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Opinions as Facts

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The rise of opinion programs has transformed television news. Because they present anchors' subjective commentary and analysis, opinion programs often convey conflicting narratives about reality. We experimentally document that people across the ideological spectrum turn to opinion programs over "straight news", even when provided large incentives to learn objective facts. We then examine the consequences of diverging narratives between opinion programs in a high-stakes setting: the early stages of the COVID-19 pandemic in the US. We find stark differences in the adoption of preventative behaviours among viewers of the two most popular opinion programs, both on the same network, which adopted opposing narratives about the threat posed by the COVID-19 pandemic. We then show that areas with greater relative viewership of the program downplaying the threat experienced a greater number of COVID-19 cases and deaths. Our evidence suggests that opinion programs may distort important beliefs and behaviours.

Key words: Opinion programs, Media, Narratives.

JEL Codes: C90, D83, D91, Z13

1. INTRODUCTION

Over the past two decades, opinion programs have come to dominate cable television news. Unlike "straight news", which professes to impartially report "just the facts", opinion programs convey their anchor's perspective on the news of the day. They typically feature little original reporting; instead, they focus on story-telling, entertainment, and *subjective* commentary (Kavanagh, Marcellino, Blake, Smith, Davenport and Tebeka, 2019), at the expense of objective factual reporting (Kavanagh and Rich, 2018). Consequently, different opinion programs often present distinct, and often conflicting, narratives about reality.

Cable networks themselves distinguish their "hard" or "straight" news reporting from their opinion content. For example, when defending a leading anchor from defamation claims, Fox

The editor in charge of this paper was Nicola Gennaioli.

News successfully argued that "the 'general tenor' of the show should then inform a viewer that the host is not 'stating actual facts' about the topics he discusses and is instead engaging in 'exaggeration' and 'non-literal commentary'."[1] MSNBC successfully adopted the same approach: "For her to exaggerate the facts …was consistent with her tone up to that point, and the court finds a reasonable viewer would not take the statement as factual given this context."[2] Emphasizing the difference between straight news and opinion, Fox News President Jay Wallace wrote:

> "We've always said that we have strong opinion and strong news. And, again, I think that's part of the success. You know what you're getting."[3]

Do viewers know what they're getting? If viewers interpret opinion programs appropriately, then such programs may make valuable contributions to political discourse: they are generally more engaging than straight news programs and they can distil complex issues into easy-to-understand narratives (Jacobs and Townsley, 2011). On the other hand, if viewers trust the literal statements made on opinion programs just as they would those made on straight news, failing to distinguish between opinion and fact and to appropriately discount hyperbole and speculation, then diverging narratives across programs can lead different segments of the population to hold dramatically different views of reality. Commenting on this phenomenon in 2010, veteran journalist Ted Koppel wrote:

> "Daniel Patrick Moynihan's oft-quoted observation that 'everyone is entitled to his own opinion, but not his own facts,' seems almost quaint in an environment that flaunts opinions as though they were facts."[4]

In this article, we demonstrate that viewers turn to opinion programs for information about objective facts, and we explore the consequences of this trust for high-stakes outcomes.

We begin with a pre-registered motivating experiment conducted with a sample of regular viewers of the two most popular cable news networks, Fox News and MSNBC. We tell participants that they will provide their best guess about an objective statistic relating either to the spread of the COVID-19 pandemic or to one of four dimensions of the country's economic performance, all as of a randomly selected recent date. In order to inform their guess, respondents can choose one of four TV clips, which were all excerpted from shows broadcast on the same week as the date pertinent to their guess. These four clips comprise the two most popular straight news programs and the two most popular opinion programs on their network. 75% of Fox News viewers choose an opinion program over a straight news program, as do 60% of MSNBC viewers. Varying the reward for a correct answer from \$10 to \$100 has a precisely estimated zero effect, suggesting that viewers trust opinion programs to reveal factual information even when making choices with relatively higher stakes.

Programs that report objective content can differ primarily in their choices of what to cover, perhaps shaping viewers' perceptions of what is important (Bordalo, Tabellini and Yang, 2021) but with less scope for shaping viewers' beliefs about *facts* (Bennett, 2016). Because they are unconstrained by objectivity, on the other hand, opinion programs can not only diverge more in their selection of topics to cover, but they can also present different narratives about the *same*

1. See "McDougal v. Fox News Network." *JUSTIA US Law*, 2020.
2. See "Herring Networks, Inc. v. Maddow." *Casetext: Smarter Legal Research*, 22 May 2020.
3. See "Fox News Exec Jay Wallace Gets Candid About Ratings, White House Access (Q&A)." *The Hollywood Reporter*, 2 January 2018.
4. See "Ted Koppel: Olbermann, O'Reilly and the death of real news." *The Washington Post*, 14 November 2010.

set of underlying facts. This is particularly important given the dominant—and growing—role of opinion content in primetime cable news: different anchors, each drawing weekly audiences of several million, can present dramatically different narratives about reality.[5] Do these diverging narratives have consequences for real-world outcomes? Identifying the causal effect of these narratives on behaviour is challenging for several reasons: most importantly, ruling out alternative explanations for behavioural differences among consumers of different opinion programs—such as different prior beliefs, different ideologies, or different preferences—generally requires a setting in which two opinion programs that are *ex ante* similar, both in their content and in the characteristics of their viewers, suddenly and sharply diverge in their coverage of a given topic, and moreover that this topic can be linked to naturally occurring outcomes.

To overcome these empirical challenges, we examine the two most popular opinion programs in the US: *Hannity* and *Tucker Carlson Tonight*. These shows are aired back-to-back on the same network (Fox News) and had similar content prior to January 2020; indeed, we show using natural language processing techniques that both in their selection of topics and the way they covered these topics, these shows were *more* similar than almost any other pair of primetime shows across Fox News and MSNBC. However, we document that the programs differed sharply along both margins in their reporting about COVID-19. While both narratives were consistent with the anchors' right-wing slant, they had very different implications for viewers' beliefs and behaviour. Carlson emphasized the severity of the threat as early as January while placing blame on China for its lack of transparency with the international community, later hosting a Chinese virologist who alleged that COVID-19 is a bio-weapon created by the Chinese Communist Party.[6] In contrast, Hannity largely ignored or downplayed the threat posed by the virus through February and early March, blaming Democrats for using it as a political weapon to undermine the administration.[7] In the narratives they presented about the dangers of COVID-19, Carlson and Hannity were largely outliers (in opposite directions), not only on Fox News, but on broadcast and cable television as a whole—a striking divergence given the two programs' prior similarities. Focusing on these two opinion programs within the same network enables us to compare two *ex ante* similar viewer populations, allowing us to examine how exposure to diverging narratives broadcast on opinion programs drives beliefs, behaviour, and downstream health outcomes.

To shed light on the timing of common behavioural adjustments at the early stages of the pandemic (such as washing hands more often, cancelling travel plans, and avoiding large events), we fielded a survey among 1,045 Fox News viewers aged 55 or older. Consistent with a persuasive effect of content on behaviour, we find that viewership of *Hannity* is associated with changing behaviour 4 days later than other Fox News viewers, while viewership of *Tucker Carlson Tonight* is associated with changing behaviour 3 days earlier (controlling for demographics and viewership of other programs and networks). Given the critical importance of early preventive measures (Bootsma and Ferguson, 2007; Markel, Lipman, Navarro, Sloan, Michalsen, Stern and Cetron, 2007), these differences in the timing of adoption of cautious behaviour may have significant consequences for health outcomes.[8]

5. See "Fox News Changes Up Daytime Lineup, Adds New Opinion Show at 7 p.m." *The Hollywood Reporter*, 11 January 2021.

6. See "Tucker Carlson: Racist for Saying 'Chinese Coronavirus'? Now's Not the Time for the Dumbest Identity Politics." *Fox News*, 12 March 2020. "Tucker Carlson Blames Media for Coronavirus Spread: 'Wokeness Is A Cult. They'd Let You Die' Over Identity Politics." *Newsweek*, 24 February 2020.

7. See "Hannity Claims He's 'Never Called the Virus a Hoax' 9 Days After Decrying Democrats 'New Hoax'." *Vox*, 20 March 2020.

8. For example, Pei, Kandula and Shaman (2020) estimate that approximately half of all COVID-19 deaths in the US at the early stages of the pandemic could have been prevented had non-pharmaceutical interventions (NPIs) such as

Motivated by our survey evidence, we examine disease trajectories in the broader population using county-level data on COVID-19 cases and deaths (Dong, Du and Gardner, 2020). We first show that, controlling for a rich set of county-level demographics (including the local market share of Fox News), greater local viewership of *Hannity* relative to *Tucker Carlson Tonight* is associated with a greater number of COVID-19 cases starting in early March and a greater number of deaths resulting from COVID-19 starting in mid-March. We then employ an instrumental variable approach that shifts relative viewership of the two programs yet is plausibly orthogonal to local preferences for the two programs and to any other county-level characteristics that might affect the virus' spread. In particular, we predict this difference in viewership using the product of (i) the fraction of TVs on during the start time of *Hannity* (leaving out TVs watching *Hannity*) and (ii) the local market share of Fox News (leaving out *Hannity* and *Tucker Carlson Tonight*). The logic of our instrument is simple: if people like to turn on their TVs to watch *something* when *Hannity* happens to be on instead of *Tucker Carlson Tonight*, the likelihood that viewers are shifted to watch *Hannity* is disproportionately large in areas where Fox News is popular in general. We show that the interaction term is conditionally uncorrelated with any among a larger number of variables that might independently affect the local spread of COVID-19, and we show that it strongly predicts viewership in the hypothesized direction. Using this instrument, we confirm the OLS findings that greater exposure to *Hannity* relative to *Tucker Carlson Tonight* is associated with a greater number of COVID-19 cases and deaths. Consistent with the gradual convergence in scripts between the two shows beginning in late February, the effects on cases plateau and begin to decline in mid-March, while effects on deaths follow 2 weeks later.

Turning to the underlying mechanisms, we find that differential viewership affects stay-at-home behaviour (as measured by cell phone GPS data from two different sources, namely SafeGraph (2020) and Bureau of Transportation Statistics (2021)), although this is unlikely to be the primary mechanism driving our effects. The sequential timing of differences in coverage, followed by differences in behavioural change, followed by differences in COVID-19 outcomes is inconsistent with several alternative potential drivers of our estimated treatment effects, such as time-invariant unobservables correlated with our instrument and differential effects of exposure to the programs that are unrelated to their reporting about COVID-19. Instead, the timing strongly suggests a causal chain from content differences to behavioural differences to COVID-19 outcomes. Taken together, our results suggest that viewers indeed trust opinion programs as sources of *facts*, beyond these programs' entertainment value.[9] Indeed, our findings indicate that this trust shapes important beliefs and behaviours.

Our work contributes to a large literature on the economic and social effects of the media (DellaVigna and La Ferrara, 2016). This literature has examined a wide range of political, behavioural, and health outcomes (Eisensee and Strömberg, 2007; Yanagizawa-Drott, 2014; La Ferrara, 2016; Durante and Zhuravskaya, 2018; Muller and Schwarz, 2022; Bursztyn, Egorov, Enikolopov and Petrova, 2019; Levy, 2021; Martinez-Bravo and Stegmann, 2022), including the effect of Fox News on voting behaviour (DellaVigna and Kaplan, 2007; Martin and Yurukoglu, 2017). Insofar as opinion shows are more entertaining than straight news shows (Berry and Sobieraj, 2013), our article also relates to work on the effects of entertainment media on social and political outcomes (La Ferrara, Chong and Duryea,

mandated social distancing and stay-at-home orders been implemented 1 week earlier. While the behavioural changes our survey respondents report are likely not as extreme, and our survey is representative only of Fox News viewers over the age of 55, this evidence nonetheless suggests that these differences in timing may have directly affected the spread of the pandemic.

9. Consistent with this interpretation, as we discuss in Section 2, viewers in our experiment believe that opinion programs are more informative than straight news programs.

2012; Durante, Pinotti and Tesei, 2019), particularly work examining the effects of *specific* television shows (Kearney and Levine, 2015; Banerjee, Ferrara and Orozco-Olvera, 2019). Methodologically, our work relates to a literature analysing media content (Gentzkow and Shapiro, 2010; Djourelova, 2022).[10]

We provide the first direct evidence on the importance of opinion shows in driving high-stakes behaviours. Our approach holds fixed important mechanisms that may operate through exposure to biased media, such as increased partisanship or lower trust in science, which allows us to identify the effect of contemporaneous exposure to diverging narratives on behaviour. Our incentivized experiments demonstrate that people seek out opinion programs when given incentives to *get the facts right*.

The remainder of this article proceeds as follows. In Section 2, we show that viewers across the ideological spectrum turn to opinion programs over straight news even in the presence of incentives to learn objective facts. In Section 3, we examine the role of diverging narratives on opinion programs in shaping beliefs and behaviour during the early stages of the COVID-19 pandemic. Section 4 discusses implications and concludes.

2. TRUST IN OPINION SHOWS

In this section, we examine trust in opinion and "straight news" programs. Viewers might seek out opinion programs for several reasons: opinion programs tend to be more emotional and engaging than straight news (Kavanagh *et al.*, 2019), and they can distil complex issues into easy-to-grasp summaries, expose viewers to partisan perspectives, and provide a frame through which to interpret the news of the day. Widespread distrust in "straight news" also plays a role in driving demand for opinion programs: only 36% of adults (11% of Republicans and 68% of Democrats) report a "great deal" or a "fair amount" of trust in the news to report fully, accurately, and fairly (Gallup, 2021).[11] Both a cause and consequence of opinion programs' popularity is that they dominate "prime time", the window between 8 p.m. and 11 p.m. when TV viewership as a whole is highest.

Whatever mechanisms drive the demand for opinion programs, however, we would expect viewers seeking *objective facts* about the world to exhibit greater relative demand for "straight news" than viewers seeking entertainment or analysis. By their very nature, opinion programs are centred around conveying anchors' commentary on and interpretation of the news of the day rather than "just the facts". Indeed, Kavanagh and Rich (2018) summarize the growing dominance of opinions over factual reporting during prime-time between 2000 and 2017 as follows:

> We found a starker contrast between broadcast news presentation and prime-time cable programming in the post-2000 period. Compared with news

10. Related to our study is work (Simonov, Sacher, Dubé and Biswas, 2022, Ash, Galletta, Hangartner, Margalit and Pinna, 2022; Ananyev, Poyker and Tian, 2021) using the channel numbers instrument developed by Martin and Yurukoglu (2017) to establish a causal effect of exposure to Fox News as a whole on health-related behaviours. Our work differs in its focus on a specific mechanism: the role of diverging narratives on opinion shows in driving differences in behaviour and health outcomes, holding partisanship fixed. Ananyev *et al.* (2021) additionally finds that Fox News viewership has a statistically significant effect on death rates, while Ash *et al.* (2022) estimates a positive but statistically insignificant effect. These results are largely consistent with our evidence that media exposure affected health outcomes, but the *narrative* portrayed mattered, with different programs on Fox News presenting dramatically different narratives about COVID-19.

11. Sociologist Sarah Sobieraj comments that "Some fans believe [opinion] shows are the only sources they can trust for information. That's a pretty impressive feat, really, to have convinced someone that an opinion program offers the truth, while conventional news is riddled with bias." See "Wrath of the talking heads: How the 'Outrage Industry' affects politics", *PBS News Hour*, 28 February 2014.

> presentation on broadcast television, programming on cable outlets exhibited a dramatic and quantifiable shift toward subjective, abstract, directive, and argumentative language and content based more on the expression of opinion than on reporting of events.

Do consumers believe that prime-time opinion programs are less likely to accurately cover facts than straight news programs? We conduct a pre-registered motivating experiment examining via revealed preference (1) the extent to which viewers turn to opinion programs rather than straight news in order to learn objective facts and (2) how this preference is affected by substantial incentives for accuracy.[12]

2.1. *Sample and design*

In December 2020, we targeted a sample of 1,000 US-based respondents—500 Republican Fox News viewers and 500 Democrat MSNBC viewers—in cooperation with Luc.id, a survey provider widely used in social science research (Bursztyn, Egorov, Haaland, Rao and Roth, 2022).[13] We inform respondents that at the end of the survey, they will provide a guess about a historical statistic relating to a particular domain. The domain varies by treatment group: respondents are told that they will guess either about (1) a general fact relating to the US economy, (2) the unemployment rate in the US, (3) annualized GDP growth in the US, (4) median weekly earnings in the US, or (5) the number of COVID-19 cases, all as of a specific, randomly selected date from recent years. We further inform respondents that if their guess lies within 5% of the official value, they will win an Amazon gift card. Respondents are told that the date about which they are guessing will be revealed only a few seconds before they need to make their guess, ensuring that they do not expect they will be able to find the answer by web search. We cross-randomize the value of the gift card: half of the respondents are offered a \$10 gift card and half a \$100 gift card. Respondents are further told that in order to inform their choice, they can choose one of four TV clips, which were all excerpted from shows broadcast on the same week as the randomly selected date pertinent to their guess.

Fox News viewers are offered segments from the two most popular straight news programs on the network—*The Story with Martha MacCallum* and *Special Report with Bret Baier*—and from the two most popular opinion programs on the network—*Hannity* and *Tucker Carlson Tonight*. MSNBC viewers are similarly offered segments from the two most popular straight news programs and the two most popular opinion programs on the network: *MSNBC Live* and *The Beat with Ari Melber*, and *The Rachel Maddow Show* and *The Last Word with Lawrence O'Donnell*, respectively. Our key outcome of interest is whether the viewer chooses an opinion show or a news show.

Two aspects of the design merit further discussion. First, we deliberately ask respondents to make guesses about historical statistics rather than to make predictions about future statistics. Since opinion programs focus relatively more than straight news on prediction about the future and relatively less on reporting about the current state of the world (Jacobs and Townsley, 2011), this design choice pushes us towards identifying a lower bound on trust in opinion shows. Moreover, this design choice allows us to deliver gift cards to respondents immediately if they guess correctly, avoiding the possibility that respondents believe researchers will fail to deliver a gift card in the future. Second, we deliberately choose objective economic statistics that are often covered in the

12. The preregistration is available on the AEA RCT registry under ID AEARCTR-0006958, available at https://www.socialscienceregistry.org/trials/6958.

13. The survey instrument is reproduced in Supplementary Appendix F.

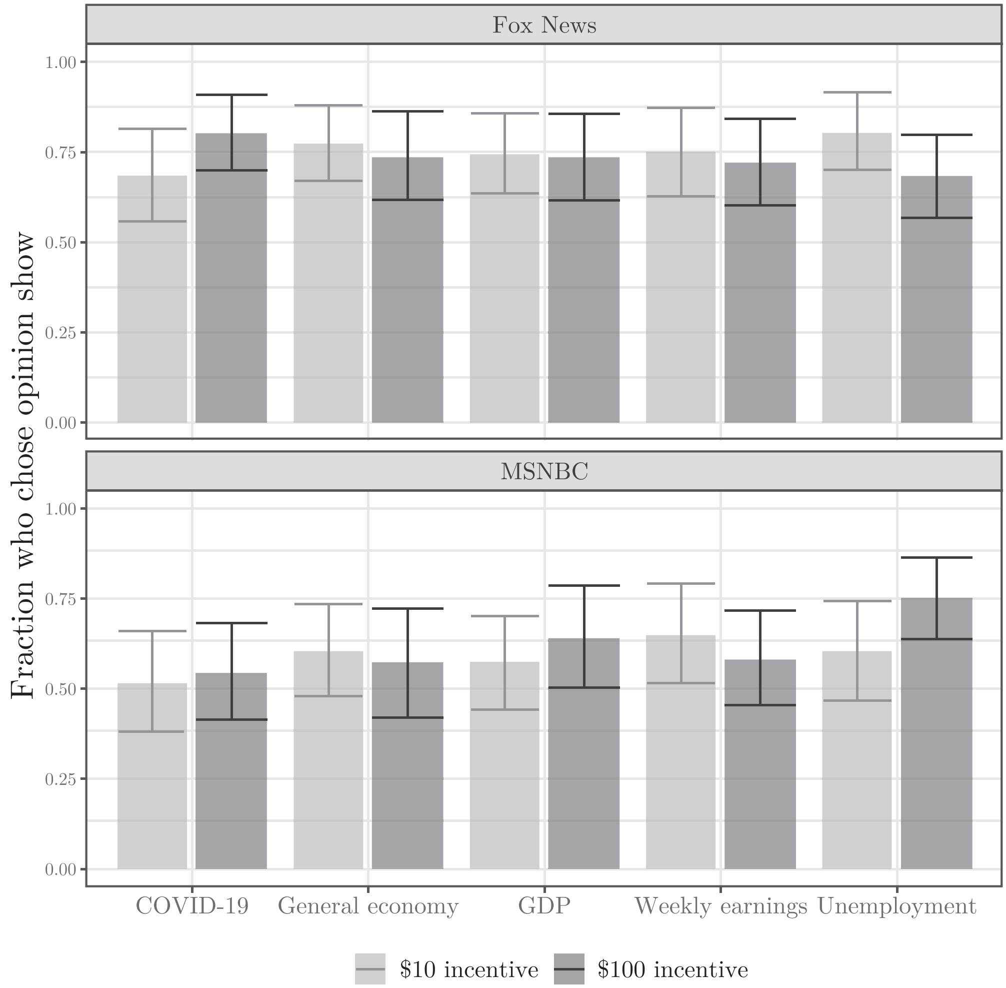

FIGURE 1

Trust in opinions

Notes: This figure plots the fraction of respondents who choose an opinion program over a straight news program, separately by network, domain of question, and level of incentive for accuracy. 95% confidence intervals based upon robust standard errors are reported.

news media (or, in the case of the COVID-19 statistic, were extensively covered during the period of interest). In contrast, there are far fewer political, cultural, or social statistics that are frequently covered. Moreover, economic statistics about the past are a domain in which we would expect to see the *lowest* selection of opinion shows, given that these shows generally favour political or cultural issues over economic issues (Berry and Sobieraj, 2013).

2.2. *Results*

Figure 1 presents the fraction of respondents in each treatment choosing an opinion show, separately for Fox News and MSNBC viewers. The levels are relatively similar across all domains and reveal a substantial preference for opinion programs: roughly 75% of Fox News viewers and 60% of MSNBC viewers choose one of the two opinion shows. For none of the five outcomes in

TABLE 1
Trust in opinion shows

	Dependent variable: Respondent chose opinion show					
	COVID-19 (1)	Economy (2)	GDP (3)	Earnings (4)	Unemployment (5)	Pooled (6)
Panel A: Fox News viewers						
$100 incentive	−0.022	−0.010	0.006	−0.049	−0.124	−0.027
	(0.104)	(0.098)	(0.096)	(0.101)	(0.093)	(0.039)
Dep. var. mean	0.748	0.759	0.741	0.735	0.739	0.745
Observations	107	112	112	102	115	548
Panel B: MSNBC viewers						
$100 incentive	0.107	−0.072	0.091	−0.014	0.095	0.058
	(0.111)	(0.113)	(0.117)	(0.109)	(0.115)	(0.045)
Dep. var. mean	0.534	0.592	0.604	0.616	0.683	0.606
Observations	103	98	101	99	104	505

Notes: The dependent variable in all columns of both panels is an indicator for whether the respondent chose to watch an opinion show (*Tucker Carlson Tonight* or *Hannity* for Panel A, and *The Rachel Maddow Show* or *The Last Word with Lawrence O'Donnell* for Panel B) rather than a straight news show. Columns 1–5 limit the sample to respondents assigned to the designated outcome; Column 6 pools all respondents. The explanatory variable is an indicator taking value one if the respondent was assigned to a $100 incentive and zero if the respondent was assigned to a $10 incentive. All specifications control for age, a set of race indicators, a Hispanic indicator, a male indicator, a set of education indicators, a set of household income indicators, and a set of employment indicators. Robust standard errors are reported.

either of the two populations does the $100 incentive significantly reduce the fraction choosing an opinion show. Indeed, for the COVID-19 condition—the condition most directly relevant to the empirical application of our article—the higher incentive *increases* the fraction choosing an opinion show, though the effect is not statistically significant. Table 1 replicates this analysis in regression table form and confirms that controlling for a range of individual demographics, including age, a set of race indicators, a Hispanic indicator, a male indicator, a set of education indicators, a set of household income indicators, and a set of employment indicators does not significantly affect the estimates.[14]

Our results indicate that respondents across the political spectrum do not internalize the differences in informativeness between news and opinion shows when making their choice of program. Thus, whatever other factors may influence their choice (e.g. preferences for popular programs, entertainment value, or habit formation), the vast majority of respondents end up trusting opinion programs over straight news programs even in the presence of substantial incentives to learn objective facts—despite the fact that both Fox News and MSNBC have argued in court that viewers should not interpret their opinion programs as factual.

One related interpretation is that respondents believe that neither straight news nor opinion programs are at all informative for their guess. Under this belief, respondents' decision of which news source to consume is (*ex ante*) payoff-irrelevant, so respondents may choose opinion programs simply because they are more entertaining. Given the low levels of trust in conventional media sources documented above, this is perhaps true for some respondents. Yet, we consider it unlikely that this drives our results given that the patterns are highly robust across the five

14. Through manual coding of episode scripts during the week relevant to the experiment, we find that straight news programs are indeed substantially more likely to cover the statistics of interest than opinion programs. In turn, viewers who choose a straight news program also make more accurate guesses than viewers who choose an opinion program, though this may reflect selection into the shows.

domains, and thus respondents would have to believe that none of the programs convey useful information across any of the dimensions we study. As an additional benchmark, we directly elicit respondents' beliefs about the likelihood that each program contained the information necessary for the guess. We find that 70% of Fox News viewers and 57% of MSNBC viewers believed that an opinion program was weakly *more* informative than either of the straight news shows, confirming the hypothesis that both conservative and liberal viewers indeed see opinion programs as more informative for objective facts.

3. OPINION PROGRAMS AND HIGH-STAKES BEHAVIOUR IN THE FIELD

What are the consequences of this trust in opinion programming? In this section, we examine how opinion programs shaped beliefs and behaviour during the early stages of the COVID-19 pandemic in the US. This setting is ideally suited to exploring the role of opinion programs for two reasons: first, because the stakes involved in acquiring accurate information were relatively high; and second, because there was substantial disagreement about the threat posed by COVID-19 across different opinion programs.

3.1. *Diverging narratives about COVID-19*

We focus on media coverage of COVID-19 on Fox News during the early stages of the COVID-19 pandemic. Fox News is the most watched cable network in the US, with an average of 3.4 million total primetime viewers in the first quarter of 2020, compared to 1.9 million for MSNBC and 1.4 million for CNN (the other two of the "Big Three" US cable news networks).[15] Moreover, the median age of primetime Fox News viewers is 68, substantially higher than that of CNN and MSNBC viewers.[16] Both due to its reach and the fact that more than half of its audience is over the age of 65—a group that the CDC warns is at elevated risk from COVID-19—Fox News may exert substantial influence on COVID-19 outcomes. This is particularly true given that the elderly both watch more TV in general than the average US citizen and because they disproportionately rely on television for news and information (Pew, 2019).

3.1.1. Narratives adopted by Carlson vs. Hannity. Our article focuses on the two most widely viewed cable news programs in the US, both of which are opinion programs: *Hannity* and *Tucker Carlson Tonight*. These shows had an average of 4.2 million and 4 million daily viewers, respectively, during the first quarter of 2020.[17] Before COVID-19 began to spread in the US in January 2020, *Hannity* and *Tucker Carlson Tonight* were relatively similar in content and viewership: both covered the news from a conservative perspective and were broadly supportive of President Trump's policy agenda (see the end of Section 3.1 for evidence on pre-2020 coverage). Yet as we document using qualitative evidence, text-analysis methods, and human coding of the shows' scripts, the two shows adopted very different narratives about COVID-19.

News outlets and politicians across the ideological spectrum, and even experts such as National Institute of Allergy and Infectious Diseases director Anthony Fauci, suggested throughout much of February that COVID-19 would likely be safely contained.[18] While most programs on broadcast

15. "Fox News Channel Ratings for First Quarter of 2020 Are the Highest in Network History." *Fox News*, 31 March 2020.
16. "Half of Fox News' Viewers Are 68 and Older." *The Atlantic*, 27 January 2014.
17. Authors' calculations based upon data from Nielsen (2020).
18. See "What Went Wrong with the Media's Coronavirus Coverage?" *Vox*, 13 April 2020.

and especially cable networks occasionally discussed COVID-19 in January and early-to-mid February, the topic did not comprise a substantial fraction of coverage until late February.[19] Tucker Carlson thus stood out not only among his colleagues at Fox News, but more broadly among both broadcast and cable news anchors, for his repeated insistence as early as late January that COVID-19 posed a serious threat to the US.[20] For example, on 28 January—more than a month before the first COVID-19-related death in the US—Tucker Carlson spent a large portion of his show discussing the subject and continued to do so throughout February.

In contrast, Hannity covered COVID-19 and its consequences substantially less than Carlson and other Fox shows, particularly during February, when the virus was first beginning to spread in the US. Even after he began discussing it more prominently in February, he downplayed the threat the virus posed and emphasized that Democrats were politicizing the virus. By mid-March, after President Trump declared a national emergency in response to COVID-19, Hannity's coverage had converged to that of Carlson and other Fox News shows, emphasizing the seriousness of the situation and broadcasting CDC guidelines.

3.1.2. Extensive margin of COVID-19 coverage. To more systematically evaluate differences in the extensive margin of coverage between primetime Fox News shows, we turn to a simple word-counting procedure. For each of the seven shows on Fox News airing between 5 p.m. and 11 p.m. local time across the four major time zones, we download episode transcripts from LexisNexis (2020). We count the number of times any of a small list of coronavirus-related terms are mentioned on each day and plot the results in Figure 2A.[21] In particular, the y-axis of the panel displays the log of one plus the word count on each day.

Compared to the other primetime shows, both *Hannity* and *Tucker Carlson Tonight* stand out. Both anchors first discussed COVID-19 in late January when the first US case was reported, but Carlson continued to discuss the subject extensively throughout February whereas Hannity did not again mention it on his show until the end of the month. The other shows fell somewhere between these two extremes. By early March, the word counts of all shows had converged.[22]

However, this simple procedure does not entirely capture differences in how shows discussed COVID-19. The qualitative evidence above suggests that while Hannity discussed COVID-19 as frequently as Carlson during early March, he downplayed its seriousness and accused Democrats of using it as a partisan tool to undermine the administration. To capture these differences in the intensive margin of coverage, we turn to human coding of the scripts.

3.1.3. Human coding of scripts. Between 2 April and 6 April, we recruited workers on Amazon Mechanical Turk to assess how seriously each of the seven shows portrayed the threat of COVID-19 between early February and mid-March. For each episode that contained at least one coronavirus-related term, five MTurk workers read the entire episode script and answered "Yes" or "No" to the following question: "Did [the show] indicate that the virus is likely to infect many people in the US, causing many deaths or serious illnesses, or that many have already become infected and have died or become seriously ill?" We explicitly asked respondents to answer

19. Budak, Muddiman, Kim, Murray and Stroud (2021) estimate that 10–15% of airtime was devoted to coverage of the pandemic on cable networks in mid-February, compared to approximately 15–20% on broadcast networks. This fraction began to rise sharply in the last week of February and stabilized at approximately 70% across both broadcast and cable networks by March 16.

20. See, for example, "His Colleagues at Fox News Called Coronavirus a 'Hoax' and 'Scam.' Why Tucker Carlson Saw It Differently." *The LA Times*, 23 March.

21. The words are "coronavirus", "virus", "covid", "influenza", and "flu."

22. We also conduct a similar content analysis of all major primetime shows on CNN and MSNBC and find little variation across shows in terms of the coverage of COVID-19 (see Supplementary Appendix Figure A2).

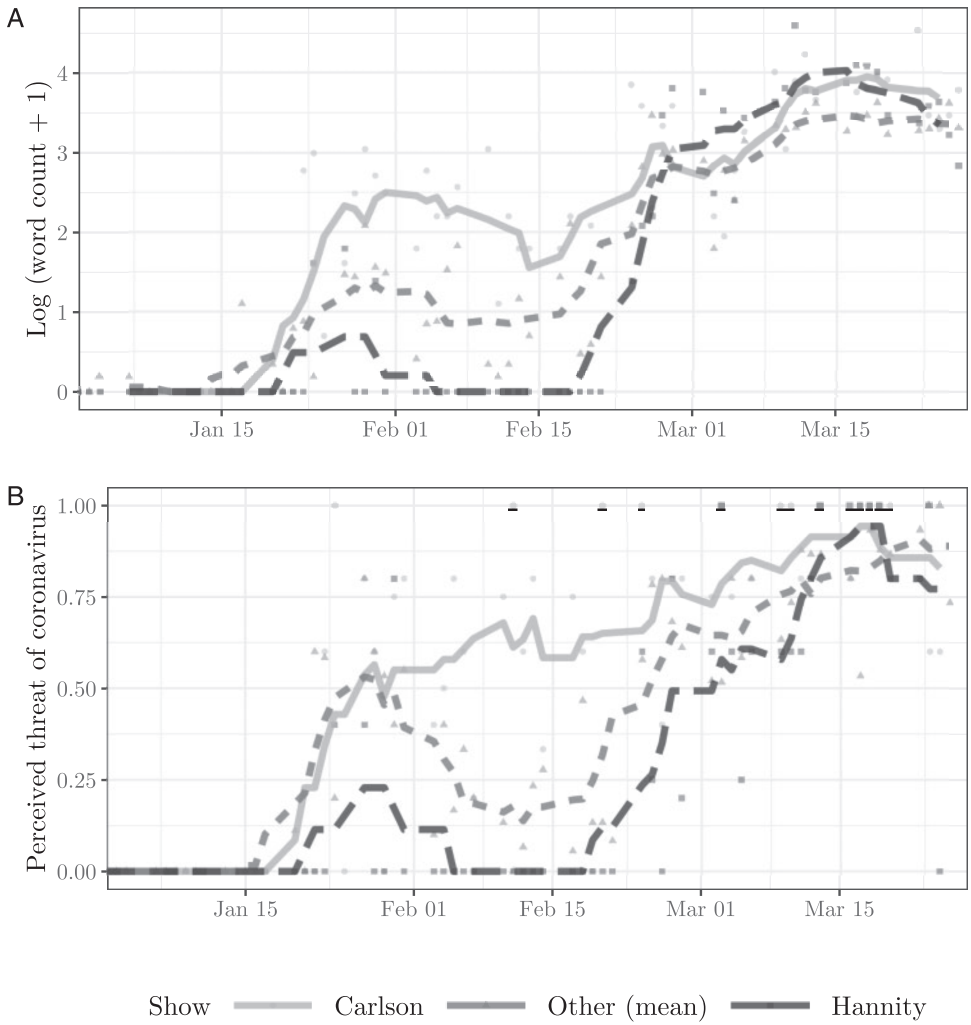

FIGURE 2

Show content validation

Notes: Panel A shows counts of coronavirus-related terms (coronavirus, COVID, virus, influenza, and flu) separately for *Hannity*, *Tucker Carlson Tonight*, and the other Fox News shows aired on Fox News between 5 p.m. and 11 p.m. local time across all four major time zones in the continental US (*The Five*, *Special Report with Bret Baier*, *The Story with Martha MacCallum*, *Fox News at Night*, and *The Ingraham Angle*). Panel B shows the seriousness rating for each episode, constructed as an average of Amazon Mechanical Turk ratings. For each show containing at least one coronavirus-related term, five MTurk workers read the entire script and answered "Yes" or "No" to the following question: "Did [the show] indicate that the virus is likely to infect many people in the US, causing many deaths or serious illnesses, or that many have already become infected and have died or become seriously ill?" We impute "No" for each episode that does not mention any coronavirus-related terms and recode "Yes" to 1 and "No" to 0.

the question based only on the scripts, not their own views on the subject. We impute "No" for each script that does not mention any coronavirus-related terms, and we code "Yes" as 1 and "No" as 0.[23]

23. We calculate Fleiss' Kappa of inter-rater agreement, a commonly used measure to assess the reliability of agreement among more than two sets of binary or non-ordinal ratings, as $\kappa = 0.629$ ($p < 0.001$), suggesting "substantial agreement" (Landis and Koch, 1977).

Figure 2B displays 1-week rolling means of this variable for Carlson, Hannity, and the other shows. Throughout almost the entire period, MTurk workers rate Carlson as portraying the threat of COVID-19 more seriously than the other shows, and in turn rate the other shows as portraying the threat more seriously than Hannity. In line with the qualitative evidence highlighted above, Hannity converges to Carlson in early to mid-March.

3.1.4. Pre-period similarity between *Hannity* and *Tucker Carlson Tonight*. Finally, we establish that *Hannity* and *Tucker Carlson Tonight* featured similar content prior to their divergence on COVID-19 by analysing all 2019 transcripts of these programs, as well as the primetime programs on Fox News and MSNBC used in the experiment described in Section 2. Because human-coding exercises are infeasible given the large number of transcripts and word-counting methods are infeasible given that we do not have priors over how (if at all) the two programs diverge in their coverage of other topics, we turn to natural language processing techniques to establish that *Hannity* was very close to *Tucker Carlson Tonight* both in the topics covered and the way they covered them, relative to the similarity between *Hannity* and the other Fox News and MSNBC programs. We provide a brief summary of our methodology and findings here, relegating a more detailed discussion to Supplementary Appendix C.

To quantify divergence in the selection of topics, we employ Latent Dirichlet Allocation (Blei, Ng and Jordan, 2003; Schwarz, 2018), an unsupervised topic model that finds underlying "topics" and then outputs vectors for each transcript characterizing the extent to which the transcript is composed of each topic. The resulting 10 topics are intuitively coherent: for example, one topic containing terms such as "Mueller", "prosecutor", "obstruction", and "judge" pertains to the Mueller investigation, while another, containing terms such as "storm", "hurricane", "water", and "Bahamas" captures hurricanes and other natural disasters.[24] For each week, we calculate the Euclidean (L2) distance between the topic vector for *Hannity* and that of each other program, plotting results in Panel A of Supplementary Appendix Figure A1. The results show that *Hannity* is substantially more similar to *Tucker Carlson Tonight* than to any other program with the exception of *The Story*, which is equally similar. Reassuringly for our measure of distance, the figure also shows that programs on MSNBC are less similar to *Hannity* than programs on Fox News.[25]

To quantify divergence in the manner in which topics were covered, we use BERT (Devlin, Chang, Lee and Toutanova, 2019), a transformer that creates high-dimensional vector representations, or contextual embeddings, capturing documents' semantic meaning. After identifying the topic of each 512-token segment from the transcripts (the maximum length that BERT can process, corresponding to approximately 300 words) using the LDA procedure outlined above, we create a vector representation of the segment. For each topic, we calculate the L2 distance between all the contextual embeddings of segments on that topic and average to collapse to a program-by-topic-by-week measure of distance. Panel B of Supplementary Appendix Figure A1 reports similarity between *Hannity* and the other programs (averaging across all 10 topics); *Tucker Carlson Tonight* is again the most similar program.[26]

24. We provide a full list of topics in Supplementary Appendix Table C1.

25. Supplementary Appendix Figure C1 reports program similarity for each topic individually. The topics where the two programs diverge the most are economic policy and Trump's impeachment; across most topics, differences are small. We also validate our measure by repeating this exercise for 2020, plotting results in Supplementary Appendix Figure C3; as in our simpler word-counting exercise, we find large differences in COVID-19 coverage between *Tucker Carlson Tonight* and *Hannity* in January and February; these differences decrease to zero by early March. Differences in other topics, on the other hand, are much smaller.

26. Supplementary Appendix Figure C2 reports program similarity for each topic individually. Differences between *Tucker Carlson Tonight* and *Hannity* are again modest.

Together, our evidence suggests that the two largest opinion shows in the US adopted dramatically diverging narratives about the threat posed by COVID-19, despite presenting relatively similar content both before the COVID-19 pandemic and on non-COVID-19 topics during the pandemic. We next present survey evidence that these differences may have affected viewers' behaviour during the period of initial spread of COVID-19 in the US.

3.2. *Timing of behavioural adjustment*

Radical behavioural changes, such as stay-at-home behaviour, did not become widespread until mid-to-late March, when the pandemic narrative gap between *Hannity* and *Tucker Carlson Tonight* had already closed.[27] To capture more subtle behavioural changes that may have occurred in February and March, and to shed light on which types of behavioural change were most common, we fielded a survey on 3 April 2020. Our survey targeted a representative sample of approximately 1,500 Republicans aged 55 or older both because this population is more likely to watch Fox News and because the elderly are at increased risk from COVID-19.[28] As we show in Supplementary Appendix Table A1, our sample is broadly representative of Republicans aged 55 and older. All survey materials are available in Supplementary Appendix F.

3.2.1. Survey design. After eliciting demographics, we ask respondents which, if any, of the "Big Three" TV news stations (CNN, MSNBC, and Fox News) they watch at least once a week. 1,045 individuals reported that they watch any show on Fox News at least once a week; this is the sample we use in our analysis, given our focus on Fox News viewers. We ask respondents to indicate the frequency with which they watch the major prime-time shows on each network on a three-point scale ("never"; "occasionally"; "every day or most days").

We then ask our respondents about any changes in their behaviour in response to COVID-19 outbreak. First, we ask whether they have changed any of their behaviours (e.g. cancelling travel plans, practicing social distancing, or washing hands more often) in response to COVID-19. For those respondents who answer that they have changed behaviour, we elicit the date on which they did so. Finally, we ask an open-ended question asking respondents to describe which behaviours they changed.

3.2.2. Sample characteristics. In Supplementary Appendix Table A2, we plot demographic characteristics of exclusive *Tucker Carlson Tonight* and *Hannity* viewers. Although there are observable differences between the two groups of viewers, these differences appear to be modest.[29] In general, relatively few Fox viewers consume other sources of news, consistent with Pew survey data on viewership and on distrust of non-Fox media sources.[30]

27. See, e.g. "Social Distancing, but Mostly During the Workweek?" *Federal Reserve Bank of St. Louis*, 26 May 2020.

28. The median age among Fox News viewers is 68. See, e.g. "Half of Fox News' Viewers Are 68 and Older." *The Atlantic*, 27 January 2014.

29. As we discuss in Section 4, we conducted a larger-scale survey between December 2020 and January 2021, which included approximately 3,700 Fox viewers. Unlike our earlier survey, this survey was constructed to be representative of the US population as a whole, rather than only Republicans over the age of 55. As shown in Supplementary Appendix Table A3, we again find that observable differences are modest. Of course, these results must be interpreted with caution, given that data were collected several months after the period we study.

30. See "Five Facts about Fox News," *Pew Research*, 8 April 2020.

3.2.3. Results. To examine the correlation between viewership of different news shows and the timing of behavioural change, we estimate the following simple specification:

$$\text{TimingChange}_i = \alpha_0 + \beta S_i + \Pi X_i + \varepsilon_i,$$

where TimingChange_i is the number of days after 1 February 2020 on which the respondent reported having significantly changed any of their behaviours in response to COVID-19, S_i is a vector of indicators for whether the respondent occasionally or regularly watches each of the seven shows, and X_i is a vector of demographic controls.[31] The dependent variable for respondents who report that they have not changed any of their behaviours at the time of the survey is recoded to the date on which the survey was administered (April 3). We employ robust standard errors throughout our analysis.

Figure 3A plots the smoothed density function of the reported date of behavioural change separately for viewers of Carlson, Hannity, and other Fox News shows. (The majority of viewers watch more than one show and thus appear in multiple panels.) We also display these results in regression table form in Table 2. Column 1 shows that viewers of *Hannity* changed their behaviour 4–5 days later than viewers of other shows ($p < 0.001$), while viewers of *Tucker Carlson Tonight* changed their behaviour 3–4 days earlier than viewers of other shows ($p < 0.01$); the difference in coefficients is also highly statistically significant ($p < 0.01$).[32] Column 2 reports a linear probability model in which the dependent variable is an indicator for whether the respondent reported changing behaviour before March 1; Carlson viewers were 11.7 percentage points more likely and Hannity viewers 11.2 percentage points less likely to have changed their behaviour before 1 March than viewers of other Fox shows.[33] We estimate identical linear probability models for each day between 1 February and 3 April (the date on which we administered the survey) and report the coefficients on both *Hannity* viewership and *Tucker Carlson Tonight* viewership for each day in Figure 3B. By this measure, the difference between the two anchors peaks around 1 March, then declines.

We also examine the timing of specific margins of behavioural adjustment by manually coding the open-ended responses to the question of which behaviours respondents changed Supplementary Appendix Figure A3 highlights that increased hand washing and physical distancing, including avoiding large events, are the most frequently mentioned behavioural changes, particularly in February, the period during which the differences in show content

31. Viewers who watch multiple shows will have multiple indicators set to one, while viewers that watch none of the five shows will have none of the indicators set to one.

32. Ash *et al.* (2022) also find survey evidence that Republican *Hannity* viewers adopt social distancing measures significantly later than Republicans who do not watch *Hannity*, while Republican *Tucker Carlson Tonight* viewers adopt social distancing measures significantly earlier than Republicans who do not watch *Tucker Carlson Tonight*.

33. To benchmark the plausibility of the estimated effects, we calculate the *persuasion rate* of viewership on the outcome of changing behaviour by 1 March, following the approach proposed by DellaVigna and Gentzkow (2010). The implied persuasion rate of *Hannity* viewership relative to *Tucker Carlson Tonight* viewership is 24.1%, well within the range of comparable estimates; for example, Martin and Yurukoglu (2017) find a Fox News persuasion rate on voting behaviour of 58% in 2000, 27% in 2004, and 28% in 2008; Adena, Enikolopov, Petrova, Santarosa and Zhuravskaya (2015) find a persuasion rate of up to 36.8%; and Enikolopov, Petrova and Zhuravskaya (2011) find persuasion rates rating from 7 to 66%. On one hand, we might expect a lower persuasion rate in our context because exposure is over a much shorter period; on the other hand, we might expect a higher persuasion rate (1) because the outcomes we study are arguably lower-stakes than the outcomes in other settings, (2) because viewers likely hold weak priors about the seriousness of the pandemic during the period under consideration, and (3) because regular viewers of a show likely place significant weight on the anchors' opinions.

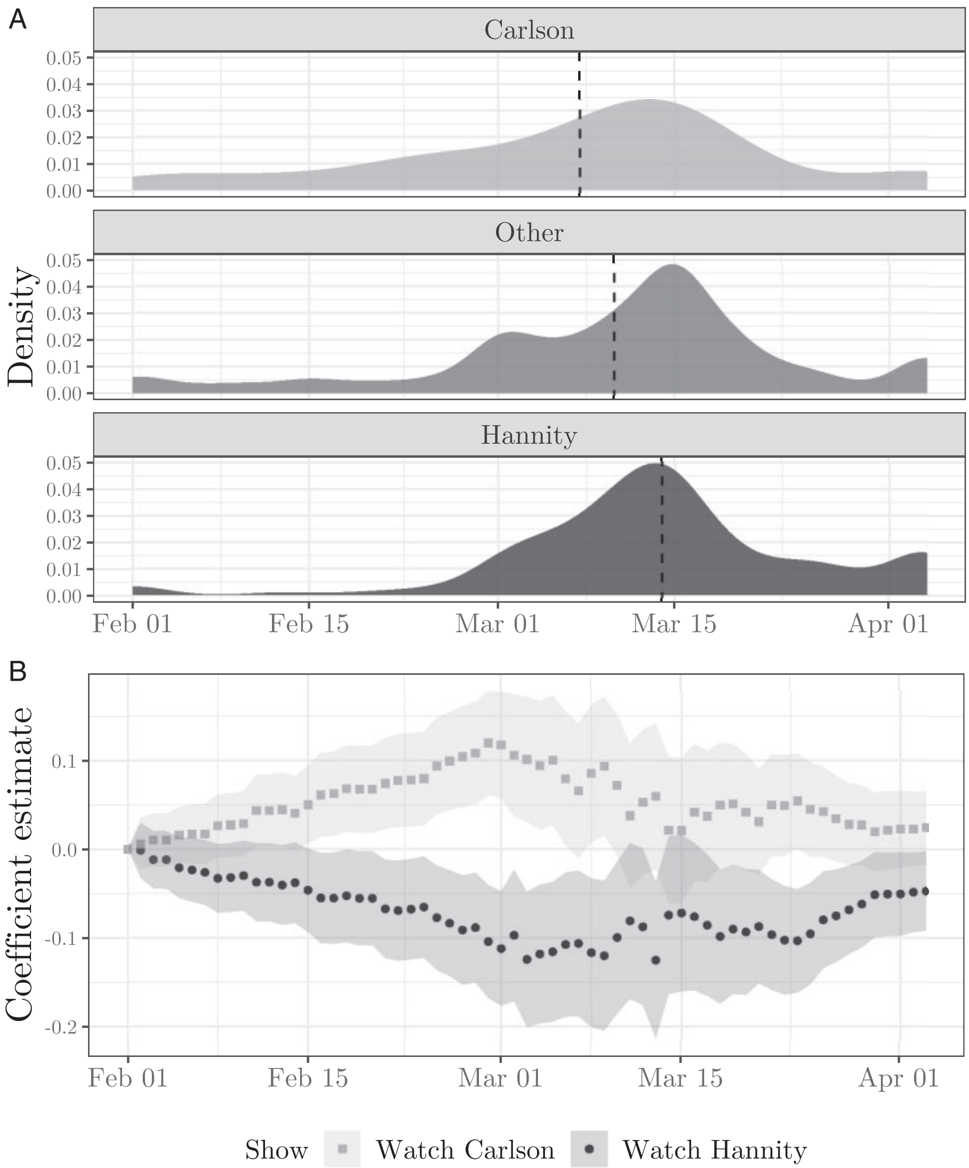

FIGURE 3

Timing of behavioural change by show viewership

Notes: Panel A displays the density function of viewers' reported day of behaviour change in response to the coronavirus. For respondents who report that they have not changed any of their behaviours by the date of the survey, we impute the date of the survey (3 April). The dashed line indicates the mean date of behaviour change among viewers of each show. To mirror our regressions, the top pane includes only *Tucker Carlson Tonight* viewers that do not watch *Hannity*, while the bottom pane includes only *Hannity* viewers that do not watch *Tucker Carlson Tonight*. Panel B reports coefficient estimates from linear probability models in which the dependent variable is an indicator for whether the respondent reported changing behaviour before the date in question and the explanatory variables include an indicator for whether the respondent watches *Tucker Carlson Tonight*, an indicator for whether the respondent watches *Hannity*, an indicator for whether the respondent watches any other Fox News shows, and controls for gender, employment status, income, race, education, and viewership of CNN and MSNBC. We report 95% confidence intervals.

were largest. Cancelling travel plans and staying at home are also frequently mentioned, though primarily in mid and late March.[34]

34. The responses highlight the importance of distinguishing between two types of social distancing. Following the Federal Reserve, we distinguish *stay-at-home behaviour*—remaining at home for all or a substantial part of the

TABLE 2
Correlation between show viewership and timing of behaviour change

	Dependent variable:			
	—	Changed before...		
	Change day	March 1	March 15	April 1
	(1)	(2)	(3)	(4)
Watches Hannity	4.452***	−0.112***	−0.076*	−0.051**
	(1.282)	(0.033)	(0.043)	(0.024)
Watches Carlson	−3.362***	0.117***	0.042	0.021
	(1.188)	(0.031)	(0.039)	(0.022)
p-value (Hannity=Carlson)	<0.001	<0.001	0.097	0.076
DV mean	39.016	0.163	0.680	0.922
R^2	0.058	0.063	0.022	0.043

Notes: The dependent variable in Column 1 is the number of days after 1 February 2020 on which the respondent reported having significantly changed any of their behaviours in response to COVID-19. For respondents who report not changing behaviour by the date of the survey, we recode the dependent variable to the date of the survey (3 April). The dependent variables in Columns 2–4 are indicators for whether the respondent reported having significantly changed their behaviours before the date specified in the column header. Demographic controls include age, a white/not Hispanic indicator, a male indicator, a set of education indicators, a set of household income indicators, and a set of employment indicators. Other viewership controls include indicators for whether the respondent watches CNN or MSNBC at least once a week. Robust standard errors are reported.

Our survey suggests that show content may have affected individual behaviours relevant for the spread of COVID-19, shedding light on specific mechanisms that may explain the treatment effects on COVID-19 cases and deaths we document in Sections 3.3 and 3.4. However, the correlations might be driven by omitted variable bias or reverse causality: viewers who did not want to believe that the COVID-19 was a serious problem or viewers less inclined to changing their behaviour may have selected into watching *Hannity*. Moreover, our outcome is self-reported, which may bias our estimates if respondents systematically misremember that they changed their behaviour earlier or later than they actually did (and this tendency differs between *Hannity* and *Tucker Carlson Tonight* viewers). To address these issues, we turn to data on county-level COVID-19 cases and deaths, and later to an instrumental variable strategy shifting relative viewership of the two shows.

3.3. *OLS estimates on health outcomes*

In this section, we discuss the empirical challenge in identifying causal effects. We then present OLS evidence on the effects of differential viewership of *Hannity* and *Tucker Carlson Tonight* on COVID-19 cases and deaths.

3.3.1. Data. We employ several primary categories of data in our observational analysis, which we describe in detail in Supplementary Appendix B. Our TV viewership data are provided by Nielsen (2020) at the Designated Market Area (DMA) level, of which there are 210 in the US. We focus on the continental US, excluding the two DMAs in Alaska (Anchorage and Fairbanks)

day—from *physical distancing*—continuing with day-to-day activities, but keeping a distance (e.g. of 6 feet) from others and avoiding large, potentially "superspreader" events such as sports games or concerts. While stay-at-home behaviour becomes widespread only in mid-to-late March (see e.g. Allcott, Boxell, Conway, Gentzkow, Thaler and Yang, 2020), our survey responses suggest that physical distancing and avoiding large events was widespread even in February among the population we survey.

and the single DMA in Hawaii (Honolulu). Our dataset contains viewership data between 5 p.m. and 11 p.m. (local time) at the DMA-by-timeslot-by-day level (i.e. hourly ratings).[35] In addition to the fraction of TVs watching Fox News, we observe the fraction of TVs turned on during each timeslot. We supplement this dataset with 2018 data, previously acquired, on the local market share of each of the "Big Three" networks: CNN, MSNBC, and Fox News.[36] Our key outcome variables on county-level *confirmed* COVID-19 cases and deaths are drawn from Johns Hopkins University (Dong *et al.*, 2020). Throughout our main analyses, we take the logarithm of one plus the cumulative number of cases and deaths, both to prevent outliers with a large number of cases from skewing the estimates and because the exponential nature by which a virus spreads makes the logarithm normalization natural. Finally, we compile a rich set of data on county level characteristics, including local vote shares, educational attainment, incomes, and the demographic age structure.

Data on COVID-19 cases are potentially subject to both classical and non-classical measurement error. For example, many COVID-19 cases are unreported and if differential media coverage of the pandemic influences the rate of case detection, then our coefficient estimates will be biased. If viewers of *Hannity* are less concerned about the virus, and thus counties with greater viewership of *Hannity* have lower rates of case detection—this should bias our estimates *downward*. Classical measurement error will not bias our estimates but will decrease their precision. Nonetheless, we urge caution in interpreting our estimated effects on cases given these potential data limitations. COVID-19 death counts are far less subject to either classical or non-classical measurement error.

3.3.2. OLS specification. Our explanatory variable of interest is the DMA-level average difference between viewership of *Hannity* and viewership of *Tucker Carlson Tonight* across all days in January and February 2020 when both shows are aired. We scale this variable to take mean zero and standard deviation one for ease of interpretation. In our primary analysis, we estimate the following specification at the county level separately for each day between 24 February and 15 April (for cases) and between 1 March and 15 April (for deaths):

$$Y_{mct} = \alpha_t + \beta_t D_{mc} + \Pi_t X_{mc} + \varepsilon_{mct}, \tag{1}$$

where Y_{mct} is an outcome (log one plus cases or log one plus deaths) in media market m, county c on day t, D_{mc} is the standardized difference between viewership shares of *Hannity* and *Tucker Carlson Tonight*, and X_{mc} is a vector of county-level controls.

3.3.3. Identifying variation and potential confounders. To see the potential threats to identifying causal effects, it is useful to understand where the variation in the main exposure variable, D_{mc}, comes from. By definition, it is the difference between the share of households that regularly watch *Hannity* ($v_{mc,H}$) and the share that regularly watch *Tucker Carlson Tonight* ($v_{mc,T}$). More broadly, for any show that airs at a certain hour-long time slot h in the evening, we

35. This is in contrast to previous work, e.g. Martin and Yurukoglu (2017), which uses data from 2005 to 2008 at the cable system-by-year level.

36. Our primary analysis uses January and February viewership data; however, given the high degree of persistence in show viewership, our results are quantitatively extremely similar and qualitatively identical if we instead use only January data (to rule out concerns about reverse causality in our OLS estimates) or if we use data from 1 January through 8 March (the beginning of Daylight Savings Time, a natural stopping point given the structure of our identification strategy).

can define the share of households that watch *any channel* on TV as $s_{mc,h}$ and, among those, the share at that moment that tunes in to Fox News as $f_{mc,h}$.

Thus, D_{mc} is driven by four factors:

$$D_{mc} = (s_{mc,H} \times f_{mc,H}) - (s_{mc,T} \times f_{mc,T}).$$

This means that the OLS specification effectively exploits variation arising from differences in *timing preferences* and *channel preferences*:

$$Y_{mct} = \alpha_t + \beta_t (s_{mc,H} \times f_{mc,H} - s_{mc,T} \times f_{mc,T}) + \Pi_t X_{mc} + \varepsilon_{mct}. \quad (2)$$

Since we are interested in examining the effects of differential exposure to two major shows on Fox News, Equation (2) makes it clear that if areas where Fox News is relatively popular experience more COVID-19 cases for any other (unobservable) reason—for example if populations in these areas live further away from high quality hospitals, tend to trust science less, or have certain life styles which make them more or less vulnerable to the virus—our estimate will be biased. To deal with this issue, we always control for the average evening TV market share of Fox News: $\overline{f}_{mc,h}$, where h denotes 8 p.m. to 11 p.m. Eastern Time. Moreover, since there may be selection into competing cable news networks specifically, rather than TV watching *per se*, we analogously always control for the "Big Three" cable TV market shares of Fox News and MSNBC (with CNN omitted since it is collinear with the other two). The inclusion of these controls hold fixed many potential confounders related to *channel preferences*.

Equation (2) also makes clear that if localities which have a tendency to watch evening TV *per se* around the time of *Hannity*, rather than *Tucker Carlson Tonight*, consist of populations which differ in their vulnerability to the virus, the OLS estimate could easily be biased. (Again, *ex ante* it is unclear which way the bias would go, given that we are comparing differential exposure to two shows on the same network.) To address concerns about local preferences for watching TV at certain times in the evening correlating with other determinants of COVID-19 trajectories—such as the extent to which people like to socialize in restaurants and bars (in ways which spread the virus) instead of staying home watching TV—we always include the average share of households with TVs turned on during each hourly slot between 8 p.m. and 11 p.m. Eastern Time (three variables, each capturing 1 h): $s_{mc,8-9pm}$, $s_{mc,9-10pm}$, $s_{mc,10-11pm}$. These controls hold fixed many potential confounders related to *timing preferences*.

Given this approach, the remaining (residual) variation in exposure effectively comes from the difference in the two interaction terms of Equation (2), *holding constant* local preferences for watching TV in general and watching Fox News in general. We also include additional observable characteristics as controls. For example, since we study the early stages of the COVID-19 pandemic and initial outbreaks occurred around metropolitan hotspots, one concern may be that viewership patterns across the two shows correlate with such hot spot locations. For this reason, we show results with and without controls for rurality and population density and transparently show how much the estimate fluctuates as a result. More broadly, in addition to *population* controls, we show results with and without county-level controls for a range of observable characteristics: *race* (the share of the population white, Hispanic, and black); *education* (the share lacking high school degrees and the share lacking college degrees, for women and men separately); *age* (the share over the age of 65); *economic* factors (the share under the federal poverty line, log median household income, and the unemployment rate); *health* factors (the share lacking health insurance and an age-adjusted measure of the average physical health in the county from 2018); *health capacity* (the number of different types of health personnel per capita); *political* factors (Republican vote share and the log total number of votes cast in the 2016 Presidential election).[37] To account for additional unobservable determinants of health outcomes that differ across localities, we show results using (1) no geographical fixed effects, (2) Census division (nine in total) fixed effects, and (3) state fixed effects. Since time zones are absorbed by the geographical indicator variables in the latter two cases, the fixed effects imply that we hold constant what time the two shows air locally. Our most extensive OLS specification—which is our preferred in that it helps rule out a host of concerns beyond the ones explicitly outlined above—includes state fixed effects and a full set of control variables.

To capture the effects in a transparent manner over time, we run separate cross-sectional regressions each day; in specifications including state fixed effects, this implicitly controls for state-level policies varying at the day level, such as shelter-in-place orders and closures of nonessential businesses. Because our viewership data is at the DMA level and to allow for within-market correlation in the error term, we cluster standard errors at the DMA level (m), resulting in a total of 204 clusters.[38]

3.3.4. Results. We report day-by-day results for cases and deaths in Figure 4, including all controls and state fixed effects. The association between relative viewership and both cases and deaths becomes stronger over time until the coefficient on cases peaks in late March and then begins to decline; the coefficient on deaths follows with a 2-week lag, consistent with the approximately 2-to-3-week lag between the appearance of COVID-19 symptoms and deaths (Wu, Leung, Bushman, Kishore, Niehus, de Salazar, Cowling, Lipsitch and Leung, 2020). Effects on cases are statistically significant at the 5% level throughout the majority of the period, while effects on deaths become statistically significant in late March and remain significant or marginally significant throughout the remainder of the period. Effects on cases start to rise in late February and peak in mid-to-late March before starting to decline, consistent with the convergence in coronavirus coverage between Hannity and Carlson. A one standard deviation greater viewership difference is associated with 2% more deaths on 21 March, 4% more deaths on 28 March, and 9% more deaths on 11 April. We report these results at weekly intervals in regression table form in Table 3.

3.3.5. Robustness. To probe the robustness of our estimates, we choose a single day for cases—14 March, 2 weeks into March—and a single day for deaths—28 March, 2 weeks after our chosen date for cases (given the lag between cases and deaths). We then run our specifications under every possible combination of our nine sets of county-level controls (rurality, race, age, economic, education, health, health capacity, and politics) and three levels of fixed effects (no fixed effects, census division fixed effects, and state fixed effects). Supplementary Appendix Figure A6 reports coefficient estimates for each of these 1,536 models for cases as of 14 March as well as deaths as of 28 March. The majority of coefficient estimates on cases and deaths are statistically significant at the 1% level. All coefficient estimates from specifications including state fixed effects, our most demanding and most precisely estimated

37. In Supplementary Appendix Figure A4, we report regressions of an extensive range of county-level demographic characteristics, scaled to standard deviation one to facilitate interpretation, on our measure of relative viewership of the two shows. For none of these outcomes is our coefficient estimate statistically distinguishable from zero at the 5% level, though counties with a relative preference for *Hannity* are slightly more Hispanic and less black, have slightly fewer residents over the age of 65, and are somewhat less educated.

38. Our results are also statistically significant if we instead cluster at the state level, as we show in Supplementary Appendix Figure A5.

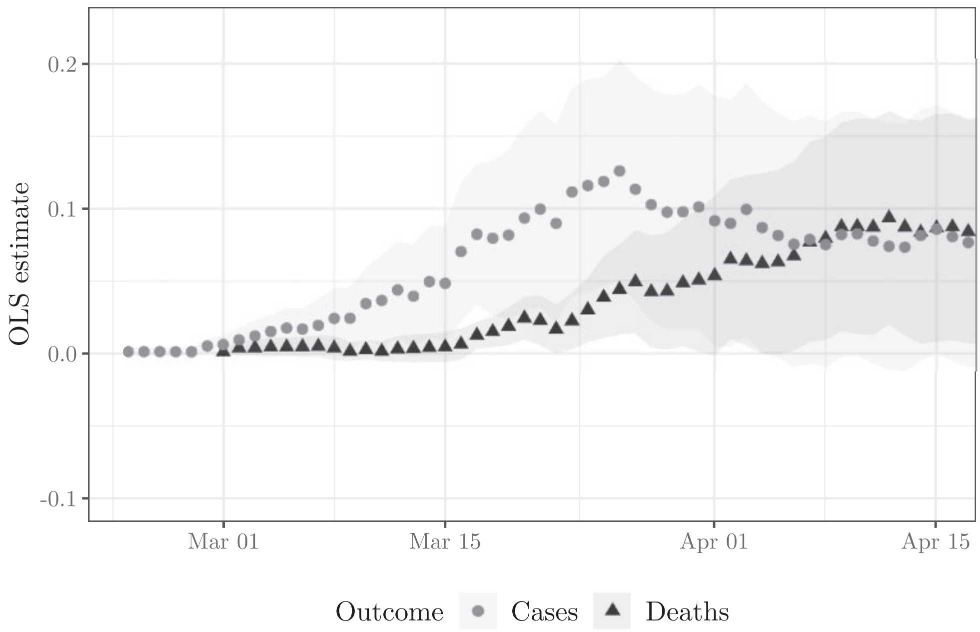

FIGURE 4

OLS estimates of effect of differential viewership on cases and deaths

Notes: This figure displays effects of differential viewership of *Hannity* and *Tucker Carlson Tonight* on log one plus cases and log one plus deaths. We report day-by-day results for the correlation between log deaths and log cases with the standardized viewership difference between *Hannity* and *Tucker Carlson Tonight*. All regressions are conditional on state fixed effects and a large set of controls: the November 2018 and January 2020 market share of Fox News, the November 2018 market share of MSNBC, log total population, population density, the share of TVs turned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*, the population-weighted latitude and longitude, the percent in the county living in rural areas, the percent white, Hispanic, and black, the percent over the age of 65, the share of men and women lacking high school degrees, the share of men and women lacking college degrees, the fraction of the population lacking health insurance, an age-adjusted measure of the average physical health in the county from 2018, the percent under the federal poverty line, log median household income, the unemployment rate, the 2016 Republican vote share, and the log total number of votes cast in 2016. We cluster standard errors at the DMA level and report 95% confidence intervals.

specifications, are significant at the 1% level. Moreover, our coefficient estimates are relatively stable.[39] Supplementary Appendix Figure A7 shows a generally positive correlation between the R^2 of each model and the coefficient estimate, suggestive evidence that omitted variables downward bias our estimates. Indeed, a simple exercise to estimate omitted variables bias, following best practice recommendations from Oster (2019), suggests that the true effect may be several times larger.[40]

39. We repeat this exercise for every date between 24 February and 15 April for cases and between 1 March and 15 April for deaths. The resulting coefficient stability plots for each day are accessible at https://raw.githubusercontent.com/AakaashRao/aakaashrao.github.io/master/files/ols-cases.gif (cases) and https://raw.githubusercontent.com/AakaashRao/aakaashrao.github.io/master/files/ols-deaths.gif (deaths).

40. The method requires assuming a maximum amount of variation that a hypothetical regression including all observable and unobservable covariates could explain; we follow the recommendation provided in Oster (2019) of using 1.3 times the R^2 value of the most extensive specification. The method also requires specifying the relative importance of observables and unobservables in explaining variation in the outcome variable; we again follow the guidance in Oster (2019) and assume observables and unobservables are equally important.

TABLE 3
Effect of differential viewership on COVID-19 outcomes

	Dependent variable: COVID-19 outcomes						
	Feb 29 (1)	Mar 07 (2)	Mar 14 (3)	Mar 21 (4)	Mar 28 (5)	Apr 04 (6)	Apr 11 (7)
Panel A: Estimates on cases							
Subpanel A.1: OLS							
Hannity–Carlson viewership difference	0.005**	0.019**	0.050**	0.100***	0.103**	0.087**	0.078*
	(0.002)	(0.009)	(0.020)	(0.035)	(0.041)	(0.044)	(0.043)
Subpanel A.2: Two-stage least squares							
H–C viewership difference (predicted)	0.044***	0.177***	0.382***	0.310**	0.286	0.170	0.169
	(0.014)	(0.048)	(0.106)	(0.146)	(0.186)	(0.196)	(0.190)
Panel B: Estimates on deaths							
Subpanel B.1: OLS							
Hannity–Carlson viewership difference	0.001	0.005	0.004	0.023***	0.043**	0.062*	0.087**
	(0.001)	(0.004)	(0.005)	(0.009)	(0.020)	(0.032)	(0.038)
Subpanel B.2: Two-stage least squares							
H–C viewership difference (predicted)	0.004*	0.018*	0.023	0.085***	0.267***	0.373**	0.341*
	(0.002)	(0.010)	(0.014)	(0.031)	(0.085)	(0.156)	(0.182)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,100	3,100	3,100	3,100	3,100	3,100	3,100

Notes: The dependent variable is the log of one plus the cumulative number of COVID-19 cases in the county as of the date referenced in the column. Panel A.1 reports OLS estimates of the log of one plus cases upon the standardized difference in Hannity–Carlson viewership; Panel B.1 replicates for deaths. Panel A.2 reports two-stage least squares estimates of the log of one plus cases upon the standardized difference in Hannity–Carlson viewership, instrumented by $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$—that is, the number of TVs on during Hannity's timeslot based on other DMAs in the same time zone, excluding TVs watching *Hannity*, multiplied by Fox News' viewership share, excluding *Hannity* and *Tucker Carlson Tonight*.; Panel B.2 replicates for deaths. All specifications include controls for the predicted share of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*, Fox News' and MSNBC's share of cable in January 2018, Fox News' share of television in January 2020, and the full set of county-level controls. Standard errors are clustered at the DMA level.

3.4. *Instrumental variables estimates on health outcomes*

We may remain concerned about factors driving both viewership preferences for *Hannity* over *Tucker Carlson Tonight* and COVID-19 outcomes. In this section, we describe our approach to generate plausibly exogenous variation in relative viewership of *Hannity* over *Tucker Carlson Tonight*. As Equation (2) makes clear, the underlying variation in D_{mc} is driven by the combination of timing preferences and channel preferences. A lingering concern may be that these preferences are correlated with other unobservable determinants of COVID-19 outcomes. In particular, while the political slant of different shows on Fox News are similar and arguably cater the content towards viewers with similar beliefs and political viewpoints, the shows are not identical. Therefore, it could be that counties that favour *Hannity* over *Tucker Carlson Tonight* are somehow fundamentally different along dimensions that matter for health outcomes. Here, we alleviate some of these concerns by employing a leave-out approach, isolating cleaner variation that is less subject to confounders.

3.4.1. Leave-out IV. The logic of the instrument is as follows. The OLS specification already flexibly controls for the tendency to watch TV at certain hours in the evening. If timing preferences are homogeneous across Fox and non-Fox viewers, timing preferences that determine health outcomes do not bias the OLS estimates. However, if timing preferences are heterogeneous across people that regularly watch Fox compared to those that prefer other channels, estimates may be biased. For example, if during the time *Hannity* airs, regular Fox viewers tend to prefer to stay home and watch TV while non-Fox viewers like to socialize in restaurants and bars (facilitating the spread of the virus), the OLS estimates would be (negatively) biased. To purge the treatment variable D_{mc} from any such variation, we isolate variation in timing preferences among only *non-Fox* viewers: $\tilde{s}_{mc,H}$, the average share of households that watch TV when *Hannity* airs, leaving out households that watch Fox News.

We use an analogous approach for channel preferences. The OLS estimations already control for the market share of Fox News, which may correlate with other determinants of health outcomes. Under the assumption that these other determinants do not also correlate with the *interaction* between channel preferences and timing preferences, the OLS estimates are unbiased. However, if regular Fox viewers that like to socialize in restaurants and bars prefer to watch TV slightly later in the evening when *Hannity* airs, whereas regular Fox viewers that seldom go to restaurants and bars stay home and watch TV earlier while *Tucker Carlson Tonight* is on, the OLS estimates would be (negatively) biased. To address this concern, we isolate variation in channel preferences during other timeslots outside of when *Hannity* and *Tucker Carlson Tonight* is live on air: $\tilde{f}_{mc,-HT}$, the average market share of Fox News, leaving out ratings during the 8–10 p.m. Eastern Time.

Based on this logic, our leave-out instrument, Z_{mc}, consists of the interaction $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$. The resulting first-stage regression is:

$$D_{mc} = \alpha + \beta_1 Z_{mc} + \beta_2 \tilde{s}_{mc,H} + \beta_3 \tilde{f}_{mc,-HT} + \Pi_t X_{mc} + \varepsilon_{mc}. \quad (3)$$

Our identification strategy leverages distinct sources of identifying variation depending on the set of fixed effects that we include. In specifications without any geographic fixed effects, we exploit variation across time zones, thus exploiting variation in local airing time of the shows relative to the local "prime time"—the period in the evening where the number of TVs turned on peaks. For example, *Hannity* airs 1 h after the prime time in EST, while it airs 2 h before the prime time in PST. On the other hand, specifications with Census division and state fixed effects only exploit variation within a given time zone. Reassuringly, our coefficient estimates are relatively similar in magnitude across different choices of controls and fixed effects.

3.4.2. Correlation with pre-determined characteristics. To illustrate the spatial distribution of the induced variation, Figure 5 plots our instrument values, residualized by the baseline controls in specification 3. In Supplementary Appendix Figure A8, we report regressions using each county-level covariate as an outcome, scaled to a standard normal distribution to facilitate interpretation, on our instrument. Only a single coefficient (percentage black) is significantly significant at the 5% level, and coefficient magnitudes are generally small. Similarly, in Supplementary Appendix Figure A9, we use data from the Cooperative Congressional Elections Study (Schaffner, Ansolabehere and Luks, 2021) to show that our instrument is not correlated with a wide range of policy preferences, including attitudes toward women and minorities. We additionally use data from the Yale Climate Opinion Maps (Howe, Mildenberger, Marlon and Leiserowitz, 2015) to show that our instrument is uncorrelated with belief in anthropogenic climate change (a measure of trust in science). Again, only a single coefficient (belief that the military should promote democracy abroad) is statistically significant at the 5% level, and coefficient magnitudes are small. Taken together, this evidence helps mitigate

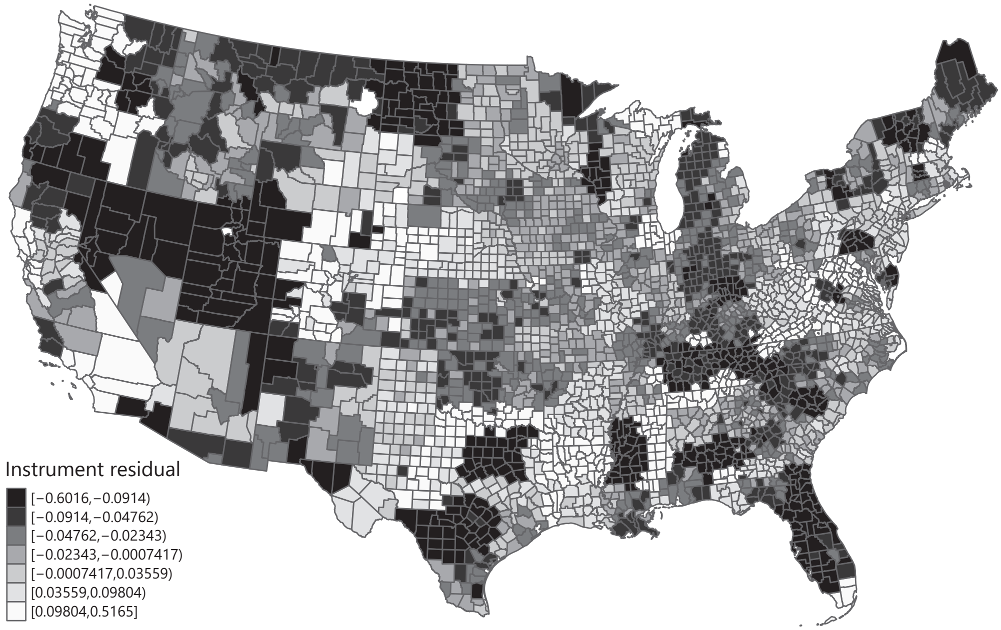

FIGURE 5

Residualized Hannity–Carlson instrument values

Notes: This figure plots the values of our instrument, $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$, residualized by our full set of controls: the November 2018 and January 2020 market share of Fox News, the November 2018 market share of MSNBC, log total population, population density, the predicted share of TVs turned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*, the population-weighted latitude and longitude, the percent in the county living in rural areas, the percent white, Hispanic, and black, the percent over the age of 65, the share of men and women lacking high school degrees, the share of men and women lacking college degrees, the fraction of the population lacking health insurance, an age-adjusted measure of the average physical health in the county from 2018, the percent under the federal poverty line, log median household income, the unemployment rate, the 2016 Republican vote share, and the log total number of votes cast in 2016.

concerns that the differences in the content of the two programs reflect a choice by Fox News or the individual anchors to tailor their programs toward differences in their audiences, as such differences would have to be latent and uncorrelated with any of the observables we examine. Nevertheless, as in the OLS approach, we show in a transparent manner the extent to which results are robust to permutations across all possible combinations of the groups of covariates.

One potential confound is that our effects reflect not differences in exposure to the diverging narratives presented on *Hannity* and *Tucker Carlson Tonight*, but rather heterogeneity in the overall persuasive effect of Fox News on partisanship across counties, which correlates with these counties' timing preferences for TV viewership. In this case, the effects we estimate would be driven not by differences in opinion content, but rather by differences in partisanship prior to the onset of the pandemic. Reassuringly, the instrument is uncorrelated with the 2016 county Republican vote share. A more subtle concern is that there exist differences in the latent persuasive potential of Fox News across counties that became relevant only during the pandemic. We see this contingency as unlikely, especially given the timing of effects we document in Section 3.5.

3.4.3. Exclusion restriction. Our approach is motivated by the fact that (1) *Hannity* and *Tucker Carlson Tonight* are the most-viewed cable news programs in the US, and by the fact that (2) the two shows conveyed very different narratives about the threat posed by COVID-19 at the early stages of the pandemic. In this sense, the instrumental variable approach is designed to shift exposure to different opinions through its effects on the relative viewership of these two programs. However, the assumption that all of the effects of the instrument on COVID-19 outcomes operate exclusively through differential exposure to *Hannity* over *Tucker Carlson Tonight*—the outcome variable in the first-stage regressions—requires that the instrument does not have any spillovers, negative or positive, onto viewership of other shows. This assumption would be violated if, for example, our instrument's effects on relative viewership of *Hannity* and *Tucker Carlson Tonight* induces viewers to change their consumption of other Fox News shows. Such spillovers could be very complex and may violate a narrow exclusion restriction, complicating interpretation of the two-stage least squares regressions. For these reasons, while we proceed in this section under the assumption that the exclusion restriction described above holds, in Supplementary Appendix Section D.1, we relax this assumption to employ a more general approach allowing for arbitrary spillovers across evening Fox News programs, while still allowing us to investigate the hypothesized mechanism of exposure to differential narratives about COVID-19 crisis.

3.4.4. Instrument relevance. As we show in Supplementary Appendix Table A4, our instrument strongly predicts viewership of *Hannity* relative to *Tucker Carlson Tonight*. The first-stage coefficient estimates remain relatively constant over Census division and state fixed effects and as we include controls for population and population density, MSNBC's share of cable, and our rich set of county-level covariates: a one standard deviation higher value of the instrument is associated with approximately a one standard deviation higher viewership of *Hannity* relative to *Tucker Carlson Tonight* ($p < 0.001$), with somewhat tighter confidence intervals when fixed effects are included. As in the OLS specification, we cluster standard errors at the DMA level.[41]

3.4.5. Results on COVID-19 cases and deaths. Figure 6, which for consistency and ease of comparison mirrors the OLS specification of Figure 4 (i.e. the specification with the most extensive set of controls and fixed effects), shows the day-by-day 2SLS estimates of the effects of the standardized Hannity–Carlson viewership difference on cases and deaths. Effects on cases start to rise in early March and peak in mid-March before gradually declining, consistent with Hannity's changing position on COVID-19. Consistent with estimated lags between case and death reporting, effects on deaths start emerging approximately three weeks after cases.[42] A one standard deviation greater viewership of *Hannity* relative to *Tucker Carlson Tonight* is associated with 27 percent more deaths on March 28 ($p < 0.01$), 37 percent more deaths on April 4 ($p < 0.05$), and 34 percent more deaths on April 11 ($p < 0.10$).

The initial divergence and eventual plateauing of effects on COVID-19 outcomes are consistent with our proposed mechanism that differential reporting between Hannity and Carlson about COVID-19 throughout February and early March are driving our results, as we explore in Section 3.5.2. We report 2SLS results at weekly intervals in regression table form in Table 3.[43]

41. The analogous results with standard errors clustered at the state level are reported in Supplementary Appendix Figure A10.

42. See, e.g., "A Second Coronavirus Death Surge is Coming." *The Atlantic*, 15 July 2020.

43. Consistent with the pattern that including richer controls increases OLS coefficient estimates, our estimated IV coefficients are larger than the estimated OLS coefficients. In addition to the possibility of measurement error in Nielsen's (sample-based) measure of viewership, this also may be due to the fact that our instrument, while uncorrelated with observables, varies across counties in the strength of its first stage. For example, the instrument has a larger first stage in counties with above-median age. Thus, the induced variation may lead our instrumental variables estimate to place greater weight (relative to the OLS estimate) on counties with higher case and death loads.

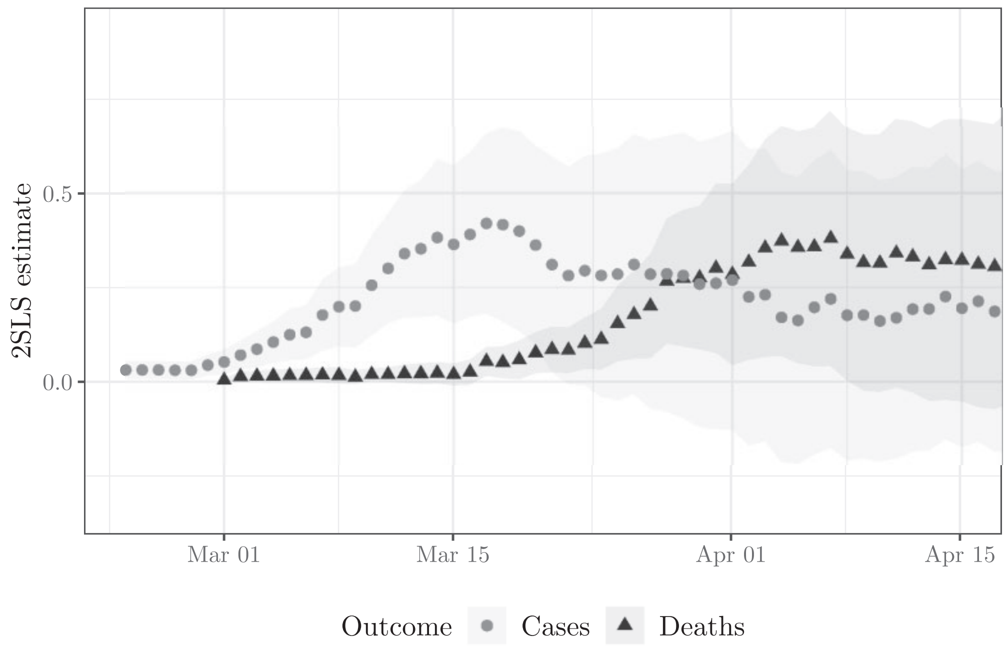

FIGURE 6

2SLS estimates of effect of differential viewership on cases and deaths

Notes: This figure shows day-by-day 2SLS estimates on log one plus cases and log one plus deaths. We report day-by-day effects of the standardized difference in viewership of *Hannity* vs. *Tucker Carlson Tonight*, instrumented by $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$ and controlling for state fixed effects and a large set of controls: Fox News' and MSNBC's share of cable in January 2018, Fox News' share of television in January 2020, the population density of the county, the log of the county's total population, the predicted share of TVs turned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*, the population-weighted latitude and longitude, the percent in the county living in rural areas, the percent white, Hispanic, and black, the percent over the age of 65, the share of men and women lacking high school degrees, the share of men and women lacking college degrees, the fraction of the population lacking health insurance, an age-adjusted measure of the average physical health in the county from 2018, the percent under the federal poverty line, log median household income, the unemployment rate, the 2016 Republican vote share, and the log total number of votes cast in 2016. We cluster standard errors at the DMA level and report 95% confidence intervals.

3.4.6. Robustness to choice of specification. As in Section 3.3.4, we run our specifications under every possible combination of our nine sets of county-level controls and our three levels of geographical fixed effects. Supplementary Appendix Figure A6 reports coefficient estimates for each of these 1,536 models for cases as of 14 March and deaths as of 28 March. Confidence intervals for models without any geographical fixed effects are wider due to unobservable variation in the outcome; once division or state fixed effects are included, the coefficients are relatively stable and tightly estimated. The majority of coefficient estimates on cases and deaths are statistically significant at the 1% level, as are all estimates drawn from specifications with state fixed effects included.[44]

The estimated OLS coefficients are generally increasing as we control for more observables, suggesting that unobservables generate a negative bias. In contrast, the 2SLS coefficient estimates are relatively stable across these same permutations of controls, suggesting less of a bias. The

44. We repeat this exercise for every date between 24 February and 15 April for cases and between 1 March and 15 April for deaths. Animations of the resulting coefficient stability plots for each day are accessible at https://raw.githubusercontent.com/AakaashRao/aakaashrao.github.io/master/files/iv-cases.gif (cases) and https://raw.githubusercontent.com/AakaashRao/aakaashrao.github.io/master/files/iv-deaths.gif (deaths).

OLS estimates can thus be interpreted as a plausible lower bound on the true causal effect of differential viewership on COVID-19 trajectories.

One potential concern is that COVID-19 hotspots with large numbers of cases or deaths may skew our results. We probe robustness to outliers by residualizing our outcome variables and the instrument by our controls and fixed effects, then plotting the residuals of our outcome variables against the residuals of the instrument in Supplementary Appendix Figure D1. As in the OLS estimates, neither plot gives cause for concern that our estimates are driven by outliers. To further ensure that counties with large number of cases or deaths are not driving our results, in Supplementary Appendix Figure A11, we estimate our time series figures leaving out entire states containing prominent COVID-19 hotspots, leaving out the top 1% of counties by cases, and leaving out the highest-case county in each state. Point estimates decrease slightly but remain statistically significant at the 5% level in all but the most demanding specification (leaving out the entire states of CA, MA, NJ, NY, and WA), in which they are significant at the 10% level. We next replicate our estimates in Supplementary Appendix Table A5 using Poisson and zero-inflated negative binomial regression. While these coefficients and associated standard errors must be interpreted with caution due to the high number of controls and the high-dimensional fixed effects (Cameron and Trivedi, 2015), we again estimate statistically significant and relatively stable effects of our instrument on both cases and deaths.

In Supplementary Appendix D, we carry out a number of exercises to probe the robustness of our results. In particular, we demonstrate that our estimates are not driven by zero values, we conduct several randomization exercises to assess the validity of our inference, and we show our estimates remain stable under two alternative instrumental variable strategies. In Supplementary Appendix E, we assess the plausibility of our estimated magnitudes through the lens of an epidemiological model.

3.5. *Mechanisms*

3.5.1. Stay-at-home behaviour. Based on our survey results and the timing of differences between *Tucker Carlson Tonight* and *Hannity*—which had largely converged in their coverage by mid-March—we do not expect stay-at-home behaviour to be a primary mechanism driving our results. Indeed, very few Americans had begun staying at home in response to the pandemic before mid-March (Allcott *et al.*, 2020), and our survey suggests that behavioural changes such as physical distancing (i.e. staying more than 6 feet apart from others and avoiding large events) were far more prominent. Nonetheless, we investigate the extent to which differential narratives affected stay-at-home behaviour. We use smartphone GPS data from the Bureau of Transportation Statistics, which aggregates data "from merged multiple data sources that address the geographic and temporal sample variation issues often observed in a single data source," mitigating concerns about measurement error. We use these data to create a panel at the day-by-county level tracking the number of devices that remain home throughout the day.[45] We then estimate our primary instrumental variables specification, using the share staying home in each county as the outcome. In addition to the controls above, we also control for the share of devices staying home on the same day in 2019 in order to increase the precision of our estimates, and we report one-week rolling means.

We report results in Supplementary Appendix Figure A12, focusing on the period before state and local stay-at-home orders were implemented. Throughout most of February, our

45. See https://www.bts.gov/browse-statistical-products-and-data/trips-distance/daily-travel-during-covid-19-pandemic.

estimated effects of differential coverage on the fraction staying home are small and statistically indistinguishable from zero. We detect significant negative effects on stay-at-home behaviour in the first 2 weeks of March, consistent with the gap in narratives presented on the two shows. We estimate relatively small effects (peaking at approximately 0.8 percentage points, or approximately 5% of the 2019 mean), consistent with stay-at-home behaviour not being a primary mechanism driving our estimated treatment effects. Our results are not statistically significant if we use mobility data from the SafeGraph GPS panel rather than the BTS data; although the coefficient estimates are similar, the standard errors are much larger.

3.5.2. Timing of effects. We now examine the timing of deaths and cases relative to the timing of differences in content of the two shows more closely. To construct a Carlson–Hannity "pandemic narrative gap", we use our coding results from Section 3.1: for each day, our index is defined as the difference between the average of the five ratings of the *Tucker Carlson Tonight* episode and the average of the five ratings of the *Hannity* episode on that day. Thus, higher values of the index indicate that the *Tucker Carlson Tonight* episode that aired on that day portrayed COVID-19 as a much more serious threat than the *Hannity* episode on the same day, while lower values of the index indicate that the two episodes were similar in their coverage. Second, to construct the Carlson–Hannity "behavioural change gap," we return to our survey results from Section 3.2: for each day, the gap is defined as the associated Hannity coefficient minus the same-day Carlson coefficient from Figure 3B—that is, the difference between the marginal effects of viewership of these two shows on the event that the respondent had changed their behaviour to act more cautiously in response to COVID-19 by the date in question. Thus, we should expect the behavioural change gap to lag the pandemic narrative gap, since viewers react to the differences in narratives presented on the two shows.

Figure 7 plots the pandemic narrative gap and the behavioural change gap. To facilitate plotting on the same figure, we rescale the pandemic coverage and behavioural change gaps by dividing each series' coefficients by the maximum coefficient value over the series, such that the maximum value is 1. Figure 7 also plots the (rescaled) 2SLS estimates of the effect of the Hannity–Carlson viewership gap (instrumented by Z_{mc}) on the fraction leaving home each day, log one plus cases, and log one plus deaths.

The pandemic narrative gap peaks in mid-February, a period during which there was no discussion of COVID-19 on *Hannity* and during which *Tucker Carlson Tonight* discussed the topic on virtually every episode, before declining to zero by mid-March. The behavioural change gap and gap in the share leaving home follow a similar shape with a 2-week lag, peaking in early March before declining. The trend in coefficient estimates on cases closely mirrors the trend in the pandemic narrative gap (with a lag of approximately 1 month) and the trend on the behavioural change gap (with a lag of approximately 2 weeks), while the trend in coefficient estimates on deaths follows with an additional 2-week lag. These findings suggest that the effects of differential exposure to *Hannity* and *Tucker Carlson Tonight* that we document are *not* driven by longer-term past differential exposure to the shows or unobservable factors correlated both with the spread of the virus and preferences for one show over the other, but rather by differences in how the two shows covered the pandemic as it began to spread.

4. DISCUSSION AND CONCLUSION

Opinion programs represent a dominant and growing share of primetime cable television. Because they are less anchored in factual reporting, different opinion programs offer different, and often contradictory, narratives about reality. We examine the role of these narratives in shaping high-stakes decisions. Motivated by an experiment showing that people turn to opinion programs for

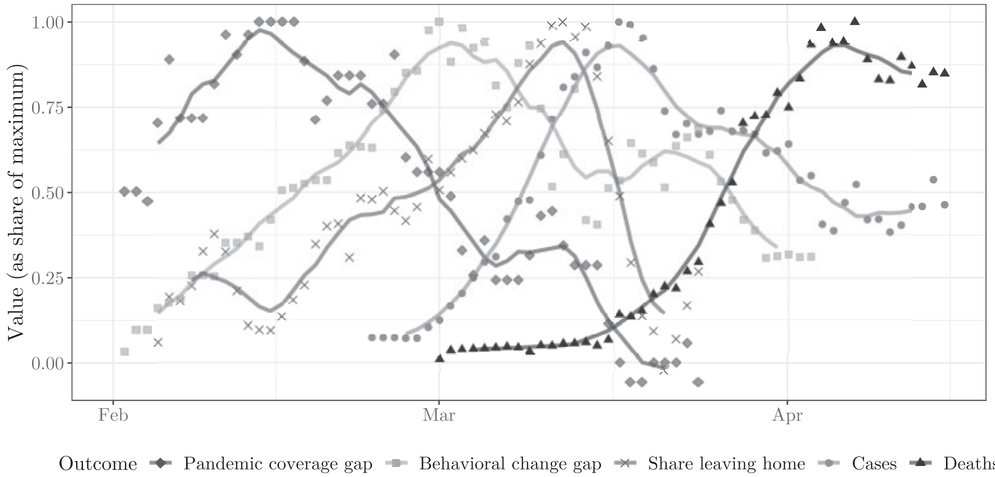

FIGURE 7

Carlson–Hannity content gaps and effects on cases and deaths

Notes: Figure 7 shows five time series. First, in diamonds, we plot the "pandemic coverage gap": the difference in portrayed seriousness of the coronavirus threat on *Tucker Carlson Tonight* vs. *Hannity*. Second, in squares, we plot the "behavioural change gap": the difference between the *Hannity* and *Tucker Carlson Tonight* coefficients in regressions of an indicator variable for whether the respondent has changed their behaviour by the date in question on indicators for viewership of different Fox News shows. In crosses, circles, and triangles, we plot the 2SLS estimates of the Hannity-Carlson viewership gap (instrumented by $\tilde{s}_{mc,H} \times \tilde{f}_{mc,-HT}$) on the share leaving home, log one plus cases, and log one plus deaths, respectively. These latter three specifications control for state fixed effects, Fox News' and MSNBC's share of cable in January 2018, Fox News' share of television in January 2020, the population density of the county, the log of the county's total population, the predicted share of TVs tuned to non-Fox channels during *Hannity*, *Tucker Carlson Tonight*, and *The Ingraham Angle*, the population-weighted latitude and longitude, the percent in the county living in rural areas, the percent white, Hispanic, and black, the percent over the age of 65, the share of men and women lacking high school degrees, the share of men and women lacking college degrees, the fraction of the population lacking health insurance, an age-adjusted measure of the average physical health in the county from 2018, the percent under the federal poverty line, log median household income, the unemployment rate, the 2016 Republican vote share, and the log total number of votes cast in 2016. We show one-week moving averages for each time series. All coefficients are rescaled to facilitate plotting on the same figure.

information about objective facts, even in the presence of large incentives, we study the effects of the two most popular opinion programs in the US—*Hannity* and *Tucker Carlson Tonight*—which diverged sharply in their narratives about the dangers posed by COVID-19 at the early stages of the pandemic. We validate these differences in content with independent coding of shows' transcripts and present survey evidence that, consistent with these content differences, viewers of *Hannity* changed behaviour in response to the virus later than other Fox News viewers, while viewers of *Tucker Carlson Tonight* changed behaviour earlier. Using both a selection-on-observables strategy with a rich set of controls and different instrumental variable strategies exploiting variation in the timing of TV viewership, we then document that greater exposure to *Hannity* relative to *Tucker Carlson Tonight* increased COVID-19 cases and deaths in the initial stages of COVID-19 pandemic.

4.1. *Broader implications*

The initial period of the COVID-19 pandemic was characterized by substantial objective uncertainty, with little known about how the virus spreads, its medium and long-term effects, and the best measures to contain it. This uncertainty was reflected not only on cable and broadcast news but also in the rapidly changing public health recommendations (Rafkin, Shreekumar and Vautrey, 2021). How might opinion-based news influence beliefs and behaviour in contexts characterized by less objective uncertainty? On one hand, we might expect opinion-based news to be less influential in contexts where the facts are largely established. Yet, narratives featuring exaggerations and distortions of the truth—and viewers' propensity to take such narratives literally—appears widespread even in these contexts. For example, Tucker Carlson claimed in September 2020 that climate change is a "liberal invention"[46]; Sean Hannity repeatedly claimed that the ACA established "death panels" to decide whether individuals were worthy of health care[47]; and Rachel Maddow claimed that new abortion restrictions in Ohio would require women seeking abortions to undergo "mandatory vaginal probes"[48]. While causality remains unclear, all three contexts are characterized by substantial disagreement about objective facts.

Perhaps an even more striking such example is the dramatic growth of election conspiracism following the 2020 election and the historic Capitol Riot of 6 January 2021. On 7 November 2020, "straight news" anchors—including those on Fox News—declared Biden the winner of the election and, over the course of the next several weeks, pushed back against the narrative that Democrats had stolen the election.[49] In contrast, opinion anchors continued to question or outright challenge the election's legitimacy, giving outsized weight to conspiracy theories and personal anecdotes from observers at the expense of unambiguous statements from election officials and judges.[50] To shed light on the relationship between the diverging narratives on opinion vs. straight news shows on Fox News, we conducted a large-scale representative survey ($n = 13,744$) in which we elicited rich data on people's news consumption as well as their beliefs about election fraud. The results highlight robust correlations between viewership of opinion programs and beliefs about election fraud (see Figure 8). Table 4 shows that controlling for a rich set of observable characteristics, Fox News viewers who regularly watched opinion shows, relative to Fox News viewers who did not watch opinion shows, were 17 percentage points more likely to believe that Trump had received more votes than Biden, 19 percentage points more likely to believe that voting machines had switched votes from Trump to Biden, and 8 percentage points more likely to believe that Trump would be inaugurated on January 20.[51] Consistent with our findings, the social media feeds of participants in the 6 January Capitol Riot (including Ashli Babbitt, the woman fatally shot while attempting to breach the Speaker's Lobby) disproportionately feature content from these anchors.[52]

46. See "Tucker Carlson says climate change is a liberal invention 'like racism' in shocking on-air rant," *The Independent*, 13 September 2020.

47. See "The return of ObamaCare's 'death panels"', *Hannity*, 30 July 2013.

48. See "Rachel Maddow says that Ohio budget includes requirement for transvaginal ultrasound," *Cleveland.com*, 9 July 2013.

49. See "The Moment Fox News Called the Election and Ended the Trump Love Affair." *The Independent*, 8 November 2020. "Bret Baier Corners Josh Hawley About Contesting Election, Makes Senator Squirm." *The Wrap*, 4 January 2021.

50. See "Tucker Carlson Claims Virtually Every Power Center on Earth Rigged the Election for Joe Biden." *Media Matters for America*, 4 January 2021. "Opinion: Sean Hannity, Americas No. 2 Threat to Democracy: An A-to-Z guide." *The Washington Post*, 14 December 2020. The Fox News Decision Desk was in fact the first major outlet to project Arizona, a state crucial for Trump's reelection chances, for Biden. Faced with criticism from opinion anchors Sean Hannity and Tucker Carlson, Decision Desk director Arnon Mishkin defended his team's call, stating "The primetime schedule at Fox is the opinion part of Fox. And, you know, the great thing about opinion is that everyone can have an opinion." See "The Man Behind the Fox News Decision Desk." *The Dispatch*, 6 November 2020.

51. Supplementary Appendix Figure A13 presents a coefficient stability plot demonstrating the robustness of these correlations to different combinations of demographic controls, including the strength of partisan identification.

52. See "Fox Settled a Lawsuit Over Its Lies. But It Insisted on One Unusual Condition." *The New York Times*, 17 January 2021. "After Deadly Capitol Riot, Fox News Stays Silent On Stars' Incendiary Rhetoric." *National Public Radio*, 13 January 2021.

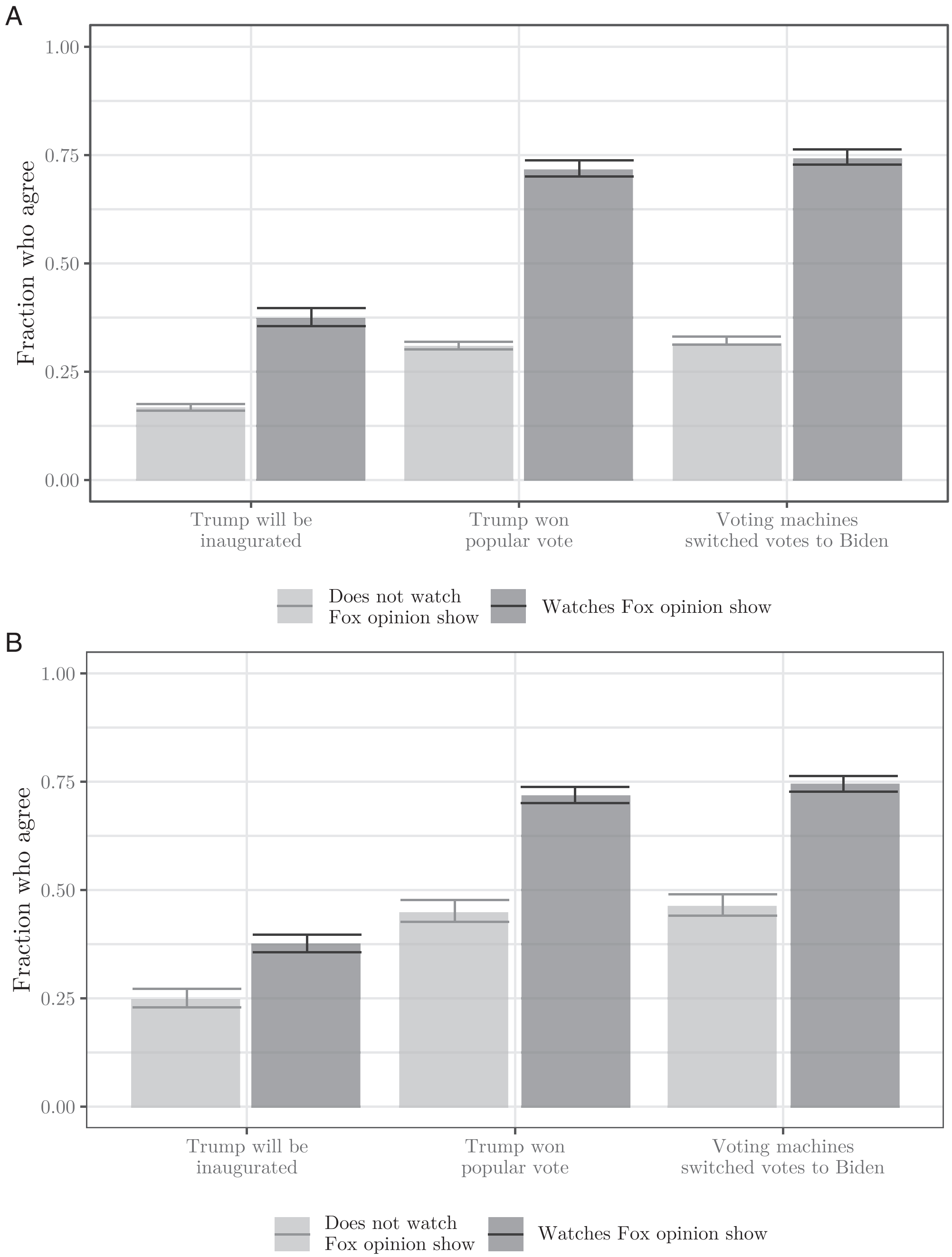

FIGURE 8

Opinion show viewership and election conspiracism

Notes: This figure reports data from an election survey conducted between 30 December and 2 January. The figure plots the mean level of agreement with statements indicating beliefs in various election-related conspiracy theories, separately for respondents who watch Fox News opinion shows and respondents who do not. (A) presents estimates using the full sample; (B) restricts to Fox News viewers. 95% confidence intervals based upon robust standard errors are reported.

TABLE 4
Correlation between opinion show viewership and election conspiracism

	Dependent variable:		
	Voting machines (1)	Popular vote (2)	Inauguration (3)
Panel A: All respondents			
Watches Fox opinion show	0.196***	0.177***	0.078***
	(0.014)	(0.014)	(0.012)
Watches MSNBC opinion show	−0.091***	−0.093***	−0.006
	(0.026)	(0.025)	(0.022)
Watches Fox News	0.046***	0.043***	−0.001
	(0.012)	(0.012)	(0.011)
Watches MSNBC	−0.068***	−0.038*	−0.059***
	(0.023)	(0.023)	(0.020)
Watches CNN	−0.060***	−0.064***	−0.048***
	(0.010)	(0.009)	(0.008)
Dep. var. mean	0.390	0.376	0.201
Observations	13,744	13,744	13,744
Panel B: Fox News viewers only			
Watches Fox opinion show	0.191***	0.166***	0.082***
	(0.015)	(0.015)	(0.015)
Dep. var. mean	0.632	0.612	0.325
Observations	3,681	3,681	3,681

Notes: The dependent variable in Column 1 is an indicator taking value 1 if the respondent believed that Trump would be inaugurated on 20 January 2021. The dependent variable in Column 2 is an indicator taking value 1 if the respondent believes that Trump won the popular vote in the 2020 US Presidential election. The dependent variable in Column 3 is an indicator taking value 1 if the respondent believes that voting machines switched votes from Trump to Biden. Panel A presents estimates on the full sample; Panel B restricts to Fox News viewers. All specifications control for age, a white indicator, a Hispanic indicator, a male indicator, a set of education indicators, a set of household income indicators, a set of employment indicators, a married indicator, and the respondent's political party. Robust standard errors are reported.

Neither the examples of narratives about climate change, the Affordable Care Act, or abortion restrictions nor our survey can establish causality. The evidence suggests, however, that opinion-based news may be important not only in contexts with high objective uncertainty, such as the COVID-19 pandemic, but also in contexts where the facts are largely established.

4.2. *Open areas for research*

Our article suggests several directions for future research. While we study the effects of *short-run*, contemporaneous exposure to diverging narratives on opinion programs, equally important are the effects of *long-run* exposure to opinion programming and other media untethered from factual reality. Such content undermines the role of expertise—e.g. that of climate scientists, election administrators, or public health officials—and promotes subjective commentary and personal reactions over factual reporting. Particularly given the dramatic growth in opinion programming at the expense of straight news reporting, this trend may fuel conspiracism, disagreement about objective facts, and affective and belief polarization. Empirical work that is able to identify these long-run effects—and more fundamentally, greater behavioural evidence on the determinants of trust in subjective vs. objective statements, including the role of personal experiences and reference points—would be particularly valuable.

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Supplementary Data

Supplementary data are available at *Review of Economic Studies* online.

Data Availability Statement

The data and code underlying this research is available on Zenodo at https://doi.org/10.5281/zenodo.7050175.

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