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ARTICLE

Finding Fauci

How Visual and Textual Information Varied on Cable News Networks During the Covid-19 Pandemic

Bryce J. Dietrich
University of Iowa
bryce-dietrich@uiowa.edu

Hyein Ko
University of Iowa
hyein-ko@uiowa.edu

Abstract
As the Covid-19 pandemic progressed, the public increasingly relied on news outlets to provide up-to-date health information. Often times this information was provided by Dr. Anthony Fauci during the course of on-air interviews. Consequently, when Dr. Fauci appeared less and less, many became concerned that the public was not receiving the full picture, especially since Dr. Fauci was often not afraid to voice concerns over how the pandemic was being handled at the federal, state and local level. Using text and image data from 6,587 CNN, Fox News and MSNBC programs, this paper determines the extent to which Dr. Fauci appeared on air and whether the rate of his appearances (or lack thereof) diminished over time. We then look at whether Dr. Fauci's appearances (or lack thereof) are conditioned on what is being said during broadcasts. Not only do we find that Dr. Fauci appeared significantly less on Fox News, but this discrepancy increases as the pandemic progresses and when public health information is discussed. Regardless of whether this constitutes "misinformation" or "framing," our study speaks volumes to two important research areas and broader concerns over the balance of Covid-19 coverage, especially when the public needed it the most.

Keywords: Image data, cable news, covid-19, misinformation

At the time of writing, the Covid-19 pandemic has claimed 4,240,173 lives, of which 613,769 were in the United States (JHU, 2021). Although much has been written about Covid-19, this study speaks to concerns over media bias (e.g., Hamilton, 2011; Peng, 2018), especially as they relate to pandemic news coverage (e.g., AlAfnan, 2020). In particular, one of the more popular narratives revolved around the appearance of Dr. Anthony Fauci (or lack thereof) (e.g., Acosta, 2020). Given Dr. Fauci's extensive expertise, some were concerned that his silence (whether forced or not) would negatively impact public health (e.g., Darcy, 2020). Using 102,498 images and the associated text from 6,587 programs, this study tries to find Dr. Fauci on the 2020 broadcasts of CNN, Fox News and MSNBC. These coverage patterns are then used to determine whether some viewers received starkly different messages about Covid-19.

Although some may view such coverage disparities as evidence of misinformation (Motta et al., 2020), this study argues it is perhaps more indicative of bias (for review, see Lichter, 2017). In particular, we focus on framing bias (also called "second order agenda setting" and "presentation bias") which may lead news organizations to focus their coverage on one aspect of a topic at the expense of another (for review, see Morstatter et al., 2018). In the case of Dr. Fauci, such biases could lead him to appear more on news organizations interested in emphasizing public health concerns surrounding Covid-19, whereas networks interested in focusing on other aspects (like the economic effects) may be less inclined to include Dr. Fauci in their coverage. Given the persuasive effects of such frames (Entman, 2007), both popular (Weixel, 2020) and scholarly accounts (Ash et al., 2020) have argued these coverage choices may have had a detrimental effect on public health. By enumerating when and where Dr. Fauci appeared on air, we will determine whether these concerns have any empirical foundation.

This paper proceeds as follows. In the next section, we position our study in the media bias literature, emphasizing the importance of framing and partisan (ideological) filtering. We then describe our theoretical expectations in the subsequent section, with our data and methods following shortly thereafter. Our results are then presented in four main tables with a descriptive plot appearing immediately before. Ultimately, we find evidence that Dr. Fauci appeared increasingly less on Fox News, especially when discussing health-related issues. Not only do these results provide evidence consistent with our main hypothesis, but they also lay an important foundation for future scholars. These new research directions and the larger implications of our study is discussed in the final section.

Literature Review

News organizations play a crucial role in shaping public opinion and policy (Jordan & Page, 1992; McCombs & Shaw, 1972; Page & Shapiro, 1989; Strange & Leung, 1999). Given the media's broader importance, many have become increasingly concerned about the effects of potential biases (for review, see Groeling, 2013), especially in regards to Covid-19 (Roozenbeek et al., 2020). Related to deviations from journalistic norms (Schudson, 2001), media bias can take many different forms, most notably structural (e.g., Bagdikian, 2004) and ideological (also known as partisan) biases (e.g., Jamieson & Cappella, 2008). This study focuses on "framing bias" which occurs when networks highlight certain aspects of a story in order to fit a broader (and typically ideological) narrative (Entman, 2007). Generally speaking, frames define problems, diagnose causes, make moral judgments and offer solutions (Entman, 1993). Thus, when two networks framing of a given issue diverge, then bias could be offered as one potential explanation.

Given the complexity of the Covid-19 pandemic, networks had many options when selecting who and what to cover. For example, considerable coverage was afforded to the economic impacts of stay-at-home orders which, according to one estimate, led to a $10 billion decrease in spending and $15 billion in lost earnings (Crucini & O'Flaherty, 2020). Conversely, other stories tended to focus on the public health benefits of mask mandates which cut down on Covid-19 deaths (Peeples, 2021). Previous studies have shown how such framing choices can influence perceptions of abortion (Carmines & Stimson, 1980), race (Kellstedt, 2000), immigration (McLaren et al., 2018) and social spending (Faricy & Ellis, 2014; Nelson et al., 1997). Perhaps most applicable to the present study, Mebane et al. (2003) and Pieri (2019) found that media framing affected public concerns over Anthrax and Ebola, respectively. Consequently, when networks choose to focus their Covid-19 coverage on one frame (e.g., stay-at-home orders) at the expense to another (e.g., mask mandates) they could impact viewer beliefs about the pandemic.

In many of these studies, Fox News is of particular concern. Not only does Fox News routinely have the highest ratings of any channel on cable television (Schneider, 2020), but it also has a well-documented conservative slant that has increased over time (Budak et al., 2016; Groseclose & Milyo, 2005; Martin & Yurukoglu, 2017). Moreover, several studies have found Fox News coverage has also influenced voting behavior in the United States (Della Vigna & Kaplan, 2007; Martin & Yurukoglu, 2017; Warshaw et al., 2021). These general patterns have also been found with respect to issue coverage. For example, Feldman et al. (2012) found Fox News tended to take a more dismissive tone towards climate change, like interviewing more climate change doubters. Similarly, Aday (2010) found Fox tended to be much more sympathetic to the second Bush administration during their Iraq and Afghan war coverage.

Although similar biases have been found in other media outlets (e.g., Baum & Groeling, 2008), most studies of Covid-19 coverage have focused on Fox News. For example, a recent working paper by Ash et al. (2020) not only found that Fox News tended to downplay the risks posed by the coronavirus, but they also found in localities with higher Fox News viewership people were less likely to follow public health guidelines. Similar results were found in another working paper posted by Pinna et al. (2021). Like Ash, these authors leveraged the quasi-random assignment of channel positions in cable services as an instrument for viewership (Martin & Yurukoglu, 2017). Ultimately, Pinna and colleagues found that Fox News viewership increased Covid vaccine hesitancy, whereas CNN and MSNBC viewership had no effect. Using the same instrumental variable approach, Fox News viewership has also been found to contribute to less mask wearing (Gonzalez et al., 2020) and social distancing (Simonov et al., 2020). In each instance, Fox News is said to have downplayed the health-related consequences of the pandemic, but considerably less attention has been paid to the ways in which Fox News achieved this end (for an exception, see Bursztyn et al., 2020).

Theoretical Expectations

The present study begins to addresses this gap in the literature by determining when and where Dr. Fauci appeared on CNN, Fox News and MSNBC. As alluded to in the introduction, one of the most common questions as the pandemic progressed was, "Where is Dr. Fauci?" At first, the White House said Dr. Fauci and others were too busy to make media appearances (Acosta, 2020), but as he appeared less and less he began hinting that the Trump administration was preventing him from appearing on television (Weixel, 2020). Competing news organizations, like CNN, then began to frame Dr. Fauci's disappearance as one of the many ways the Trump administration was attempting to shift focus away from the pandemic's impact on public health (Breuninger & Lovelace, 2020; Cathey, 2020; Kelly, 2020). This leads to our initial hypothesis:

> Hypothesis 1: Dr. Anthony Fauci should appear less on Fox News as compared to CNN and MSNBC and this difference should increase as the pandemic progresses.

However, if Dr. Fauci is found to appear less on Fox News, this does not necessarily imply a deliberate intent to misinform the public. Instead, some cable news networks, like Fox News, may have simply wanted to highlight a different aspect of the Covid-19 pandemic. For example, if a cable news network was mostly interested in covering the economic ramifications of Covid-19, then it would make little sense to interview Dr. Fauci. This underlines the importance of considering visual and textual information simultaneously. Indeed, it is one thing to say Dr. Fauci is less likely to appear on Fox News and quite another to say this effect is more pronounced when the network is talking about public health. In fact, we expect the opposite since Dr. Fauci is still a good source for public health information, even if a cable network decides to cover that topic less than others. This discussion leads to our final hypothesis:

> Hypothesis 2: The differences in Dr. Fauci appearances between Fox News, CNN and MSNBC should be less pronounced when coverage focuses on public health.

Previous studies have argued that Fox News' Covid-19 coverage negatively affected public health (e.g., Warshaw et al., 2021). Given Dr. Fauci's prominent role in disseminating health information to the public, then his appearances (or lack thereof) on CNN, Fox News and MSNBC directly speaks to this question. Indeed, polling showed many Americans looked to Dr. Fauci for Covid-19 information (e.g., Czachor, 2020; Pramuk, 2020), meaning networks who took him off the air, in many ways, were doing the public a disservice. Again, it is beyond the scope of this paper to speak to intent, but any significant differences between CNN, Fox News and MSNBC Covid-19 coverage underlines how framing bias can potentially have detrimental effects (Entman, 2007).

Data and Methods

The Internet Archive is a non-profit organization which aims to make digital document collections, such as audio recordings and news program videos, publicly accessible. Our study uses a portion of their collection, known as the TV News Archive, which dates back to 2009 and includes over 2 million television shows. Our data consists of all 2020 programming from CNN, Fox News, and MSNBC with search terms *Covid* and *coronavirus*[1]. The date of our first program is from February 11, 2020 and our last program was recorded on

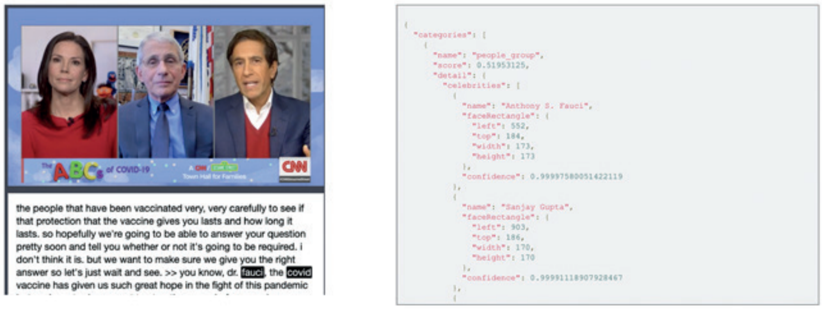

Figure 1 Internet Archive Example with Image and Text Output From Microsoft's Vision API

Note. In the left panel of Figure 1, we provide an example of the Internet Archive data we scrapped. The right panel provides an example of the output from the celebrity recognition API.

December 31, 2020. We then scraped the closed-captioning and thumbnails provided by the Internet Archive for each program. Here, the Internet Archive segments a broadcast into 1-minute intervals and provides the first frame of each interval as a thumbnail. On average, these thumbnails were around 720 by 402 pixels and the associated closed-captioning entry was around 73 words in length. The left panel of Figure 1 provides an example of our data. Ultimately, we collected data from 6,587 programs, yielding 102,498 closed-captioning entries where we have both image and text data.

To determine the extent to which Dr. Fauci appeared on air, we used the celebrity recognition application programming interface (API) from Microsoft Azure. As shown in the right panel of Figure 1, this API identifies a number of prominent figures and returns bounding boxes, labels and confidence scores. Although we could not find previous research that used the celebrity recognition portion of Microsoft's Vision API, the API itself has been effectively used by a number of previous scholars (e.g., Boxell, 2021; Del Sole, 2018). On average, the confidence scores returned by the API were quite high (0.980), suggesting the API only returns results when it has a high degree of confidence. To assess the accuracy, we randomly selected 100 images the API said did and did not include Dr. Fauci and then determined whether Dr. Facui actually appeared in the images. For these sample images, we found the API was 100 percent accurate, meaning we never found an instance where the API said Dr. Fauci appeared and he actually did not. More details and the images themselves are found in the Appendix.

We employ the 2007 Linguistic Inquiry and Word Count (LIWC) dictionary to analyze the closed-captioning data (Pennebaker et al., 2007). LIWC is a program that examines each word in a given text using meaningful dictionary categories, such as psychological dimensions (e.g., positive and negative emotion) and content specific categories (e.g., work, death, religion) (Pennebaker et al., 2007; Pennebaker et al., 2001). Due to its ease of use and flexibility, LIWC has been used across a wide range of studies, including sentiment in tweets (Tumasjan et al., 2010), floor speeches (Yu et al., 2008), and authoritarian leaders' comments (Windsor et al., 2018).

Although many argue dictionary-based approaches can yield meaningful insights (Albaugh et al., 2013; Young & Soroka, 2012), we also acknowledge their limitations (Grimmer & Stewart, 2013; Loughran & McDonald, 2011). With that said, we use the *health* and *death* categories to operationalize our second hypotheses. To help better tune the LIWC dictionary to our use case, we added Covid-specific words to each category. These were obtained from published sources (CDC, 2021; Kathy, 2020) and our own keyword searches. Table 1 gives examples of the base words and all those we added for study.

We validated our *health* and *death* categories by showing the correlation between them and the topics derived from a 30-category LDA topic model. This supplemental analysis can be found in the Appendix. There we show that the topic most correlated (ρ = 0.093) with our *health* category is one that has the following keywords: "may", "risk", "ill", "doctor", "can", "condit", and "serious". Conversely, our *death* category has the highest correlation (ρ = 0.414) with a topic having keywords like "death", "countri", "coronavirus", "million", "die", "american" and "unit". In each instance, the opposing category is negatively correlated with the aforementioned topics, providing some evidence the *health* and *death* categories are orthogonal. Undoubtedly, these results do not fully address the arguments levied against dictionary-based methods, but we hope they assuage some of those concerns, at least with respect to this study.

Given that our three main dependent variables – "Fauci" appearances, "death" mentions, and "health" mentions – are all counts, we employ negative binomial regressions in all analyses reported below. To standardize our models, we aggregated our data to the show-week level, meaning each row is a single week for a given show. This means some shows, like "Hannity", may appear multiple times. Although not reported in the main text, we estimated separate versions of our models in STATA including standard errors clustered at the show level. We did not use this in the main text, because it is unclear how STATA estimates predicted values which are necessary to disentangle some of our interactive effects. As shown in the Appendix, the substantive results are the same, ultimately giving us confidence that what we report in the main text cannot be easily attributed to show-level clustering.

Our main independent variables are two dummy variables for CNN and MSNBC which both equal 1 when the show appeared on each network,

Table 1 Examples of Base Words in LIWC 2007 and Newly Added COVID Related Words

	LIWC 2007 Base Words Examples
Death	bury, coffin, fatal*, kill, suicid*, war
Health	ache*, clinic, dose*, flu, pill, surger*, therap*, wash
	Added COVID-19 Words
Death	pandemic*
Health	asymptom*, cdc, hygien*, quarantin*, respirat*, screening*, telehealth*, vaccin*, ventilat*

Note. In the first two rows, we provide examples of the words in the "death" and "health" categories in the 2007 Linguistic Inquiry and Word Count (LIWC) dictionary. The last two rows are the Covid-19 words we added to the aforementioned categories. In both instances a star indicates a wildcard, meaning "quarantin*" will capture "quarantine," "quarantining," etc.

respectively. Given this coding, our baseline is Fox News, meaning any positive coefficients imply the dependent variable appears more often on either CNN or MSNBC as compared to Fox News. To test our first hypothesis, we interact this variable with the 2020 week which ranges from 9 to 53. The second hypothesis is tested by interacting the CNN and MSNBC dummy variables with the number of "death" and "health" mentions. Given that counts, like the number of Dr. Fauci appearances, are impacted by the level of exposure, in all models we include appropriate offsets. More specifically, when the dependent variable is the number of Dr. Fauci appearances the offset is the number of celebrities returned by Microsoft's API for that show-week. When the dependent variable is either LIWC category, the offset is the number of words for that show in the given week. For these reasons, the majority of our analyses will focus on the rate at which our three dependent variables appear on CNN, Fox News and MSNBC, given the level of exposure.[2]

Results

Where is Dr. Fauci?

We begin our analysis with Figure 2, where we show the proportions of Fauci appearances, death mentions, and health mentions by month. In terms of the proportion of words utilized during their broadcasts, CNN uses the most "health" words (0.038), followed by MSNBC (0.031) and Fox News (0.031). Not only are these differences statistically significant (χ^2 = 2302.00, df = 2,

$p < 0.001$), but they are mirrored by words from our "death" category. Here, we again find a statistically significant difference ($\chi^2 = 1137.80$, $df = 2$, $p < 0.001$) between CNN (0.010), MSNBC (0.009) and Fox News (0.007), with CNN using proportionally the most "death" words and Fox News using the least.

Similar results are found for Dr. Fauci's appearances (or lack thereof). In terms of the proportion of celebrities detected by Microsoft's API during their broadcasts, we find Dr. Fauci appeared significantly ($\chi^2 = 37.34$, $df = 2$, $p < 0.001$) more on CNN (0.012) and MSNBC (0.009) as compared to Fox News (0.004). Dr. Fauci's appearances were also found to decrease on Fox News as the pandemic progressed. More specifically, of the celebrities detected by Microsoft's API on Fox News in March 2020 (first full month in our data), 1.5 percent of them were Dr. Fauci. By comparison, in December 2020 (last full month in our data), none of the celebrities detected by Microsoft's API on Fox News were Dr. Fauci. Not only is this difference statistically significant ($\chi^2 = 11.32$, $df = 1$, $p = 0.001$), but it provides initial support for our first hypothesis which we directly test in Table 2.

Again, we expect Dr. Fauci to appear less on Fox News and this relationship will become more pronounced as the pandemic progresses. Beginning with Model 1, we find that Dr. Fauci appeared significantly more on CNN ($p < 0.001$) and MSNBC ($p < 0.001$) as compared to Fox News. The significant interaction between our CNN dummy variable and the week in Model 2 ($p < 0.0001$), suggests this difference also became more pronounced as the Covid-19 pandemic progressed. A similar interactive effect was not found for MSNBC ($p > 0.05$), suggesting the difference between Fauci appearances on this network as compared to Fox News did not change over time. This latter conclusion is further supported by the significant main effect for our MSNBC dummy variable in Model 2 ($p < 0.05$).

Figure 3 reports the predicted rates for the CNN interaction term in Table 2, Model 2. A similar plot is provided for MSNBC in the Appendix, but is not reported here given the insignificant interaction term. To create the predicted values, we allowed the week to vary from the minimum (9) to maximum (53) which corresponds to February 23, 2020 to December 28, 2020. To make the intercept more interpretable we zeroed-out the week before entering this variable into our model, so it began at 0 and ended at 44. The offset was set to the median number of celebrities – reported by the Microsoft API – appearing on each network for a given week. For both networks this value was 8. Finally, 95-percent confidence intervals were calculated by multiplying 1.96 by the standard error of the prediction interval.

Beginning with the first week in our data, Dr. Fauci is predicted to appear on 8.39 percent of Fox News shows. That predicted rate is 14.18 percent less than CNN where Dr. Fauci is predicted to appear in 9.58 percent of their shows during the same time period. Looking at the last week in our data, Dr. Fauci is predicted by our model to appear in 6.66 percent and 0.27 percent of CNN and Fox News shows, respectively. Although this substantial difference is consistent with our first hypothesis, it is purely theoretical since Dr. Fauci did not appear on any show in the last week of our data. The last appearance Dr. Fauci makes in our data occurred on CNN in the 52nd week which corresponds with December 21, 2020. The last Fox News appearance was in the 48th week, corresponding to November 23, 2020. Perhaps more surprising, the last week Dr. Fauci appeared more than once on a Fox News show was the 20th week which corresponds with May 11, 2020. The aforementioned 52nd week was the latest Dr. Fauci appeared at this same rate on CNN.

We now outline three important caveats to help frame our results. First, our data only includes frames where either *Covid* or *coronavirus* appeared in the closed-captioning. Given that, we cannot rule out the possibility that Dr. Fauci appeared elsewhere on Fox News. For some, this may undermine the generalizability of our results, while for others this may be viewed as compounding the problem. Indeed, many wanted to hear from Dr. Fauci about the coronavirus and the fact that he appears significantly less on Fox News when that word is uttered is problematic.

Second, Dr. Fauci's appearances are entirely dependent on Microsoft's API and we cannot say for sure whether Dr. Fauci is speaking or whether the cable news networks are simply showing an image of him on the screen. In terms of the API itself, we have provided some validation, but there are undoubtedly some Dr. Fauci appearances that may have been missed. With that said, unless the API errors are unequally distributed across Fox News, CNN and MSNBC we cannot easily write off our results to this type of measurement error.

Finally, given this analysis relies solely on Internet Archive thumbnails, we cannot exclude the possibility that Dr. Fauci did not appear in an interval that mentioned "Covid" or "coronavirus" in one minute, but then appeared in the next. Similarly, we cannot say whether Dr. Fauci appeared later in a given one-minute interval or may have appeared in the previous one-minute interval prior to when either "Covid" or "coronavirus" are mentioned. Again, if we assume these errors are equally distributed across Fox News, CNN and MSNBC, then it is difficult to easily dismiss our results based on such concerns.

Table 3 Fox News is Significantly Less Likely to Use Words from LIWC's "Death" Category When Discussing Covid-19

	Dependent variable:	
	"Death" Mentions	
	(1)	**(2)**
Constant	-4.905***	-4.729***
	(0.019)	(0.033)
CNN	0.324***	0.141***
	(0.025)	(0.047)
MSNBC	0.251***	0.114**
	(0.025)	(0.048)
Week		-0.009***
		(0.001)
CNN × Week		0.010***
		(0.002)
MSNBC × Week		0.008***
		(0.002)
N	2,307	2,307
Log Likelihood	-7,999.654	-7,977.959
θ	6.145*** (0.268)	6.352*** (0.280)
Akaike Inf. Crit.	16,005.310	15,967.920

* p<0.1
** p<0.05
*** p<0.01
Note. Negative binomial regressions predicting the number of times a word from our modified LIWC "death" category are used (see Table 1). Data has been aggregated to the show-week, meaning shows can appear multiple times. All models are offset by the log of the total number of words for a show in a given week.

When Dr. Fauci Appears on Cable News Broadcasts, What is Being Discussed?

Our second hypothesis helps us better understand this main result. More specifically, Dr. Fauci may not appear on Fox News simply because they are covering other aspects of the Covid-19 pandemic. To gain traction on this question, we analyse the closed-captioning associated with Dr. Fauci's appearances. If Dr. Fauci is found to appear *more* when CNN, Fox News and MSNBC are discussing public health and the coronavirus, then it provides evidence consistent with our second hypothesis. Evidence of the inverse would suggest Dr. Fauci is appearing less when discussing these matters, despite his extensive expertise in the area. Such a result would also underscore concerns about some Covid-19 coverage negatively impacting public health.

We begin with Table 3 which reports models identical to those shown in Table 2, but the dependent variable is the number of times a word from LIWC's "death" category appear in a week on a given show. Again, LIWC does not include Covid-19 specific words, like "pandemic", which we included for the purpose of our analysis. As is clear from both Models 1 and 2, CNN and MSNBC are significantly more likely than Fox News to use words like "death" and "pandemic" when also using terms like "Covid" and "coronavirus." Moreover, the significant interaction terms for both networks in Model 2 not only suggests this difference increases over time, but CNN is also not unique in this regard.

Table 4 reports nearly identical results. Here, the dependent variable is the number of times a word from LIWC's "health" category appear in a week on a given show. To help capture Covid-specific references, we also included words like "quarantine" and "vaccine" in this category. Again, Models 1 and 2 show a statistically significant difference between the use of these words by Fox News as compared to CNN and MSNBC. Not only are the coefficients very similar to those reported in Table 3, but the interaction terms are also significant. Ultimately, these results suggest Fox News tended to use fewer "health" and "death" related words when discussing the coronavirus and this disparity increased over time.

Table 5 provides a direct test of our second hypothesis. Here, we converted the raw counts of the words used in the "health" and "death" categories to dummy variables where a 1 is returned when a show (in a given week) exceeded the category median. For example, the "death" category median for the "Hannity" show is 6, meaning in a given week we should expect 6 words from the "death" category to be used on that show. In weeks 12 and 13, the "Hannity" show used 23 and 5 words from the "death" category, respectively. In these weeks, our dummy variable would return a 1 for week 12 and a 0 for weeks 13, since the former exceeded the show's median (6), whereas the later did not. Hypothetically, if 6 words from the "death" category were used in either week, that week would also be coded as 0. We standardized our text variables in this way to (1) make the interaction term easier to interpret and (2) to account for the fact that networks and shows likely use "death" and "health" words at different rates, something we already demonstrated in Tables 3 and 4.

With that said, our primary variable of interest is the interaction between the dummy variables associated with CNN and MSNBC and the

Table 5 Are Dr. Anthony Fauci's Appearances Conditioned on the Text?

	Dependent variable: Fauci Appearances
Constant	-7.744***
	(1.008)
CNN	3.034***
	(1.049)
MSNBC	3.240***
	(1.044)
"Death" Mentions	2.067*
	(1.245)
"Health" Mentions	2.802**
	(1.136)
CNN × "Death" Mentions	-3.456**
	(1.503)
CNN × "Health" Mentions	-2.024
	(1.239)
MSNBC × "Death" Mentions	-3.123**
	(1.419)
MSNBC × "Health" Mentions	-3.030**
	(1.260)
"Death" Mentions × "Health" Mentions	-2.316*
	(1.380)
CNN ×	2.975*
"Death" Mentions × "Health" Mentions	(1.683)
MSNBC ×	3.372**
"Death" Mentions × "Health" Mentions	(1.628)
N	2,101
Log Likelihood	-549.583
θ	0.143*** (0.025)
Akaike Inf. Crit.	1,123.167

* p<0.1
** p<0.05
*** p<0.01
Note. Negative binomial regressions predicting the number of times Dr. Fauci appears. Data has been aggregated to the show-week. Offset of the number of celebrities included in all models (see Table 2). "Death" and "health" mentions (see Table 1).

aforementioned dummy variables associated with the modified "death" and "health" categories from LIWC. If positive, then it suggests that when words from *both* categories are used Dr. Fauci is *less* likely to appear on Fox News as compared to the other cable news networks we considered. For both CNN ($p < 0.078$) and MSNBC ($p < 0.039$), we find a positive and

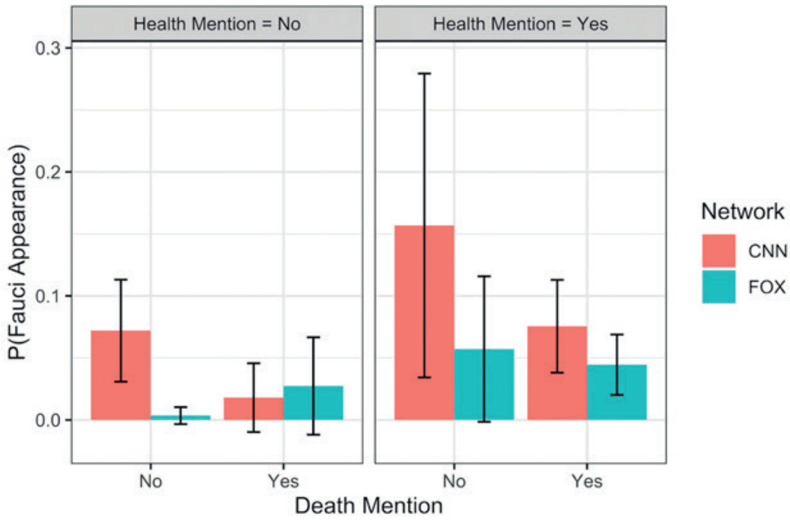

Figure 4 Predicted Difference between Fauci Appearances on CNN and Fox News Conditioned on Text

Note. Predicted values from Table 5, Model 1 for both CNN and Fox News. On the x-axis, the number of "death" mentions for a given show is either higher ("Yes") or lower ("No") than the previous week. In the left panel (Health Mentions = No), the number of "health" mentions for a given show in the current week is lower than the previous week. Conversely, in the right panel (Health Mentions = Yes) the are higher. The offset is set to the median number (8) and 95 percent confidence intervals are plotted as brackets.

significant interaction, although the former is not statistically significant at the 0.05-level. This provides initial evidence contrary to our second hypothesis. However, it is easier to interpret the substantive meaning of this result through plots of predicted values which we provide in Figures 4 and 5 for CNN and MSNBC, respectively.

In Figure 4, we begin with the bars furthest to the right in the right-most panel. These bars correspond to instances when both the modified LIWC "death" and "health" categories were used at higher rates as compared to the previous week. The red and blue bars represent CNN and Fox News, respectively. Here, we find that Dr. Fauci is predicted to appear 7.55 percent of the time on CNN as compared to 4.45 percent of the time on Fox News. Although sizeable, this difference is far from the greatest. The greatest difference between Fox News and CNN is found when "health" is used at a higher rate, but "death" is not. When this occurs, Dr. Fauci is predicted to appear 15.68 percent of the time on CNN, but only 5.71 percent of the time on Fox News. This runs counter to our second hypothesis since it suggests Dr. Fauci is *less* likely to appear on Fox News (as compared to CNN) when the closed-captioning includes health-related words.

Although the results for the MSNBC interaction in Table 5 look similar to those of CNN, Figure 5 highlights some slight differences. Here, we find no substantial differences between Fox News and MSNBC, except for the bars furthest to the left in the left-most panel. These bars correspond to shows which used the modified "death" or "health" categories at a higher rate as compared to the previous week. More specifically, when words from neither dictionary categories are used at higher rates, Dr. Fauci is predicted to appear 7.74 percent and 0.35 percent on MSNBC and Fox News, respectively. Without death and health mentions, Dr. Fauci's appearances are significantly different between news networks. With death and health mentions, on the contrary, there are no significant disparities. The results are consistent with our second hypothesis by suggesting differences in coverage decline when news networks cover relevant death and health topics.

Discussion and Conclusion

In an attempt to find Dr. Fauci, this study used 102,498 images from 6,587 cable news programs who used either "Covid" or "coronavirus" during their broadcasts beginning in February 23, 2020 and ending December 28, 2020. Ultimately, we found Dr. Fauci was significantly less likely to appear on Fox News broadcasts when the coronavirus was discussed. Moreover, we found the difference between Fox News and the other cable news networks widened as the pandemic progressed. These results coupled with the dramatic differences between Fox News and the other cable news networks in the use of words related to "death" and "health" provide evidence that Fox News likely covered Covid-19 differently than CNN and MSNBC. We also find evidence that Dr. Fauci was especially unlikely to appear on Fox News (as compared to CNN) when health-related words were present in the closed-captioning, but this result was not replicated when MSNBC served as the point of comparison.

Previous scholars have shown how media bias can affect public behavior (for review, see Lichter, 2017). More recently, this argument has been extended to coverage of Covid-19 (e.g., Ash et al., 2020). Here, scholars

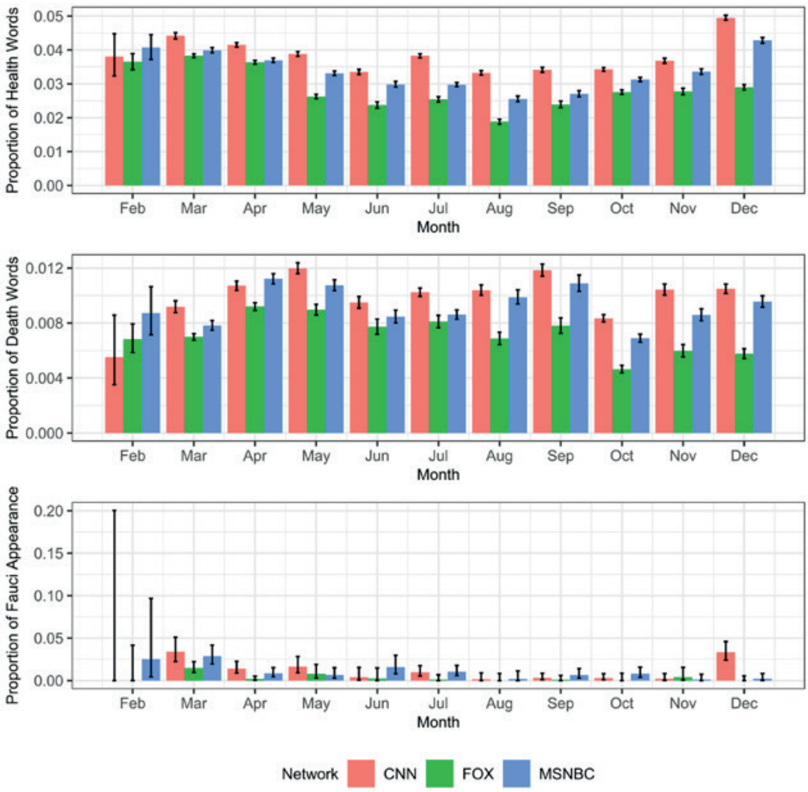

Figure 2 Proportion of "Health" Words, "Death" Words and Fauci Appearances by Month and Network

Note. Figure 2 presents descriptive information of our data. Each plot corresponds to proportion of health words (top), proportion of death words (middle), and proportion of Dr. Fauci appearances (bottom). X-axis shows month which ranges from February to December 2020. Red bars indicate CNN, green bars are used for Fox News, and MSNBC proportions are marked with blue bars. 95% confidence intervals are provided at the top of each bar.

have used an instrumental variable approach to demonstrate the negative effects of Fox News coverage on public health. However, we still know very little about how Fox News' coverage differed from its competitors. One popular narrative was the "silencing" of Dr. Fauci (e.g., Acosta, 2020) which many argued was part of a deliberate effort by the Trump administration to downplay the severity of the pandemic (Kelly, 2020). Although this study cannot speak to intent, we show not only did Dr. Fauci appear less

Table 2 Dr. Anthony Fauci is Less Likely to Appear on Fox News When the Network is Discussing Covid-19

	Dependent variable: Fauci Appearances	
	(1)	**(2)**
Constant	-5.551***	-4.558***
	(0.218)	(0.346)
CNN	0.935***	0.132
	(0.275)	(0.473)
MSNBC	0.958***	0.874**
	(0.271)	(0.440)
Week		-0.078***
		(0.023)
CNN × Week		0.070***
		(0.026)
MSNBC × Week		0.026
		(0.027)
N	2,206	2,206
Log Likelihood	-597.792	-581.626
θ	0.124*** (0.020)	0.151*** (0.026)
Akaike Inf. Crit.	1,201.583	1,175.252

* p<0.1
** p<0.05
*** p<0.01
Note. Negative binomial regressions predicting the number of times Dr. Fauci appears. Data has been aggregated to the show-week, meaning shows can appear multiple times. All models are offset by the log of the total number of celebrities identified in a given week.

on Fox News, but this disparity increased when many in the public may have needed him the most. Our results show such concerns have some empirical support. Indeed, at least with respect to CNN, we found Dr. Fauci was less likely to appear when health was discussed and as the pandemic progressed.

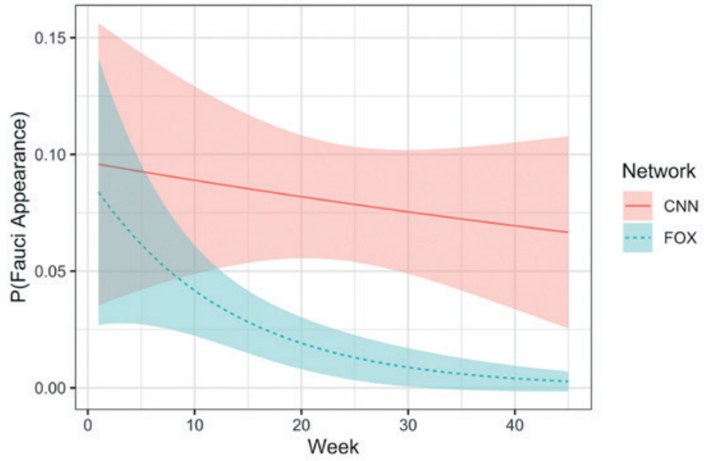

Figure 3 Predicted Number of Fauci Appearances by Network

Note. Predicted values from Table 2, Model 2 for both CNN and Fox News. On the x-axis, the week is allowed to vary from the minimum (0) to maximum (44) which corresponds to February 23, 2020 to December 28, 2020, respectively. The offset is set to the median (8) and 95 percent confidence intervals are plotted around each line.

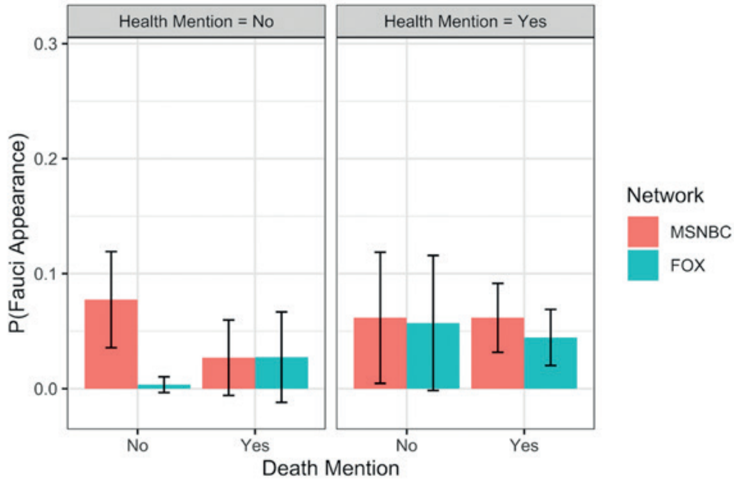

Figure 5 Predicted Difference between Fauci Appearances on MSNBC and Fox News Conditioned on Text

Note. Predicted values from Table 5, Model 1 for both MSNBC and Fox News. On the x-axis, the number of "death" mentions for a given show is either higher ("Yes") or lower ("No") than the previous week. In the left panel (Health Mentions = No), the number of "health" mentions for a given show in the current week is lower than the previous week. Conversely, in the right panel (Health Mentions = Yes) the are higher. The offset is set to the median number (8) and 95 percent confidence intervals are plotted as brackets.

Table 4 Fox News is Significantly Less Likely to Use Words from LIWC's "Health" Category When Discussing Covid-19

	Dependent variable:	
	"Health" Mentions	
	(1)	**(2)**
Constant	-3.577***	-3.418***
	(0.027)	(0.015)
CNN	0.308***	0.159***
	(0.021)	(0.039)
MSNBC	0.151***	0.017
	(0.020)	(0.039)
Week		-0.008***
		(0.001)
CNN × Week		0.008***
		(0.002)
MSNBC × Week		0.007***
		(0.002)
N	2,307	2,307
Log Likelihood	-10,453.200	-10,423.290
θ	7.509*** (0.273)	7.787*** (0.286)
Akaike Inf. Crit.	20,912.400	20,858.580

* p<0.1
** p<0.05
*** p<0.01
Note. Negative binomial regressions predicting the number of times a word from our modified LIWC "health" category are used (see Table 1). Data has been aggregated to the show-week, meaning shows can appear multiple times. All models are offset by the log of the total number of words for a show in a given week.

Supporting Information for: Finding Fauci: How Visual and Textual Information Varied on Cable News Networks During the Covid-19 Pandemic

December 15, 2021

S1 Microsoft Vision API Validation

In order to validation Microsoft Vision's API, we randomly sampled 50 images that the API said included Dr. Fauci and 50 images that the API said did not include Dr. Fauci. Examples of these images are shown in Figure S1. After randomizing the order, we then went through all 100 images and determined whether Dr. Fauci appeared in the image. Ultimately, there was no instance in which the API said Dr. Fauci appeared in an image and in fact he did not. Similarly, we never encountered an instance where the API appeared in an image that the API said he did not. Thus, this simple validation exercise suggests the Microsoft API is well-suited for this task. We cannot speak to the API's ability to identify other "celebrities."

S2 *Health* and *Death* Dictionary Validation

In order to validate our LIWC dictionary categories, we estimated a k=30 LDA topic model, the results of which are reported in Table S1. In the first column, we assign each topic a number and keywords are provided in the second column. The words that have the highest probability of appearing in the topic are listed as keywords. In the columns labeled "Health" and "Death", we show the correlations between a given topic and our "health" and "death" categories, respectively. In Table S1, the row highlighted in light gray has the highest positive correlation with our "health" category, whereas the row highlighted in dark gray has the highest positive correlation with our "death" category.

Ultimately, we find that our "health" category has the highest correlation with a topic that includes words like "doctor" and "ill" (see Topic 6). Conversely, the "death" category has the highest correlation with a topic including keywords like "death" and "die" (see Topic 20). We also note that in each instance, the opposing category has a noticeably weaker positive correlation. For example, the correlation between our "death" and "health" categories and Topic 20 are 0.414 and 0.023, respectively. This suggests the

(a) Contains Fauci (b) Does Not Contain Fauci

Figure S1 Examples of Images Used in Validation Exercise

Note: Examples of the images we used for our validation exercise. In Panel A, Microsoft's API said Dr. Fauci was present. Conversely, in Panel B, the API did not find Dr. Fauci.

former captures words like "die", whereas the latter does not, providing some evidence our dictionary categories are orthogonal.

Although not shown here, we also estimated k=10 and k=20 LDA topic models. Here, the results were nearly identical with the "health" category being mostly correlated with topics that included words like "doctor" and "virus". Conversely, the "death" category has the highest correlation with topics whose keywords are "case" and "coronavirus". These results provide some validation for our "health" and "death" categories, or at least provide some sense of what those categories are measuring in our data.

S3 Dr. Scott Atlas Analysis

As Dr. Fauci appeared less and less on television, some speculated he was being replaced by Dr. Scott Atlas. Unfortunately, since Dr. Atlas is not included in the Microsoft API we could not use the celebrity recognition technique we used for Dr. Fauci in order to determine whether this was the case. In Table S2, we attempt to gain some traction by simply counting the number of times the words "fauci" and "atlas" appeared in our closed-captioning data. Once this was done, we noticed two things: (1) Dr. Fauci was always referenced more, regardless of network and (2) both Fauci and Atlas references were conditioned on the number of words uttered during a show-week. To address the latter problem, we divided the total number of "fauci" and "atlas" references by the total number of words used in the closed-captioning for a given show-week. To address the former problem, we use the difference between in the proportion of Atlas and Fauci mentions as our dependent variable.

Table S1 LDA Topic Model Keywords and Correlation between Health and Death Mentions (K=30)

Topic	Keywords	Health	Death
topic 1	say, health, said, public, american, administr, respons	−0.009	−0.018
topic 2	now, right, time, come, well, take, back	0.003	0.065
topic 3	know, think, peopl, want, dont, thing, just	0.033	−0.045
topic 4	famili, offic, polic, year, covid-, friend, love	−0.003	−0.002
topic 5	bill, senat, relief, money, republican, democrat, congress	−0.098	−0.051
topic 6	may, risk, ill, doctor, can, condit, serious	0.093	0.002
topic 7	biden, joe, elect, vote, campaign, trump, donald	−0.144	−0.037
topic 8	case, state, number, report, new, day, now	0.012	0.004
topic 9	test, posit, virus, contact, covid-, quarantin, day	0.037	−0.055
topic 10	hous, white, presid, forc, coronavirus, task, report	−0.004	−0.002
topic 11	florida, state, counti, california, texa, south, weekend	−0.032	0.018
topic 12	presid, trump, hes, event, coronavirus, ralli, say	−0.002	−0.002
topic 13	school, safe, children, kid, learn, student, univers	−0.019	−0.028
topic 14	thank, much, join, next, great, fight, stori	−0.028	−0.045
topic 15	get, see, look, that, even, still, happen	0.066	−0.065

topic 16	vaccin, will, develop, first, effect, approv, fda	0.009	−0.005
topic 17	will, week, two, last, month, day, first	−0.049	−0.054
topic 18	help, can, pay, free, insur, stay, get	0.029	−0.043
topic 19	virus, diseas, doctor, studi, drug, data, medic	0.080	0.041
topic 20	death, countri, coronavirus, million, die, american, unit	0.023	0.414
topic 21	economi, job, year, crisi, econom, america, coronavirus	−0.002	−0.002
topic 22	peopl, mani, theyr, countri, weve, there, concern	0.002	0.004
topic 23	need, make, work, can, care, everi, sure	0.042	−0.047
topic 24	one, didnt, show, said, never, got, saw	0.011	−0.007
topic 25	hand, use, food, power, check, store, eye	−0.018	−0.014
topic 26	mask, wear, peopl, social, distanc, stay, order	−0.013	−0.027
topic 27	hospit, patient, nurs, care, home, medic, bed	0.009	0.004
topic 28	news, good, morn, hour, coronavirus, tonight, break	−0.016	0.022
topic 29	new, york, governor, citi, mayor, state, coronavirus	0.025	0.080
topic 30	china, world, coronavirus, virus, organ, report, govern	−0.041	0.013

Note: Table reports LDA topic model with k=30 with high probability words as keywords. “Health” and “Death” columns show the correlation between the proportion of each LDA topic and each dictionary category. In the light gray row, we highlight the topic that has the highest positive correlation with our “health” category. The dark gray row is the same for the “death” category.

Table S2 Dr. Atlas is More Likely To Appear on Fox News as Compared to Other Networks

	Dependent variable:	
	"Atlas" Mentions –	
	Total Number of Words	
	Total Number of Words	
	(1)	**(2)**
Constant	−0.001***	−0.001***
	(0.00005)	(0.0001)
CNN	−0.0004***	0.001***
	(0.0001)	(0.0001)
MSNBC	−0.0001*	−0.0003**
	(0.0001)	(0.0001)
Week		0.00000
		(0.00000)
CNN × Week		0.00001*
		(0.00001)
MSNBC × Week		0.00001
		(0.00001)
Observations	2,307	2,307
R^2	0.015	0.022
Adjusted R^2	0.014	0.020

* p<0.1
** p<0.05
*** p<0.01
Note: OLS regressions predicting the difference in the proportion of "atlas" and "fauci" references. The former is calculated by taking the total number of "atlas" references and dividing by the total number of words for a given show-week. The latter is calculated the same way, but "fauci" references are used instead. Standard errors are reported in parentheses.

Since our dependent variable ranges from -1 ("fauci" used 100 percent of the time and "atlas" used 0 percent) to 1 ("atlas" used 100 percent of the time and "fauci" used 0 percent), then a censored regression is appropriate in this instance. However, Table S2 reports the results from simple OLS regressions to make our results easier to interpret. When a censored regression is used, like a Tobit model, the substantive results are the same. The same can be said for standard errors clustered at the show-week. Again, we found the results were similar to those reported in Table S2 when clustered standard errors were used.

Turning now to Table S2, we find the main effects of both CNN and MSNBC are negative and statistically significant in both Models 1 and 2.

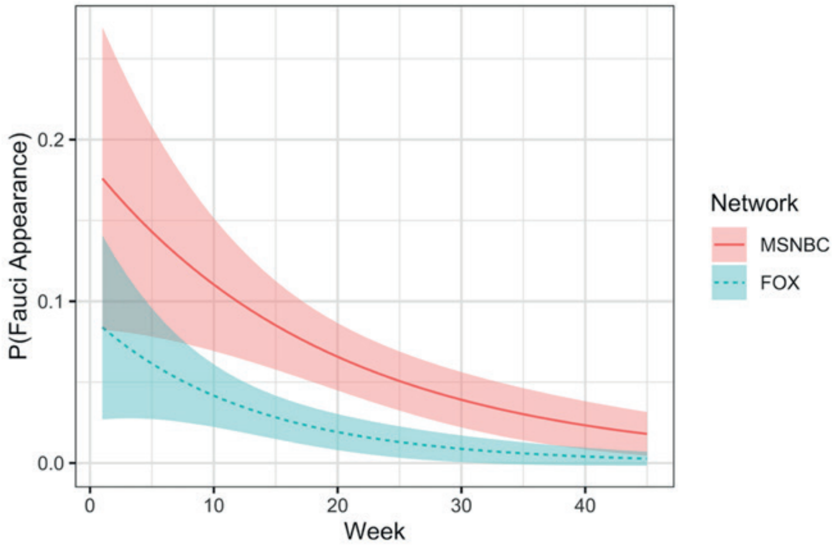

Figure S2 Predicted Effect of Network on Fauci Appearances

Note: Predicted values from Table 2, Model 2 for both CNN and Fox News. On the x-axis, the week is allowed to vary from the minimum (0) to maximum (44) which corresponds to February 23, 2020 to December 28, 2020, respectively. The offset is set to the median (8) and 95 percent confidence intervals are plotted around each line.

This implies that "atlas" is mentioned *more* than "fauci" on Fox News as compared to CNN and MSNBC, although the main effect of the latter is only statistically significant at the .09-level. We also note the main effects in Model 2 capture the difference between Fox News and the other networks at week 0 which corresponds to the week containing February 11, 2020. In Model 2, we also find a significant positive interaction between "CNN" and "Week" which implies CNN's references to Dr. Atlas (or "atlas") vis-á-vis Dr. Fauci (or "fauci") increasingly approximates Fox News as the pandemic progressed. Finally, we note that the coefficient associated with this interaction is only statistically significant at the 0.07-level. No significant interaction was found for the MSNBC interaction.

S4 Robustness Checks

S4.1 MSNBC Results

As explained in the main text, no significant interaction was found in Table 2 for for MSNBC. However, for interested readers, we show the plot for that

Table S3 Re-estimating Table 2 Using Logistic Regression

	Dependent variable: Fauci Appearances			
	(1) Logit	(2) Firth Logit	(3) Logit	(4) Firth Logit
Constant	−3.483***	−3.461***	−2.002***	−2.002***
	(0.222)	(0.219)	(0.329)	(0.326)
CNN	0.804***	0.791***	−0.286	−0.271
	(0.270)	(0.267)	(0.435)	(0.388)
MSNBC	1.058***	1.042***	0.554	0.559
	(0.257)	(0.254)	(0.391)	(0.388)
Week			−0.110***	−0.105***
			(0.029)	(0.028)
CNN × Week			0.091***	0.086***
			(0.031)	(0.030)
MSNBC × Week			0.056*	0.052*
			(0.031)	(0.030)
N	2,206	2,206	2,206	2,206
Log Likelihood	−487.007	−481.576	−460.712	−442.837
Akaike Inf. Crit.	980.015	969.152	933.424	897.674

* $p<0.1$
** $p<0.05$
*** $p<0.01$
Note: Logistic and Firth logistic regressions predicting whether Fauci appeared (1) or did not appear (0) in a given week. All models estimated in STATA (version 16). Standard errors are reported in parentheses.

interaction in Figure S2. Ultimately, shows the trend in Fauci appearances was roughly the same for Fox News and MSNBC, but the starting points were different with Fauci appearing more on the latter.

S4.2 Logistic Regressions

In the main text, we test our hypotheses using negative binomial regressions with offsets to control for the rate of exposure. This means that each dependent variable entered into the question as a rate (or proportion). However, this may cause some confusion for readers, especially since the last table we present had to rely on dummy variables to make the results easier to interpret. Given that, we re-estimated all models reported in the main text using logistic regressions which predict whether Fauci did/did not appear on air in a given week (see Tables S3 and S6). The same was done for "health" and "death" mentions, so positive coefficients imply that variable lead to at least one "health" and "death" word being used

Table S4 Re-estimating Table 3 Using Logistic Regression

	Dependent variable: "Death" Mentions			
	(1) Logit	(2) Firth Logit	(3) Logit	(4) Firth Logit
Constant	3.209***	3.193***	4.335***	4.277***
	(0.189)	(0.188)	(0.473)	(0.465)
CNN	2.703***	2.497***	0.022	0.023
	(0.733)	(0.661)	(1.182)	(1.099)
MSNBC	0.999***	0.975**	0.047	0.008
	(0.347)	(0.341)	(0.785)	(0.764)
Week			−0.046***	−0.454***
			(0.016)	(0.015)
CNN × Week			0.152*	0.118*
			(0.087)	(0.684)
MSNBC × Week			0.039	0.039
			(0.028)	(0.027)
N	2,307	2,307	2,307	2,307
Log Likelihood	−199.061	−195.746	−193.163	−179.175
Akaike Inf. Crit.	404.122	397.491	398.327	370.3498

* $p<0.1$
** $p<0.05$
*** $p<0.01$
Note: Logistic and Firth logistic regressions predicting whether a word from our modified LIWC "death" category was (1) or was not mentioned (0) in a given week. All models estimated in STATA (version 16). Standard errors are reported in parentheses.

in a given week (see Tables S4 and S5). Finally, since Fauci appearances are rare on some networks, we also report the results from Firth logistic regressions. Regardless of the table, our main results hold when either type of logistic regression is used, suggesting our results are robust to our modeling choice.

S4.3 Clustered Standard Errors

As explained in our data and methods section, some may be concerned that we did not cluster our standard errors by show since some shows can appear multiple times in our data. As explained in that section, we did this because no such implementation existed in R and we were concerned about how STATA calculated its predicted values. Tables S7–S10 re-estimate all models reported in the main text with standard errors clustered at the show-level. When this is done, we find essentially the same substantive results.

Table S5 Re-estimating Table 4 Using Logistic Regression

	Dependent variable: "Health" Mentions			
	(1) Logit	**(2) Firth Logit**	**(3) Logit**	**(4) Firth Logit**
Constant	4.407***	4.353***	4.091***	4.017***
	(0.335)	(0.327)	(0.589)	(0.570)
CNN	0	2.948**	0	2.695
	(omitted)	(1.452)	(omitted)	(2.614)
MSNBC	2.300***	1.949**	1.981	1.538
	(1.055)	(0.327)	(1.856)	(1.514)
Week			0.016	0.015
			(0.027)	(0.026)
CNN × Week			0	−0.019
			(omitted)	(0.108)
MSNBC × Week			0.015	0.007
			(0.085)	(0.067)
N	1,566	2,307	1,566	2,307
Log Likelihood	−56.423	−56.057	−56.156	−46.949
Akaike Inf. Crit.	116.845	118.114	120.312	105.898

* $p<0.1$
** $p<0.05$
*** $p<0.01$
Note: Logistic and Firth logistic regressions predicting whether a word from our modified LIWC "health" category was (1) or was not mentioned (0) in a given week. All models estimated in STATA (version 16). Standard errors are reported in parentheses.

Table S6 Re-estimating Table 5 Using Logistic Regression

	Dependent variable: Fauci Appearances	
	(1) Logit	**(2) Firth Logit**
Constant	-5.687^{***}	-5.283^{***}
	(1.002)	(0.819)
CNN	2.600^{***}	2.235^{**}
	(1.044)	(0.868)
MSNBC	2.986^{***}	2.606^{***}
	(1.029)	(0.851)
"Death" Mentions	1.528	1.522
	(1.421)	(1.163)
"Health" Mentions	2.811^{***}	2.518^{***}
	(1.126)	(0.952)
CNN × "Death" Mentions	−2.091	−1.908
	(1.618)	(1.360)
CNN × "Health" Mentions	-2.121^{*}	-1.805^{*}
	(1.229)	(1.281)
MSNBC × "Death" Mentions	−1.895	−1.801
	(1.529)	(1.281)
MSNBC × "Health" Mentions	-2.606^{**}	-2.274^{**}
	(1.216)	(1.052)
"Death" Mentions × "Health" Mentions	−1.377	−1.451
	(1.534)	(1.287)
CNN × "Death" Mentions × "Health" Mentions	2.104	1.957
	(1.777)	(1.532)
MSNBC × "Death" Mentions × "Health" Mentions	2.122	2.061
	(1.693)	(1.460)
N	2,101	2,101
Log Likelihood	−443.183	−432.183
Akaike Inf. Crit.	910.366	888.366

* $p<0.1$
** $p<0.05$
*** $p<0.01$
Note: Logistic and Firth logistic regressions predicting whether Fauci appeared (1) or did not appear (0) in a given week. All models estimated in STATA (version 16). Standard errors are reported in parentheses.

Table S7 Table 2 Re-estimated in STATA with Standard Errors Clustered at the Show-Level

	Dependent variable:	
	Fauci Appearances	
	(1)	**(2)**
Constant	-5.551^{***}	-4.558^{***}
	(0.258)	(0.231)
CNN	0.935^{***}	0.132
	(0.360)	(0.421)
MSNBC	0.958^{***}	0.874^{***}
	(0.303)	(0.317)
Week		-0.078^{***}
		(0.025)
CNN × Week		0.070^{**}
		(0.028)
MSNBC × Week		0.026
		(0.027)
Observations	2,206	2,206
Log Likelihood	−596.792	−580.626
Log α	2.089^{***} (0.215)	1.890^{***} (0.222)
Akaike Inf. Crit.	1,201.583	1,175.252

* p<0.1
** p<0.05
*** p<0.01
Note: Negative binomial regressions predicting the number of times Dr. Fauci appears. Data has been aggregated to the show-week, meaning shows can appear multiple times. All models are offset by the log of the total number of celebrities identified by Microsoft's API for a show in a given week. Finally, STATA uses reports log α instead of θ for the dispersion parameter. We updated our notation to follow their convention. Standard errors clustered at the show-level are shown in parentheses.

Table S8 Table 3 Re-estimated in STATA with Standard Errors Clustered at the Show-Level

	Dependent variable:	
	"Death" Mentions	
	(1)	**(2)**
Constant	-4.905^{***}	-4.729^{***}
	(0.046)	(0.044)
CNN	0.324^{***}	0.141^{**}
	(0.054)	(0.061)
MSNBC	0.251^{***}	0.114^{*}
	(0.056)	(0.068)
Week		-0.009^{***}
		(0.002)
CNN × Week		0.010^{***}
		(0.002)
MSNBC × Week		0.008^{***}
		(0.003)
Observations	2,307	2,307
Log Likelihood	−7,998.654	−7,976.959
Log α	-1.816^{***} (0.079)	-1.849^{***} (0.080)
Akaike Inf. Crit.	16,005.310	15,967.920

* p<0.1
** p<0.05
*** p<0.01
Note: Negative binomial regressions predicting the number of times a word from our modified LIWC "death" category are used. Data has been aggregated to the show-week, meaning shows can appear multiple times. All models are offset by the log of the total number of words for a show in a given week. Finally, STATA uses reports log α instead of θ for the dispersion parameter. We updated our notation to follow their convention. Standard errors clustered at the show-level are reported in parentheses.

Table S9 Table 4 Re-estimated in STATA with Standard Errors Clustered at the Show-Level

	Dependent variable:	
	"Health" Mentions	
	(1)	**(2)**
Constant	–3.577***	–3.418***
	(0.015)	(0.027)
CNN	0.308***	0.159***
	(0.021)	(0.039)
MSNBC	0.151***	0.017
	(0.020)	(0.039)
Week		–0.008***
		(0.001)
CNN × Week		0.008***
		(0.002)
MSNBC × Week		0.007***
		(0.002)
Observations	2,307	2,307
Log Likelihood	–10,453.200	–10,423.290
Log α	–2.016*** (0.072)	–2.052*** (0.070)
Akaike Inf. Crit.	20,912.400	20,858.580

* p<0.1
** p<0.05
*** p<0.01
Note: Negative binomial regressions predicting the number of times a word from our modified LIWC "health" category are used. Data has been aggregated to the show-week, meaning shows can appear multiple times. All models are offset by the log of the total number of words for a show in a given week. Finally, STATA uses reports log α instead of θ for the dispersion parameter. We updated our notation to follow their convention. Standard errors clustered at the show-level are reported in parentheses.

Table S10 Table 5 Re-estimated in STATA with Standard Errors Clustered at the Show-Level

	Dependent variable:
	Fauci Appearances
Constant	-7.744^{***}
	(1.027)
CNN	3.034^{***}
	(1.094)
MSNBC	3.240^{***}
	(1.060)
"Death" Mentions	2.067
	(1.664)
"Health" Mentions	2.802^{***}
	(1.136)
CNN × "Death" Mentions	-3.456^{*}
	(1.821)
CNN × "Health" Mentions	-2.024^{*}
	(1.189)
MSNBC × "Death" Mentions	-3.123^{*}
	(1.734)
MSNBC × "Health" Mentions	-3.030^{***}
	(1.164)
"Death" Mentions × "Health" Mentions	−2.316
	(1.670)
CNN × "Death" Mentions × "Health" Mentions	2.975
	(1.919)
MSNBC × "Death" Mentions × "Health" Mentions	3.372^{*}
	(1.776)
Observations	2,101
Log Likelihood	−548.583
Log α	1.943^{***} (0.212)
Akaike Inf. Crit.	1,123.167

* p<0.1
** p<0.05
*** p<0.01
Note: Negative binomial regressions predicting the number of times Dr. Fauci appears. Data has been aggregated to the show-week. Offset of the number of celebrities included in all models (see Table 2). "Death" and "health" mentions described on page 14 of the main text. Finally, STATA uses reports log α instead of θ for the dispersion parameter. We updated our notation to follow their convention. Standard errors clustered at the show-level are reported in parentheses.

Notes

1. Search terms are case insensitive since TV news archive captions are provided with lowercase letters.
2. In count models, like negative binomial regressions, offsets are used to adjust estimates for the level of exposure. For example, if Dr. Fauci appears on “Hannity” 10 times, while only appearing on “The Rachel Maddow Show” 5 times, then it may be logical to conclude that Dr. Fauci is more likely to appear on the former instead of the latter. However, if only 5 total people appeared on “The Rachel Maddow Show,” whereas 100 people appeared on “Hannity,” then the *rate* in which Dr. Fauci appeared on the “The Rachel Maddow Show” would be higher. This study accounts for such difference by including relevant offsets in all the negative binomial regressions reported below. Please refer to the Appendix for additional robustness checks, including logistic regressions which show essentially the same results as those reported in the main text. Those interested in learning more about our estimation procedure should consult Hilbe (2011).

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About the authors

Corresponding Author. Assistant Professor of Social Science Informatics, Department of Political Science, University of Iowa.

Ph.D. Candidate, Department of Political Science, University of Iowa.