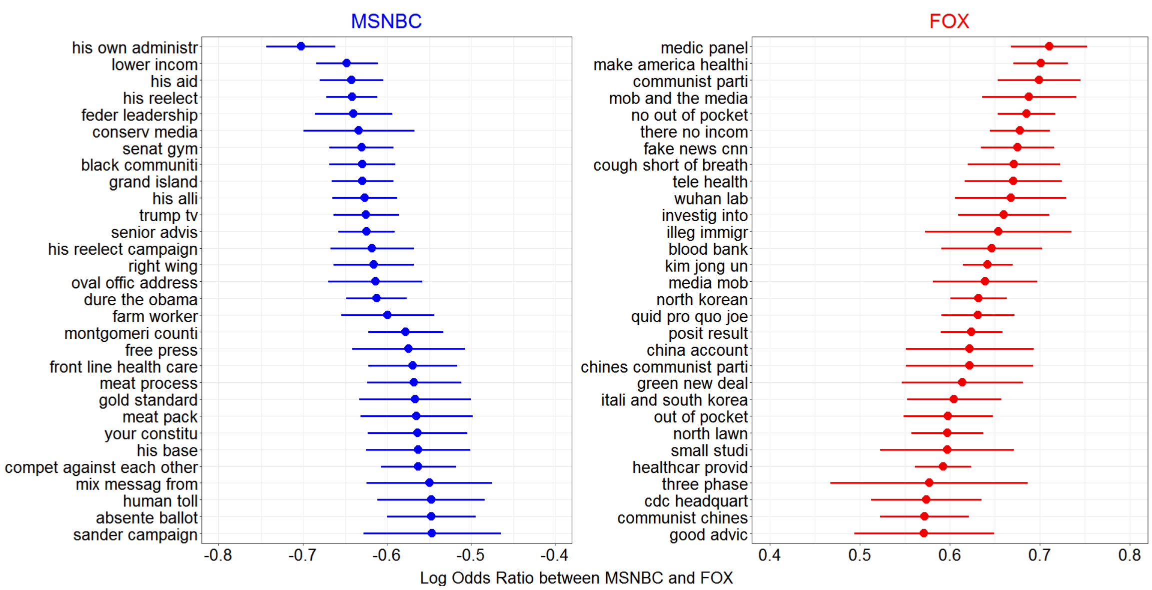

Figure 1. Polarized Phrases between MSNBC and Fox.

Note. Top 25 most polarized n-grams (2 or more words) between MSNBC and Fox.

Examining the top polarized terms, and the top terms by keywords, is informative, but crude and manual. In the next step, we ran a 100-topic structural topic model (Roberts et al., 2014) over the data, dropping 31 of 100 topics at non-germane to COVID-19. We use these topics as our 69 topics about COVID-19 that are covered in our time-frame from January 1, 2020 to April 30, 2020.

Table 1: Polarized Phrases by Theme

Theme	FOX	MSNBC
General	*Blame China* (communist parti, wuhan lab, chines propaganda, chinatown); *Blame Media* (fake news cnn, fearmongering, media mob, disinform campaign)	*Processing Plants* (grand island, jbs, meat plant, meat pack); *Vulnerable Communities* (lower incom, black communiti, peopl of color, nativ american, latino); *Blame Trump* (presid daili brief, trump tv)
Chloroq	improv, treat patient, big news, remarkable, great success	misinform, bleach, cult, disinfectants, number of death
Reopen	nasdaq, econom recoveri, overreach, pentup demand, enthusiasm	safeti measur, contract the virus, nervous about, asymptomat carrier, largest outbreak, increas risk,
Test	veri impress, move fast, higher level	undercount, cant trust, insuffici

Note. Selection of top polarized terms on FOX and MSNBC in all segments (general) and in subsets of segments that contain certain keywords (i.e., chloroq, reopen, test).

Local news and cable news has much sharper differences in selection of topics than between cable news. This may feel obvious due to the different job of local news, but ex-ante it would be reasonable to also focus on the distinct viewership of FOX and MSNBC, and how that drives differences in selection of topics. Table 2 shows the top 5 most different topics in terms of topic selection polarization by (a) MSNBC versus FOX, and (b) local versus cable news. We only include topics that have been substantially covered in this ranking. Local provides a mix of local angles such as the current number of people infected or dead, but also softer news about tourism, college, events, and information more necessary for every-day decisions of the viewers, relative to national politics.

Focusing in on the comparison between FOX and MSNBC, we chart on the x-axis of Figure 2 the selection of topics: how much do the topics skew between these two stations. This is created just as we do for Table 2, and you can see many of the top topics by difference on the far right of Figure 2, as highly polarized by topic selection. Among the topics that MSNBC was very keen to talk about are: Facts and Science, Racial Disparities, Frontline Workers, and Nursing Homes, while FOX disproportionately discussed China Blame, Blood Immunity, Market Impact, and Health Complications. On the y-axis we show the framing or polarization (i.e., how much the terms differ) within a topic (Gentzkow et al., 2019; Demszky et al., 2019). Whereas in Table 1, we did this crudely in when we examined polarized terms within keywords, this figure provides a more principled way of examining the polarization by systematically examining topics.

Table 2: Topics Disproportionately Covered by Different News Outlets

(a)	FOX	China Blame	Vaccine/Treatment	Stimulus Bill	Stock Market	Trump Quotes
	MSNBC	Facts and Science	Racial Disparities	PPE Shortage	Ventilator Supply	Testing
(b)	Local	Increase Local Cases	Schools	Food Insecurity	Health Officials	Business Impact
	Cable	Facts and Science	Case Numbers/Models	Trump Quotes	China Blame	WH Task Force

Note. Top 5 topics by size of selection difference between (a) MSNBC versus FOX (b) local versus cable news.

There are many topics with high polarization of coverage and low differences in framing[3]. This is expected as framing differences can only emerge when the topic is sufficiently covered by both stations. FOX liked to talk about travel restrictions more than MSNBC (about mean on the x-axis), but they used very similar language to each other conditional on discussing the topic (bottom on the y-axis). Three interesting topics that stand

[3]In some respects, the tradeoff between topic selection and topic framing is a function of the number of topics used. For example, if we had run a model with 1000 topics, we would have many tiny topics with high topic selection effects but low topic framing effects. However, this is true only to a point. If differences in our topic data were purely a function of selection versus framing, we would see two clusters of topics. First, a cluster of topics with low framing polarization but high selection polarization, filled with topics that have a small number of documents, where each network's particular spin on a topic would be assigned its own topic. The second cluster would be of large topics with high framing polarization and low selection polarization, where the differences between multiple networks are reflected in the framing polarization measure. This is not the pattern we see in Fig 2, where the largest topics (Transmission, WH Task Force, Facts & Science) have relatively small topic framing polarization, but vary substantially in their levels of topic selection polarization

out for differences in framing are Food Production, Foreign Response, and Disinfecting. FOX and MSNBC used very different language when discussing these topics. For example, in Food Production MSNBC talked about infections and deaths at food processing plants, while FOX focused on the quality and reliability of the supply chains.

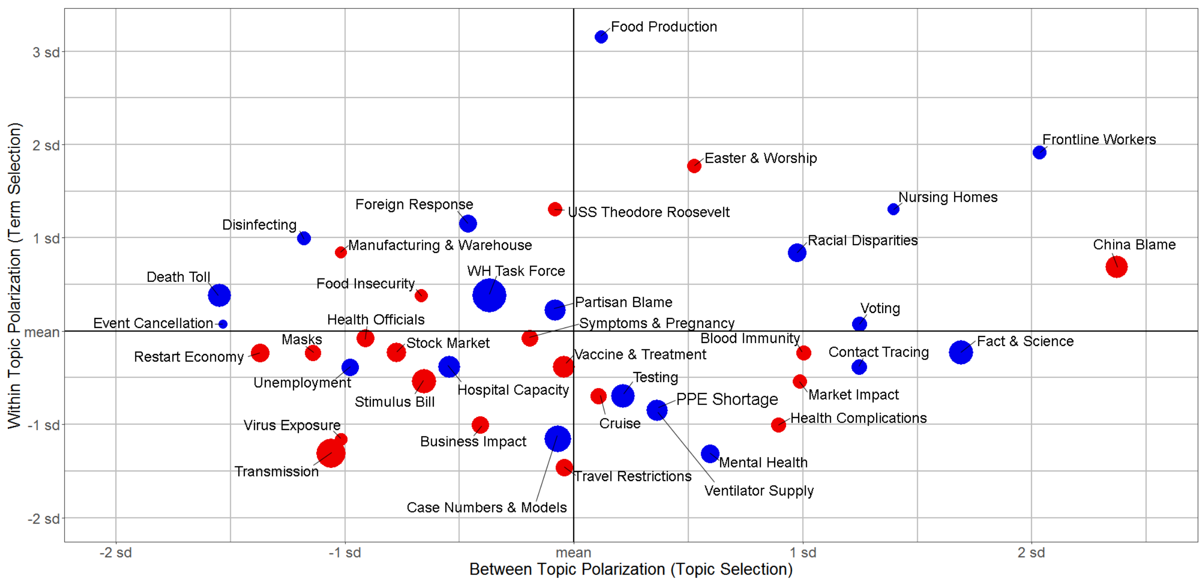

Figure 2. Polarization of COVID-19 Topics Between Fox News and MSNBC.

Note. Selection and framing differences between Fox News and MSNBC in their coverage of COVID-19 from January 1 to April 30, 2020. X-axis displays topic-selection polarization and y-axis displays term-selection polarization. The units of value on both the x-axis and y-axis are the z-score. Size of the dots corresponds to the mean topic proportion for that topic across the dataset. Red dots were topics discussed more by Fox News, Blue dots were topics discussed more by MSNBC.

Resonance and Contrast between Press Conferences and Media Narratives

In the previous section, we showed that, even during a time of crisis, the media has ample room to choose what to talk about and how to talk about it. On the other hand, President Trump held daily briefings during the early stage of COVID-19 pandemic, which provided him a unique opportunity and platform to provide his own narratives. Between the media and the president, how were the messages about COVID reflected by the general public and how were these messages related to one another? In this section, we investigate these questions.

To understand how the three cable news channels covered the President's daily briefings, we examined the semantic textual similarity between cable news content and Trump's speech in the daily briefings. Thanks to the recent advances in Neural Network methods for Natural Language Processing, we leveraged the state-of-art sentence BERT model to obtain vector representations for text segments via neural embeddings (Reimers and Gurevych, 2019). Recent studies have documented that these embedding models are incredibly good at capturing context and semantic meaning of text and are particularly suitable for measuring semantic textual similarity (Camacho-Collados and Pilehvar, 2018).

In Figure 3, we show the average semantic textual similarity before, during, and after presidential briefings between news content and Trump's daily briefing. The similarities between cable news and the President's daily briefing before the briefings occur is relatively low compared to the during and after periods, as we would expect. The similarities jump during the time of press conference as the three cable channels begin to carry the event live to different extents. FOX has a significantly higher semantic textual similarity with Trump's speech than the other two cable news channels. Note that the similarities are not approaching one (i.e., the maximum similarity) during the press conference for two reasons: 1) the different channels insert their own commentaries and carry the event live to different extents; 2) the two sources of text content (i.e., TV and press conference transcripts) are segmented differently and have different segment lengths. Nonetheless, the relative change in similarities is meaningful. The decision to carry a presidential press conference live, to interrupt with commentary or break-away at points, is a major power of the newsroom, not something the president actually forces; frequently under President Obama, and even later in the COVID-19 crisis under President Trump, they have chosen to simply ignore presidential press conferences both live and in later coverage of the day.

Post-briefings similarities drop but interestingly remain at significantly higher levels than in the before period for all channels. Although not direct causal evidence, we do not attempt to confirm the mechanism, this indeed indicates that news coverage was plausibly influenced by the president's agenda, even for MSNBC (though, to a lesser degree), a channel that is ideologically less congruent with the president. The influence can be manifested by news coverage reiterating what the president said, and directing the discussion toward the issues brought up by the president during the briefings. Both forms of influence reflect the president's ability to set the agenda. The three shaded points and error bars in the after period represent the average similarity after we have excluded all news segments that contain at least one direct quote from Trump. That similarities of all three channels decrease after excluding direct quotes, but are still higher than their pre-briefings level indicates that the increased similarity is due to both forms of influence.

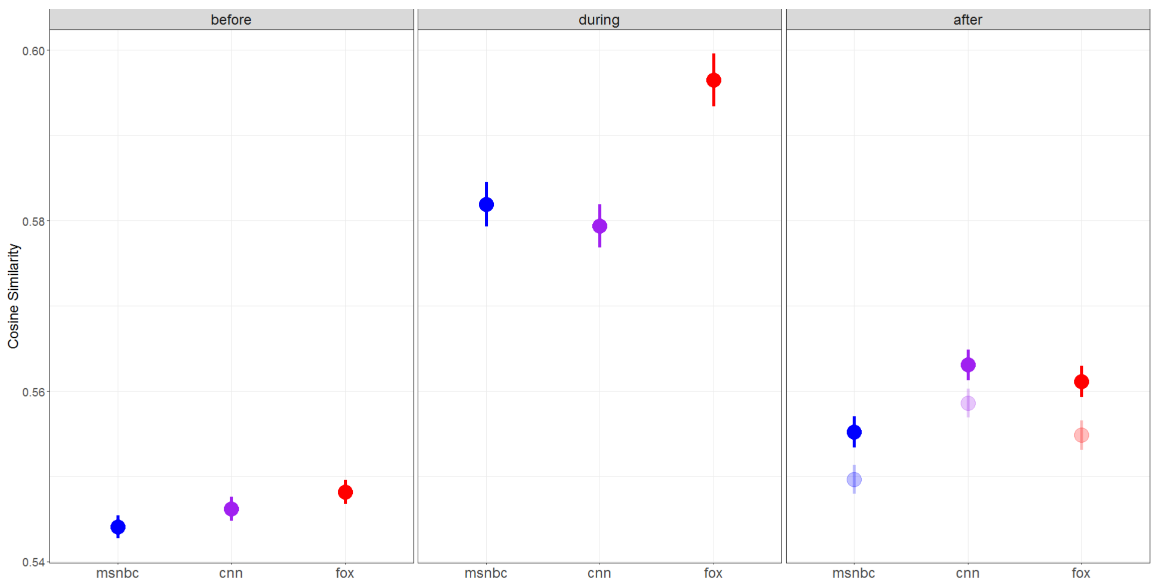

Figure 3. Language Similarity between Cable News and Trump Presser.

Note. The figure displays the average language similarity of Fox News (red), MSNBC (blue), and CNN (purple) COVID-19 news coverage with President Trump's press conference speech before, during and after the press conference. The shaded points in the after period represent similarity after removing all segments that contain direct quotes of the President's speech during the press conference. Bars represent one standard error of the mean similarity. The analysis is conducted across 39 daily Presidential press conferences held from March 14th to April 24th.

We also conducted regression modeling of the semantic textual similarity, controlling for channel and date fixed effect. The fixed effect model can account for channel-specific heterogeneity and common time trends across channels. The modeling results produce qualitatively similar insights as Figure 3 and hence we leave the details of the models and their results to the supplementary materials. One thing to note from the modeling result is that the lifting effect of textual similarity in the after period is about 38% of the similarity in the during period, averaging across the three cable channels. Given that all channels extensively focused on Presidential briefings when they aired live, a 38% lift in similarity in the after period (relative to the during period) indicates a strong lift in magnitude.

Not only do the news media choose to what extent they cover the issues brought up by the president during his daily briefings, they also choose how to talk about them. To understand how, we adapted techniques from Genzkow et al. (2019) to measure the polarization between MSNBC and FOX based on their news content. In this case, we measured the overall term polarization irrespective of topic, grouping TV segments based on their time period relative to the press conferences (i.e., before, during, after the President's daily briefing). This provides an overall measure of the difference in language between FOX and MSNBC during each time period. Figure 4 shows that the overall term polarization between FOX and MSNBC is relatively stable on days without a presidential press conference. On briefing days, however, the polarization drops during the briefing as the channels carry the presidential briefing live, and hence have similar news content. The most interesting pattern can be observed in the after briefing period, where the polarization increases and is substantially higher than on days when a briefing did not occur. FOX and MSNBC use different language to discuss the issues provoked by the briefings, likely invoking their own spin. We draw two conclusions from Figures 3 and 4: First, COVID-19 coverage on cable news media after the president's briefings correlate with issues he focused on in the briefings, likely caused by a mix of direct (i.e., airing clips of the president speaking) and indirect (i.e., commentary about what the president said) coverage. Second, different cable news picked up on different issues with different frames, thus there was increased polarization between them on days with the president's briefings.

A clear example of post-presser polarization comes in the two cable channels' analysis of Trump's comments about using UV light and injecting disinfectant as a potential cure for COVID-19. On April 24th, 2020, FOX aired 13 segments that contained the terms "disinfectant|bleach" and "trump|president". In the same time period, MSNBC aired 64 segments. The tone and content of the segments varied dramatically.

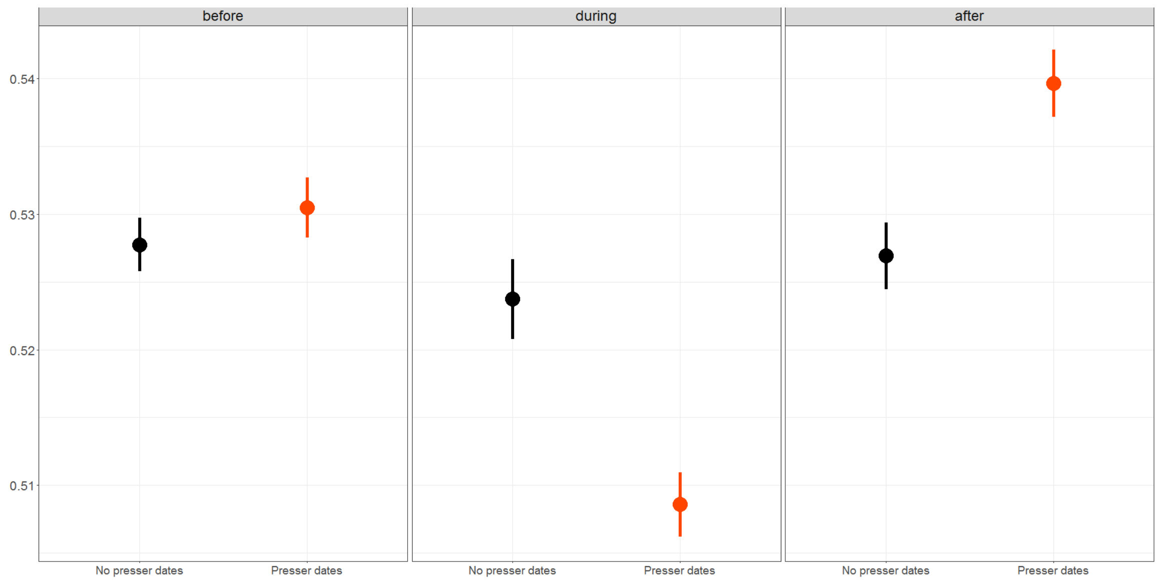

Figure 4. Polarization Between FOX and MSNBC on Dates With and Without a Presser.

Note. The average overall (topic-independent) term polarization between Fox News and MSNBC before, during, and after the briefings (red); and for dates when no briefing was held (black). Bars are one standard error of the mean term polarization. The President's briefings had a polarizing effect on subsequent COVID-19 coverage.

FOX responded by defending Trump's claims as medically sound. "Just when you thought we were only talking about science fiction, there is this tonight from Cedars Sinai a statement acknowledging that they are in fact in the preclinical stages of developing a technology that harnesses intermittent UV light for treating viruses and bacteria internally and externally." It also spent a great deal of time contextualizing Trump's remarks, including the following analysis: "When he gets new information he likes to talk about it out loud and he really has the dialogue and so that is what the dialogue he was having about the concept of some sort of way to get ultraviolet light inside the body, though the president was correct and in fact earlier this week a company out of Colorado announced it studied the new device that would invent l.e.d. light that admitted UV rays into breath tubes and ventilators in that way he could attack the virus from inside the trachea."

On the other hand, MSNBC did not imply that there was any scientific merit to Trump's claims, focusing on how his comments illuminated his lack of understanding and unfitness for the job. "The idea of telling people to inject or use you know disinfect and take them and have Lysol company have to come out and say please don't do that and doctors all over the country today are having to kind of do a cleanup for Trump's foolish remark. It wasn't sarcasm. It was ignorance." Trump's comments were placed in a broader context of his failures as a president and his failures during the pandemic, "He is impervious to new information, often when he decides he know something, even if he doesn't know it. He has decided he knows it therefore that's the way it has to be and that's the way everybody has to pretend it has to be. Yesterday was just just a disaster. It was horrifying to listen to him recommend injecting disinfect and talk about some method of get ultraviolet light inside your body."

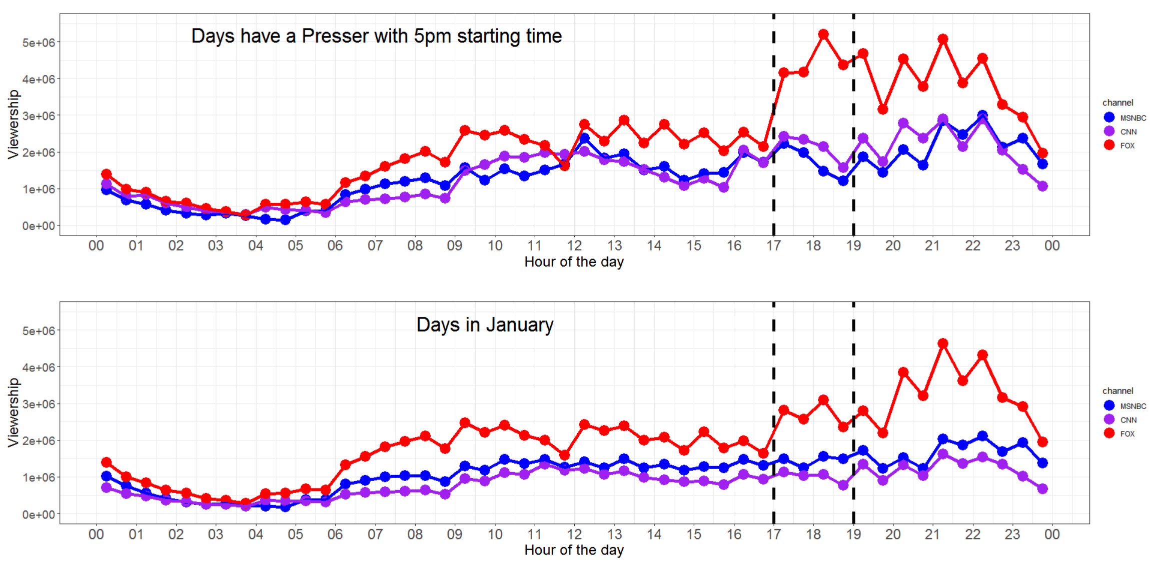

Figure 5. Viewership on Presser Dates vs January.

Note. TV viewership, especially on Fox News, was higher during the presidential press conferences than during comparable days in January. Post-conference cable, by virtue of being prime-time, also has substantially higher viewership than pre-conference cable, potentially magnifying the effect of Trump's press conferences.

Viewership data helps us further understand, compare, and contrast the agenda-setting powers of the media and the president. People tuned into the president's press conference, but not to the same extent as other presidential communications, such as Oval Office addresses (for example President Trump had 41 million viewers for his immigration address on January 8, 2019). Instead, viewership was more similar to typical primetime news numbers. Yet, with several hours of primetime news in the evening and continued coverage throughout the full 24 hours: the President's viewership numbers for the 1 to 2 hour duration of his press briefings are still dwarfed by the collective viewership of mainstream news. On average, press conferences received about 8.3 million viewers across the three cable news channels, up from an average of 5.2 million across these channels during the same time of day but prior to the pandemic. However, viewership during the pandemic on a weekday when there isn't a briefing was also higher than pre-pandemic numbers, at 6.6 million, indicating that on average, during the pandemic, more people tune in in general.

It is also important to note that about 4.5 million of the 8.3 million viewers were viewing on FOX, suggesting that the president's briefings are likely reaching sympathetic viewers, rather than marginal voters. And, while viewership of FOX stayed steady into the evening, it increased on MSNBC and CNN into primetime: the 3 stations combined for about 8.7 million viewers on average for the 4 hours after the press conferences. Thus, by virtue of higher ratings and more time, post-press conference cable gets about 2.1x the viewership of press conferences. More detailed analysis of the viewership can be found in the supplementary materials.

In addition, viewers who tune in during the presidential briefings were exposed to relatively homogenous coverage of the briefings, while viewers who tune into the media after the briefings were exposed to more polarized coverage. Not only were more people exposed to the news coverage curated by the media, they were exposed to the polarized narratives set by the media. This effect further emphasizes the agenda-setting power of the media beyond that of the president's daily briefings.

Searches Resemble Media Coverage More Than They Do Press Conferences

Finally, we ask: to what degree do the president and the media influence the aspects of the COVID-19 crisis people find most relevant and important? We test it by directly comparing daily web searches for topics covered by national TV news (cable and network) with the topics most prominently featured in the president's daily press conferences.

We find that the relationship between search and television news is much stronger than the relationship between search and the president's press conferences. In Table 3, we show the association between web search volume for Topic X (as a proportion of all COVID-19 searches) and the coverage of Topic X on both TV news and the president's press conferences. We find that the proportion of a topic in national news is highly correlated with the proportion of that topic in search. However, while the association between the proportion of a topic in the press conference is positive, it is not significant and also much smaller in magnitude than the association between search and TV news. These results hold even when we examine the relationships between TV/search and presser/search separately. Columns 2 and 3 of Table 3, show that while there is a correlation between presser content and searches, it is substantially weaker than the correlation between media content and searches. Further robustness checks show that there is no significant correlation between television or press conference and search for the day before, the day after, or on random days. This shows that the regression is not picking up artifacts of search patterns across the crisis that match television coverage, but real day-to-day coverage. This all suggests that television news messages are more strongly reflected in public information-seeking behavior than those of the president.

We further explore this correlation in Figure 6. In theory, it is possible that while most topics that the president mentioned had little association with collective attention, a handful may have had a strong correlation. Similarly, the strong relationship between search and media may be the artifact of only one or two topics. To test this, we plot the normalized search proportion and normalized media/press conference proportion for the top 8 topics with the strongest correlation between media/search and presser/search. Panel A of Figure 5 shows that the 8 topics have a clear, consistent, and visually striking association between their media coverage and their search proportion - on days when the media covers these topics the most, we see that these topics' share of COVID-19 searches is high as well. Panel B of Figure 5 shows little to no relationship between even the topics with the highest correlation between press conference and search. If anything, many of these topics seem to relate to upcoming events (”graduation”, ”event cancellation”, ”reopening”), suggesting that the correlation is likely driven by the contemporaneous relevance, rather than any potential agenda setting. These two panels further reinforce the finding that the public's search interest in COVID-19 topics were more congruent with media coverage than the president's press conferences.

Table 3: Media and Presser Topics Reflected in Search

	Dependent variable:		
	Web Searches For Topic		
	(1)	(2)	(3)
Media Proportion	0.129*** (0.027)	0.133*** (0.027)	
Presser Proportion	0.015 (0.019)		0.034* (0.018)
Date	0.025** (0.013)	0.025** (0.013)	0.026** (0.013)
Day of Week FE	X	X	X
Topic FE	X	X	X
Topic x Date FE	X	X	X
Constant	−469.924** (233.270)	−470.032** (233.309)	−476.755** (232.542)
Note:			*p<0.1; **p<0.05; ***p<0.01

Note. Proportion of topics in web search regressed on proportion of topics in mainstream media and press conferences. Regression is binomial logit, with a search for Topic X counted as a success, and any other search containing the terms ”covid”, ”corona” or ”virus” counted as a failure. Standard errors clustered by date.

How do we square these results with the results of the previous section, which finds increased congruence between press conferences and media narratives in the post-presser period? On average, while congruence between the press conferences and the media increased in the post-presser period, the press conferences did not dominate media coverage. As a result, we see that there is more congruence between media coverage and searches than there is between press conferences and searches.

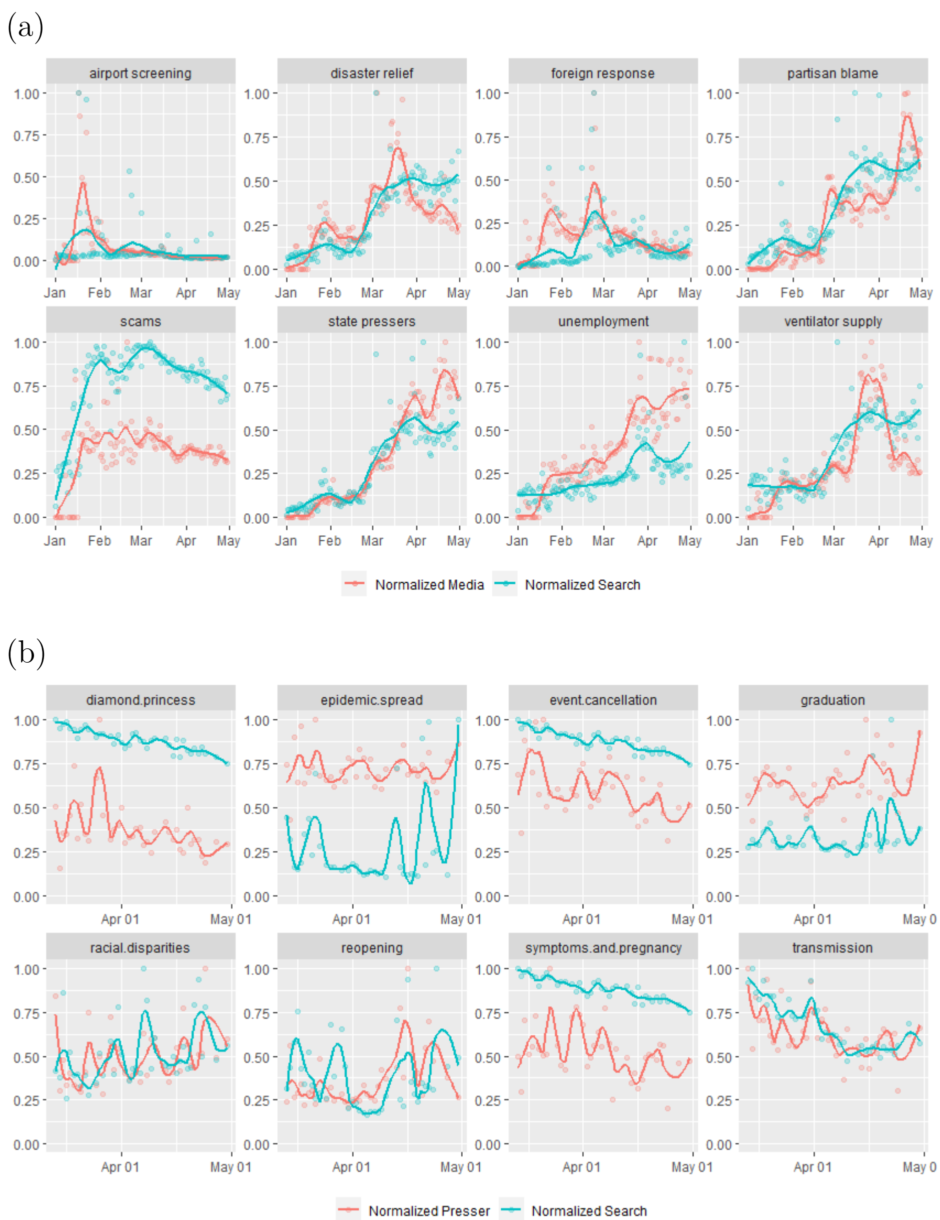

Figure 6. Most Correlated Media/Search and Presser/Search Topics

Note. Normalized proportion of coverage about COVID-19 on a particular topic covered on cable and network news (Fox News, MSNBC, CNN, ABC, NBC, and CBS) compared with search as proportion of search about COVID-19 on a particular topic. A date with a value of "1" represents that date with the highest proportion of media/presser/search for that topic, and all other y-axis values represent the relationship between that date and the date with the highest proportion.

Discussion

The early stages of the COVID-19 crisis generated a unique set of informational circumstances in the US. The issue was so overwhelming that it became a top news story for months, dominating media coverage across outlets of all ideological stripes. Furthermore, the president leveraged his bully pulpit to deliver daily press conferences, which were usually televised and often contained significant misinformation. Throughout all this, many Americans were stuck at home, glued to their television sets for updates on a crisis that had already altered many aspects of their daily lives.

The COVID-19 crisis also posed a singular challenge for the mainstream media: What aspects of the pandemic were most important for the public to know? Should media outlets run presidential communications live, even if those communications often contain misinformation? How much time should they devote to disagreeing with inaccurate claims about the virus? We find substantial differences in the topics covered by outlets that are ideologically right versus left of the center, including differing assignations of blame, concerns about COVID-19 vulnerability, and recommended solutions. Furthermore, we found that in the time period after press briefings, FOX and MSNBC were more likely to disagree than the same time period on days with no press briefings.

Despite the extraordinary power that the president wields in times of crisis, harnessed to its fullest by President Trump with his daily press conferences, there was little evidence that he controlled which aspects of COVID-19 the public searched for. Instead, we find that web searches tracked media coverage to a much greater extent than they tracked the president's press conferences. These results provide valuable information about choices different media outlets made in covering this public health emergency, and how those choices interacted with communication choices made by the president. Ultimately, the narratives presented by the media emerged much more consistently within users' web searches, even after taking into the account the relationship between press conferences narratives and media narratives.

In the context of disaster communications by the media and government, this paper raises several important questions for further research. First, we find substantial polarization in the topics and terms used to discuss the COVID-19 crisis. Some topics and phrases were much more common on right-leaning FOX, while others were more common on left-leaning MSNBC. On the other hand, some were common across media outlets of varying partisanship. How does the partisanship of media audience shape their choices of disaster coverage? To what degree is this polarization unique to the COVID-19 crisis, versus other disasters? Perhaps most importantly, despite substantial differences between media outlets, why were some terms and phrases common to all?

Second, we find substantial differences in pre-, during- and post- press-conference media coverage. In the post-conference time period, different media outlets may have been responding differently to the press conferences. These effects are heightened by the fact that post-press conference media coverage occurred in the prime-time TV viewing period. How much does this polarized coverage influence attribution of blame during natural disasters? To what degree is there similar media polarization after other live events centering a president or candidate, and how does it shape partisans' divergent perceptions of candidates?

Finally, we find a much larger relationship between media coverage and collective attention (web search) than between press conferences and search. This is interesting, given that the COVID-19 press conferences were atypical in two potentially countervailing ways: (1) The president had an unusual amount of influence and viewership for his press conferences, relative to virtually all other presidential communications and (2) Trump's style during the press conferences was highly unusual, with a different focus than most government communications during natural disasters. Essentially, are the conclusions we draw the result of a Trump effect, where viewers fund him entertaining but few take his suggestions literally? Or are they a broader indication of the disproportionate agenda-setting power of the media, which dwarfs presidential agenda-setting power even at its peak? More research is needed to clear up these important questions.

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Appendix

Contents

Data

TV Transcripts

We use complete transcripts of national cable news, network news, and local news from approximately 800 local TV channels across all 210 Designated Media Areas in the United States. The transcripts are sourced from the TVEyes database. We analyzed media coverage of the COVID-19 public health crisis in America from its very beginning in January up until April 30, 2020 – the first 120 days of coverage. We analyzed 150,670 documents in total. This is made up of 33,155 CNN segments, 30,695 Fox News segments, 30,694 MSNBC segments, 44,850 network news segments, and 75,335 local news segments. The 75,335 local news segments come from a random sample of the full local news dataset, taken to avoid having local news dominate the topic model. 150,000 local news segments were randomly sampled prior to pre-processing of the data (e.g., removal of segments dominated by advertising or irrelevant topics such as traffic or weather). The number 150,000 was chosen because it was roughly equal to the total number of segments from all three cable news channels (before pre-processing).

The television news transcripts were divided into pages or short chunks of text. Each page is about 616 words or 4.2 minutes broadcasting on average. We retrieve all the pages that contained at least one of our set of covid related keywords, which are as follows: coronavirus, corona-virus, ”corona virus”, ”wuhan virus”, chinavirus, china-virus, ”china virus”, chinesevirus, chinese-virus, ”chinese virus”, SARS, MERS, covid covid-19 pandemic quarantine travelrestriction ”travel restriction” travel-restriction flatteningthecurve ”flattening the curve” flattening-the-curve flattenthecurve ”flatten the curve” flatten-the-curve self-isolation ”self isolation” self-isolation selfquarantine ”self quarantine” self-quarantine shelterinplace ”shelter in place” shelter-in-place socialdistancing social-distancing ”social distancing” contacttracing contact-tracing ”contact tracing” superspreader ”super spreader” super-spreader ventilator respirator lockdown ”lock down” lock-down ”national emergency” national-emergency nationalemergency huanan hubei

In Figure A1, we plot the daily count of COVID-related pages by channel and over time. Since the middle of March, all three cable channels have around 225 pages per day hit containing at least one of our keywords, representing about 15.75 hours of daily news time. This demonstrates the overwhelming focus of daily news on coverage related to COVID-19 during our study period (i.e. the first one hundred day of COVID crisis). Note that this likely overestimates coverage, as a ”page” could contain discussion of other coverage unrelated to COVID, as well.

Figure A2 displays plots of the daily count of some interesting words and phrases by channel and over time.

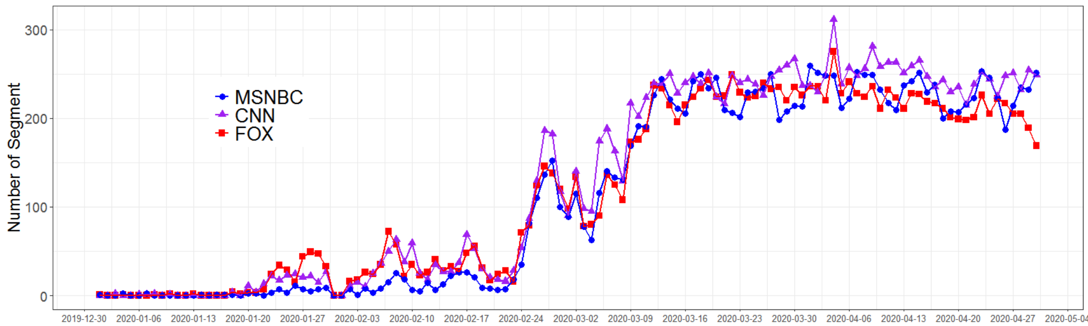

Figure A1. Number of COVID-19 Segments on Cable News Channel Per Day.

Note. This figure represents the number of COVID-19 segments on cable news. There were approximately the same number of segments on the three cable networks.

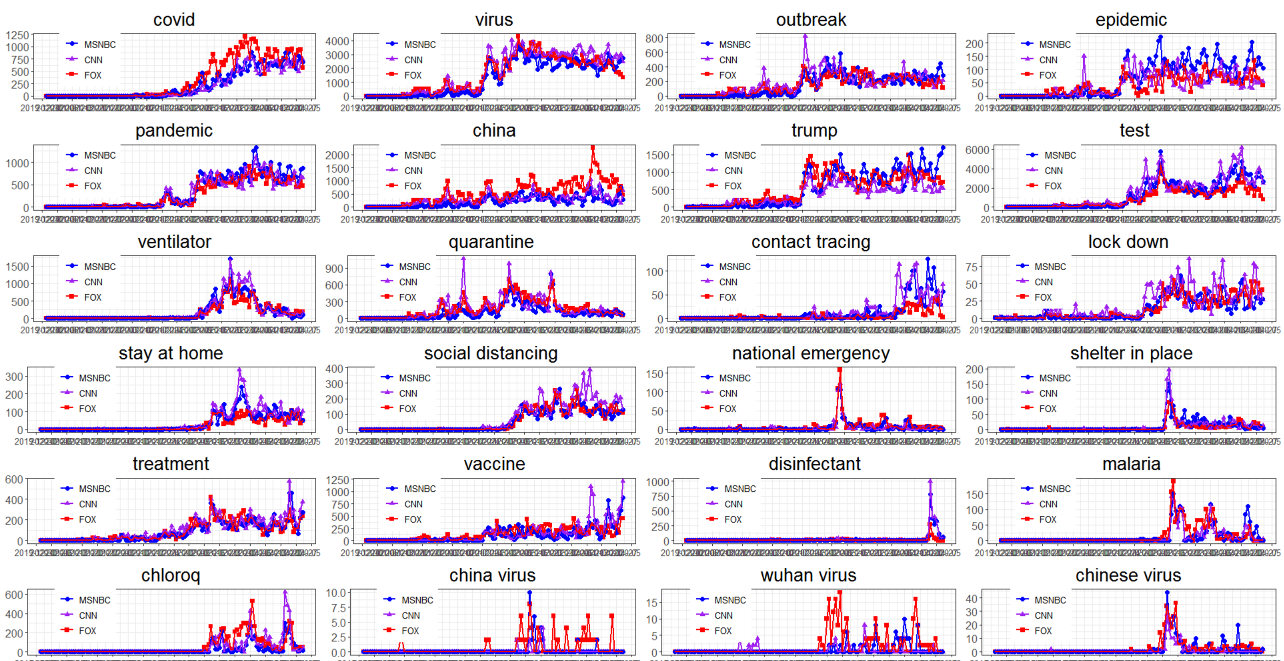

Figure A2. Selected Phrases by Channel Over Time.

Note. This figure shows the number of daily occurrences of specific phrases over time. Some phrases/words such as ”china”, ”chlorq”, and ”china virus”/”wuhan virus” were clearly more common on Fox News. In general, the differences in the phrase timing illustrates some of the early dynamics of the pandemic.

Program Classification

We classify cable news, network news, and local news with the following procedure

Cable news: We collect the covit hit page for channel MSNBC, CNN, and FOX as our sample of Cable news.

Network news: Any programs aired in local channels and meet with the following program title: Nightline, Good Morning America, The View, GMA3: What You Need to Know, ABC World News Tonight with David Muir, 20/20, Good Morning America: Weekend Edition, This Week with George Stephanopoulos, Today with Hoda and Jenna, Early Today, Today, Today 3rd Hour, NBC Nightly News with Lester Holt, Dateline NBC, Sunday Today with Willie Geist, Meet the Press CBS Morning News, CBS This Morning, CBS Evening News with Norah O'Donnell, 48 Hours, CBS Sunday Morning, Face the Nation, CBS Weekend News, 60 Minutes, NHK Newsline, BBC World News, DW News, PBS NewsHour, Amanpour and Company,Firing Line with Margaret Hoover, PBS NewsHour Weekend, Frontline

Local news: News content aired on local channel but not belong to any network program titles. Table A1 displays all of the local channels from which we derived our transcripts by DMA.

Local News Channels by DMA

Table A1: Local TV Channels by DMA

DMA	List of Channels
Abilene-Sweetwater	KRBC,KTAB,KTXS,KXVA
Albany-Schenectady-Troy	WNYT,WRGB,WTEN,WXXA
Albany, GA	WALB,WSWG,WFXL
Albuquerque-Santa Fe	KOAT,KOB,KRQE,KRQEDT2
Alexandria, LA	KALB,KALBDT2,WNTZ,KLAX
Alpena	WBKB,WBKBDT2
Amarillo	KFDA,KAMR,KCIT,KVII
Anchorage	KTUU,KTBY,KTVA,KYUR
Atlanta	WAGA,WGCL,WSB,WXIA
Augusta-Aiken	WAGT,WRDW,WFXG,WJBF
Austin	KEYE,KTBC,KVUE,KXAN
Bakersfield	KBAK,KBFX,KERO,KGET
Baltimore	WBAL,WBFF,WJZ,WMAR
Bangor	WABI,WFVX,WLBZ,WVII
Baton Rouge	WAFB,WBRZ,WGMB,WVLA
Beaumont	KBMT,KBTV,KFDM,KJAC
Bend, OR	KFXO,KOHD,KTVZ
Billings	KHMT,KSVI,KTVQ,KULR
Biloxi-Gulfport	WLOX,WXXV
Binghamton	WBGH,WBNG,WICZ,WIVT
Birmingham (Anniston-Tuscaloosa)	WBRC,WBMA,WIAT,WVTM
Bluefield-Beckley-Oak Hill	WOAY,WVNS,WVNSDT2,WVVA
Boise	KNIN,KBOI,KIVI,KTVB
Boston (Manchester)	WBTS,WBZ,WCVB,WFXT,WHDH,WMUR
Bowling Green	WBKO,WNKY
Buffalo	WGRZ,WIVB,WKBW,WUTV
Burlington-Plattsburgh	WCAX,WFFF,WPTZ,WVNY
Butte-Bozeman	KBZK,KTVM,KWYB,KWYBDT2

Casper-Riverton	KCWY,KGWC,KFNB,KTWO
Cedar Rapids-Waterloo-Iowa City-Dubuque	KCRG,KFXA,KGAN,KWWL
Champaign	WAND,WCCU,WCIA,WICD,WRSP
Charleston,SC	WCBD,WCIV,WTAT,WCSC
Charleston-Huntington	WSAZ,WCHS,WOWK,WVAH
Charlotte	WBTV,WCNC,WJZY,WSOC
Charlottesville	WCAV,WVAW,WVIR,WAHU
Chattanooga	WDSI,WDEF,WRCB,WTVC
Cheyenne-Scottsbluff, NE	KGWN,KLWY
Chicago	WBBM,WFLD,WLS,WMAQ
Chico-Redding	KCVU,KHSL,KNVN,KRCR
Cincinnati	WXIX,WCPO,WKRC,WLWT
Clarksburg-Weston	WDTV,WVFX,WBOY
Cleveland-Akron (Canton)	WOIO,WEWS,WJW,WKYC
Colorado Springs-Pueblo	KKTV,KOAA,KRDO,KXRM
Columbia, SC	WIS,WACH,WLTX,WOLO
Columbus, GA	WTVM,WXTX,WLTZ,WRBL
Columbus, OH	WBNS,WCMH,WSYX,WTTE
Corpus Christi	KIII,KRIS,KSCC,KZTV
Dallas-Fort Worth	KDFW,KTVT,KXAS,WFAA
Davenport-Rock Island-Moline	KWQC,KLJB,WHBF,WQAD
Dayton	WDTN,WHIO,WKEF,WRGT
Denver	KCNC,KDVR,KMGH,KUSA
Des Moines	KCCI,KDSM,WHO,WOI
Detroit	WWJ,WDIV,WJBK,WXYZ
Dickinson (Williston)	KMOT,KMOTBACK
Dothan	WRGX,WTVY,WDFX,WDHN
Duluth	KBJR,KDLH,KQDS,WDIO
El Paso	KDBC,KFOX,KTSM,KVIA
Elmira (Corning)	WYDC,WENY,WENYDT2,WETM
Erie	WFXP,WICU,WJET,WSEE
Eugene	KEZI,KLSR,KMTR,KVAL

Eureka	KAEF,KBVU,KIEM,KVIQ
Evansville	WFIE,WEHT,WEVV
Fairbanks	KTVF,K13XD,KATN
Fargo-Moorhead-Grand Forks	KVRR,WDAY,KXJB,KVLY
Flint-Saginaw-Bay City	WJRT,WEYI,WNEM,WSMH
Florence	WBTW,WFXB,WPDE
Fort Myers-Naples	WBBH,WFTX,WINK,WZVN
Fort Wayne	WPTA,WANE,WPTADT2
Fresno-Visalia	KFSN,KGPE,KMPH,KSEE
Fort Smith-Fayateville-Springdale-Rogers	KFSM,KFTA,KHOG,KNWA
Gainesville	WCJB,WGFL,WNBW,WOGX
Glendive	KGMB,KXGN,KXGNDT2
Grand Junction-Montrose	KKCO,KJCT,KFQX,KREX
Grand Rapids-Kalamazoo-Battle Creek	WOOD,WWMT,WXMI,WZZM
Great Falls	KBGF,KFBB,KFBBDT2,KRTV
Green Bay-Appleton	WBAY,WFRV,WGBA,WLUK
Greensboro–High Point–Winston-Salem	WFMY,WGHP,WXII,WXLV
Greenville-New Bern-Washington	WITN,WCTI,WNCT,WYDO
Greenville-Sparta-Asheville	WHNS,WLOS,WSPA,WYFF
Greenwood	WABG,WABGDT2,WXVT
Harlingen-Weslaco-Brownsville-McAllen	KFXV,KRGV,KVEO,KVEODT2, KGBT
Harrisburg-Lancaster-Lebanon-York	WGAL,WHP,WHTM,WPMT
Harrisonburg	WSVF,WHSV
Hartford-New Haven	WFSB,WTIC,WTNH,WVIT
Hattiesburg-Laurel	WDAM,WHPM,WHLT
Helena	KHBB,KHBBLD2,KTVH,KXLH
Honolulu	KHNL,KHON,KITV
Houston	KHOU,KPRC,KRIV,KTRK
Huntsville-Decatur (Florence)	WAFF,WAAY,WHNT,WZDX
Idaho Falls	KIDK,KIFI,KPVI
Indianapolis	WRTV,WTHR,WTTV,WXIN,WLFI,WPBI

Jackson, MS	WLBT,WDBD,WAPT,WJTV
Jackson, TN	WJKT,WBBJ,WBBJDT3,WNBJ
Jacksonville	WFOX,WJAX,WJXX,WTLV
Jefferson City	KMIZ,KOMU,KQFX,KRCG
Johnstown-Altoona-State College	WATM,WJAC,WTAJ,WWCP
Jonesboro	KAIT,KJNBLD1,KJNBLD2
Joplin	KFJX,KOAM,KODE,KSNF
Juneau	KATH,KJUD,KXLJ
Kansas City	KCTV,KMBC,KSHB,WDAF
Knoxville	WVLT,WATE,WBIR,WTNZ
La Crosse-Eau Claire	WEAU,WKBT,WLAX,WQOW
Lafayette, IN	WPBY
Lafayette, LA	KADN,KATC,KLAF,KLFY
Lake Charles	KPLC,KVHP,KSWL
Lansing	WILX,WLAJ,WLNS,WSYM
Laredo	KGNS,KYLX,KXOF
Las Vegas	KLAS,KSNV,KTNV,KVVU
Lexington	WKYT,WDKY,WLEX,WTVQ
Lima	WLIO,WLIODT2,WLMO,WLQP
Lincoln-Hastings-Kearney	KSNB,KOLN,KFXL,KLKN
Little Rock-Pine Bluff	KARK,KATV,KLRT,KTHV
Los Angeles	KABC,KCAL,KCBS,KNBC,KTTV
Louisville	WAVE,WDRB,WHAS,WLKY
Lubbock	KCBD,KAMC,KJTV,KLBK
Macon	WGXA,WMAZ,WMGT
Madison	WMTV,WISC,WKOW,WMSN
Mankato	KEYC
Marquette	WLUC,WLUCDT2,WBUP,WJMN
Medford-Klamath Falls	KDRV,KMVU,KOBI,KTVL
Memphis	WMC,WATN,WHBQ,WREG
Meridian	WTOK,WGBC,WGBCDT,WMDN
Miami-Fort Lauderdale	WFOR,WPLG,WSVN,WTVJ

Milwaukee	WDJT,WISN,WITI,WTMJ
Minneapolis-St. Paul	KARE,KMSP,KSTP,WCCO
Minot-Bismarck	KFYR,KMCY,KMCYBaCK,KXMC, KXMCBACK,WDAZ,KXND,KXNDBACK
Missoula	KECI,KPAX,KTMF,KTMFDT2
Mobile-Pensacola (Navarre)	WALA,WEAR,WKRG,WPMI
Monroe-El Dorado	KNOE,KARD,KTVE,KAQY
Monterey-Salinas	KCBA,KION,KSBW
Montgomery-Selma	WSFA,WAKA,WCOV,WNCF
Myrtle Beach-Florence	WMBF
Nashville	WKRN,WSMV,WTVF,WZTV
New Orleans	WVUE,WDSU,WGNO,WWL
New York	WABC,WCBS,WNBC,WNYW
Norfolk-Portsmouth-Newport News	WAVY,WTKR,WVBT,WVEC
North Platte	KNOP,KIIT
Odessa-Midland	KOSA,KMID,KPEJ,KWES
Oklahoma City	KFOR,KOCO,KOKH,KWTV
Omaha	WOWT,KETV,KMTV,KPTM
Orlando-Daytona Beach-Melbourne	WESH,WFTV,WKMG,WOFL
Ottumwa-Kirksville	KYOU,KTVO,KTVODT2
Paducah-Cape Girardeau-Harrisburg	KBSI,WPSD,WSIL,KFVS
Palm Springs	KPSP,KDFX,KESQ,KMIR
Panama City	WJHG,WECP,WPGX,WMBB
Parkersburg	WTAP,WOVA
Peoria	WEEK,WMBD,WYZZ,WHOI
Philadelphia	KYW,WCAU,WPVI,WTXF
Phoenix (Prescott)	KNXV,KPHO,KPNX,KSAZ
Pittsburgh	KDKA,WPGH,WPXI,WTAE
Portland-Auburn	WCSH,WGME,WMTW,WPFO
Portland, OR	KATU,KGW,KOIN,KPTV
Presque Isle	WAGM,WAGMDT1
Providence-New Bedford	WJAR,WLNE,WNAC,WPRI

Quincy	KHQA,KHQADT2,WGEM,WGEMDT3
Raleigh-Durham (Fayetteville)	WNCN,WRAL,WRAZ,WTVD
Rapid City	KOTA,KEVN,KCLO,KNBN
Reno	KOLO,KRNV,KRXI,KTVN
Richmond-Petersburg	WWBT,WRIC,WRLH,WTVR
Roanoke-Lynchburg	WDBJ,WFXR,WSET,WSLS
Rochester	WHAM,WHEC,WROC,WUHF
Rochester-Mason City-Austin	KAAL,KIMT,KTTC,KXLT
Rockford	WIFR,WQRF,WREX,WTVO
Sacramento-Stockton-Modesto	KCRA,KOVR,KTXL,KXTV
Salisbury	WBOC,WBOCDT2,WMDT,WRDE
Salt Lake City	KSL,KSTU,KTVX,KUTV
San Angelo	KIDY,KLST,KSAN
San Antonio	KABB,KENS,KSAT,WOAI
San Diego	KFMB,KGTV,KNSD,KSWB
San Francisco-Oakland-San Jose	KGO,KGOBACK,KNTV, KNTVBACK,KPIX,KPIXBACK,KTVU,KTVUBACK
Santa Barbara	KCOY,KEYT,KKFX,KSBY
Savannah	WTOC,WJCL,WSAV,WTGS
Seattle-Tacoma	KCPQ,KING,KIRO,KOMO
Sherman	KTEN,KTENDT3
Shreveport	KSLA,KMSS,KTAL,KTBS
Sioux City	KCAU,KMEG,KPTH,KTIV
Sioux Falls (Mitchell)	KDLT,KSFY,KELO,KTTW
South Bend-Elkhart	WNDU,WBND,WSBT,WSJV
Spokane	KAYU,KHQ,KREM,KXLY
Springfield-Holyoke	WGGB,WSHM,WWLP
Springfield, MO	KYTV,KYTVBACK,KSPR ,KSPRBACK,KOLR
St. Joseph	KNPN,KQTV
St. Louis	KDNL,KMOV,KSDK,KTVI
Syracuse	WSTM,WSYR,WSYT,WTVH

Tallahassee-Thomasville	WTWC,WCTV,WTXL
Tampa-St. Petersburg (Sarasota)	WWSB,WFLA,WFTS,WTSP,WTVT
Terre Haute	WAWV,WTHI,WTWO
Toledo	WTVG,WNWO,WTOL,WUPW
Topeka	WIBW,KSNT,KTKA,KTMJ
Traverse City-Cadillac	WFQX,WGTQ,WPBN,WWTV
Tri-Cities, TN-VA	WCYB,WEMT,WJHL,WJHLDT2
Tucson (Sierra Vista)	KOLD,KGUN,KMSB,KVOA
Tulsa	KJRH,KOKI,KOTV,KTUL
Tupelo	WCBI,WLOV,WTVA,WTVADT2
Twin Falls	KMVT,KSVT,KSAW,KTFT
Tyler-Longview (Lufkin-Nacogdoches)	KLTV,KETK,KFXK,KYTX
Utica	WFXV,WKTV,WUTR
VICTORIA	KAVU,KMOL,KVCT,KXTS
Waco-Temple-Bryan	KBTX,KAGS,KCEN,KWKT,KWTX,KXXV
Washington (Hagerstown)	WJLA,WJLABACK,WRC, WR-CBACK,WTTG,WTTGBACK,WUSA,WUSABACK
Watertown	WWNY,WNYF,WVNC,WWTI
Wausau-Rhinelander	WSAW,WAOW,WFXS,WJFW
West Palm Beach-Fort Pierce	WFLX,WPBF,WPEC,WPTV
Wheeling	WTOV,WTRF,WTRFDT3
Wichita-Hutchinson	KWCH,KAKE,KSAS,KSNW
Wichita Falls-Lawton	KAUZ,KSWO,KFDX,KJTL
Wilkes-Barre–Scranton–Hazleton	WBRE,WNEP,WOLF,WYOU
Wilmington	WECT,WSFX,WILM,WWAY
Yakima-Pasco-Richland-Kennewick	KAPP,KEPR,KFFX,KNDO
Youngstown	WFMJ,WKBN,WYFX,WYTV
Yuma	KECY,KYMA,KSWT
Zanesville	WHIZ

Press Conference Schedule and Transcripts

We collected the schedule and transcripts of all Trump daily press briefings during March and April 2020 from factba.se (https://factba.se/topic/calendar). We focus on the time period when Trump hosted daily briefings (excluding a few briefings that occured on weekends) and exclude the few press conferences before this period as they all have major announcements and may be covered differently by the media. Our analysis includes the press conferences from March 14th, 2020 to April 24th 2020 All of the speech in press conference transcripts is labeled by its speaker. We select Trump's speech for our text analysis as we are interested in presidential communication. Table A2 and Figure A3 provide some descriptive statistics about the press conferences.

Table A2: Basic Statistics About Daily Briefings.

Number of Pressers	39
Total Hours	55.68
Total Number of Words	619,108
Hours (Trump speaking)	28.52
Number of Words (Trump speaking)	319,818

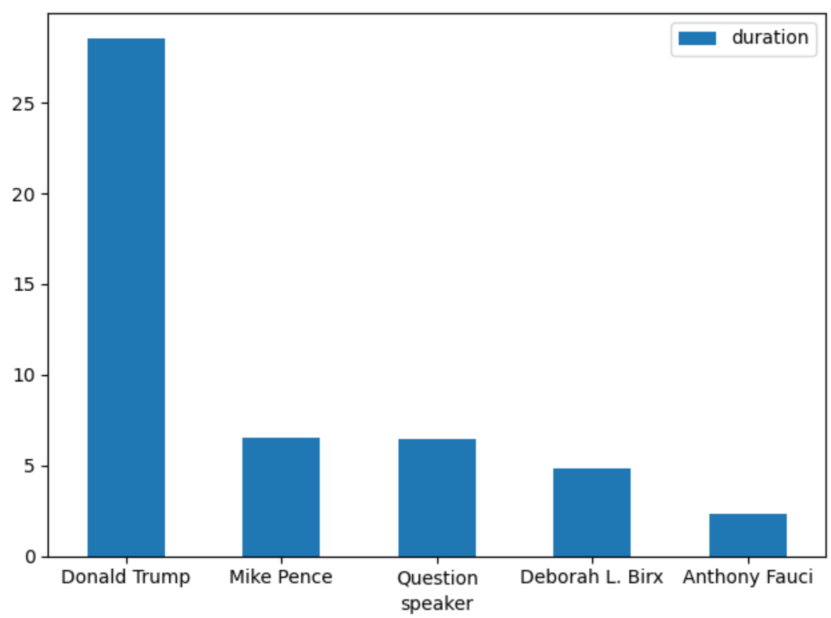

Figure A3. Mean Minutes Spoken per Conference by Speaker.

Note. This plot shows the mean minutes spoken per press conference by the 5 most common speakers in the dataset. Trump's speech dominated the COVID-19 press conferences.

Nielsen TV Ratings

We use Nielsen TV rating data to determine the audience size of both Trump pressers and Cable news. The viewership estimates are built from individual-level data from Nielsen's national representative panel. The panel is all adult (18+) Americans and viewership estimates are captured at the 30 minute level and aggregated across the US based on demographic weight. We use these viewership estimates for three cable channels (MSNBC, CNN, FOX) from January to April 2020.

Table A3 shows the average hourly viewership for MSNBC, CNN, and FOX in the first four month of 2020. Viewership was highest in March and April when the COVID-19 pandemic received overwhelming attention in media coverage. FOX has a higher viewership than MSNBC and CNN. The viewership for CNN is lower than it for MSNBC in January and February, but they become very similar in March and April.

Table A3: Average hourly viewership per channel by month (millions)

	Jan	Feb	Mar	April
MSNBC	2.27	2.02	2.65	2.53
CNN	1.7	1.41	2.56	2.51
FOX	3.99	3.97	4.4	4.28

Note. This table shows the average hourly viewership per channel for the first four months of 2020. All three cable channels had a substantial increase in viewership between February and March 2020.

Structural Topic Model

Topic Model Specification

In order to measure topical coverage, we use a 100-topic structural topic model (Roberts et al., 2014). The two structural variables we specify in the model are

”channel” and ”date”. Channel takes five discrete values: MSNBC, CNN, FOX, Network, Local; Date takes on a continuous value with first date (January 1st, 2020) equal to 0 and last date (April 30, 2020) equal to 1.

We split the transcript data into approximately 200-word text segments from news pages that aired between January 1, 2020 and April 30, 2020. Consecutive pages (end times within 10 minutes of each other) are concatenated, and pages with fewer than 2 mentions of the words ”virus” or ”covid” are dropped. To generate the segments, we extracted the text between the first and last mentions of ”virus” or ”covid”, and split the text into approximately 200 word segments, ending on the sentence containing the 200th word. This procedure was performed on both national and local news segments.

Prior to fitting the topic model on the segments, the following cleaning procedures were performed. First, there were a handful of segments that were clearly related to weather, traffic, or crime mostly on local news, and not related to covid. These segments were filtered out using a the following keywords : ”jail”, ”prosecutor”, ”sexual”, ”rape”, ”police”, ”road”, ”lane”, ”fire”, ”highway”, ”firefight”, ”gunshot”, ”crash”, ”shoot”, ”court”, ”charg”, ”judg”, ”rain”, ”temperatur”, ”temperate”, ”temperature”, ”fahrenheit”, ”weather”, ”shower”, ”thunderstorm”, ”meteorologist”, ”cloud”, ”chillier”, ”snow”, ”wind”, ”polic”, ”sheriff”, ”shoot”, ”temperatur”, ”rain”, ”shower”, ”temp”, ”sunshine”, ”breeze”, ”cloud”, ”snow”, ”wind”.

Next, we filtered out segments that contained the names of brands or products, as these are indicative of commercial breaks, using the following keywords: ”John Deere”, ”bloomberg”, ”state farm”, ”kellogg”, ”skycam”, ”cadbury”, ”cellular”, ”alexa”, ”colgate”, ”verzenio”, ”volkswagen”, ”nicorette”, ”linzess”, ”nexgard”, ”toyota”, ”babybel”, ”johnsonvill”, ”swiffer”, ”driver”, ”truck”, ”vehicle”, ”invisalign”, ”pizza”, ”sandwich”, ”buck”, ”popcorn”, ”papdia”, ”white-meat”, ”deodorant”, ”arfid”, ”mucinex”, ”colbert”, ”audience”, ”applause”, ”laughter”, ”gmc”, ”buick”, ”Osteo Bi-Flex”, ”nantucket blend”, ”Duracell”, ”In America we all count”,

”Ensure Max Protein”, ”maybelline”, ”Blue Cross Blue Shield”, ”olay”, ”walgreens express”, ”vicks”, ”country crock”, ”magic eraser”, ”annual fee”, ”holiday inn”, ”stelara”, ”old spice”, ”allegra”, ”chase”, ”sleep number”, ”audible”, ”cream cheese”, ”aarp medicare supplement”, ”tide”, ”northwestern mutual”, ”verizon”, ”cascade”, ”lysol laundry lanitizer”, ”unitedhealthcare”, ”voya”, ”harry’s”, ”almondmilk”, ”adaptagrip”, ”abreva”, ”gum”, ”downy”, ”tums”, ”claritin”, ”chobani”, ”heartburn”, ”zzzquil”, ”ask your doctor”, ”tell your doctor”, ”crest”, ”aimovig”, ”vraylar”, ”vascepa”, ”epclusa”, ”life insurance”, ”grease”, ”powerwash”, ”samsung”, ”humira”, ”dovato”, ”silverado”, ”baskin”, ”safelite”, ”seresto”, ”prevagen”, ”aldex”, ”eczema”, ”febrez”, ”belvitget”, ”dishwasherbrand”, ”sfx”, ”serum”, ”zyrtec”, ”charmin”, ”metamucil”, ”comcast”, ”.com”, ”aag”, ”jardiance”, ”botox”, ”juvederm”, ”anoro”, ”aleve”, ”aliskiren”, ”bachelor”, ”safelit”, ”oral-b”, ”liberty”, ”schwab”, ”carvana”, ”humira”, ”neutrogena”, ”cologuard”, ”western.com”, ”subaru”, ”lexus”, ”eliquis”, ”sofi”, ”robinhood”, ”rakuten”, ”nexium”, ”kisqali”, ”etrade”, ”trulicity”, ”intuit”, ”flonase”, ”febreze”, ”brita”, ”visionworks”, ”tendercrisp”, ”shipstation”, ”glucerna”, ”geico”, ”skyrizi”, ”therabreath”, ”lobsterfest”, ”miracleear”, ”hotels.com”, ”chevy”, ”mercedes”, ”allstate”, ”wayfair”, ”lamivudine”, ”dolutegravir”, ”atazanavir”, ”prevagen”, ”ibrance”, ”brilinta”, ”letrozole”, ”petmeds”, ”neuriva”, ”tmobile”, ”biktarvy”, ”xarelto”, ”astrazeneca”, ”aromatase”, ”piqray”, ”mavyret”, ”plavix”, ”trelegy”, ”dofetilide”, ”tikosyn”, ”pik3ca”, ”rifampin”, ”1 800”, ”1800”, ”1-800”, ”liberty mututal”, ”usaa”, ”xfiniti”, ”silverado”, ”samsung”, ”booking.com”, ”t-mobile”, ”otezla”, ”chantix”, ”rinvoq”, ”ozemp”, ”trip.com”, ”xfinity”, ”dovato”, ”xeljanz”, ”cosentyx”, ”trulic”, ”tremfya”.

Next, to prevent specific topics from being too dependent on local words, the names of states, governors, and state capitals plus the top 100 largest cities in the US were replaced with STATENAME, GOVNAME, and CITYNAME respectively. County names were replaced with COUNTYNAME unless they were dictionary words (tested by using the ”spelling” package in R). We preprocessed the segments as follows. Words were stemmed using the Snowball stemmer, and all words and stems with 3 or fewer characters were dropped. The following custom stopwords were included in the model, in addition to the default English stopwords: ”virus”, ”covid”, ”covid-

19", "covid19", "tucker", "sean", "laura", "fox", "msnbc", "nbc", "cbs", "abc","cnn", "north", "south", "eyewitness", "news", "live", "breaking", "watch", "story", "plus", "ahead", "anchor", "newsroom", "channel", "newscast", "tonight", "today", "thank", "thanks", "much", "great", "join", "joins", "joining", "joined", "well", "question", "appreciate", "appreciated", "appreciates". The top 100 most common male and female names (as measured by the SSA), plus common nicknames thereof, were also included as stopwords. Finally, we dropped numbers and punctuation.

Due to the sheer number of local news stations, the raw data contains more local news segments than national news segments. To remedy this, we took a random sample of the local news segments, to make the number of local news segments exactly equal to the number of national news segments. Network news segments were derived from local news transcripts prior to sampling. This procedure resulted in 75,335 local news segments, 21,134 network segments, 19,609 cnn segments, 16,949 fox segments, and 17,643 msnbc segments.

Topics Details

To select topics that were substantively meaningful and coherent, we relied on the judgement of 4 coders. Each coder independently assigned the topic a label and whether it was sufficiently informative and consistent to justify inclusion. In order to justify inclusion, the top words for the topic needed to be consistent with each other and with the top documents that contained the highest topic proportion. Furthermore, the documents needed to be clearly about covid. For example, the topic about the 2020 Democratic presidential primary had very consistent words, which matched the topic documents closely, but the topic itself had little content about covid.

Table A4 contains all of the topics, with topics included in the analysis noted with bold text.

Table A4: Topics

Topic 1 (dropped)	Highest Prob: head, straight, hair, chair, desk, color, look FREX: christi, gotta, hday, haircut, desk, straight, chair Score: hair, hday, desk, straight, self-isol, laugh, chair	Topic 51 (dropped)	Highest Prob: harri, harvard, contributor, bret, queen, pair, griff FREX: griff, siegel, saphier, jedediah, font, outnumb, marc Score: harri, harvard, griff, siegel, contributor, bret, princ
Topic 2 (disaster relief)	**Highest Prob: avail, privat, continu, addit, state, expand, direct** **FREX: partnership, privat, avail, prioriti, expand, priorit, coordin** **Score: avail, fema, privat, sector, partnership, expand, resourc**	**Topic 52 (personal hygiene)**	**Highest Prob: hand, wash, sanit, precaut, avoid, take, extra** **FREX: hand, elbow, wash, sanit, hygien, distilleri, distil** **Score: hand, wash, sanit, precaut, soap, shake, hygien**
Topic 3 (spring break)	**Highest Prob: break, spring, parti, view, express, generat, beach** **FREX: view, lindsey, topic, graham, cherri, shannon, express** **Score: view, break, spring, parti, beach, express, topic**	Topic 53 (dropped)	Highest Prob: good, morn, right, corona, hour, night, come FREX: morn, good, welcom, hour, night, watch, minut Score: morn, good, hour, right, corona, welcom, night
Topic 4 (diamond princess)	**Highest Prob: quarantin, base, japan, american, corona, olymp, week** **FREX: evacue, japanes, tokyo, japan, diamond, lackland, olymp** **Score: quarantin, japan, olymp, diamond, tokyo, evacu, evacue**	**Topic 54 (stock market)**	**Highest Prob: market, stock, point, economi, econom, street, corona** **FREX: stock, market, nasdaq, selloff, wall, investor, recess** **Score: market, stock, wall, economi, trade, investor, street**
Topic 5 (dropped)	Highest Prob: power, author, attack, threat, damag, full, storm FREX: power, storm, rebuild, terror, justic, tornado, unleash Score: power, author, attack, damag, tornado, constitut, storm	**Topic 55 (mental health)**	**Highest Prob: health, care, communiti, provid, support, servic, respond** **FREX: provid, mental, telehealth, communiti, access, care, ensur** **Score: health, care, provid, communiti, mental, support, servic**
Topic 6 (stimulus)	**Highest Prob: money, fund, dollar, program, check, loan, billion** **FREX: deposit, loan, payment, paycheck, evict, money, landlord** **Score: money, loan, payment, fund, dollar, billion, stimulus**	**Topic 56 (unemployment)**	**Highest Prob: million, week, last, unemploy, claim, peopl, file** **FREX: jobless, unemploy, million, file, benefit, claim, laid** **Score: unemploy, million, file, claim, benefit, week, jobless**
Topic 7 (comparative countries)	**Highest Prob: lock, elimin, southeast, molli, logic, sweden, bubbl** **FREX: molli, sweden, zealand, mont, hunter, visual, cove** **Score: lock, sweden, molli, beaumont, hunter, southeast, zealand**	Topic 57 (dropped)	Highest Prob: know, like, just, dont, that, right, realli FREX: know, your, that, okay, yeah, realli, dont Score: know, dont, like, realli, your, that, thing

Topic 8 (trump quotes)	**Highest Prob: fight, general, spoke, battl, involv, ground, surgeon** **FREX: general, enemi, mine, surgeon, horribl, involv, spoke** **Score: general, fight, battl, surgeon, spoke, enemi, involv**
Topic 9 (testing)	**Highest Prob: test, result, week, swab, still, process, rapid** **FREX: swab, diagnost, test, sampl, reagent, widespread, criteria** **Score: test, swab, result, laboratori, sampl, diagnost, capac**
Topic 10 (dropped)	Highest Prob: legal, immigr, thee, doesn, ther, thes, earli FREX: thet, amer, countr, ning, thise, ameri, theg Score: immigr, legal, thee, undocu, ther, thes, andi
Topic 11 (dropped)	Highest Prob: rural, odonnel, norah, even, stretch, languag, learn FREX: rural, lenghi, adriana, shoulder, stretch, mola, bright Score: odonnel, norah, rural, mola, bright, spanish, stretch
Topic 12 (dropped)	Highest Prob: talk, think, thing, point, hear, heard, want FREX: talk, sanjay, sort, heard, gupta, listen, hear Score: talk, think, thing, listen, sort, point, hear
Topic 13 (Boris Johnson)	**Highest Prob: report, here, warn, countynam, reveal, bori, promis** **FREX: report, trevor, johnson, costello, whit, bori, ault** **Score: report, bori, here, whit, warn, trevor, johnson**
Topic 14 (dropped)	Highest Prob: play, game, season, sport, team, player, athlet FREX: player, leagu, footbal, quarterback, gobert, playoff, lebron Score: play, game, sport, season, player, tournament, leagu
Topic 58 (health complications)	**Highest Prob: condit, heart, diseas, pain, lung, under, risk** **FREX: apoquel, allerg, stroke, vape, kidney, chronic, smoker** **Score: condit, heart, lung, pain, diabet, under, chronic**
Topic 59 (dropped)	Highest Prob: wake, southern, flag, enorm, inevit, cycl, begun FREX: wake, taylor, toto, enorm, wanna, cycl, zurik Score: wake, southern, enorm, flag, cycl, zurik, brave
Topic 60 (food production)	**Highest Prob: plant, food, process, anxieti, farmer, meat, produc** **FREX: farmer, agricultur, tyson, crop, rancher, meatpack, farm** **Score: plant, farmer, meat, food, anxieti, farm, pork**
Topic 61 (symptoms and pregnancy)	**Highest Prob: symptom, breath, fever, doctor, cough, corona, feel** **FREX: fever, runni, birth, breath, woke, cold, headach** **Score: symptom, fever, breath, cough, babi, husband, pregnant**
Topic 62 (manfacturing/warehouse)	**Highest Prob: worker, compani, healthcar, employe, work, design, hire** **FREX: printer, ford, healthcar, worker, hire, compani, hazard** **Score: worker, compani, healthcar, employe, hire, amazon, frontlin**
Topic 63 (stimulus bill)	**Highest Prob: senat, congress, hous, packag, pass, democrat, billion** **FREX: schumer, pelosi, negoti, congress, speaker, mitch, mcconnel** **Score: senat, congress, packag, trillion, democrat, pelosi, vote**
Topic 64 (ventilator supply)	**Highest Prob: ventil, suppli, feder, govern, need, equip, medic** **FREX: stockpil, ventil, invok, feder, suppli, equip, strateg** **Score: ventil, suppli, feder, equip, govern, stockpil, shortag**

Topic 15 (local cases)	**Highest Prob: citynam, statenam, citi, area, mayor, spot, across** **FREX: metro, citynam, citi, mayor, blasio, metropolitan, area** **Score: citynam, citi, statenam, mayor, area, spot, metro**	**Topic 65 (stay at home)**	**Highest Prob: home, stay, social, distanc, keep, peopl, safe** **FREX: social, distanc, stay, feet, apart, practic, physic** **Score: distanc, social, stay, home, feet, keep, practic**
Topic 16 (ppe shortage)	**Highest Prob: need, make, sure, protect, enough, person, take** **FREX: sure, need, enough, make, protect, adequ, person** **Score: need, sure, protect, make, enough, equip, person**	**Topic 66 (china blame)**	**Highest Prob: china, wuhan, chines, chine, januari, govern, origin** **FREX: chine, communist, china, jinp, beij, wuhan, hubei** **Score: china, wuhan, chine, chines, hong, januari, kong**
Topic 17 (dropped)	Highest Prob: love, happi, remind, want, beauti, birthday, brother FREX: love, brother, goodby, birthday, happi, beauti, grandma Score: love, birthday, happi, remind, brother, beauti, sister	Topic 67 (dropped)	Highest Prob: media, post, stori, read, quot, time, piec FREX: articl, media, read, write, stori, columnist, editori Score: media, read, post, stori, book, piec, write
Topic 18 (dropped)	Highest Prob: gave, repres, congressman, rare, chairman, deputi, peac FREX: deputi, congressman, mcadam, aixa, taliban, arrang, afghanistan Score: gave, congressman, repres, chairman, deputi, rare, afghanistan	**Topic 68 (blood immunity)**	**Highest Prob: antibodi, immun, recov, blood, plasma, donat, help** **FREX: plasma, convalesc, transfus, blood, antibodi, survivor, donor** **Score: antibodi, blood, immun, plasma, recov, donat, cancer**
Topic 19 (essential business)	**Highest Prob: store, order, essenti, groceri, shop, custom, peopl** **FREX: essenti, store, shopper, groceri, pharmaci, shop, costco** **Score: store, groceri, essenti, shop, order, custom, pharmaci**	**Topic 69 (death toll)**	**Highest Prob: case, death, number, confirm, state, corona, statenam** **FREX: rise, toll, case, climb, confirm, death, surpass** **Score: case, death, confirm, number, toll, state, statenam**
Topic 20 (dropped)	Highest Prob: call, phone, offic, wait, reach, without, save FREX: newday, call, apprai, refi, streamlin, dental, telephon Score: call, phone, hotlin, newday, dental, refi, offic	Topic 70 (dropped)	Highest Prob: anim, human, natur, smith, traffic, garden, land FREX: bird, crystal, gray, paint, speci, lawn, butt Score: anim, fish, traffic, smith, human, bird, garden
Topic 21 (case numbers/models)	**Highest Prob: look, number, seen, weve, happen, case, countri** **FREX: number, scenario, term, seen, weve, exponenti, compar** **Score: number, look, case, term, weve, seen, scenario**	Topic 71 (dropped)	Highest Prob: famili, time, life, friend, togeth, live, moment FREX: friend, emot, life, sleep, famili, father, bless Score: famili, friend, life, father, sleep, time, togeth

Topic 22 (dropped)	Highest Prob: just, facebook, page, neighbor, five, start, make FREX: census, censusgov, page, facebook, gift, bike, banner Score: facebook, page, census, neighborhood, card, gift, internet	**Topic 72 (hc worker safety)**	**Highest Prob: nurs, doctor, gear, there, work, medic, sick** **FREX: practition, malloy, bowser, sinai, mount, nypd, paramed** **Score: nurs, doctor, sinai, gear, mount, profession, sick**
Topic 23 (music performance)	**Highest Prob: music, perform, song, danc, sing, ladi, togeth** **FREX: musician, elton, song, lyric, grammi, marsali, music** **Score: music, song, sing, danc, artist, perform, ladi**	Topic 73 (dropped)	Highest Prob: sander, statenam, biden, berni, campaign, democrat, state FREX: deleg, sander, berni, abort, victori, buttigieg, caucus Score: sander, biden, berni, deleg, campaign, democrat, voter
Topic 24 (state pressers)	**Highest Prob: statenam, state, governor, govnam, order, announc, issu** **FREX: governor, govnam, stay–hom, newsom, state, statewid, cappabianca** **Score: governor, state, statenam, govnam, order, stay–hom, announc**	**Topic 74 (disinfecting)**	**Highest Prob: clean, touch, water, paper, disinfect, surfac, wipe** **FREX: bleach, disinfect, surfac, doorknob, ultraviolet, pepto, toilet** **Score: clean, disinfect, touch, surfac, water, toilet, paper**
Topic 25 (trump quotes 2)	**Highest Prob: work, think, peopl, want, done, differ, weve** **FREX: done, work, hard, think, quick, weve, everybodi** **Score: work, think, done, want, peopl, togeth, hard**	**Topic 75 (foreign response)**	**Highest Prob: countri, itali, lockdown, korea, minist, prime, govern** **FREX: spain, itali, prime, madrid, lockdown, minist, korea** **Score: itali, korea, lockdown, minist, prime, countri, spain**
Topic 26 (epidemic spread)	**Highest Prob: nation, second, contain, guard, wave, wors, first** **FREX: rochell, wave, rochel, contain, redfield, nation, guard** **Score: nation, contain, second, wave, guard, zone, wors**	**Topic 76 (uss theodore roosevelt)**	**Highest Prob: secretari, militari, letter, navi, deploy, personnel, command** **FREX: sailor, pentagon, theodor, roosevelt, crozier, aircraft, azar** **Score: secretari, militari, navi, sailor, letter, command, captain**
Topic 27 (global impact)	**Highest Prob: world, around, pandem, organ, global, wonder, globe** **FREX: world, around, whitney, wonder, globe, organ, global** **Score: world, around, organ, global, pandem, wonder, globe**	**Topic 77 (nursing homes)**	**Highest Prob: home, facil, staff, resid, member, center, care** **FREX: kirkland, resid, rehabilit, staff, facil, holyok, longterm** **Score: facil, staff, resid, home, nurs, center, member**

Topic 28 (racial disparities)	**Highest Prob: rate, death, popul, higher, black, communiti, high** **FREX: dispar, disproport, orlean, mortal, tragic, statist, fatal** **Score: rate, death, popul, black, mortal, dispar, africanamerican**	**Topic 78 (restart economy)**	**Highest Prob: back, month, start, come, normal, economi, soon** **FREX: normal, back, sooner, restart, soon, timelin, push** **Score: back, economi, normal, soon, month, return, push**
Topic 29 (presser text/official guidelines)	**Highest Prob: american, everi, countri, america, slow, singl, guidelin** **FREX: everi, singl, america, american, slow, strong, mitig** **Score: american, everi, countri, america, guidelin, mitig, slow**	**Topic 79 (schools)**	**Highest Prob: school, student, close, district, parent, learn, class** **FREX: elementari, student, superintend, classroom, school, campus, curriculum** **Score: school, student, district, teacher, class, parent, educ**
Topic 30 (dropped)	Highest Prob: outbreak, fear, dead, corona, caus, kill, amid FREX: outbreak, dead, amid, fear, novel, caus, tape Score: outbreak, dead, kill, caus, fear, amid, novel	**Topic 80 (voting)**	**Highest Prob: elect, vote, poll, primari, mail, ballot, voter** **FREX: absente, mailin, mail-, absent, elect, legislatur, ballot** **Score: vote, elect, ballot, poll, voter, primari, mail**
Topic 31 (reopening)	**Highest Prob: open, reopen, park, close, restrict, allow, guidelin** **FREX: alley, spas, tattoo, reopen, open, re-open, parlor** **Score: reopen, open, park, beach, restrict, salon, phase**	Topic 81 (dropped)	Highest Prob: plan, prepar, readi, cost, panic, insur, option FREX: plan, supplement, prepar, cost, panic, medicaid, conting Score: plan, prepar, insur, panic, cost, medicar, readi
Topic 32 (dropped)	Highest Prob: gonna, meant, boost, opposit, twice, excus, crack FREX: gonna, leland, meant, mari, quicker, donni, gillian Score: gonna, meant, leland, opposit, vitamin, quicker, gillian	**Topic 82 (facts/science)**	**Highest Prob: crisi, deal, fact, know, matter, handl, govern** **FREX: trust, hurrican, leadership, crise, credibl, massachusett, scienc** **Score: leadership, crisi, scienc, trust, fact, govern, handl**
Topic 33 (wh task force)	**Highest Prob: presid, trump, hous, white, administr, forc, brief** **FREX: brief, white, presid, trump, penc, administr, task** **Score: presid, trump, white, brief, hous, administr, vice**	**Topic 83 (health officials)**	**Highest Prob: corona, health, offici, spread, public, diseas, concern** **FREX: offici, monitor, c-dc, spread, public, health, infecti** **Score: health, offici, spread, corona, public, diseas, depart**
Topic 34 (scams)	**Highest Prob: inform, answer, question, visit, corona, pleas, check** **FREX: scam, inform, scammer, question, text, email, awar** **Score: inform, question, visit, answer, pleas, scam, text**	**Topic 84 (partisan blame)**	**Highest Prob: polit, protest, state, republican, democrat, want, stayathom** **FREX: stayathom, texa, committ, kentucki, tenness, kansa, partisanship** **Score: polit, republican, protest, democrat, stayathom, texa, liber**

Topic 35 (masks)	**Highest Prob: mask, face, wear, cover, protect, glove, recommend** **FREX: scarf, bandanna, bandana, wear, scarv, mask, nonmed** **Score: mask, wear, face, glove, gown, surgic, cover**	**Topic 85 (vaccine/treatment)**	**Highest Prob: vaccin, drug, studi, treatment, research, trial, effect** **FREX: remdesivir, drug, hydroxi, vaccin, chloroquin, azithromycin, anti-malaria** **Score: drug, vaccin, trial, studi, hydroxychloroquin, treatment, research**
Topic 36 (increase local cases)	**Highest Prob: countynam, counti, case, depart, confirm, peopl, total** **FREX: counti, bassigood, dahlkemp, d-hh-r, rufffirst, dhec, fayett** **Score: counti, countynam, case, depart, confirm, recov, statewid**	**Topic 86 (hospital capacity)**	**Highest Prob: hospit, patient, medic, treat, emerg, care, center** **FREX: javit, hospit, noncovid, tent, patient, makeshift, overrun** **Score: hospit, patient, medic, treat, care, capac, javit**
Topic 37 (transmission)	**Highest Prob: peopl, infect, risk, know, sick, dont, mani** **FREX: asymptomat, infect, contagi, risk, transmiss, transmit, influenza** **Score: infect, peopl, risk, sick, asymptomat, dont, know**	**Topic 87 (trump quotes 3)**	**Highest Prob: said, didnt, never, thought, went, happen, told** **FREX: didnt, wasnt, wrong, nobodi, truth, knew, said** **Score: didnt, said, nobodi, truth, wasnt, wrong, februari**
Topic 38 (event cancellation)	**Highest Prob: cancel, event, schedul, postpon, march, gather, decis** **FREX: event, cancel, parad, festiv, sxsw, schedul, irish** **Score: cancel, event, postpon, festiv, schedul, trip, parad**	**Topic 88 (airport screening)**	**Highest Prob: screen, intern, flight, airport, airlin, arriv, transport** **FREX: airport, screen, ohar, chao, abdi, domest, intern** **Score: airport, screen, flight, intern, airlin, passeng, domest**
Topic 39 (food insecurity)	**Highest Prob: help, food, donat, need, famili, peopl, give** **FREX: salvat, nonprofit, volunt, help, non-profit, pantri, feed** **Score: help, food, donat, meal, volunt, bank, feed**	Topic 89 (dropped)	Highest Prob: tabl, cook, make, kitchen, dinner, fresh, favorit FREX: chef, dinner, ninja, foodi, butter, chees, bake Score: cook, tabl, kitchen, dinner, chef, fresh, cooki
Topic 40 (travel restrictions)	**Highest Prob: travel, unit, state, restrict, border, close, announc** **FREX: border, travel, advisori, canada, mexico, kingdom, suspend** **Score: travel, border, restrict, unit, europ, state, suspend**	**Topic 90 (contact tracing)**	**Highest Prob: system, trace, contact, learn, huge, abil, epidem** **FREX: trace, system, strategi, pathogen, scale, robust, infrastructur** **Score: system, trace, contact, epidem, strategi, huge, scale**
Topic 41 (easter/worship)	**Highest Prob: sunday, church, easter, servic, mass, peopl, faith** **FREX: church, pastor, jesus, parishion, christian, communion, faith** **Score: church, easter, sunday, pastor, faith, worship, servic**	Topic 91 (dropped)	Highest Prob: former, biden, debat, campaign, obama, race, democrat FREX: barack, obama, debat, former, impeach, endors, abram Score: biden, former, campaign, obama, presidenti, democrat, debat

Topic 42 (business impact)	**Highest Prob: busi, restaur, small, close, owner, shut, employe** **FREX: owner, busi, restaur, casino, small, afloat, boutiqu** **Score: busi, restaur, owner, small, employe, shut, industri**	Topic 92 (dropped)	Highest Prob: veri, becaus, know, befor, just, realli, respon FREX: veri, befor, becaus, dure, increa, signif, disea Score: veri, becaus, befor, disea, respon, cour, deci
Topic 43 (models)	**Highest Prob: week, data, curv, still, model, peak, project** **FREX: flatten, curv, model, peak, plateau, project, predict** **Score: curv, flatten, model, peak, data, project, predict**	**Topic 93 (local response)**	**Highest Prob: local, meet, leader, oper, manag, emerg, take** **FREX: local, ordin, votak, council, amarillo, manag, poconnor** **Score: local, oper, leader, meet, council, execut, manag**
Topic 44 (dropped)	Highest Prob: overnight, even, jami, that, tick, moral, kris FREX: seth, nigh, herniw, yucca, cbsnewscom, erni, erniw Score: overnight, kris, herniw, jami, drone, nigh, seth	Topic 94 (dropped)	Highest Prob: video, countynam, look, movi, quarantin, pictur, shes FREX: rita, film, episod, slider, netflix, photo, tiktok Score: video, movi, film, instagram, photo, hank, tiger
Topic 45 (graduation)	**Highest Prob: year, senior, high, summer, graduat, last, juli** **FREX: cadet, commenc, ceremoni, year, graduat, camp, derbi** **Score: year, graduat, senior, summer, ceremoni, juli, prom**	Topic 95 (dropped)	Highest Prob: show, announc, blue, harvey, imag, appar, corona FREX: harvey, show, graphic, beard, ingraham, display, circus Score: show, harvey, announc, blue, imag, graphic, display
Topic 46 (virus exposure)	**Highest Prob: posit, contact, isol, person, negat, symptom, corona** **FREX: posit, self, self-quarantin, negat, prison, isol, expos** **Score: posit, contact, isol, negat, symptom, test, expos**	**Topic 96 (frontline workers)**	**Highest Prob: line, front, long, just, theyr, scare, afraid** **FREX: scare, front, line, island, heartbreak, afraid, hero** **Score: line, front, scare, island, hero, afraid, long**
Topic 47 (cruise)	**Highest Prob: ship, cruis, passeng, board, coast, crew, peopl** **FREX: crui, dock, ship, maggi, cruis, sail, holland** **Score: ship, cruis, passeng, princess, dock, crui, crew**	**Topic 97 (market impact)**	**Highest Prob: price, percent, drop, sell, quarter, industri, demand** **FREX: price, goug, crude, buyer, arabia, saudi, invest** **Score: price, percent, sale, sell, consum, quarter, invest**
Topic 48 (dropped)	Highest Prob: serv, veteran, deliveri, commit, honor, corona, club FREX: beer, uber, brew, booz, breweri, nasa, sentenc Score: serv, veteran, deliveri, beer, commit, club, drink	Topic 98 (dropped)	Highest Prob: group, plea, target, upon, vital, hate, equal FREX: discrimin, upon, plea, incid, vega, strip, hate Score: group, plea, upon, vital, target, hate, discrimin
Topic 49 (dropped)	Highest Prob: updat, websit, site, list, also, monday, locat FREX: thru, abccom, tupelo, hclose, networkh, kourtney, websit Score: websit, site, updat, list, locat, hall, monday	**Topic 99 (homeless)**	**Highest Prob: place, shelter, peopl, hotel, homeless, adopt, room** **FREX: shelter, homeless, place, motel, foster, veterinari, adopt** **Score: place, shelter, homeless, hotel, adopt, foster, street**

Topic 50 (tech)	**Highest Prob: track, connect, technolog, virtual, tool, phone, network** **FREX: googl, user, softwar, privaci, track, technolog, password** **Score: track, connect, technolog, zoom, googl, phone, virtual**	Topic 100 (dropped)	Highest Prob: come, time, take, also, first, mani, even FREX: come, take, time, mani, even, first, also Score: come, time, take, mani, first, even, also

Polarized Phrases between MSNBC and FOX

Phrase Detection

Prior research has shown that phrases are better at capturing semantic meaning and characteristics of text than single words [cite]. We detect phrases from our TV news corpus using a simple heuristics [cite]:

$$\frac{(bigram\_count - min\_count) * length\_vocab}{word_a\_count * word_b\_count}$$

Any bigram scores above threshold value 5 in the above formula were kept as a phrase. We excluded phrases that appeared less than 20 times in our corpus. We ran the above phrase detector twice, to obtain both bigram and trigram phrases. We also allowed some common interstitial words to appear in phrases without contributing to the phrase limit length.. The list of interstitial words are: ”of”, ”with”, ”without”, ”and”, ”or”, ”the”, ”a”, ”as”, ”for”.

Polarized Phrases

We estimated the polarization of phrases based on their topic-level log odds ratio between MSNBC and FOX for all topics that have a significant number of documents belonging to it (i.e. at least 200 documents have topic proportions greater than 0.15 for that topic). We manually filtered out phrases that were the names of hosts, anchors or news correspondents (e.g. Tucker Carlson), channel-specific language (e.g.

Fox News Alert), commercials (e.g. Xfinity), etc. This process resulted in a list of polarized phrases for each topic (i.e. phrases with high absolute log odds ratio). A positive log odds ratio indicates the tendency for Fox News to use the phrase more than MSNBC, while a negative log odds ratio indicates the tendency for MSNBC to use the phrase more than Fox News.

To determine general polarized phrases (i.e., not topic-specific), we selected all phrases that appeared in more than 10 topics. Each token (word or phrase) has a distribution of log odds ratios across all topics, indicating the extent to which it is polarized for each topic. To determine overall polarization (independent of topics), we calculated the mean and standard error of this distribution. Table A5 displays the top 50 polarized phrases (by absolute value) for both MSNBC and FOX:

Table A5: Selected Phrases

FOX News

Token	Mean	SE	N
medic panel	0.710	0.042	20
make america healthi	0.701	0.031	23
communist parti	0.699	0.046	16
mob and the media	0.688	0.052	11
no out of pocket	0.685	0.032	28
there no incom	0.678	0.033	30
fake news cnn	0.675	0.040	15
cough short of breath	0.671	0.052	14
tele health	0.671	0.054	14
wuhan lab	0.668	0.062	13
investig into	0.660	0.051	19
illeg immigr	0.654	0.082	19
blood bank	0.647	0.056	14
kim jong un	0.642	0.028	40
media mob	0.639	0.058	29
north korean	0.632	0.031	20
quid pro quo joe	0.631	0.041	13
posit result	0.624	0.034	27
china account	0.622	0.071	16
chines communist parti	0.622	0.071	27
green new deal	0.614	0.068	21
itali and south korea	0.605	0.052	24
out of pocket	0.598	0.050	35
north lawn	0.597	0.040	33
small studi	0.597	0.074	14
healthcar provid	0.593	0.031	31
three phase	0.577	0.110	13
cdc headquart	0.574	0.061	29
communist chines	0.572	0.049	14
good advic	0.571	0.078	22
save countless	0.570	0.077	17
diamond princess cruis ship	0.569	0.076	17
tom hank and his wife	0.557	0.080	15
crack down	0.554	0.083	25
mortgag rate	0.553	0.062	23
spend bill	0.548	0.061	29
move fast	0.541	0.079	21
state of the union	0.539	0.091	19
healthcar worker	0.535	0.025	50
health organ	0.535	0.076	18
chines author	0.535	0.089	20
healthcar system	0.532	0.046	46
under medic condit	0.531	0.063	25
base on the data	0.531	0.077	23
antivir drug	0.526	0.085	20
patient zero	0.526	0.081	22
vitamin c	0.521	0.106	15
michell obama	0.515	0.118	11
travel advisori	0.515	0.063	31
clean bill	0.506	0.060	19

MSNBC

Token	Mean	SE	N
his own administr	-0.702	0.041	16
lower incom	-0.647	0.037	21
his aid	-0.642	0.038	22
his reelect	-0.642	0.030	24
feder leadership	-0.640	0.046	20
conserv media	-0.633	0.066	16
senat gym	-0.630	0.038	13
black communiti	-0.629	0.039	22
grand island	-0.629	0.037	15
his alli	-0.626	0.038	18
trump tv	-0.625	0.039	21
senior advis	-0.624	0.034	18
his reelect campaign	-0.617	0.050	16
right wing	-0.616	0.048	18
oval offic address	-0.614	0.056	17
dure the obama	-0.612	0.036	18
farm worker	-0.599	0.055	12
montgomeri counti	-0.577	0.045	12
free press	-0.574	0.067	19
front line health care	-0.569	0.053	28
meat process	-0.568	0.056	21
gold standard	-0.566	0.067	23
meat pack	-0.565	0.067	21
your constitu	-0.564	0.059	30
his base	-0.563	0.062	25
compet against each other	-0.562	0.045	18
mix messag from	-0.549	0.074	20
human toll	-0.547	0.064	30
absente ballot	-0.547	0.053	13
sander campaign	-0.546	0.082	11
communiti of color	-0.545	0.053	32
peopl of color	-0.545	0.074	25
third wave	-0.544	0.076	18
by mail	-0.543	0.088	20
econom advis	-0.542	0.076	23
nurs home resid	-0.542	0.048	16
fact check	-0.542	0.072	26
meat plant	-0.542	0.081	19
ebola outbreak	-0.540	0.072	21
so far behind	-0.536	0.046	23
there arent enough	-0.535	0.069	25
nativ american	-0.530	0.091	16
racial dispar	-0.528	0.095	18
direct cash payment	-0.527	0.054	13
relief check	-0.526	0.069	18
expand medicaid	-0.526	0.085	23
general elect	-0.522	0.056	22
health dispar	-0.521	0.067	18
three feet	-0.517	0.087	23
medic advis	-0.515	0.067	22

Measures of Polarization

Topic Selection Polarization

We use a simple estimator of topic selection polarization by channel based on the topic proportion estimated by our structural topic model. The intuition is that this estimator indicates the skew of a given topic distributed across two channels (i.e. MSNBC and FOX in our case). This gives us a measure of what the media choose to talk about. Let i index the segment and T index the topic. Each document has a vector of weights for each topic that sum to 1. We can speak of $W_{T,i}$ which is the weight of topic T for a particular segment i. For each topic, we can calculate two numbers that correspond to the probability of a document that is about topic T being sourced from MSNBC or FOX, respectively:

$$P(MSNBC|T) = \frac{\sum_{i \in MSNBC} W_{T,i}}{\sum_i W_{T,i}} \qquad P(FOX|T) = \frac{\sum_{i \in FOX} W_{T,i}}{\sum_i W_{T,i}}$$

Clearly, $P(MSNBC|T) + P(FOX|T) = 1$. The topic selection polarization of a given topic can be defined as:

$$\rho_T^{Topic} = \max(P(MSNBC|T), P(FOX|T))$$

Term Selection Polarization

We adopt the estimator of group differences from Gentzkow et al. (2019) and measure term-selection polarization based on the broadcasted text content chosen by the channels. This approach takes advantage of recent advances in machine learning and out-of-sample validation using Congressional speech has demonstrated that it outperforms standard approach in reducing bias and variance. Polarization is defined as likelihood of which an observer with a neutral prior could infer a TV segment's correct source (i.e. FOX or MSNBC) after observing a single token drawn at random from the segment. If there is no difference in token usage between the two sources, this probability should be 0.5, i.e. we cannot guess the document's source any better after observing a token. The details of this estimator can be found in Gentzkow et al. (2019). We adapt this measure and replace the "leave-out" count with total count as we are interested in inferring the source of news content and do not have the concept of "author" in our data structure as in the original paper. The estimator consistently estimates polarization under the assumption that a user's tokens are drawn from a multinomial logit model. The estimate of polarization π between MSNBC $i \in D$ and FOX $i \in R$ is

$$\hat{\pi} = \frac{1}{2}(\hat{q}_i^R \cdot \hat{\rho} + \hat{q}_i^D \cdot (1 - \hat{\rho}))$$

Where $\hat{q}_i = \frac{c_i}{m_i}$ is the vector of empirical token frequencies for segment i, with c_i being the vector of token counts for segment i and m_i is the sum of token counts for segment i; and $\hat{\rho} = \frac{q_D}{(q_D + q_R)}$ is a vector of empirical posterior probabilities. The estimator can be viewed as a weighted average of word-level features, where features are weighted by their distribution over the two channels.

Topic Level Measures

We first apply our term-selection polarization measure at the topic level. In order to do so, we first translated the topic mixture of documents from our structural topic model (STM) to a hard assignment. We assigned a document to a topic if its topic proportion estimated by our STM was greater than 0.15. In this way, a document was hard assigned to one or more topics. This threshold was chosen to restrict hard topic assignments only to cases where the document was substantially comprised of the topic. Our results are robust to different choices of this threshold.

This procedure yielded a collection of documents for each topic. We calculated term-selection polarization for each topic that had at least 200 documents assigned to it. When applying this measure to a group of documents about a given topic, this polarization estimator measures how different channels talk about the same topic differently. Therefore, it gives us an intuitive measure of how media ”frame” coverage of a particular topic.

Time Level Measures

We also apply this measure to all documents in a time period in our presser analysis (i.e. before, during, and after the presser) without considering topics classification. In doing so, this measure gives us an overall measure of polarization of both what you talk about and how you talk about it.

Semantic Textual Similarity: Sentence Transformers

We use the state-of-art neural language embedding to obtain vector representation of both TV segment and Presser segment. Neural embeddings project high-dimension text to a low-dimensional vector space and can capture context and semantic meaning of text much better than traditional NLP techniques that rely on bag-of-words representation (Camacho-Collados and Pilehvar, 2018). We choose ”sentence-BERT”, a state-of-art pretrained model that has been shown to achieve excellent performance in a variety of language tasks. (Reimers and Gurevych, 2019), which is our use case. We used the pretrained sentence transformer model ”bert-base-nli-stsb-mean-tokens”. The model was further fine-tuned on training data from the STS benchmark so it is specifically well suited for measuring semantic textual similarity, which is our use case. The training code and pretrailed models are publicly accessible through a python library: https://github.com/UKPLab/sentence-transformers. Punctuations and special characters are removed before feeding text into the model. After obtaining embeddings representation for 53,164 cable news segments and 7,468 Trump pressers segments, we calculate the pairwise cosine similarity between the two sets of texts, resulting in 397,028,752 pairwise similarity values. For each of the 53,164 TV segments, we match them with a presser segment that happened within the same day and has the highest similarity value. We calculate average similarity to pressers for all three cable channels in before, during, and after period by averaging all best matched similarity values for the TV segments in the respective time period.

Media Responsiveness to Trump Briefings

In this section, we look at how the cable news channels cover Trump briefings. In particular, we focus on the semantic textual similarity of cable news to Trump briefings before, during, and after the briefings.

Before, During, and After Press Conference

The starting times vary slightly across the 39 press conferences with most of them starting at 17:00 pm EST. See the table A6.

Table A6: Trump Presser Start Times.

Start Time	n
11:00:00	1
11:30:00	2
11:45:00	1
12:00:00	1
12:30:00	1
13:00:00	1
15:30:00	2
17:00:00	26
17:30:00	2
18:00:00	1
19:00:00	1

We calculate the difference between the timestamps of news segments and the start times press conferences and align the cable news coverage relative to the start time of the presser conferences. News segments fall into -5 hour to 0 hour relative to the start time of press conferences will be classified as belonging to the before period; News segments fall into 0 hour to 2 hour relative to the start time of press conferences will be classified as belonging to the during period; News segments fall into 2 hour to 5 hour relative to the start time of press conferences will be classified as belonging to the after period.

Identifying Trump Quotes

Media responses to Trump Briefings through both directly quote what he said and more generally change their news content to focus on the issue he brought up. We are interested in both. To check our results of language similarity between news and Trump briefings are not just because news quote what Trump said in briefings, we identify direct Trump quotes in the news content during the after briefing period and exclude them in the analysis as a robustness check. To identify direct Trump quotes, we generate all possible 9-gram from Trump speech in the daily briefings. We identify all TV segments that contain at least one of those 9-gram in Trump briefings and exclude them in the additional analysis. A TV segment is around 200 words so it should contain both the quote and some discussions around the quote. Over the time period, we identify 1,068 TV segments in total that have at least one Trump briefing 9-grams: 392 from MSNBC, 356 from CNN, 320 from FOX.

Model Free Evidence

Table A7 shows the summary statistics of TV segment similarity to Trump presser before, during, and after the presser.

Table A7: Average Semantic Textual Similarity by Channel and Period.

Period	Channel	Mean	SE	N
Before	MSNBC	0.544	0.001	2472
Before	CNN	0.546	0.001	2377
Before	FOX	0.548	0.001	2296
During	MSNBC	0.582	0.003	1258
During	CNN	0.579	0.003	1356
During	FOX	0.597	0.003	951
After	MSNBC	0.555	0.002	2026
After	CNN	0.563	0.002	1967
After	FOX	0.561	0.002	2047
After (without quotes)	MSNBC	0.55	0.002	1941
After (without quotes)	CNN	0.559	0.002	1887
After (without quotes)	FOX	0.555	0.002	1964

Modelling Media Responsiveness

In addition to the model-free plot in the main paper, we also fit a linear regression model with both channel and date fixed effect. The model helps account for channel heterogeneity and common time trends across channels and makes sure the results are not just driven by a few high similarities from a few dates. We run this model with semantic textual similarity between cable news and Trump briefings as outcome variable and both including and excluding Trump quote TV segments as shown in column (1) and column (2) respectively in the following two tables. We can see from column (1) of Table A8 that the effect size for the after period is about 38% of the during period. When excluding direct Trump quotes, the effect for after period drops to about 26% of the during period. This is consistent with our expectation as direct quotes by definition have high semantic textual similarities. Removing them from after period will lower the average similarity for the after period. Nonetheless, we observe strong media amplification of Trump briefings with or without Trump quotes from both the model-free plot and model estimates.

Table A8: Media Amplification.

	Dependent variable:	
	Language Similarity with Trump Presser	
	(1)	(2)
during	0.039***	0.039***
	(0.004)	(0.004)
after	0.015***	0.010***
	(0.002)	(0.002)
Channel Fixed Effect	Yes	Yes
Date Fixed Effect	Yes	Yes
Observations	16,750	16,502
R^2	0.186	0.188
Note:		*p<0.1; **p<0.05; ***p<0.01

Furthermore, we include channel dummies and their interactions with time periods to investigate heterogeneous effects for different channels. Again, we run the linear regression model with date fixed effect for average semantic textual similarity with or without Trump quotes. The results are shown in column (1) and (2) in Table A9 and the base group is CNN. The media amplification main effect is little bit lower for MSNBC than CNN (with marginal significance). FOX in the during period has a significantly (both magnitude and statistical) higher semantic textual similarity than CNN.

Table A9: Media Amplification.

	Dependent variable:	
	Language Similarity with Trump Presser	
	(1)	(2)
during	0.032***	0.033***
	(0.005)	(0.005)
after	0.015***	0.011***
	(0.003)	(0.003)
MSNBC	−0.004*	−0.004*
	(0.002)	(0.002)
FOX	−0.0001	0.0002
	(0.002)	(0.002)
during_MSNBC	0.006	0.006
	(0.006)	(0.006)
after_MSNBC	−0.001	−0.002
	(0.003)	(0.003)
during_FOX	0.015**	0.015**
	(0.006)	(0.006)
after_FOX	0.00001	−0.00001
	(0.003)	(0.003)
Channel Fixed Effect	No	No
Date Fixed Effect	Yes	Yes
Observations	16,750	16,502
R^2	0.187	0.189
Note:		*p<0.1; **p<0.05; ***p<0.01

Viewership Pattern

We get viewership estimates from Nielsen's national representative panel.The viewership estimates are built from individual-level data from Nielsen's national representative panel. The panel is all adult (18+) Americans and viewership estimates are captured at the 30 minutes level and is aggregated across the US based on demographic weight.

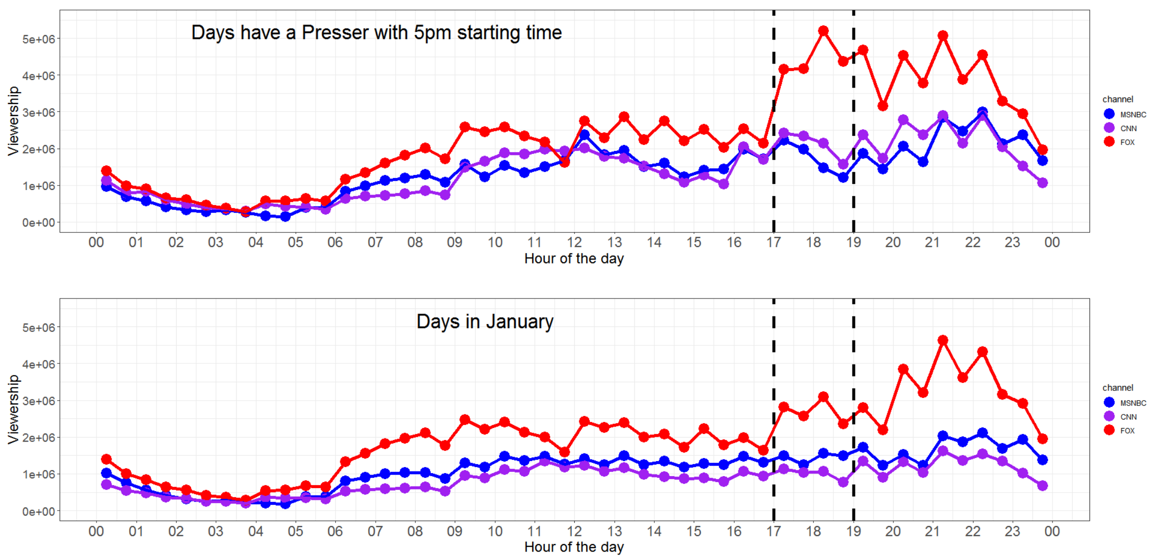

Figure A4. Viewership on Presser Dates vs January.

We first plot the average viewership pattern over a 24 hours cycle for 1) days in January as a baseline for comparison; 2) days where the pressers were held at 5pm that day. We use viewership in January as a baseline (bottom panel) as the coronavirus pandemic hasn't attracted much public and media attention back then. The two black dashed lines represent 17:00h and 19:00h EST, i.e. the begin and the end of the presser if held. A few patterns emerge the plot:

1. FOX viewership has a spike during presser time compared to January. The spike makes the average viewership during presser hours (17h-19h) on par with

average viewership during prime hours (20h-22h).

2. CNN and MSNBC do not see such a spike during presser hours, but their viewership is still higher than their counterpart hours (17h-19h) in January. For CNN and MSNBC, average viewership during prime hours is higher than presser hours.

To facilitate the comparison of viewership during and after the press conference, now we turn to the hours after 5pm of a day and provide detailed viewership numbers

More findings from examining the viewership numbers:

1. People in general watch more cable news (average over 24 hour) during presser days than in January - 29% higher on average over the 24 hour period. It's likely a combination effect of stay at home and demand for information. This pattern is even more salient for prime hours (20h-22h) - 33% higher than January. There are more eyeballs on cable news during the crisis.

2. Prime hours have a higher viewership per hour than presser hours on average for the three cable news channels. When we break down by channel. Compared to press conferences, prime time viewership is 20% higher for CNN, 31% higher than MSNBC, and 4% lower for FOX.

Table A10: Cable Viewership.

Channel	Hour	Presser Date Rating	January Rating
MSNBC	17	2103721	1363040
MSNBC	18	1335715	1529052
MSNBC	19	1650331	1474712
MSNBC	20	1847060	1376108
MSNBC	21	2656193	1941777
MSNBC	22	2560590	1899119
MSNBC	23	2020550	1653117
CNN	17	2377333	1086378
CNN	18	1851235	920161.1
CNN	19	2050336	1122991
CNN	20	2571803	1183225
CNN	21	2520379	1493339
CNN	22	2471827	1446331
CNN	23	1290346	849443.7
FOX	17	4162056	2685652
FOX	18	4780829	2726346
FOX	19	3915058	2492932
FOX	20	4155127	3523378
FOX	21	4469120	4121222
FOX	22	3915400	3738160
FOX	23	2447002	2430781

Bing Search Results

To measure search patterns, we relied on search results from the Bing.com search engine. For each topic selected as relevant, we used the top 10 highest probability words, frex words, and score words (removing duplicates). We then limited the results based on search queries that contained the strings ”covid”, ”corona”, or ”virus”. For example, Topic 9 would contain search queries such as ”covid test”, ”swap corona”, and ”rapid virus test”, while Topic 58 would contain search queries such as ”covid heart”, ”covid risk”, and ”coronavirus lung”. A full list of topic words used to determine each topic is displayed in Table A11.

Table A11: Search Terms

Topic	Terms
2	avail, privat, continu, addit, state, expand, direct, resourc, effort, guidanc, partnership, priorit, coordin, fema, sector, commerci
3	break, spring, parti, party, view, express, generat, beach, peopl, young, topic, lindsey, graham, cherry, cherri, shannon, outlet, blossom, survey, narrat
4	quarantin, base, japan, american, corona, olymp, week, diamond, evacu, back, evacue, japanes, tokyo, lackland, yokohama, travi, cambodia, princess, passeng
6	money, fund, dollar, program, check, loan, billion, payment, small, bank, deposit, paycheck, evict, landlord, rent, budget, stimulus
7	lock, elimin, southeast, molli, molly, logic, sweden, bubbl, tiny, hunter, stack, zealand, mont, visual, cove, patt, erickson, erika, beaumont, denmark
9	test, result, week, swab, still, process, rapid, capac, ramp, widespread, diagnost, sampl, reagent, criteria, specimen, laboratori, laboratory, symptom
13	report, here, warn, reveal, boris, promis, johnson, whit, -year-old, trevor, costello, ault, llama, intensifi, intensify
15	citi, city, area, mayor, spot, across, west, first, major, metro, blasio, metropolitan, garcetti, yorker
16	need, make, sure, protect, enough, person, take, doctor, care, dont, adequ, ration, appropri, proper, equip
19	store, order, essenti, groceri, grocery, shop, custom, peopl, limit, servic, enforc, shopper, pharmaci, pharmacy, costco, walmart, deem, shelv, retail
21	look, number, seen, weve, happen, case, countri, country, term, start, differ, scenario, exponenti, compar, probabl, larger, unit
23	music, perform, song, danc, sing, ladi, togeth, band, artist, concert, musician, elton, lyric, grammi, grammy, marsali, prine, roger, album, singer
24	state, governor, order, announc, issu, said, also, stay–hom, newsom, statewid, cappabianca, acton, extend
26	nation, second, contain, guard, wave, wors, first, third, difficult, zone, rochell, rochel, redfield, cluster
27	world, around, pandem, organ, global, wonder, globe, anoth, victim, halt, whitney, grip, refug, polka
28	rate, death, popul, higher, black, communiti, community, high, fatal, mortal, among, dispar, disproport, orlean, tragic, statist, poorest, africanamerican
31	open, reopen, park, close, restrict, allow, guidelin, beach, phase, still, alley, spas, tattoo, re-open, parlor, loosen, lift, salon
33	presid, trump, hous, white, administr, forc, brief, task, vice, said, penc, press, downplay, fauci
34	inform, answer, question, visit, corona, pleas, check, awar, send, email, scam, scammer, text, phish
35	mask, face, wear, cover, protect, glove, recommend, public, gown, cloth, scarf, bandanna, bandana, scarv, nonmed, surgic, shield
36	counti, county, case, depart, confirm, peopl, total, three, health, bring, bassigood, dahlkemp, d-hh-r, rufffirst, dhec, fayett, nextplus, d-hec, manate, recov, statewid, -hundr
37	peopl, infect, risk, know, sick, dont, many, spread, serious, mean, asymptomat, contagi, transmiss, transmit, influenza, older, lethal, elder, symptom
38	cancel, event, schedul, postpon, march, gather, decis, trip, corona, impact, parad, festiv, sxsw, irish, patrick, reschedul
39	help, food, donat, need, famili, family, peopl, give, meal, volunt, deliv, salvat, nonprofit, non-profit, pantri, pantry, feed, insecur, hunger, bank, distribut
40	travel, unit, state, restrict, border, close, announc, citizen, suspend, europ, advisori, advisory, canada, mexico, kingdom, homeland, entri, entry, oversea
41	sunday, church, easter, servic, mass, peopl, faith, pray, prayer, celebr, pastor, jesus, parishion, christian, communion, holi, holy, basilica, worship
42	busi, restaur, small, close, owner, shut, employe, many, industri, industry, door, casino, afloat, boutiqu, tourism, dine-, patron, custom
43	week, data, curv, still, model, peak, project, flatten, hope, next, plateau, predict, apex, metric, trajectori
45	year, senior, high, summer, graduat, last, july, univers, pandem, next, cadet, commenc, ceremoni, ceremony, camp, derby, prom, miller
46	posit, contact, isol, person, negat, symptom, corona, expos, anyon, test, self, self-quarantin, prison, pend, gosar, notifi, notify, quarantin
47	ship, cruis, passeng, board, coast, crew, peopl, princess, grand, dock, crui, maggy, sail, holland, port, onboard
50	track, connect, technolog, virtual, tool, phone, network, zoom, tech, googl, user, softwar, privacy, password, appl
52	hand, wash, sanit, precaut, avoid, take, extra, shake, best, hygien, elbow, distil, handshak, bump, soap, sneez, cough
54	market, stock, point, economi, economy, econom, street, corona, wall, impact, trade, nasdaq, selloff, investor, recess, uncertainti, uncertainty, burr, plung
55	health, care, communiti, community, provid, support, servic, respond, access, also, resourc, mental, telehealth, ensur
56	million, week, last, unemploy, claim, peopl, file, benefit, month, lost, jobless, laid, labor, appli

58	condit, heart, diseas, pain, lung, under, risk, medic, caus, complic, apoquel, allerg, stroke, vape, kidney, chronic, smoker, itch, diabet, asthma, skin
60	plant, food, process, anxieti, anxiety, farmer, meat, produc, suppli, supply, farm, chain, agricultur, tyson, crop, rancher, meatpack, pork, dairi
61	symptom, breath, fever, doctor, cough, corona, feel, short, husband, babi, babi, runny, birth, woke, cold, headach, pregnant, sore, newborn, pneumonia
62	worker, compani, company, healthcar, employe, work, design, hire, make, build, first, printer, ford, hazard, frontlin, bonus, amazon, factori
63	senat, congress, hous, packag, pass, democrat, billion, relief, hill, trillion, schumer, pelosi, negoti, speaker, mitch, mcconnel, nancy, lawmak, oversight, vote, republican, stimulus
64	ventil, suppli, supply, feder, govern, need, equip, medic, shortag, product, state, stockpil, invok, strateg, manufactur
65	home, stay, social, distanc, keep, peopl, safe, everyon, practic, away, feet, apart, physic, maintain
66	china, wuhan, chines, chine, january, govern, origin, human, come, intellig, communist, jinp, beij, hubei, hong, kong
68	antibodi, antibody, immun, recov, blood, plasma, donat, help, cancer, cross, patient, convalesc, transfus, survivor, donor, platelet, anti-bodi
69	case, death, number, confirm, state, corona, near, peopl, thousand, rise, toll, climb, surpass, -thousand, deadliest, total
72	nurs, doctor, gear, there, work, medic, sick, mount, profession, crisi, practition, malloy, bowser, sinai, nypd, paramed, -hour, hospic
74	clean, touch, water, paper, disinfect, surfac, wipe, toilet, light, insid, bleach, doorknob, ultraviolet, pepto, lysol, knob, germ
75	countri, country, itali, italy, lockdown, korea, minist, prime, govern, spain, europ, measur, madrid, contin, germany, traci, iran, franc
76	secretari, secretary, military, letter, navy, deploy, personnel, command, mission, sent, sailor, pentagon, theodor, roosevelt, crozier, aircraft, azar, troop, captain
77	home, facil, staff, resid, member, center, care, nurs, live, famili, family, kirkland, rehabilit, holyok, long-term, inmat, rehab, parol, visitor
78	back, month, start, come, normal, economi, economy, soon, next, push, return, sooner, restart, timelin, paus, fall
79	school, student, close, district, parent, learn, class, children, educ, onlin, elementary, superintend, classroom, campus, curriculum, semest, teacher, colleg
80	elect, vote, poll, primari, primary, mail, ballot, voter, novemb, state, absente, mailin, mail-, absent, legislatur, postal
82	crisi, deal, fact, know, matter, handl, govern, public, understand, scienc, trust, hurrican, leadership, crise, credibl, massachusett, knowledg, katrina, role
83	corona, health, offici, spread, public, diseas, concern, prevent, depart, control, monitor, c-dc, infecti, ghebreyesus
84	polit, protest, state, republican, democrat, want, stayathom, like, economi, economy, side, texa, committ, kentucki, kentucky, tenness, kansa, partisanship, liber, wyom, partisan
85	vaccin, drug, studi, study, treatment, research, trial, effect, doctor, develop, clinic, remdesivir, hydroxi, chloroquin, azithromycin, anti-malaria, malaria, antivir, hydroxychloroquin
86	hospit, patient, medic, treat, emerg, care, center, doctor, room, come, javit, noncovid, tent, makeshift, overrun, surgeri, surgery, triag, elmhurst, capac, surg
88	screen, intern, flight, airport, airlin, arriv, transport, domest, passeng, come, ohar, chao, abdi, delta, checkpoint, aviat
90	system, trace, contact, learn, huge, abil, epidem, approach, strategi, strategy, scale, pathogen, robust, infrastructur, surveil, ebola, societi
93	local, meet, leader, oper, manag, emerg, take, execut, respons, action, ordin, votak, council, amarillo, poconnor, agenc, director
96	line, front, long, just, theyr, scare, afraid, island, hero, doctor, heartbreak, good-by, frighten, terrifi
97	price, percent, drop, sell, quarter, industri, industry, demand, consum, sale, product, goug, crude, buyer, arabia, saudi, invest, bitcoin, opec, cent

Table 3 OLS Replication

To ensure that our model is robust to different model specifications, we replicated the results of Table 3 using OLS. We find that using OLS provides substantively similar results to using logit.

Table A12: Media and Presser Topics Reflected in Search (OLS)

	Dependent variable:		
	Web Searches For Topic		
	(1)	(2)	(3)
Media Proportion	0.004*** (0.001)	0.004*** (0.001)	
Presser Proportion	0.0004 (0.001)		0.001 (0.001)
date	0.0003 (0.0002)	0.0003 (0.0002)	0.0003* (0.0002)
Day of Week FE	X	X	X
Topic FE	X	X	X
Topic x Date FE	X	X	X
Constant	−6.109 (3.728)	−6.110 (3.729)	−6.328* (3.715)
Note:			*p<0.1; **p<0.05; ***p<0.01

Note. This table is a replication of Table 3 in the body of the paper. Media topics had a stronger relationship to search than did presser topics.