The University of Texas at Austin
Center for Media Engagement
Moody College of Communication

CABLE AND NIGHTLY NETWORK NEWS COVERAGE OF CORONAVIRUS

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SUMMARY

Throughout the coronavirus pandemic, the public has turned to television news for updates, prompting a surge in ratings. To see how coverage differed across networks, the Center for Media Engagement examined the content of cable and nightly network news programs between January and June of 2020.

The results show that coverage of the virus is politicized in ways that seem to put profit and partisanship above public health, particularly on Fox News and MSNBC. We found differences in the people and organizations referenced, the language used, and the factual claims made in coverage of the virus.

SUGGESTED CITATION:

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PROBLEM

Throughout the coronavirus pandemic, television has been an important source of information for many Americans. A surge in news watching turned into record ratings for cable and nightly network news programs, prompting headlines like "The Evening News is Back" and "Cable news soars to record ratings during coronavirus pandemic."

This report delves into what Americans saw when they watched the news during the most disruptive public health event in recent times. The Center for Media Engagement examined cable and nightly network news coverage of the coronavirus between January 21, the day of the first confirmed case of the coronavirus in the United States, and June 12, 2020, right after the country passed two million confirmed or probable cases.

The U.S. public encountered different coronavirus coverage depending on which network they watched. We analyzed 4,589 transcripts of the nightly news programs, amounting to 486,068 paragraphs of content. The data show that coverage varied across the evening line-ups on the major cable news networks (CNN, Fox News, and MSNBC) and also differed between these cable outlets and the nightly network news broadcasts (ABC, CBS, and NBC). The networks paid different amounts of attention to the coronavirus, mentioned different people and organizations, used different language when covering the pandemic, and discussed facts about the coronavirus differently. The results show that coverage of the virus is politicized in ways that seem to put profit and partisanship above public health, particularly on Fox News and MSNBC.

As part of this report, we've gathered information about the networks' board members and shareholders. These individuals and organizations knowingly or unknowingly condone politicized coverage. If you find the coverage troubling, you can contact them to advocate for change. Thank you to our funder, Mark Gibson, CEO, Capital Markets, JLL Americas, for funding this study.

KEY FINDINGS

Amount of Coverage

- On average across the six networks, 45% of the coverage was about the coronavirus
- Fox News discussed the coronavirus the least and NBC Nightly News discussed it the most

People and Organizations Referenced

- Fox News and MSNBC dedicated more air time to partisans than to health officials and organizations
- Fox News was more likely to mention Democrats, and MSNBC was more likely to mention Republicans

Language Used to Discuss the Coronavirus

We compared the phrases used across pairs of networks to identify phrases unique to each. Our analysis revealed the following.

Fox News vs. MSNBC

- Fox News was more likely to discuss the coronavirus in terms of business and the economy, whereas MSNBC was more likely to discuss the effects of the pandemic on healthcare institutions
- MSNBC was more likely to use words related to the scale of the virus than Fox News
- Fox News was more likely to use terms related to China than MSNBC

Fox News vs. CNN

- Fox News was more likely to use words associated with business and the economy, whereas CNN was more likely to use words related to prevention
- Fox News was more likely to discuss drug treatments, whereas CNN was more likely to discuss testing and vaccines
- Fox News was more likely to mention China and related terms than CNN

CNN vs. MSNBC

- MSNBC was more likely to use economic terms than CNN
- CNN was more likely to discuss a wide range of treatments than MSNBC
- MSNBC was more likely than CNN to use words describing the widespread scale of the virus

Cable vs. Broadcast

- Broadcast nightly news programs on ABC, CBS, and NBC used similar language
- Broadcast news was more likely than cable news to use specific terms (e.g., numbers, roles such as parent or child, places such as stores or hospitals, and locations such as New York or Los Angeles)

Tone of coverage

- Fox News coverage was perceived as less negative and left people feeling prouder and more hopeful
- Broadcast news coverage generated significantly more worry and fear

Factual Claims

Mask-wearing

- Across the networks, most of the information shared was correct
- All networks had some instances where they shared incorrect information and times when they presented both correct and incorrect information in a segment
- Fox News was, proportionally, the least likely to present correct information after the CDC released its mask-wearing guidelines

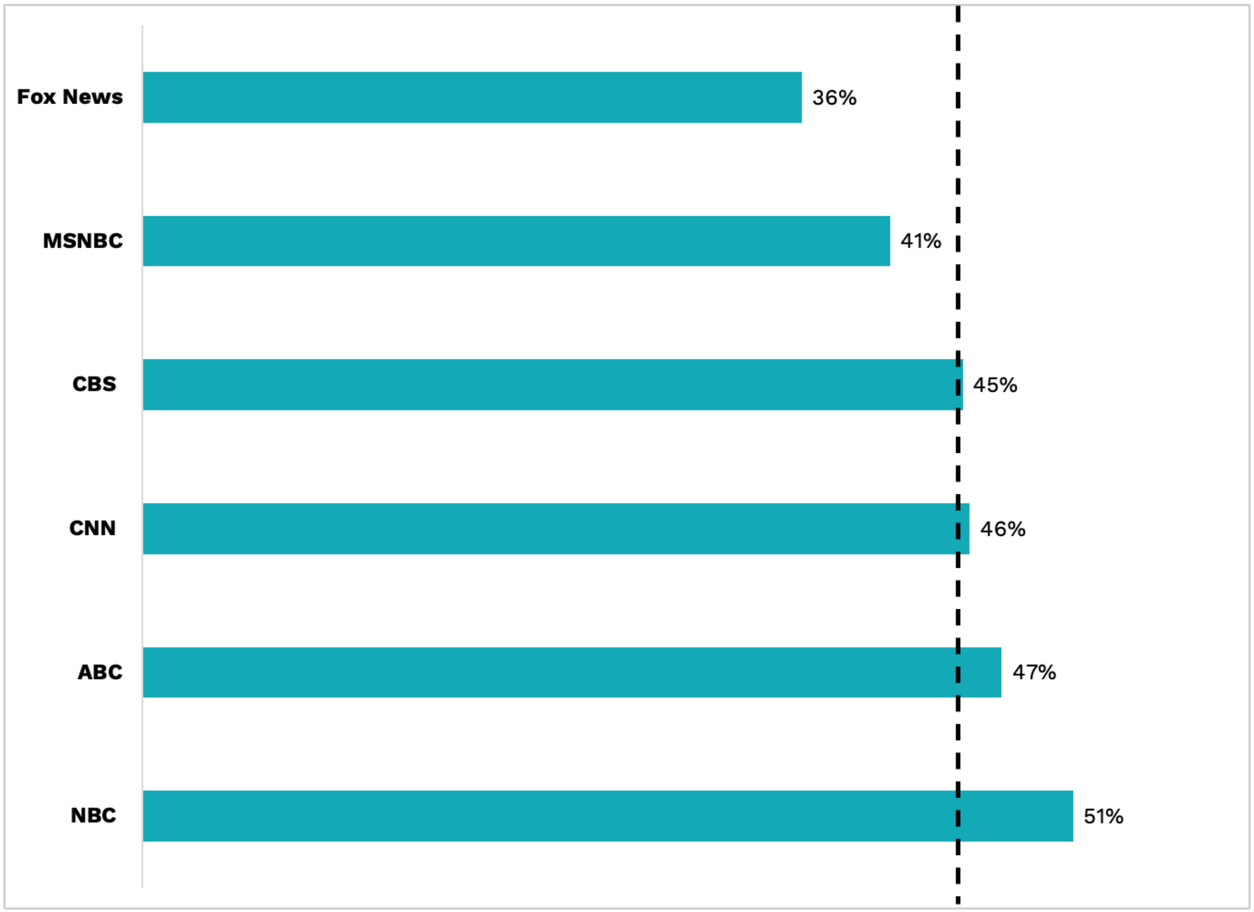
Use of Disinfectants/Ultraviolet light

- CNN and broadcast news covered misleading/incorrect information in the same way, but were also likely to include correct information in the same segment
- MSNBC and Fox News included a higher proportion of content that only included incorrect/misleading information
- Fox News covered this topic less frequently than the other networks

AMOUNT OF CORONAVIRUS COVERAGE

On average across the six networks, 45% of the transcript paragraphs were about the coronavirus (indicated by the black dashed line in the chart below). Fox News discussed the coronavirus the least, with 36% of paragraphs about the virus. NBC Nightly News discussed it the most, with 51% of paragraphs about the virus.

PERCENTAGE OF COVID-RELATED PARAGRAPHS BY NETWORK

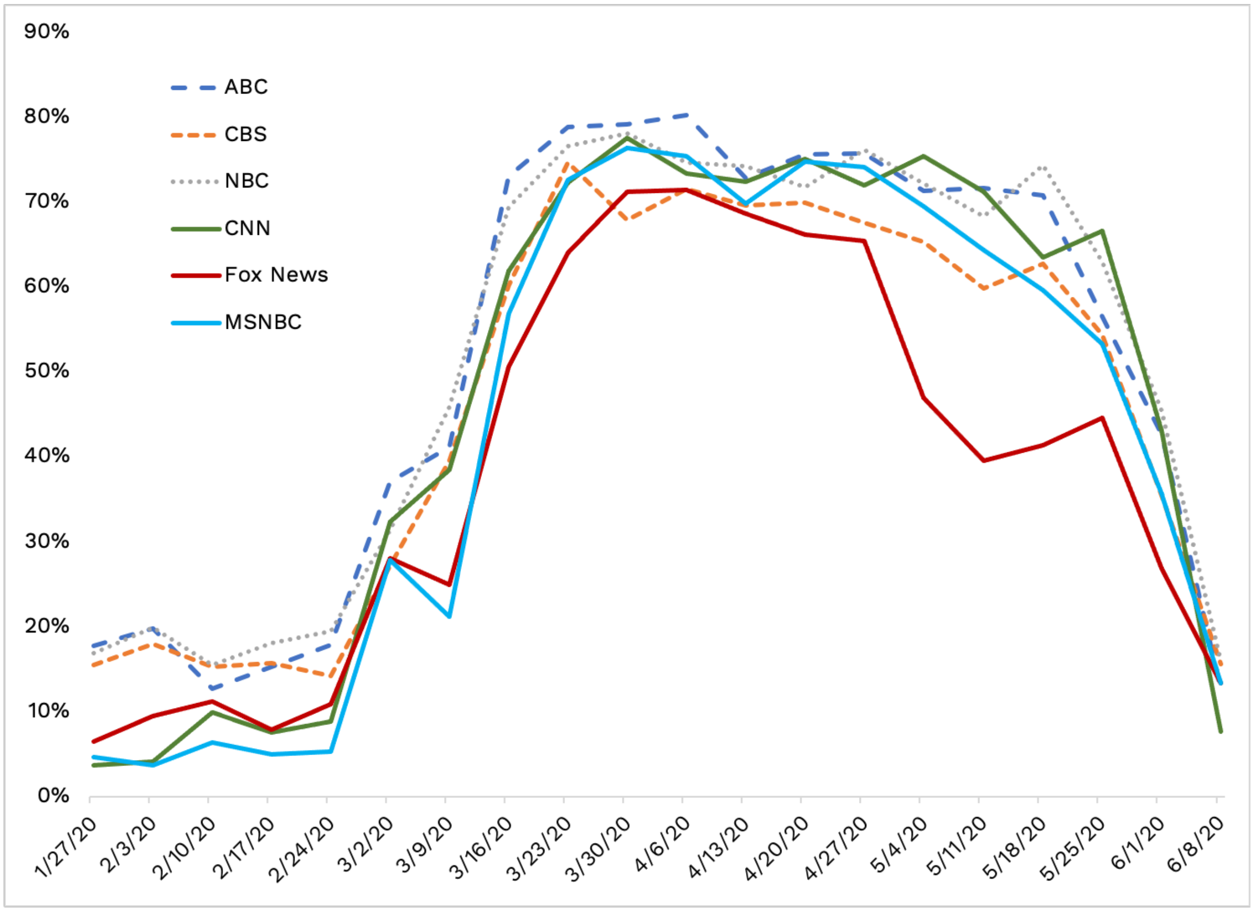


Data from the Center for Media Engagement

Notes: Analysis of primetime programming on CNN, Fox News, and MSNBC and nightly national news programs on ABC, CBS, and NBC between January 21 and June 12, 2020.

If we inspect coronavirus-related paragraphs over time, coverage tends to rise and fall in a similar pattern across the networks. In late February, coronavirus coverage began to increase across all outlets, corresponding with rising U.S. cases and the discovery of community spread of COVID-19; it continued to rise in early March when the Dow Jones dropped and throughout the month as the first stay-at-home orders began. Coverage peaked the week leading into April as cases continued to rise in hotspots such as New York and surpassed 100,000 nation-wide. In late April, Fox News coronavirus coverage began to decline. In late May, COVID-related coverage dropped off across the networks as media focus turned to the protests regarding the killing of George Floyd. Throughout the coverage period, ABC and NBC consistently had the highest rate of coronavirus-related paragraphs and Fox News had the lowest.

PERCENTAGE OF COVID-RELATED PARAGRAPHS ACROSS NETWORKS AND WEEKS



Data from the Center for Media Engagement

Notes: Analysis of primetime programming on CNN, Fox News, and MSNBC and nightly national news programs on ABC, CBS, and NBC between January 21 and June 12, 2020.

Although there were some differences in how the broadcast networks discussed the coronavirus, our analysis showed substantial similarities in their coverage (see the Methodology section at the end of this report). Given this, we combine the broadcast networks (ABC, CBS, and NBC) into one category in subsequent sections.

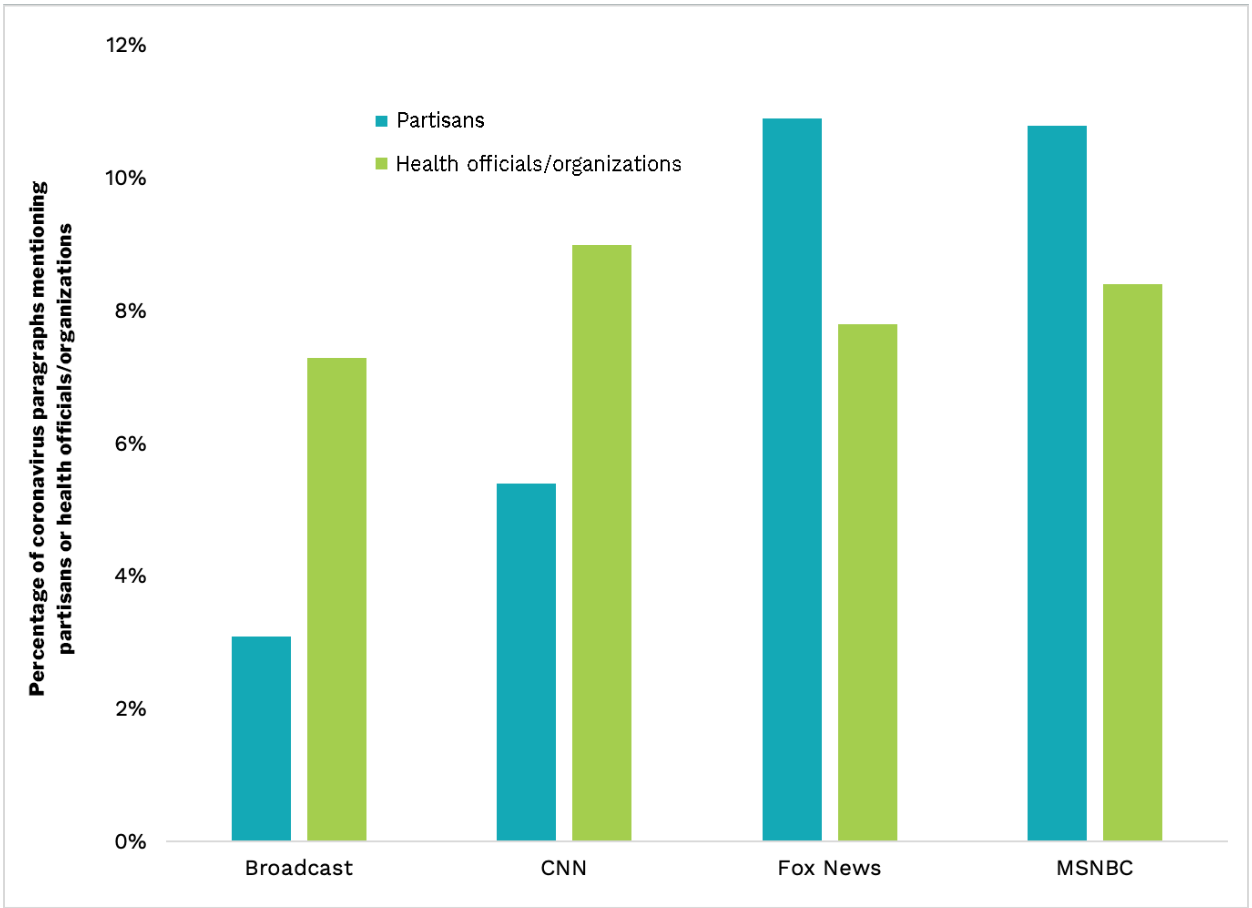
PEOPLE AND ORGANIZATIONS REFERENCED

We examined the people and organizations referenced in the coronavirus coverage. There were differences in how often the networks mentioned health officials/organizations and how often they mentioned partisans, by which we mean people or organizations that identify as Democrats, liberals, Republicans, or conservatives.

More Fox News and MSNBC paragraphs mentioned partisans than mentioned health officials and organizations, whereas more broadcast and CNN paragraphs mentioned health officials and organizations than mentioned partisans.[1] Ten percent of paragraphs on MSNBC and Fox News mentioned partisans compared to 5% on CNN, and less than 3% on broadcast news.

There are few differences in mentions of health officials and organizations across networks — the percentage of paragraphs varied from 7% on broadcast to 9% on CNN, with Fox News and MSNBC falling in the middle with approximately 8%.

PERCENTAGE OF PARAGRAPHS MENTIONING PARTISANS AND HEALTH OFFICIALS/ORGANIZATIONS ACROSS NETWORKS

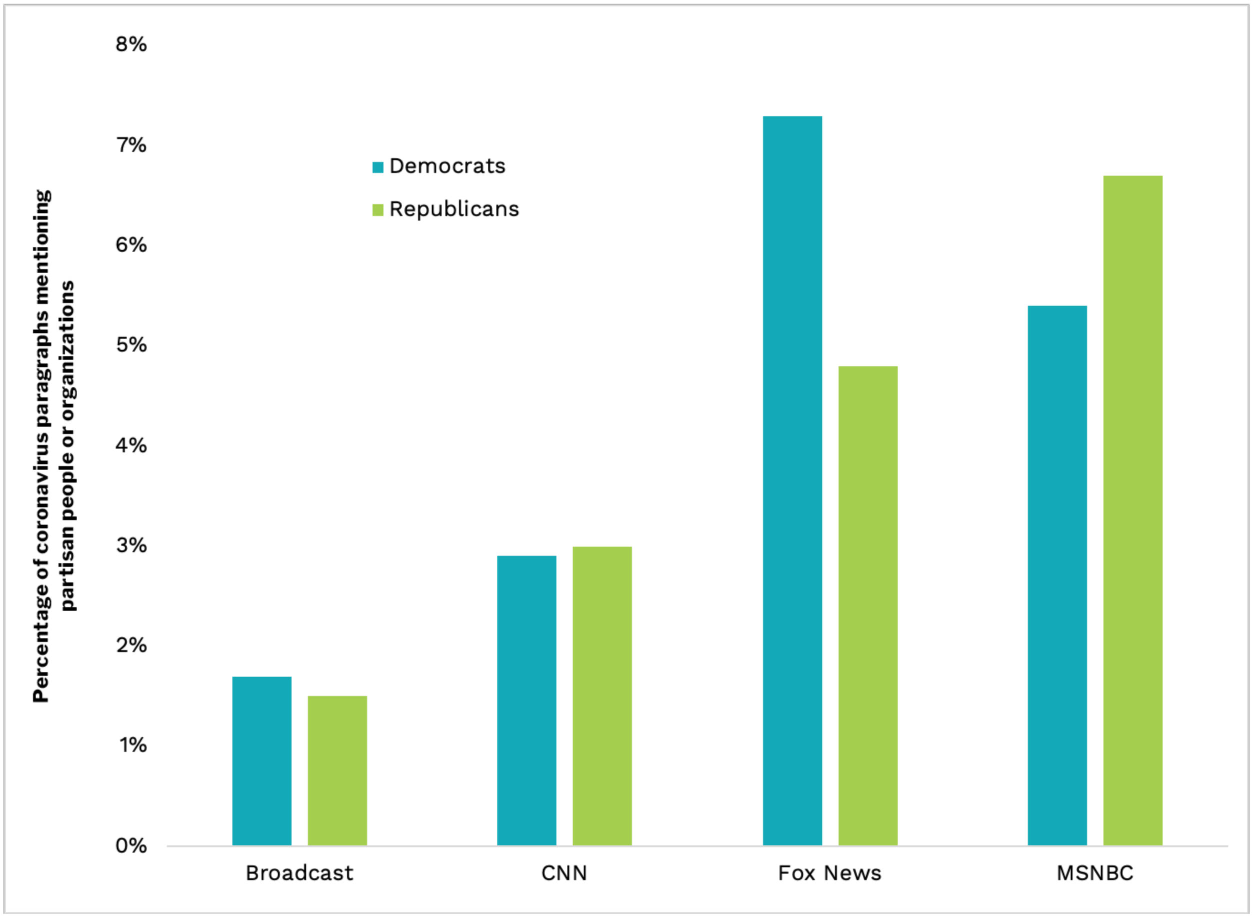


Data from the Center for Media Engagement

Notes: Analysis of content between January 21 and June 12, 2020. Nightly national news programs on ABC, CBS, and NBC combined as "Broadcast."

When looking specifically at *which* partisans were mentioned, further differences across the networks appeared. Fox News paragraphs were more likely to mention Democrats—7% of paragraphs—compared to MSNBC (5%), CNN (3%), and broadcast news (2%). Alternatively, MSNBC was more likely to mention Republicans (7%) than Fox News (5%), CNN (3%), or broadcast (2%).

PERCENTAGE OF PARAGRAPHS MENTIONING DEMOCRATS OR REPUBLICANS ACROSS NETWORKS



Data from the Center for Media Engagement

Notes: Analysis of content between January 21 and June 12, 2020. Nightly national news programs on ABC, CBS, and NBC combined as "Broadcast."

LANGUAGE USED

We next analyzed how the news organizations discussed the coronavirus. In particular, we looked at differences in the language used by each network. To do this, we identified words that were being used significantly more often on one network compared to another. Once these words were isolated, we ran an additional analysis to group the words into categories based on how they were used in the text. We include the full analysis in the appendix and highlight subsets of the findings here. In the pages that follow, we present comparisons in the language used between Fox News and MSNBC, followed by CNN and Fox News, and then CNN and MSNBC. We then offer brief observations about differences in coverage between cable and broadcast news.

Fox News vs. MSNBC

Economic and Healthcare System Impacts

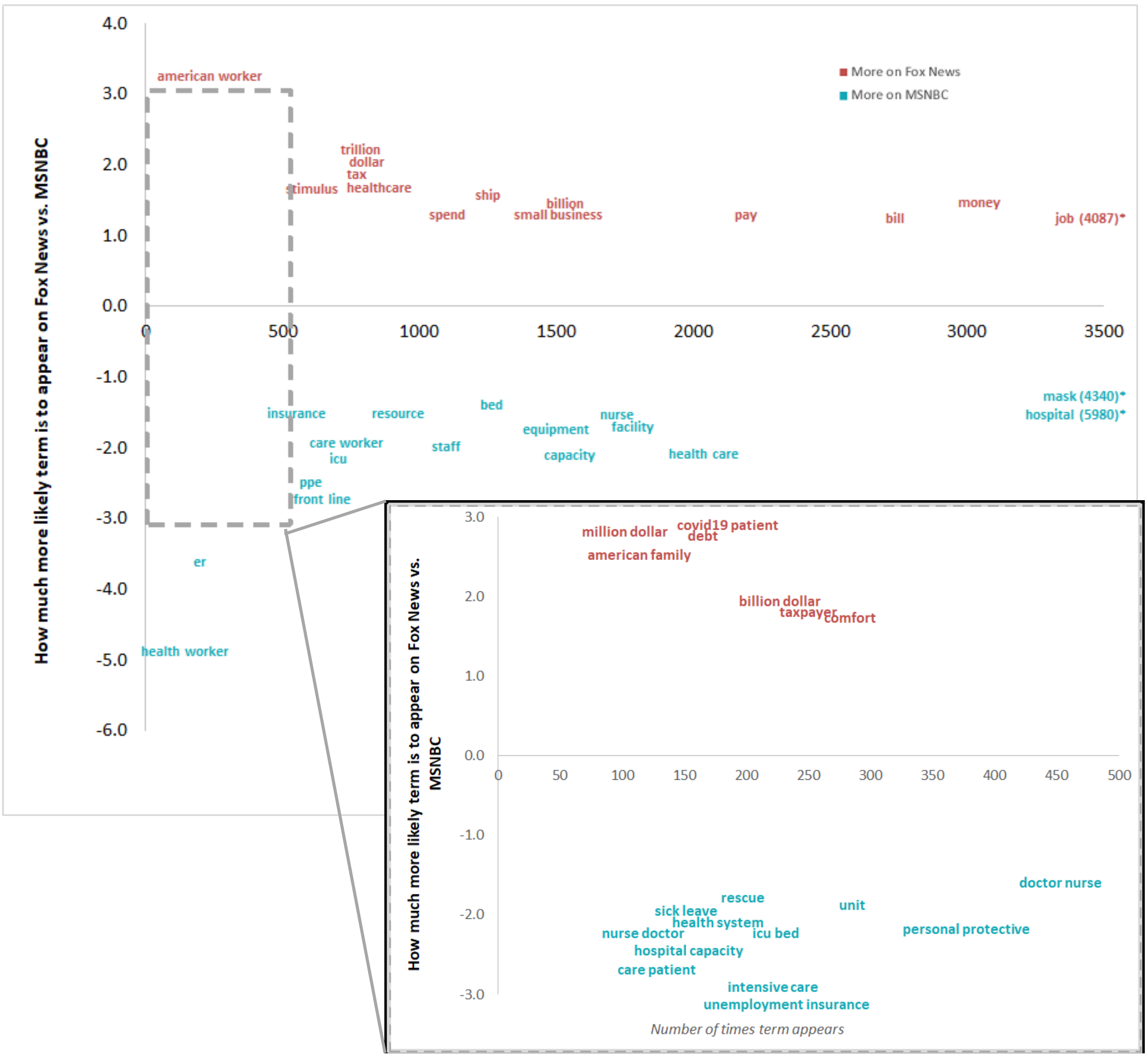
Fox News discussed the coronavirus more frequently in terms of business and the economy, whereas MSNBC discussed the coronavirus in terms of health responses.

The next chart shows the words that were more likely to appear on one network than another. The red words, found in the top half of the chart, were more likely to appear on Fox News than on MSNBC. The blue words, found in the bottom half of the chart, were more likely to appear on MSNBC than on Fox News.

The vertical axis indicates how much more likely the word is to appear on one network than another. “American worker,” for instance, was just over three times more likely to appear on Fox News than on MSNBC. The horizontal axis indicates how frequently the word was used across the two networks. The words “money” and “bill,” for example, appeared frequently in the coverage across both Fox News and MSNBC. Note that the words “job,” “mask,” and “hospital” appeared most frequently and are not included at scale to maintain the readability of the chart.

As the chart shows, words like “debt” and “small business” were significantly more likely to appear on Fox than on MSNBC. The opposite trend is observed for words like “personal protective” and “health care”.

TERMS ASSOCIATED WITH CORONAVIRUS HEALTHCARE SYSTEM AND ECONOMIC IMPACTS, FOX NEWS VS. MSNBC



Data from the Center for Media Engagement

Notes: Analysis of content between January 21 and June 12, 2020. Chart shows terms that were significantly more likely to appear on Fox News than on MSNBC (shown in red in the top half of the chart) or more likely to appear on MSNBC than on Fox News (shown in blue in the bottom half of the chart). The vertical axis shows how much more likely the term was to appear on one network compared to the other; “American worker” was 3.2 times more likely to appear on Fox News than on MSNBC, for example, and “health worker” appeared 4.9 times more likely to appear on MSNBC than on Fox News. The horizontal axis shows the total number of times the term appeared. “Money” appeared 3,041 times across Fox News and MSNBC and “bill” appeared 2,740 times. ”Job” appeared 4,087 times, “mask” appeared 4,340 times, and “hospital” appeared 5,980 times and are not included at scale to ensure that the chart is readable.

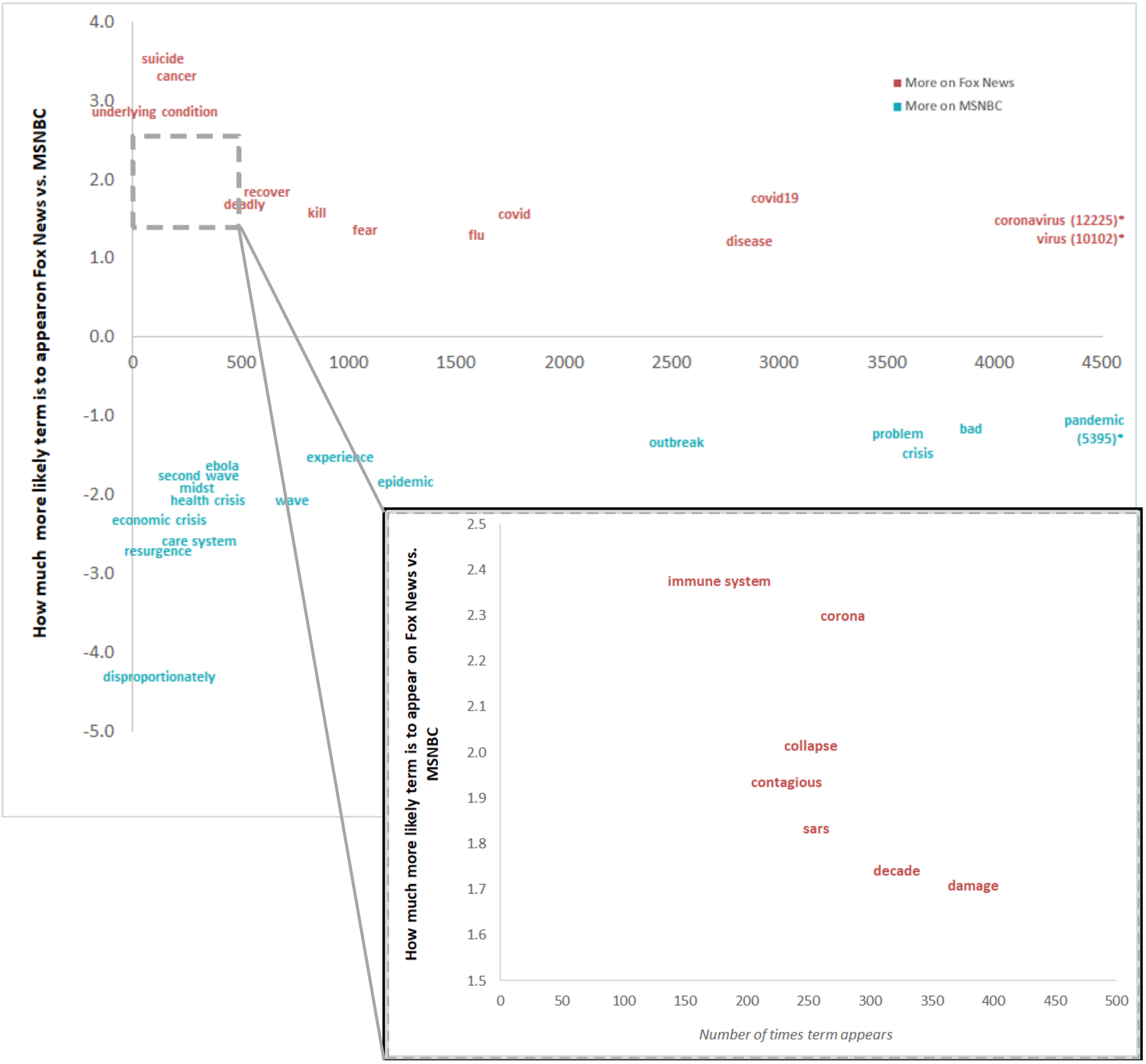
A few examples of how these words were used in context include:

- Fox News host Sean Hannity said, “This is -- this is important stuff, direct payments to Americans. $367 **billion** for business loans, $500 **billion** for distressed companies. Another $150 **billion** for hospitals and health care workers.” (Hannity, March 25)
- MSNBC host Rachel Maddow said, “The state with the worst weekly rise in cases last week was Alabama -- weekly increase of 28 percent in their cases. Alabama, we have frankly been pretty worried about the **hospital capacity** in Montgomery, the state’s capital city. **ICU capacity** has been filled in Montgomery, Alabama, **hospitals**, for days now.” (The Rachel Maddow Show, May 27)

Scale

In general, MSNBC was more likely to use words that conveyed the scale of the virus than Fox News was. Although Fox News was more likely to use words like “deadly” and “kill,” MSNBC was more likely to use words like “crisis,” “pandemic,” and “problem.” For example, MSNBC host Lawrence O’Donnell said, “And the response to the coronavirus in the United States is being led by the most incompetent and ignorant president in history, who shook up his administration today by announcing the replacement of his White House chief of staff in the middle of this **crisis**” (The Last Word with Lawrence O’Donnell, March 6). Fox News, alternatively, was more likely to mention “suicide,” the “flu,” and “underlying condition,” words that relate to a more minimal impact of the virus and the mental health consequences of staying home.

TERMS ASSOCIATED WITH CORONAVIRUS SCALE, FOX NEWS VS. MSNBC



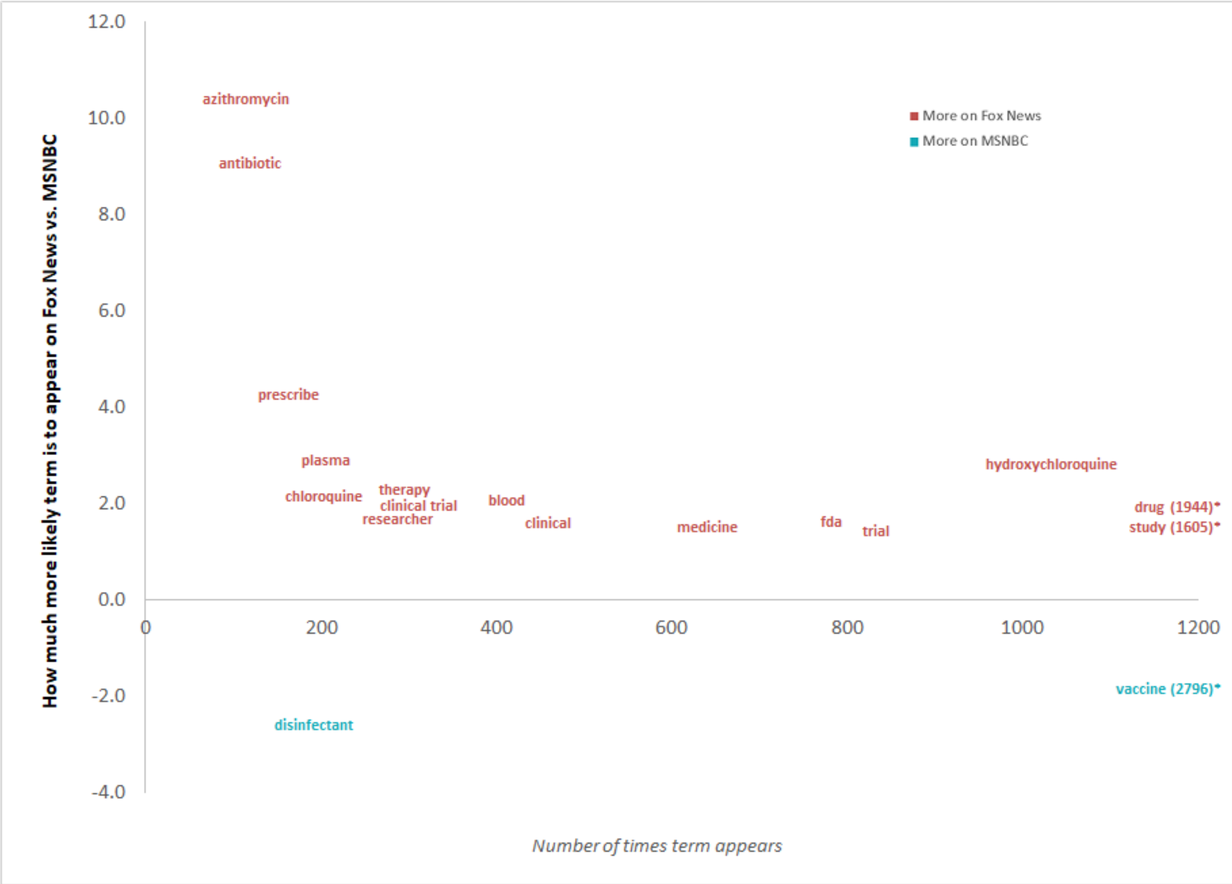
Data from the Center for Media Engagement

Notes: Analysis of content between January 21 and June 12, 2020. Chart shows terms that were significantly more likely to appear on Fox News than on MSNBC (shown in red in the top half of the chart) or more likely to appear on MSNBC than on Fox News (shown in blue in the bottom half of the chart). The vertical axis shows how much more likely the term was to appear on one network compared to the other; "suicide" was 3.5 times more likely to appear on Fox News than on MSNBC, for example, and "disproportionately" was 4.3 times more likely to appear on MSNBC than on Fox News. The horizontal axis shows the total number of times the term appeared across the two networks. "covid19" appeared 2,979 times across Fox News and MSNBC and "bad" appeared 3,887 times. *"Coronavirus" appeared 12,225 times, "virus" appeared 10,102 times, and "pandemic" appeared 5,395 times and are not included at scale to ensure that the chart is readable.

Treatments

Several words associated with possible treatments more likely to appear on Fox than on MSNBC. Words like “hydroxychloroquine” and “azithromycin’’ were more likely to appear on Fox. These two drugs were described by President Trump as “having a real chance to be one of the biggest game changers in the history of medicine.” For example, Fox News host Sean Hannity said, “According to reports we are getting from serious experts, **hydroxychloroquine** is now looking more and more like an important tool in treating this virus” (Hannity, April 7).

TERMS ASSOCIATED WITH CORONAVIRUS TREATMENTS, FOX NEWS VS. MSNBC



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Origins

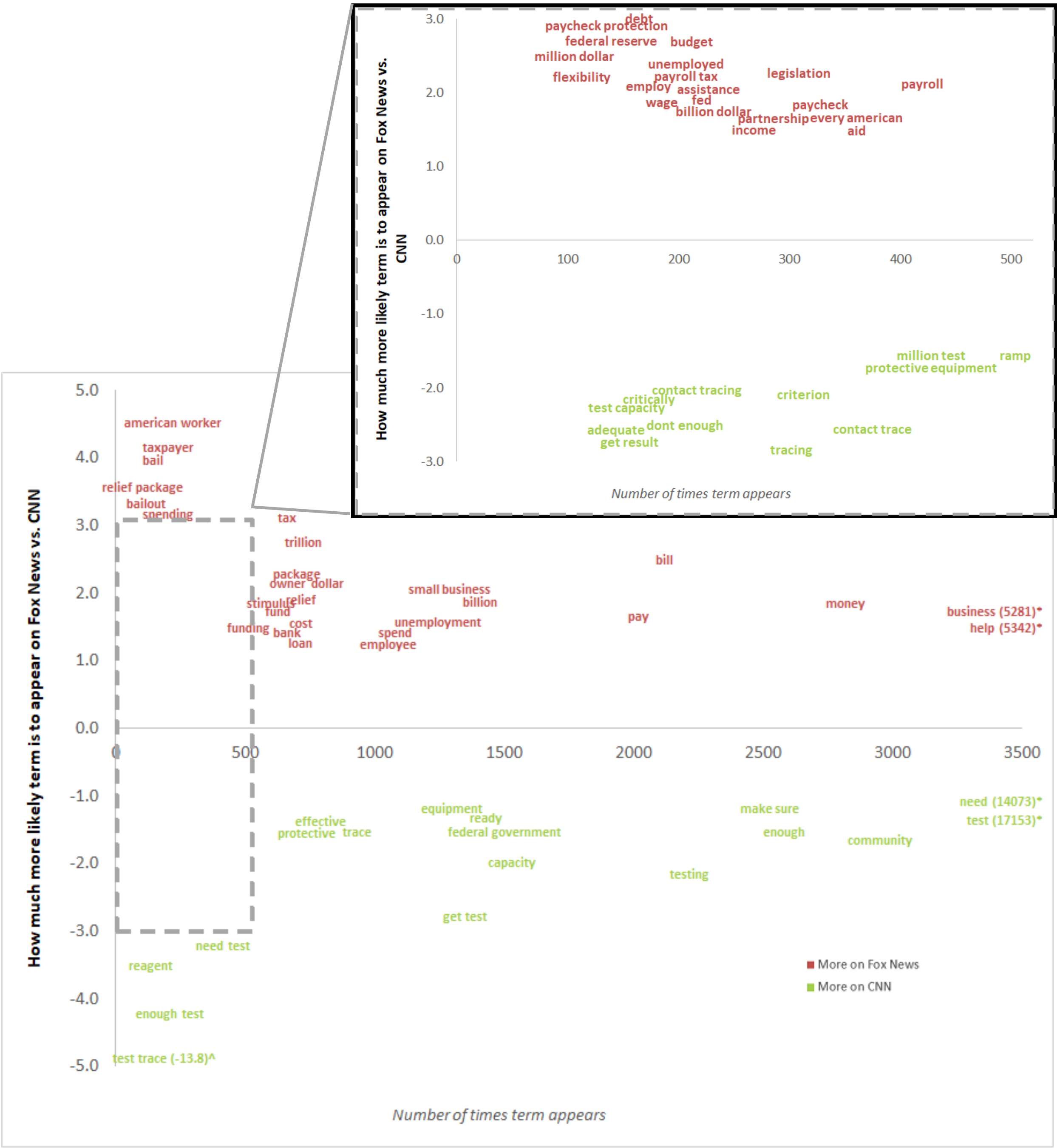
Fox News associated the virus with China and focused on the origin of the coronavirus more than MSNBC did. Although each of the following words appeared less than 250 times in coronavirus coverage on Fox News and MSNBC, “communist party” was 45 times more likely to appear on Fox News than on MSNBC, followed by “Beijing” (37 times more likely), “Chinese communist” (22 times more likely), and “wet market” (22 times more likely). Fox News was also more likely to use the words “originate” and “origin” than MSNBC.

Fox News vs. CNN

Economy and Prevention

In coverage of the coronavirus, Fox News was more likely to use words associated with business and the economy, whereas CNN was more likely to use words related to prevention.

TERMS ASSOCIATED WITH THE ECONOMY AND PREVENTION, FOX NEWS VS. CNN



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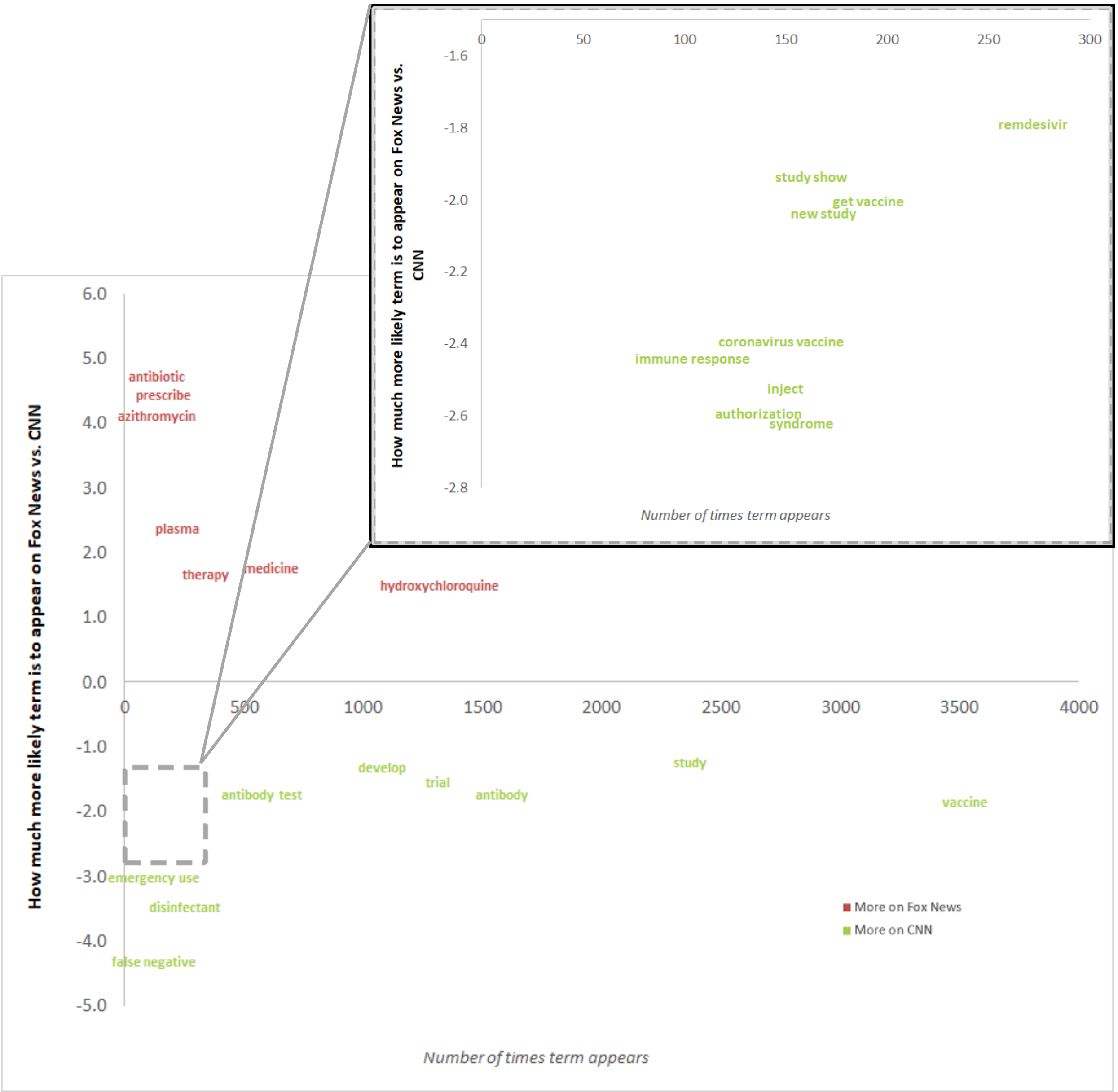
A few examples of how these words were used in context include:

- Fox News White House Correspondent John Roberts said, “Topping the list, a **payroll tax** holiday for both **employees** and employers, temporarily eliminating the entire 12.4 percent **payroll tax**. Democrats who embraced a two percentage point cut in 2010 were quick to slam the idea” (Special Report with Bret Baier, March 10).
- On CNN’s The Situation Room, correspondent Jim Acosta said, “On the government’s response to the pandemic, an inspector general’s report looked at how hospitals are coping and finding severe shortages of **testing** supplies and extended waits for **test** results and widespread shortages of **personal protective equipment**, put staff and patients at risk.” (The Situation Room, April 6)

Treatments

Fox News and CNN both discussed ways of addressing the coronavirus, but there were differences in the language used. As with the MSNBC and Fox News comparison, Fox News was more likely to discuss hydroxychloroquine and azithromycin. CNN used words like trial, study, and vaccine more frequently.

TERMS ASSOCIATED WITH CORONAVIRUS TREATMENTS, FOX NEWS VS. CNN



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Origins

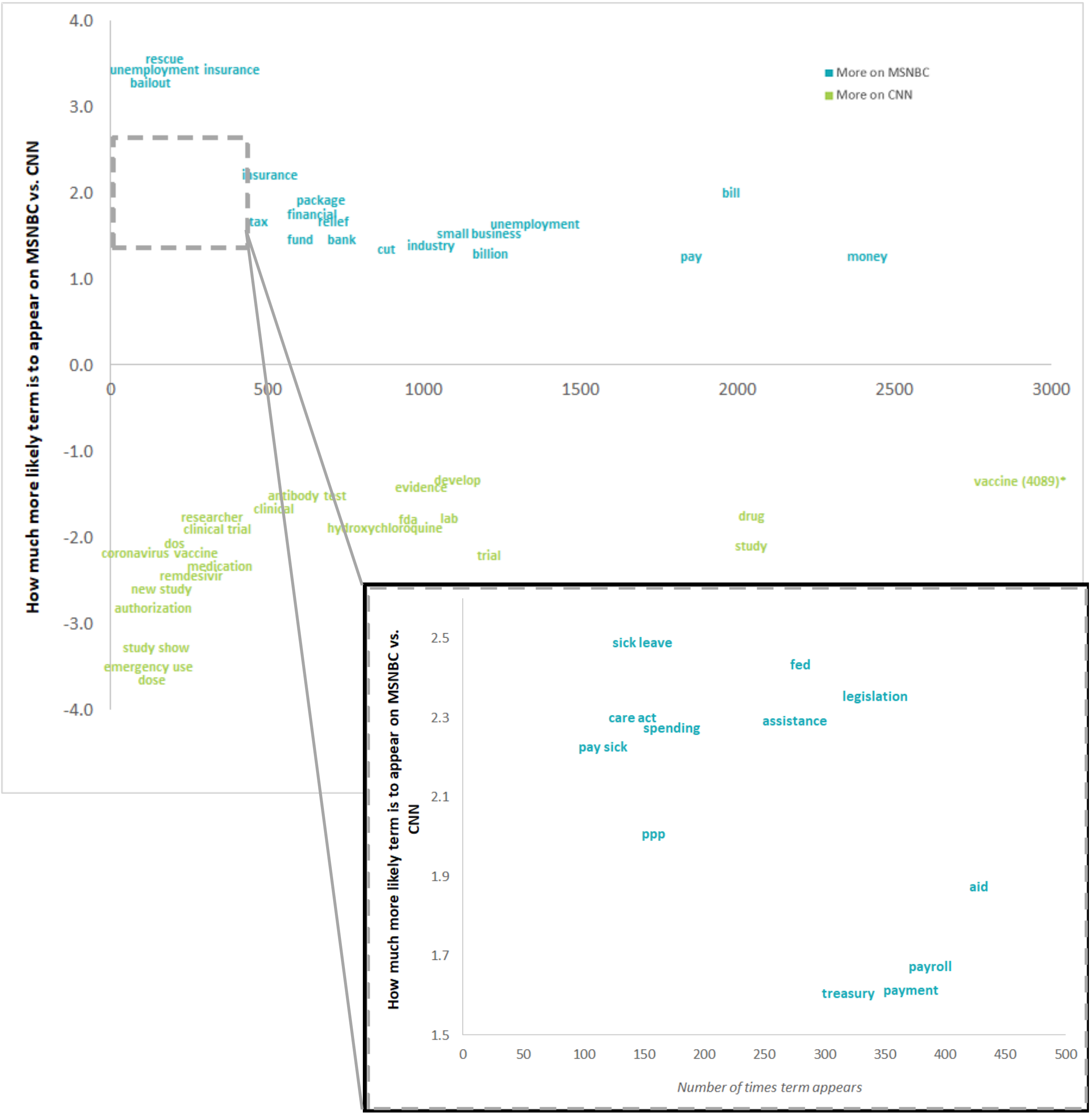
Fox News associated the virus with China and discussed the origin of the coronavirus more frequently than CNN did. Although each of the following words appeared less than 250 times in coronavirus coverage on Fox News and CNN, “Chinese communist” was 47 times more often on Fox News than on CNN, followed by “communist party” (23 times more often), and “wet market” (10 times more often). Fox News was also more likely to use the words “originate” and “origin” than CNN.

CNN vs. MSNBC

Economy and Treatment

MSNBC used economic terms more frequently when describing the coronavirus than did CNN. This included more frequent use of terms like “unemployment insurance,” “tax,” “small business,” and “money” on MSNBC relative to CNN. CNN discussed a wider range of treatments and more ways to address the coronavirus compared to MSNBC using words like “antibody test,” “vaccine,” “clinical trial,” “hydroxychloroquine,” and “remdesivir” more frequently.

TERMS ASSOCIATED WITH CORONAVIRUS ECONOMIC IMPACTS AND TREATMENTS, MSNBC VS. CNN



Data from the Center for Media Engagement

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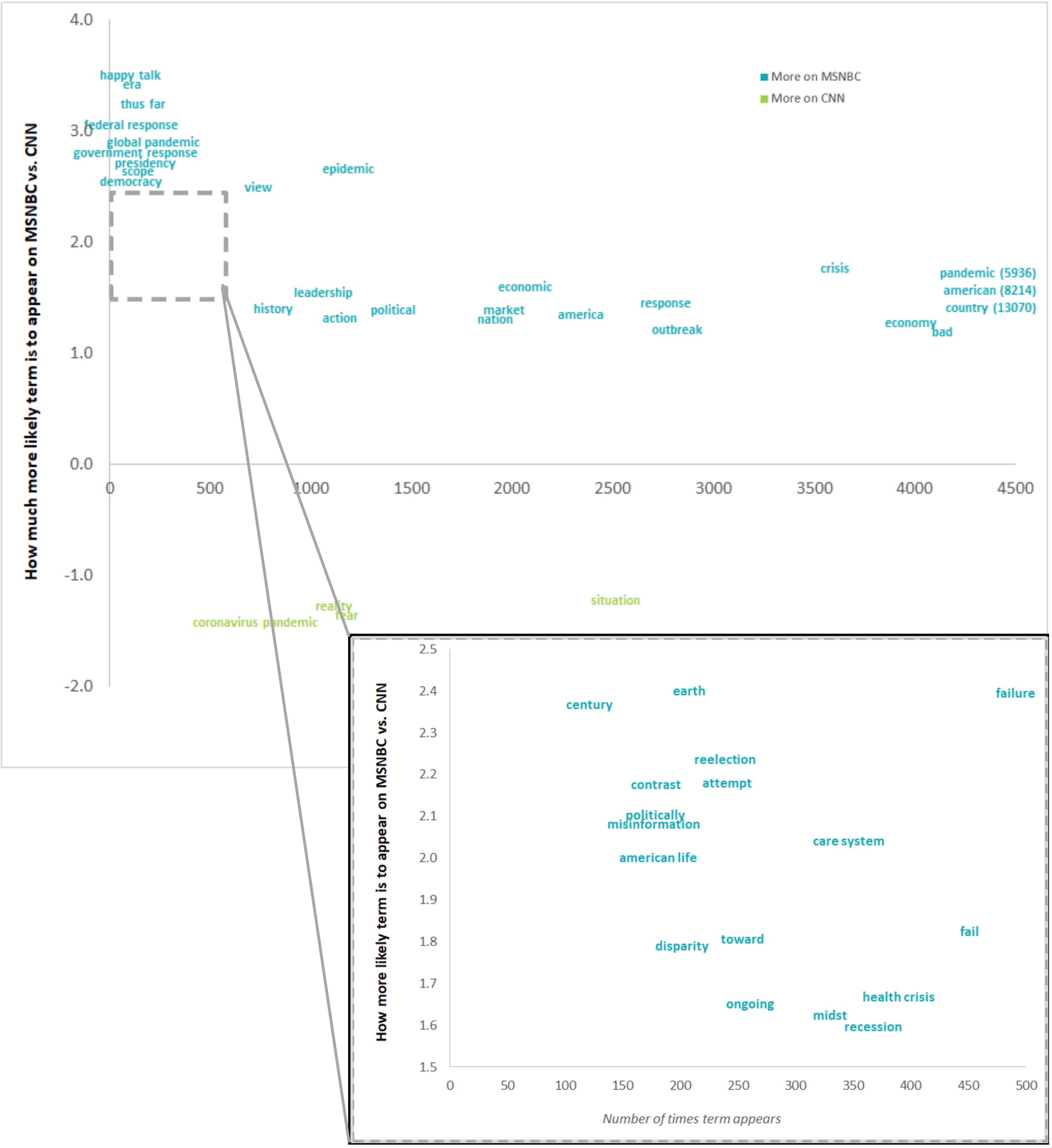
A few examples of how these words were used in context include:

- MSNBC host Ari Melber said, “The human tragedy obviously very real. We’re seeing growing lines from **unemployment** offices to food banks. And economists warn this is far from over.” (The Beat with Ari Melber, May 12).
- CNN Chief Medical Correspondent Dr. Sanjay Gupta said, “There is no evidence that this works. It’s very concerning, Anderson, and, you know, I think, irresponsible because I think it’s sending a very wrong message. It’s a message that he has sent before on **hydroxychloroquine**.” (Anderson Cooper 360, May 18)
- CNN National Correspondent Erica Hill said, “One vaccine currently in the works is showing signs of promise. All eight participants in the study developed antibodies to the virus. Moderna, which is partnering with the NIH, says if future studies go well, the **vaccine** could be available to the public as early as January.” (The Situation Room, May 18)

Scale and American Response

MSNBC used words describing the widespread scale of the coronavirus, as well as words about the U.S. response, more so than did CNN. For example, MSNBC host Lawrence O’Donnell said, “And the **response** to the coronavirus in the United States is being led by the most incompetent and ignorant president in history, who shook up his administration today by announcing the replacement of his White House chief of staff in the middle of this **crisis**” (The Last Word with Lawrence O’Donnell, March 6).

TERMS ASSOCIATED WITH CORONAVIRUS SCALE AND AMERICAN RESPONSE, MSNBC VS. CNN



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Cable vs. Broadcast

We conducted an analysis of the language used on cable and nightly network news broadcasts. The results showed that the broadcast programs had much in common, and that there were consistent differences between cable and broadcast news. Based on this analysis, included in more detail in the methodology at the end of this document, we analyzed the differences between cable and broadcast.

Overall, broadcast tended to use more specific terms than cable. The nightly network news programs were more likely to mention specific numbers; specific roles such as patient, child, and passenger; specific places such as stores, hospitals, and cruise ships; and specific locations such as New York, Los Angeles, and Texas.

FACTUAL CLAIMS

We examined what factual claims the networks presented about two issues: mask-wearing and using disinfectants or ultraviolet light to combat the coronavirus. We chose these topics for several reasons. First, the claims originated from two different governmental sources: the Centers for Disease Control and Prevention (CDC) and President Trump, respectively. Second, several health and fact-checking organizations published judgments related to these claims, which we could use to assess the validity of the information shared in the news coverage. Finally, the differences in timing for these two topics made for an interesting comparison. Mask-wearing had been discussed since the beginning of the pandemic, but the CDC did not recommend that asymptomatic individuals wear masks in public until April 3, 2020. Alternatively, the discussion of disinfectants/UV light was prompted by a specific event: a statement President Trump made on April 23, 2020 that was fact checked by several major organizations.

To do this analysis, we looked for paragraphs that mentioned factual information about either of these topics and then analyzed the two paragraphs before and the three paragraphs after the coverage mentioned the information. We call each set of six paragraphs a segment.

Mask-wearing

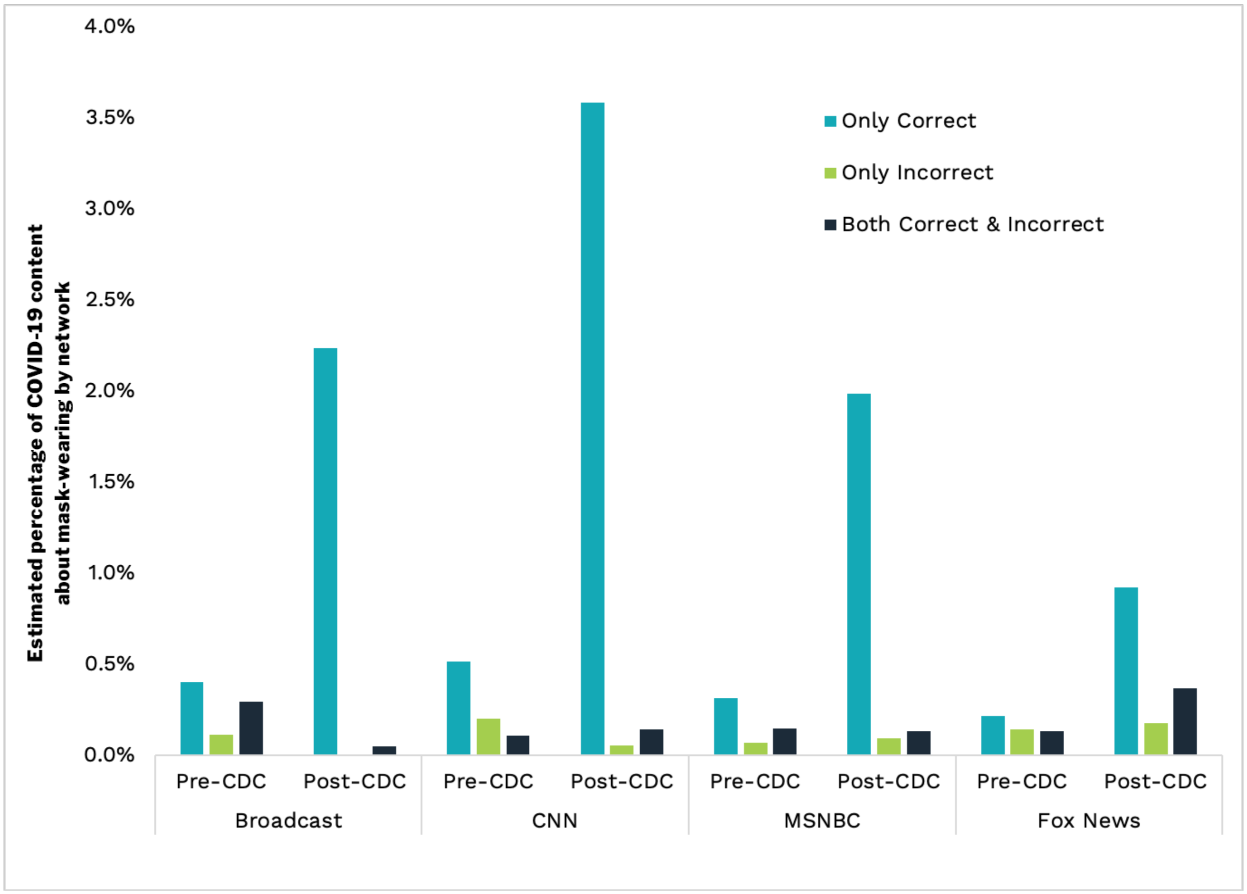
Based on what scientists now know about how the coronavirus spreads and recommendations released by the CDC on April 3, 2020, we considered "correct" any statements suggesting that people *should* wear masks in public. Statements suggesting that people should not wear masks, or that wearing masks was riskier (e.g., lung infections, breathing in CO_2) than not wearing masks, were considered misleading or incorrect.

We explored information shared by news organizations before and after the CDC released its mask-wearing guidelines, predicting that the news networks would be more likely to discuss correct information after the guidelines were released. From all of the transcripts, we randomly choose 2,000 segments that mentioned masks and similar words—1,000 segments from before the CDC announcement and 1,000 from after the CDC announcement. We then estimated how much coverage likely appeared on the different networks based on this sample of segments. Details about how the estimates were computed are available in the methodology section of this report.

In line with our expectations, correct information about mask-wearing increased after the CDC announcement on all networks. Further, the estimated percentage of segments with only incorrect information decreased after the CDC announcement on broadcast news and

CNN, and remained relatively stable on MSNBC and Fox News. The estimated percentage of segments that discussed *both* correct and incorrect information decreased on broadcast news after the CDC announcement, stayed relatively stable on CNN and MSNBC, and *increased* on Fox News. In sum, correct mask-wearing coverage increased after the CDC guidelines changed, but on Fox News, the estimated percentage of segments with both correct *and* incorrect information increased as well.

MASK-WEARING INFORMATION ACROSS NETWORKS BEFORE AND AFTER THE CDC RECOMMENDATIONS



Data from the Center for Media Engagement

Notes: Analysis of content between January 21 and June 12, 2020. Nightly national news programs on ABC, CBS, and NBC combined as "Broadcast."

To further explore this content, we pulled examples of segments containing correct, incorrect, and both correct and incorrect information. The correct information encouraged people to wear a mask, and, at times, provided more detail about why mask-wearing is important (e.g., it helps protect the people around the mask-wearer).

Some statements with incorrect information reflected changing guidelines. A Cuomo Prime Time segment, for instance, encouraged people not to wear masks prior to the CDC recommendation changes. Other incorrect information, however, came *after* the recommendations and provided sensationalized arguments that mask-wearing requirements are only symbolic (e.g., The Story with Martha MacCallum, May 18).

Segments that included both incorrect and correct information were sometimes simply reviewing how the science, and thus the CDC recommendations about mask-wearing, had evolved (e.g., Cuomo Prime Time, May 8). At other times, segments questioned scientific findings and argued that mask requirements were only put in place to keep the public panicking (e.g., Ingraham Angle, April 29).

When the news networks provided content about mask-wearing, it was largely correct. But there was some troubling content that emphasized not only that mask-wearing was unnecessary, but that it was also a way to keep the U.S. public under control.

Correct Mask-Wearing Information Only	**MSNBC, The Last Word with Lawrence O'Donnell, May 27:** "Dr. Anthony Fauci, a member of the White House Coronavirus Task Force, discussed the importance of wearing a mask today. … I wear it for the reason that I believe it is effective. It's not 100 percent effective. I mean, it's sort of respect for another person and have that other person respect you. You wear a mask, they wear a mask, you protect each other." **Fox News, Fox News @ Night, April 2:** "And some new guidance that took some New Yorkers by surprise from the mayor of New York City today that all New Yorkers should wear some kind of facial covering when they walk outside, a scarf, a bandanna, a mask, preferably not a surgical mask, saving those for medical professionals. This new policy designed to keep people who may not know they're sick from infecting others. … We want to make sure that anyone who doesn't have to get it, doesn't get it. So a face covering is just a simple way to protect other people, and to reduce the speed of that community spread and hopefully keep a number of people from being affected who don't have to be affected."

Incorrect Mask-Wearing Information Only	**CNN, Cuomo Prime Time, March 9:** "Masks, OK, we keep telling people, Anthony Fauci, everybody else, if you're sick, you need a mask. If you are not sick, don't worry about the mask. It's not just about making a policy judgment. It's about whether or not professionals have the equipment that they need because it's getting sold out." **Fox News, The Story with Martha MacCallum, May 18:** "In it, she writes, cloth masks are largely symbolic. The science hasn't changed, but the agenda has. Implementing mandatory mask policies across the society of 300 million because it makes some people feel better is absurd on its face. But the policy makes a lot of sense if you understand its purpose and usefulness to shift the American mindset."
Both Correct and Incorrect Mask-Wearing Information	**CNN, Cuomo Prime Time, May 8:** "Don't touch the mask. Leave them for the health care workers. Well, maybe a mask. Well, a mask won't hurt you. A mask is better than nothing. And, now, everybody has to have a mask. It's confusing. Me, too. I was -- I learned as we went along. As soon as we learned that coronavirus could be transmitted by people who were perfectly healthy, then, the reason to wear masks, universally, suddenly, became apparent. Because I don't know that I'm not infectious, right at this moment. If so, in order to protect you, if we were close together, I would have to wear that mask. That would help me protect you." **Fox, Ingraham Angle, April 29:** "Those are nice people. Was Chris Cuomo wearing a mask out in the Hamptons the other week? Maybe. Well, by the way, they'll say this whole mask thing is settled science, just like they do with climate change. Of course, it's not. And they know it. Our own experts have gone from masks aren't necessary to masks are essential. You have to wear them when you go jogging. Just a few weeks time. Now, Rush Limbaugh made a great point, as he always does, on the radio the other day. And he said the virus itself, as it weakens and states start reopening, the media that have been selling this panic, panic, panic for weeks and weeks and weeks, they have fewer images to sell their hysteria to justify continued lockdowns. ... But wait a second, on what scientific basis is he saying this? Is it settled science that this coronavirus will come back for sure in the fall? No, it's not settled science. Here's a totally different view from France's preeminent infectious disease expert, Professor Didier Raoult."

Disinfectants

We also investigated coverage related to whether disinfectants and ultraviolet light could kill the coronavirus when injected, ingested, or otherwise applied to the human body. During an April 23, 2020 press conference, President Trump made the following statement speculating about disinfectants and ultraviolet (UV) light:

> "So, supposing we hit the body with a tremendous, whether it's ultraviolet or just very powerful light, and I think you said that hasn't been checked, but you're going to test it. And then I said supposing you brought the light inside the body, which you can do either through the skin or in some other way. And I think you said you're going to test that too. Sounds interesting, right? And then I see the disinfectant, where it knocks it out in a minute, one minute. And is there a way we can do something like that by injection inside or almost a cleaning, because you see it gets in the lungs and it does a tremendous number on the lungs. So it'd be interesting to check that. So that you're going to have to use medical doctors with, but it sounds interesting to me. So, we'll see, but the whole concept of the light, the way it kills it in one minute. That's pretty powerful."

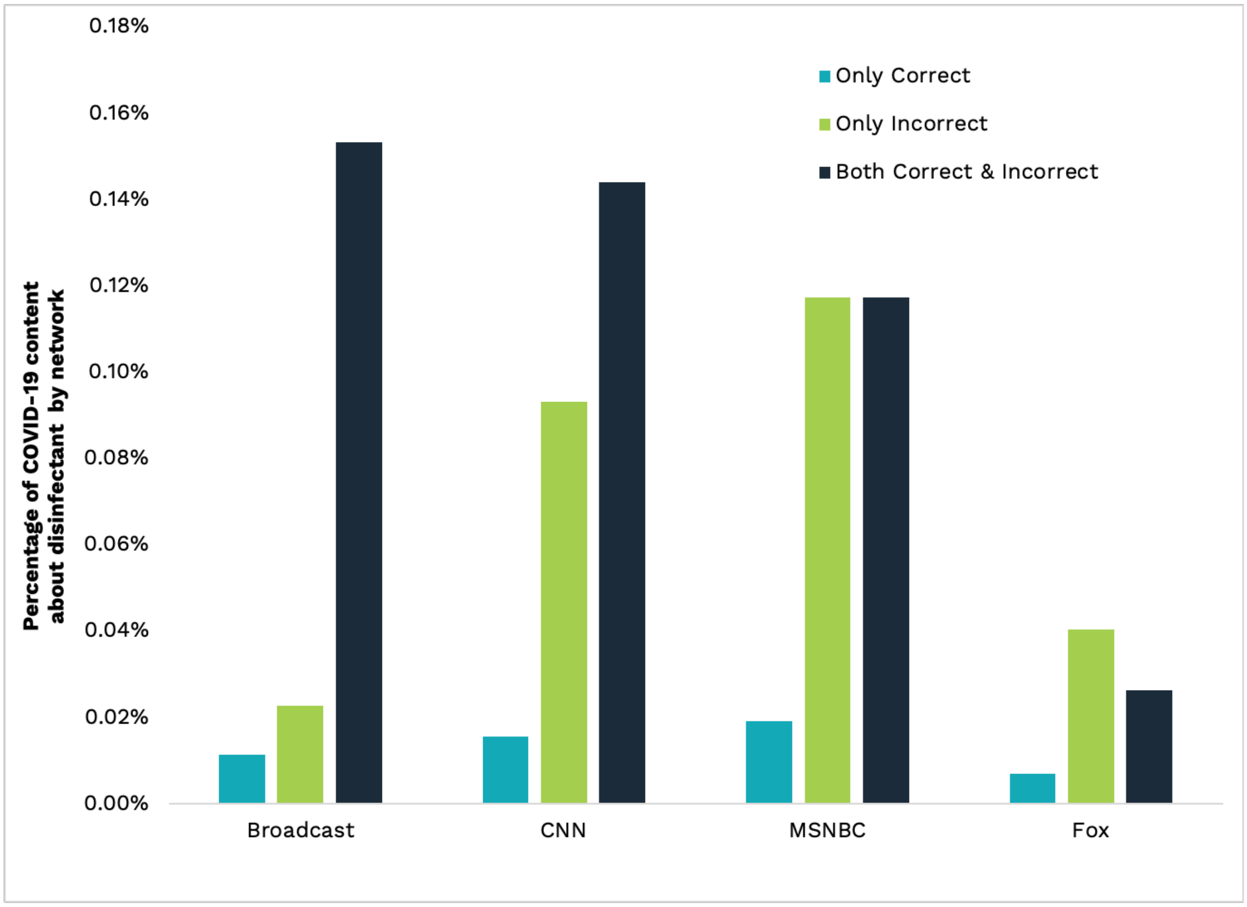
Fact-checking organizations, as well as the World Health Organization, and even Lysol, responded with statements emphasizing that ingesting disinfectants and applying UV light to the human body can be dangerous.

We examined how the news networks covered this exchange. For this topic, correct information included statements explaining that ingesting or injecting disinfectant, bleach, Lysol or something similar, or applying UV light to the body can be dangerous and is not advised. Misleading or incorrect information for this topic included statements suggesting that doctors should test injection or ingestion of bleach and content directly stating that ingesting or injecting bleach can kill the coronavirus.

All networks were more likely to include the incorrect information, whether alone or accompanied by the corrective information, than they were to include the correct information by itself. This is likely because what made disinfectants and UV light newsworthy was a misleading statement made by President Trump. Of the segments that included content related to this topic, 80% were published in the week after President Trump made his statement. Further, many of the segments quoted his comments directly. Some segments, although not all, also made a statement that ingesting disinfectant is not advisable (see examples below).

Again, there were differences across networks. Overall, Fox News covered this topic less than the other networks. CNN and broadcast news covered the misleading/incorrect information in some way, but also tended to include correct information in the same segment. MSNBC included similar amounts of only misleading/incorrect information and both correct and incorrect information. Fox News included proportionally more segments with only misleading/incorrect information than segments with only correct or with both incorrect and correct information.

DISINFECTANT INFORMATION ACROSS NETWORKS



Data from the Center for Media Engagement

Notes: Analysis of content between January 21 and June 12, 2020. Nightly national news programs on ABC, CBS, and NBC combined as "Broadcast."

Correct Disinfectant/UV Information Only	**CNN, Erin Burnett OutFront, April 24:** “Today, you have taken an extraordinary step to warn Los Angeles residents just moments ago not to inject or ingest disinfectants. Did you ever think you’d have to give a warning like that? … I do want to make it clear that people in the public need to understand it would be extraordinarily dangerous for them to ingest or to inject any of these disinfectants and we’re worried because we all want hope right now. Every single one of us wants out, we want life to go back to normal. We’re also looking for miracles. But that isn’t an appropriate step for anybody to take.” **Fox, Ingraham Angle, May 6:** “Well, it’s -- ultraviolet light to kill bacteria and viruses has been around for more than 100 years now, and it works really well. It’s used, for example, in a lot of surgical operating theaters overnight to decontaminate these theaters. So come the morning you have a nice clean environment with no bacteria, no viruses. So it really works. It’s very efficient at killing microbes. And Dr. Brenner, what about the potential harm to individuals exposed to ultraviolet light? Is there any danger there, because you also hear that a lot? Well, yes, it’s absolutely true. Conventional germicidal UV light, which is being initially used in these studies, is not safe for human exposure.”
Incorrect Disinfectant/UV Information Only	**MSNBC, MSNBC Live, April 28:** “As we get into the fall, the question of the election is going to be who can lead this country out of one of the most epic disasters it’s ever faced and when you have an incumbent who’s talking about people shooting up Lysol to deal with the coronavirus, it would suggest that he’s not up to the job, and in the end, there’s only two types of elections.” **CNN, CNN Tonight, May 6:** “This virus is far from contained, even now. And the false promises, the confusion, it’s just continued. Reaching a low point with the president shocking his own task force when he said this less than two weeks ago. ‘I said supposing you brought the light inside the body, which you can do, either through the skin or in some other way. And I think you said you’re going to test that, too. Sounds interesting. Right. And then I see the disinfectant. Where it knocks it out in a minute. One minute. And is there a way we can do something like that by injection inside or almost a cleaning? Because you see it gets on the lungs --’ Every single time it’s like the first time you’ve seen it, right? And that is why we are in no position to reopen safely. After months of misinformation and confusion. And the president who even now refuses to listen to the experts, the people on the front lines.”

Both Correct and Incorrect Disinfectant/UV Information	**CNN, Special Event, May 4:** "'That I see the disinfectant were in a minute, one minute and is there a way we can do something again by injection inside or most the cleaning--' An unbelievable and perplexing moment that had people calling hotlines asking if they should be using disinfectant on themselves to combat the virus. This idea of prompted statements from the CDC, the EPA, numerous state health officials and even the makers of Lysol and Clorox to warn 'do not try this. It could kill.' Requiring doctors, public officials and organizations to shift their focus from fighting COVID-19 to actually warn the public not to ingest disinfectant. I certainly wouldn't recommend the internal ingestion of a disinfectant." **NBC, Nightly News, April 24: "**And tonight, President Trump is facing widespread backlash after his comments wondering aloud about household disinfectants as a possible treatment for COVID-19, causing even the makers of Lysol issue a warning. ... 'So supposing we hit the body with a tremendous, whether it's ultraviolet or just very powerful light, and I think you said that hasn't been checked but you're going to test it. And then I said supposing you brought the light inside the body, which you can do either through the skin or in some other way. And I think you said you're going to test that too. Sounds interesting.'"

METHODOLOGY

This study used Nexis Uni to gather transcripts for the following programs on weeknights between January 21, 2020, the day of the first confirmed case of the coronavirus in the United States, and June 12, 2020, right after the country passed two million confirmed or probable cases and 20,000 deaths:[2]

- CNN: Anderson Cooper 360 Degrees, The Lead with Jake Tapper, Cuomo Prime Time, Erin Burnett OutFront, CNN Tonight, and The Situation Room
- Fox News: The Five, Special Report with Bret Baier, The Story with Martha MacCallum, Tucker Carlson Tonight, Hannity, Ingraham Angle, and Fox News @ Night
- MSNBC: MTP Daily, The Beat with Ari Melber, All in with Chris Hayes, The Rachel Maddow Show, The Last Word with Lawrence O'Donnell, 11th Hour with Brian Williams, and Hardball (through March 2 and programming through April 7)
- ABC World News Tonight
- CBS Evening News
- NBC Nightly News

Each transcript was broken down by paragraph, with a row dedicated to each new paragraph as indicated in the transcript. In the corpus, this amounted to 486,068 paragraphs across 4,589 transcripts.[3]

Coronavirus Classifier

We began developing the classifier through human coding of news transcripts. Coders classified each paragraph in a transcript as either directly related to COVID-19 (that is, the paragraph included words directly related to COVID-19, including the health, political, economic, and other implications of the disease), indirectly related to COVID-19 (that is, the paragraph did not include words that directly identified COVID-19, but the context of the transcripts made it clear that the health, political, economic, or other implications of the disease were being discussed), or not related to COVID-19. Two coders manually coded the transcripts for 52 news broadcasts (transcripts for two to three broadcasts from each program and two to three broadcasts for each week of content in the dataset), totaling 12,298 paragraphs. Reliability was strong (Direct COVID-19: Krippendorff's alpha = .87; Indirect COVID-19: Krippendorff's alpha = .85).

After establishing reliability, a single coder manually classified the transcripts from an additional 214 broadcasts. These transcripts included one randomly selected transcript a week from two programs on each network and a randomly selected broadcast for each month for the remaining programs. This yielded a total of 44,643 manually labeled paragraphs.

Based on the manually coded dataset, we worked to create a reliable binary classifier to label paragraphs as related to COVID-19, whether directly or indirectly, or not. To this end, we evaluated a number of classic Machine Learning approaches and a more modern language modeling approach, BERT. Given the performance statistics included below, we used BERT to categorize all of the paragraphs as to whether they were about the coronavirus.

Model	Precision	Recall	F1	Accuracy
Logistic regression	0.745	0.784	0.764	0.826
Extra-Trees	0.729	0.618	0.669	0.809
XGBoost	0.822	0.783	0.802	0.839
BERT	0.889	0.865	0.873	0.897

People and Organizations Referenced

To determine the people and organizations referenced in the COVID-19 news content, we first attempted to use the end-to-end neural named entity linking model originally introduced by Kolitsas et al., 2018. This model jointly discovers and links entities in a text document to their corresponding Wikipedia pages. We were not able to validate this approach with human coders, however. Two coders went through two rounds of coding, and, in each round, we compared the human coding to the automated model identification of the entities. In the first round, the coders and model identified entities in COVID-19 content for 3 programs (ABC's World News Tonight from May 11; CNN's Erin Burnett OutFront from February 12; CNN's The Situation Room from April 22, 5pm hour), and found 204 entities across all three transcripts. In the second round, the coders and model identified 233 more entities in the COVID-19 content in 5 additional programs (Fox New's Fox News @ Night from April 6; Fox's Special Report with Bret Baier from February 5; Fox's Tucker Carlson Tonight from April 21; MSNBC's 11th Hour with Brian Williams from June 3; MSNBC's MSNBC Live from May 18). The human coders highlighted the entities in the transcripts and identified the best Wikipedia page, in their judgment, that could be linked to that entity. We then ran inter-coder reliability, using Krippendorff's alpha, on the list of identified Wikipedia pages within each transcript. In both reliability rounds, the human coders were reliable (Round 1: Krippendorff's alpha = .79; Round 2: Krippendorff's alpha = .81). The humans were not, however, reliable with the automated model (Round 1: Krippendorff's alpha = .59; Round 2: Krippendorff's alpha = .60).

The reliability coding identified several problems stemming from the model's use of Wikipedia data. First, the automated model did not identify all people and institutions who became prominent in the COVID-19 context (e.g., U.S. Assistant Secretary of Health Brett Giror; Gov. Gretchen Whitmer of Michigan; Dr. Fauci; and Dr. Birx). This, perhaps, is because the model we employed was trained on the Wikipedia dump from March 2020, or because the individuals were not particularly prominent prior to the COVID-19 pandemic. Second, the Wikipedia pages identified were incorrect for several important entities in the COVID-19 context (e.g., FDA prompted a Wikipedia page to a Trade Union rather than the Food and Drug Administration; the West Wing of the White House sometimes prompted a link to The West Wing television show Wikipedia page; Mario Cuomo identified instead of Andrew or Chris Cuomo). Third, the requirement that there be a Wikipedia page for a person or organization was too strict for this project. The human coders reported that they noticed important people in the COVID-19 content, but could not identify them officially because those people did not have Wikipedia pages. Indeed, our alternative method (described below) did identify individuals who were mentioned in the coverage but did not have Wikipedia pages (e.g., Ramin Oskoui).

Next, we tested several other named entity identifier models, including spaCy, sfd, flair, and allen. We first ran a preliminary reliability analysis between the human coding completed in reliability round 1 (as described above). For this portion of the analysis, we were not interested in the quantities identified in the text, so we did not analyze the time, percent, quantity, date, cardinal, and other numeric entities. Even though the human coding instructions for this round were written to predict the Wikipedia model rather than the named entities models, the human coders were more reliable with the named entity models than the Wikipedia model (spaCy: Krippendorff's alpha = .68; sfd: Krippendorff's alpha = .66; flair: Krippendorff's alpha = .62; allen: Krippendorff's alpha = .62). Because spaCy produced the highest preliminary human-computer reliability, we selected spaCy for our analysis. We more formally tested spaCy by conducting a third round of reliability testing. Human coders and the spaCy model identified 553 entities in 4 news programs (CBS Evening News from June 12; CNN Special from March 19, 8pm hour; Fox's The Five from April 24; MSNBC's All In with Chris Hayes from May 13). The three human coders and the spaCy model were reliable (Krippendorff's alpha = .70). Reliability was strengthened even further when identification of definite articles were not considered in the reliability (i.e., when we counted "White House" and "the White House" as an agreement rather than a disagreement; Krippendorff's alpha = .75).

We applied spaCy named entity extraction using the English multi-task CNN pretrained model trained on OntoNotes to identify the named entities among the set of paragraphs classified as COVID-19 related. We filtered out the following irrelevant entity types: *language, date, time, percent, money, quantity, ordinal,* and *cardinal* since such entities would not correspond to people or organizations. Once spaCy identified the entities in each paragraph, we created a list of entities to categorize into thematic groups. This process produced a list of 26,253 entities. We cut any entity that was identified in fewer than five paragraphs, leaving us with 3,779 entities. We further narrowed the list in three steps: (1) deleting duplicates, (2) identifying junk entities, and (3) automatically categorizing some clear entities. First, to delete duplicates, we separated spaCy's identified entity from its entity category. For this project, we created our own categorizations of people and organizations, so we discarded the entity category (e.g., "Walter Reed, Person" and "Walter Reed, ORG" both became "Walter Reed"). Using R's "distinct" function, we removed exact duplicate entities from the file. We retained entities with different capitalizations, punctuations, etc. in case those features were significant to the interpretation of the entity (e.g., WHO, W.H.O., and who).

Second, two research team members reviewed the remaining list and identified junk entities. We defined these entities as those that were very clearly not related to a specific person or organization (e.g., I--, I\ll, that's) or those entities that were popular first names that could not be clearly linked with one person across our dataset (e.g., Zach, Taylor, Steve).

Third, we created categories of entities we could verify through outside sources (e.g., Wikipedia, governmental websites; see table below for details). For each list, we used grepl in R to search the entities list and identify content that matched each category. For full names or organizations, we ignored the case of the name (e.g., World Health Organization and world health organization would both be identified). For initials that likely referred to organizations, we searched the entities list more specifically for case and for initials that filled an entire cell (e.g., "W.H.O" and not "Look who"). In addition to the categories below, we created lists of states; cities; countries; other non-health, non-economic governmental institutions; and Black individuals killed by police officers. These categories, while important, were not related to the current project, so could be filtered out prior to manual coding. To ensure that the automation did not miscategorize any entities, a team member reviewed the automatically categorized entities and pulled any that could even potentially be categorized in a different way. These entities were then added to the list of entities to code manually, as described below.

Category	Description of Categories
Political officials Krippendorff's alpha = .81	Full category: Any person who is a current or former elected official or candidate, current/former members of a presidential cabinet, and current/former political/campaign advisors Automated: Full names of current and former presidents and vice presidents, Democratic presidential candidates from 2020 (as well as Hillary Clinton), state governors, U.S. Senators, and U.S. Representatives.
Democrats/liberals Krippendorff's alpha = .89	Full category: Any person or organization that is formally associated with Democrats or liberals Automated: Full names of the people in the "political officials" category who ran for election as Democrats, and the words "democrat" and "democrats"
Republicans/conservatives Krippendorff's alpha = .79	Full category: Any person or organization that is formally associated with Republicans or conservatives Automated: Full names of the people in the "political officials" category who ran for election as Republicans, and the words "republican" and "republicans"
Health people and organizations Krippendorff's alpha = .90	Full category: Medical doctors, health-related governmental agencies and people who work there, private governmental agencies and people who work there, health correspondents, other institutions that clearly indicate a health focus (e.g., KU Medical Center) Automated: Full names or initials of private and public health organizations (the people associated with them)[5]
Economic people and organizations Krippendorff's alpha = .73	Full category: Financial institutions and people who work there, including businesses, CEOs/business owners (though not including people who are CEOs at health organizations), market institutions, governmental institutions, labor unions Automated: Full names and initials of companies listed on the Fortune 500, prominent public and private financial organizations and the people associated with them (e.g., Secretary of the Treasury, NYSE)

Entertainment people and organizations Krippendorff's alpha = .75	Full category: Person or organization dedicated to entertainment, including celebrities, sports leagues, people who own sports teams, celebrity chefs, fiction television, etc. Automated: Full names and initials of major sports leagues, their initials, and their commissioners
Media people, organizations, and programs Krippendorff's alpha = .94	Full category: Any news organization, mass media company or digital news (not social media), news program name, or journalist/host/correspondent (e.g., CBS, HBO, Wolf Blitzer) Automated: Full names of news hosts, media organizations and their associated initials (e.g., CNN, HBO)

This process provided us with 2,556 entities to categorize manually. We expanded on the automated categories reviewed in the table above. Coders were instructed to only include an entity in any given category if, given the COVID-19 news context, it was very likely that the entity referred to a person or organization related to that category. Two coders categorized 350 of the remaining entities (14% of the remaining entities), and reached strong inter-coder reliability for each category (see reliability in table above). Disagreements were reconciled through discussion.

This process provided us with 3,747 entities: 2,556 categorized manually and 1,191 entities categorized automatically. To arrive at "partisans," which we include in the main text, we looked for paragraphs that mentioned Democrats/liberals or Republicans/conservatives.

To plot the entity categories by network, we used R. We deleted apostrophes using lapply, then used grepl to identify whether each paragraph with COVID-19 content included the categories. For a paragraph to be assigned to a category, at least one of the entities identified by spaCy for that paragraph needed to match the categorized entity.

Language Analysis

After finalizing the coronavirus classifier, we examined the coronavirus content. Our first step was to examine the language used.

Identifying language similarity across networks

We used two approaches to identify the degree to which language differed across two networks *i* and *j*: (i) Average KL-divergence and (ii) Distinctive phrase analysis using log odds with Dirichlet priors.

Average KL divergence

KL divergence, in other words relative entropy, is a measure of how different two probability distributions are. The KL divergence of probability for distributions P, Q on a finite set χ is defined as:

$$D_{\mathrm{KL}}(P \parallel Q) = \sum_{x \in \mathcal{X}} P(x) \log\left(\frac{P(x)}{Q(x)}\right)$$

By presenting the language observed in two networks as two probability distributions P and Q, we can use KL divergence to compute their distance. However, KL divergence is an asymmetric measure. Therefore, we relied on symmetric KL divergence which is defined as:

$$D_{\mathrm{KL}}(P \parallel Q) + D_{\mathrm{KL}}(Q \parallel P)$$

This symmetrised KL divergence measure has been in various language similarity based analyses, including statistical language modeling (Dagan et al. 1999), text classification (Bigi, 2003), and query expansion (Carpineto et al. 2001).

To use KL divergence, we first represented language observed in each network as a probability distribution as follows: We removed stop words and removed words that are seen in less than 10 covid-related terms.[4] We next used tf-idf vectorizer as implemented by python spaCy, to convert the bag of words seen across all COVID-19 related paragraphs in a network into a vector space representation. This provided us with the probability distribution that defines a given network. Next, the symmetric KL divergence measure given above was used to compute the distance between two networks.

Log odds with Dirichlet priors

The approach described above compares languages and identifies their distance using all (relatively popular) words. We next provided another measure by focusing only on phrases that are distinctive. These words can signal important semantic distinctions between two corpora—providing a new perspective. To compute this measure for two networks i and j, we determined the fraction of phrases used by either network that are uniquely prevalent in one of them. To identify these words/phrases that are uniquely important to a given network, we relied on the log odds method with Dirichlet priors described above.

Given two classes of documents (e.g., Fox News coronavirus coverage vs. CNN coronavirus coverage), we can find words (or phrases) more associated with one category than another by computing the differences in frequencies, ratio of frequencies, or the log odds ratio.

However, such methods do not work well for very rare words or very frequent words. For common words, all differences seem large; and for words that are very rare, no differences seem large. Monroe et al. (2008) address this concern by using a large background corpus to get a prior estimate of word frequencies. The difference in usage of a word *w* in corpus *i* and *j* is as follows using this technique:

$$\delta_w^{(i-j)} = \log\left(\frac{f_w^i + \alpha_w}{n^i + \alpha_0 - (f_w^i + \alpha_w)}\right) - \log\left(\frac{f_w^j + \alpha_w}{n^j + \alpha_0 - (f_w^j + \alpha_w)}\right)$$

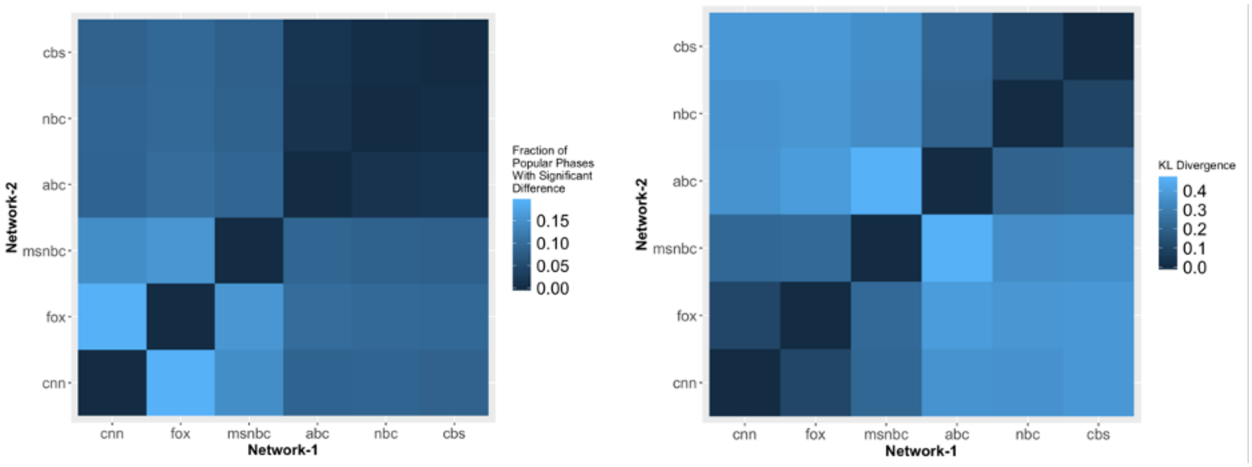
where f^i_w is the frequency of word w in corpus i, f^j_w is the frequency of word w in corpus j alpha$_w$ is the frequency of word w in the background corpus, n^i is the size of corpus i, n^j is the size of corpus j, and alpha$_0$ is the size of the background corpus. This formula essentially shrinks the estimates towards the prior by adding the corresponding values from the background corpus. As such, this prior helps better estimate the uniqueness of rare words. This measure is referred to as the z-score of word *w*. This score allows us to identify words that are distinct to corpus *i* (z-score > 2) and distinct to corpus *j* (z-score < -2).

Next, we measured the distance between networks i and j as: $(n_{\{uniq,i,k\}} + n_{\{uniq,j,k\}}) / n_k$, where n_k is the number of phrases that are observed at least *k* times across the corpora, $n_{\{uniq,i,k\}}$ is the number of such words that are unique to corpus *i* and $n_{\{uniq,j,k\}}$ is the number of such words that are unique to corpus *j*. This is simply the fraction of words with a particular popularity level that are uniquely prevalent in one corpus compared to another. In our analysis we set the popularity threshold to k=100.

Extent of differences in language usage

We inspected the degree to which language across the networks differed from each other using the two approaches described above. First, we used KL-divergence to determine differences across the six networks. Second, we identified popular enough words (e.g., total usage across the networks being compared of at least 100) and determined what fraction of these words were significantly more likely to be used by one of these networks (as opposed to having comparable prevalence). Both analyses point to one high level finding: there is a significant divide between cable and broadcast news networks.

DIFFERENCES IN LANGUAGE USE BY NETWORK



Data from the Center for Media Engagement

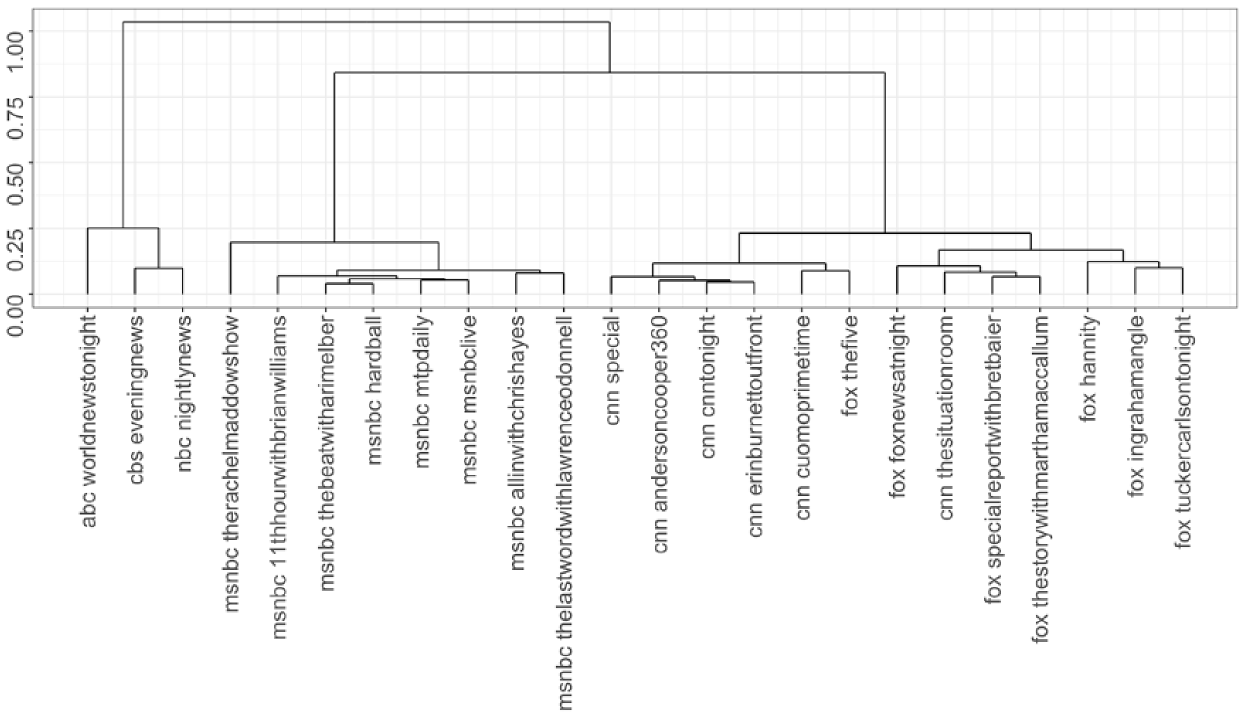
Notes: a) Language Differences measured through the fraction of popular words that were distinctly important to one of the two networks being compared b) Language differences measured through the averaged KL divergence measure. Both plots show that there is a significant divide between broadcast news and cable networks.

Beyond the cable-broadcast divide, Figure (a) shows that the most distinctions are observed across cable networks. The most dissimilar pairs are cable-to-cable, cable-to-broadcast, and then broadcast-to-broadcast. The broadcast-broadcast, cable-cable pairs look more comparable in Figure (b). Note that the KL divergence analysis is performed using all popular words as opposed to distinctive ones.

Clustering programs across networks

Next, we examined language similarity across programs. Our aim here was to determine whether treating the programs in a given network as a group, rather than individually, was a justified decision. For instance, it is possible for the differences between networks to be driven by only a subset of programs with extreme language, with the language included in other programs being more balanced. To determine whether this was the case, we next clustered programs across different networks. We first represented the program's language across the entire time period using a tf-idf based vector space model. As a result, each network is represented using a 13486 dimensional vector corresponding to the 13486 unique words observed in the entire dataset. Using these vectors and hierarchical clustering, we determined similarity across programs and how the programs cluster according to this similarity. We used 1) Euclidean distance and 2) cosine distance to define (dis)similarity between programs. The results are largely similar and are summarized in the figures below. We found that programs from the same network indeed are rather similar to each other—justifying our approach of performing only network level (as opposed to program level) comparisons.

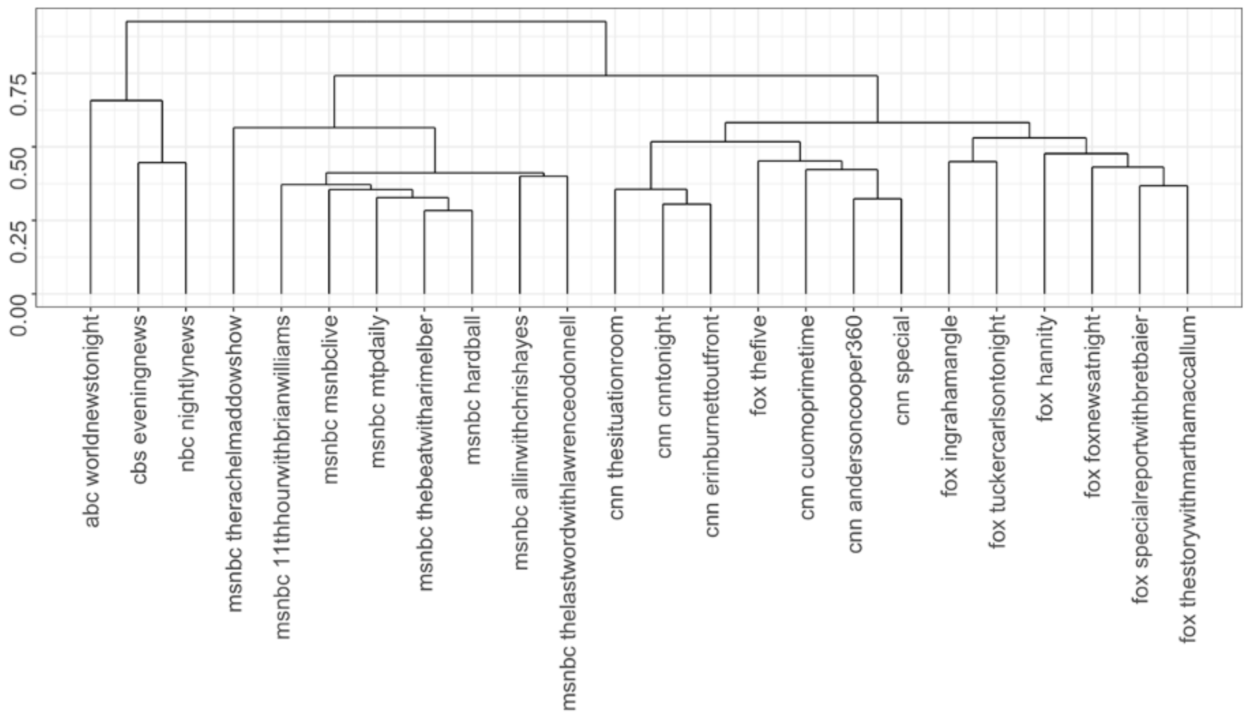
PROGRAM SIMILARITY USING COSINE DISTANCE AND HIERARCHICAL CLUSTERING



Data from the Center for Media Engagement

Notes: The dendrogram (tree structure) summarizes the clustering of programs according to language similarity. The more similar two programs are to each other, the smaller number of steps it takes to connect them in this dendrogram. For instance, we see that the "Tucker Carlson Tonight" program is most similar to "The Ingraham Angle." It is also more similar to most other Fox News programs compared to programs on CNN and MSNBC. It is also most dissimilar to the broadcast nightly news programs. Overall, we observe that programs from the same network generally cluster together, justifying our decision to perform our analysis at the network, as opposed to program, level. The only notable exception is "The Five" that is clustered with other CNN programs. We posit that this may be due to the more balanced leanings of the program hosts for this program.

PROGRAM SIMILARITY USING EUCLIDEAN DISTANCE AND HIERARCHICAL CLUSTERING



Data from the Center for Media Engagement

Notes: This plot gives the result of the same process using Euclidean distance to define dissimilarity.

Identifying clusters of distinctive words

We characterized the ways in which coverage varied across networks by identifying the clusters of distinctive words. While log-odds with Dirichlet priors helps us identify a rich set of phrases that are more commonly used by one network (or set of networks), the lists identified can be long and hard to interpret. To provide an easier interpretation, we next clustered the identified words according to their semantic similarity. Here, we relied on word embeddings to represent phrases in an n-dimensional semantic space and used these representations to cluster the words using k-means clustering.

We first pre-processed the text by removing any special characters, including punctuation, and converting the word “US” to “United States.” Using WordNetLemmatizer from NLTK in Python, each word was lemmatized after making it lowercase and using part-of-speech tagging. Next, we identified unigrams and bigrams after removing stop words and finally calculated z-scores for these unigrams and bigrams. Note that we used sentences as units of analysis when identifying bigrams. Therefore sequences of two words that cross sentence boundaries do not constitute a bigram.

Word Embeddings: Our goal was to cluster phrases according to their semantic similarity. To achieve this goal, we trained a neural embedding model (Mikolov et al., 2013) to represent the coronavirus coverage data, in which each unique word/bi-gram is represented by a vector (embedding) in high-dimensional space. This vector space geometry captures many semantic relations between words/bi-grams. Words that are closer to each other in this high dimensional vector space have close semantic similarity. This approach has been used in the past to encode semantic similarity in a variety of application areas (e.g., Hamilton et al., 2016) including the closely related topic of news article classification (Jang et al., 2019).

We computed word embeddings on bi-grams using the Python gensim package. This package allows us to detect phrases longer than one word. Using phrases, you can learn a word2vec model where "words" are multiword expressions, such as healthcare_worker. We computed the vector representations of phrases using the CBOW model. Using this approach, we represented each phrase in a 50-dimensional space.

K-means clustering: We next clustered the phrases using their 50-dimensional representation using k-means clustering. K-means clustering clusters *n* elements into k clusters by iteratively first assigning each element to the cluster with the closest centroid using the least square Euclidean distance and then updating cluster centroids accordingly, until convergence. We identified k=20 clusters in characterizing the distinctions between different cable news networks. We used k=10 when characterizing the distinctions between all cable news and all broadcast due to the smaller set of words that are identified as distinct when comparing those two groups. In the main text, we highlighted only a few of the clusters. Since z-scores are hard to interpret, we relied on a simpler measure of *likelihood to appear* in the corresponding plots. To compute the likelihood for a word to appear on a network, we divide the number of occurrences of that word in the given network by the total number of words used by the network. We then compute the ratio between this measure across two networks to compute how much more likely the word was to appear on one network compared to another. Note that in the main text, we combined some clusters into a single chart. For the Fox News and MSNBC comparison, we combined a cluster about health with a cluster about economy. For the Fox News and CNN comparison, we combined a cluster about the economy with one about prevention. For the MSNBC and CNN comparison, we combined a cluster about the economy and a cluster about possible treatments. In the pages that follow, we show the full analysis.

Number of deaths

We identified references to the number of coronavirus deaths using the following procedure. We first used the Python spaCy package to detect paragraphs that included at least one percentage, quantity, and cardinal number. Next, we considered two different lexicon-based approaches to determine whether the numbers mentioned in these paragraphs referred to (i.) coronavirus deaths, (ii.) coronavirus cases, or (iii.) coronavirus tests. The approaches both use regular expressions to detect phrases related to the aforementioned concepts and differ in strictness of lexical match. The first approach looked for phrases that occur anywhere in the paragraph (e.g., the word 'deaths' anywhere in the paragraph that includes a number). The second required a strict match (e.g., exact match for <number> deaths). For each of these three prediction tasks, we sampled 100 paragraphs where the two lexicon-based approaches agreed, 100 paragraphs where the first approach detected an instance but the other did not, 100 paragraphs where the second approach detected an instance but the first did not, and finally, 300 paragraphs where both approaches agreed there was no instance. Note that when there were fewer instances than the specified sample size, the maximum number of paragraphs are retrieved. These data were then labeled by human judges (after reliability coding where high agreement was reached). Using these assessments, we evaluated the lexicon-based approaches in terms of their precision and recall. Our results showed that the looser match predicted death numbers fairly accurately (0.85 precision and 0.76 recall). However, the two approaches did not perform as well in detecting test and case numbers. As such, these analyses are omitted in this report.

Tone of the Coverage

We randomly pulled 250 paragraphs from each cable news network and 250 from across the broadcast networks. Each paragraph was evaluated by five Republicans and five Democrats on Amazon's Mechanical Turk (MTurk), a platform where people are compensated for completing small tasks. Participants were asked to say how positive or negative they thought the paragraph was on a scale of 1 (very negative) to 5 (very positive). They also shared how strongly the statement made them feel certain emotions, including angry, afraid, hopeful, proud, worried and outraged, on a scale of 1 (not at all) to 5 (extremely).

To gather the pool of participants who completed these tasks, we first ran two identical qualification tasks on MTurk, one directed at participants who MTurk had identified as liberal and one at participants who MTurk had identified as conservative. These surveys asked participants to evaluate two paragraphs and share some demographic information, including partisanship. We deliberately chose negative paragraphs for the qualification task.

One paragraph focused on the health consequences of the virus: “Tonight, the coronavirus pandemic rages on. Nearly 1.9 million Americans have been infected, and more than a hundred and eight thousand have died. And there’s this stunning news from the CDC, more than a third of Americans have admitted to misusing bleach and cleaning products to prevent the spread, with many spraying cleaners on their food and skin.” The other focused on the economic consequences of the virus: “And after a week of massive losses on the financial markets, the Federal Reserve taking emergency action. But the move appeared at least at first to have backfired, heightening investor fears about the economic picture ahead. Chairman Jerome Powell announcing its biggest surprise rate cuts since the 2008 financial crisis, slashing its benchmark interest rate a half a percentage point. The Dow actually falling another 785 points today, nearly 3% after that up day yesterday.” Those who said that these statements were “somewhat negative” or “very negative” and that the statement made them feel “a little” or “not at all” hopeful were included for the task. They were also required to report being Democrats or Republicans. After these qualification tasks, our pool of participants included 497 Democrats and 352 Republicans. In total, 458 people participated in rating the paragraphs.

We evaluated differences in the tone of news coverage between networks using ANOVA with a Sidak correction.

The analysis presented in the text averages the 10 ratings we received per paragraph. We also conducted an analysis where we included all 10 ratings per paragraph as individual observations, and controlled for the number of words and the ideology of the rater. In general, the results replicate the ANOVA analysis. The number of words was significant in several analyses; the more words, the less positive the rating, the more anger and outrage, and the more worry and fear. Ideology was significant in the analyses; liberals rated the paragraphs as less positive and felt less proud and happy than conservatives. They also expressed more anger/outrage and worry/fear. There were no significant interactions between the networks and the rater’s ideology.

Factual Claims

To explore factual claims, we created an archive of facts about the novel coronavirus. We collected fact checks from the Poynter/IFCN CoronaVirusFacts/DatosCoronaVirus Alliance Database published between January 21 and June 12, 2020, and supplemented the fact checks with articles from Politifact and FactCheck.org that were not included in the database. We also included factual information published by the Centers for Disease Control and the World Health Organization to ensure that we included a range of both true and false health claims.

From this list, we selected two case studies to examine in the news coverage: mask-wearing and using disinfectant/ultraviolet on or in people to fight the novel coronavirus. We selected these topics because the archives we created for each topic included both correct health information provided by the CDC and WHO and fact checks of incorrect information. Additionally, the source of the information in both cases is related to the Trump administration, but whether the information from the source was correct or not differed: CDC guidance for masks was considered correct and a statement from President Trump suggesting that researchers test injection of disinfectants/UV light was considered misleading/incorrect. This difference allowed us to examine whether networks were likely to present politicized information or correct/incorrect information across issues. Finally, mask-wearing was also an intriguing topic because the CDC changed its recommendations about mask-wearing in April 2020, such that we could compare whether information that contradicted these guidelines changed before and after the CDC guidance changed. We created a specific fact check/health information archive for each of these two topics.

To narrow the paragraphs to those that were more likely to include content related to the masks and disinfectants fact archives, we created dictionaries based on the content of the fact checks and health information from the CDC and WHO. The words/phrases for the dictionary are included in the table below. These dictionary terms were intentionally broad to ensure that we captured content that could possibly be discussing information related to the fact archives we created. We then selected two different sets of COVID paragraphs: (1) all COVID paragraphs that included at least one word from the "masks" dictionary and (2) all COVID paragraphs that included at least one word from the "disinfectants/UV" dictionary.

Masks Dictionary (*n* = 7221 paragraphs)	**Disinfectants/UV Dictionary (*n* = 646 paragraphs)**
mask	alcohol
N95	bleach
disposable	disinfectant
CO2	ethanol
oxygen	Lysol
cloth	ultraviolet
face mask	uv

carbon dioxide
medical mask
filter
lung infection
brain
tuberculosis

The paragraphs that included the specific dictionary were then manually coded by two coders. The unit of analysis was a segment of coverage that included two paragraphs prior to the paragraph that mentioned a dictionary term and three paragraphs after the paragraph that mentioned a dictionary term. This decision emerged from a thorough reading of the news transcripts. We found that, at times, a paragraph mentioned a dictionary word, but the information presented in that paragraph was corrected either just before the paragraph or in the paragraphs after the paragraph. Providing context around the paragraph ensured that coders did not unfairly praise news programs for providing correct information when they also discussed incorrect information in a segment or unfairly criticize news programs for mentioning incorrect information when they also provided correct information in a segment.

For both topics, coders first identified whether there was some information present in the segment that was relevant to the facts archived for the specific dictionary. For instance, for the "masks" dictionary, relevant information included discussion of wearing masks and irrelevant information included whether hospitals were running low on mask supplies. For the "disinfectants/UV" category, relevant information included discussion of whether disinfectants or UV light should be used on or in a person's body and irrelevant information included whether disinfectants should be used on surfaces.

If there was information present related to the fact archive, coders were asked to identify whether (a) any information relevant to the fact archive in the segment was correct, (b) any information relevant to the fact archive was misleading, and (c) any information relevant to the fact archive was incorrect. These codes were dichotomous and were not mutually exclusive. A segment could include both correct and incorrect information. If coders identified that there was misleading or incorrect information in a segment, they took one more step and indicated whether that misleading or incorrect information was corrected (0 = not corrected at all, 1 = implied correction, or 2 = clear correction of information). After coding, the “corrected” categorizes were dichotomized (0 = not corrected, 1 = implied or clear correction) then combined with the “corrected” code to indicate for a final “any correct” information code. The “misleading” and “incorrect” categories were combined to indicate that there was at least some misleading/incorrect information in the segment. For inter-coder reliability testing, two research assistants coded 300 segments from the “masks” dictionary dataset and 132 of the “disinfectants/UV” segments. Coders categorizing the “masks” dictionary and coders categorizing the “disinfectants/UV” dictionary reached reliability for each of these final codes (see table below). For the analysis in the figures presented above, these correct and misleading/incorrect codes were used to create a new variable where the categories were mutually exclusive: only correct information in a segment, only incorrect information in a statement, or both correct and incorrect information in a segment.

TABLE. KRIPPENDORFF’S ALPHA FOR EACH CODE AND CATEGORY

	Masks coders	Disinfectants/UV coders
Relevant Information Present	.79	.89
Correct Information	.78	.73
Misleading/Incorrect Information	.72	.88

Once reliability was reached, the coders separately coded the remaining segments. All segments that included the “disinfectants/UV” dictionary were coded. The “masks” dictionary generated 7,221 paragraphs, from which we sampled 2,000 paragraphs: 1,000 paragraphs that aired before the April 3 CDC announcement recommending that asymptomatic individuals wear masks in public and 1,000 paragraphs that aired after the announcement (that is, on April 3 or later). For each 1,000 paragraphs, 100 were randomly selected from broadcast, and 300 from each of the cable news networks to reflect the overall proportion of broadcast paragraphs to cable news paragraphs in the full dataset.

Of the content identified by the “disinfectants/UV” dictionary, 62% (n = 400) was relevant to the facts archive. Because the research assistants coded all of the segments with at least one term from the “disinfectants/UV” dictionary, the figure presents the results as a percentage of COVID-19 content on a given network.

Of the content identified by the “masks” dictionary and sampled, 41% (n = 822) was relevant to the facts archive. Of the segments where the relevant information was present, 31% were aired prior to the CDC recommendation and 69% were aired after the CDC recommendation, a significant difference [Chi-Square (df = 1) = 190.88, $p < .001$] that suggests discussion of mask-wearing, in general, increased after the CDC made its recommendation. Because the “masks” content was sampled, the figure included in the text presents the results as the *estimated* percentage of COVID-19 content on a given network. We computed the percentage of the sampled content that included only correct, only incorrect, and both correct/incorrect content on each network both before or after the April 3 CDC announcement, then multiplied the percentage by the number of total segments pre or post-CDC announcement from that network in the “masks” dataset, then divided that number by the total number of COVID-19 segments from the network in the entire dataset.

We ran logistic regressions to test for preliminary statistical differences among the sample in predicting only correct information in a segment, only incorrect information, and both correct and incorrect information. The first table uses “broadcast” news as the reference group and the second uses “fox” as the reference group. The results suggest that CNN and MSNBC were not significantly different from broadcast news in their coverage of correct and incorrect mask-wearing information. Fox News segments that mentioned mask-wearing were less likely to include only correct information than all other networks and were more likely to include only incorrect and both correct/incorrect information than all other networks. Further, the interactions indicate that Fox’s use of correct-only and both incorrect/correct content was different before and after the CDC recommendations compared to the other networks (the figures included illustrates the different patterns).

	Only Correct	Only Correct: Before/After	Only Incorrect	Only Incorrect: Before/After	Both	Both: Before/After
(Intercept)	1.59 ***	0.00	-3.12 ***	-1.85 **	-1.93 ***	-0.56
	(0.32)	(0.43)	(0.59)	(0.62)	(0.36)	(0.44)
cnn	0.12	0.49	0.74	0.70	-0.74	-1.37 *
	(0.35)	(0.48)	(0.62)	(0.67)	(0.43)	(0.54)
msnbc	-0.14	0.29	0.45	-0.08	-0.10	-0.44
	(0.36)	(0.50)	(0.65)	(0.73)	(0.41)	(0.53)
fox	-1.35 ***	-0.23	1.64 **	0.96	0.86 *	-0.46
	(0.35)	(0.48)	(0.62)	(0.67)	(0.39)	(0.51)
cdc		3.87 ***		-15.72		-3.31 **
		(1.10)		(565.17)		(1.10)
cnn:cdc		-1.45		12.61		2.00
		(1.16)		(565.17)		(1.20)
msnbc:cdc		-1.97		14.51		1.54
		(1.15)		(565.17)		(1.18)
fox:cdc		-3.12 **		14.63		3.23 **
		(1.13)		(565.17)		(1.15)
N	822	822	822	822	822	822
AIC	850.58	747.94	524.30	469.27	616.92	584.24
BIC	869.42	785.63	543.15	506.96	635.77	621.94
Pseudo R2	0.11	0.28	0.05	0.20	0.08	0.17

All continuous predictors are mean-centered and scaled by 1 standard deviation. *** p < 0.001; ** p < 0.01; * p < 0.05.

	Only Correct	Only Correct: Before/After	Only Incorrect	Only Incorrect: Before/After	Both	Both: Before/After
(Intercept)	0.24	-0.23	-1.48 ***	-0.89 ***	-1.07 ***	-1.02 ***
	(0.14)	(0.23)	(0.18)	(0.25)	(0.16)	(0.25)
cnn	1.48 ***	0.72 *	-0.90 ***	-0.25	-1.60 ***	-0.92 *
	(0.21)	(0.31)	(0.27)	(0.34)	(0.28)	(0.40)
msnbc	1.21 ***	0.52	-1.19 ***	-1.04 *	-0.96 ***	0.02
	(0.22)	(0.34)	(0.32)	(0.45)	(0.26)	(0.38)
broadcast	1.35 ***	0.23	-1.64 **	-0.96	-0.86 *	0.46
	(0.35)	(0.48)	(0.62)	(0.67)	(0.39)	(0.51)
cdc		0.76 **		-1.09 **		-0.08
		(0.29)		(0.36)		(0.32)
cnn:cdc		1.66 ***		-2.02 **		-1.23 *
		(0.47)		(0.73)		(0.57)
msnbc:cdc		1.15 *		-0.12		-1.69 **
		(0.46)		(0.65)		(0.54)
broadcast:cdc		3.12 **		-14.63		-3.23 **
		(1.13)		(565.17)		(1.15)
N	822	822	822	822	822	822
AIC	850.58	747.94	524.30	469.27	616.92	584.24
BIC	869.42	785.63	543.15	506.96	635.77	621.94
Pseudo R2	0.11	0.28	0.05	0.20	0.08	0.17

All continuous predictors are mean-centered and scaled by 1 standard deviation. *** p < 0.001; ** p < 0.01; * p < 0.05.

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ENDNOTES

[1] Note that health officials with clear partisan leanings (e.g., the Director of the Department of Health and Human Services—a Republican and Trump administration cabinet member) are also coded as health officials. As such, we provide a conservative measure of the relatively high attention to political figures compared to health experts.

[2] All transcripts are provided to LexisNexis from the publishers of each network.

[3] Two episodes of the CBS Evening News that aired on weekend dates (March 14 and 15) and two episodes of Jake Tapper were unintentionally included in the dataset (449 COVID-related paragraphs total). We ran robustness tests to make sure that the patterns of the people and organizations referenced, as well as the coverage of health facts, did not change when the Tapper and weekend paragraphs were omitted. We found no differences in the results when these were not included in the dataset.

[4] Changing this threshold to 5 and 15 does not qualitatively change the results.

[5] We originally also included health journalists and contributors in this category, but dropped them in favor of including them as media.